2021-11-01

Microgrid Design And Component Replacement Analysis

Jose Trinidad Reyes
University of Texas at El Paso

MICROGRID DESIGN AND COMPONENT REPLACEMENT

ANALYSIS

JOSE TRINIDAD REYES PORTILLO

Doctoral Program in Environmental Science and Engineering

APPROVED:

Jose F. Espiritu, Ph.D., Chair

Heidi Taboada, Ph.D.

Jaime Sanchez, Ph.D.

Vinod Kumar, Ph.D.

Stephen L. Crites, Jr., Ph.D.
Dean of the Graduate School

MICROGRID DESIGN AND COMPONENT REPLACEMENT

ANALYSIS

By

JOSE TRINIDAD REYES PORTILLO, M.C.

DISSERTATION

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in partial fulfillment

of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

Environmental Science and Engineering

THE UNIVERSITY OF TEXAS AT EL PASO

December 2021

Abstract of The Dissertation

This study focuses on developing specific methods that can be friendly applied to obtain efficient usage and maintenance of electricity production in a micro-grid used in a residence or stand-alone building to determine long-term component replacement strategies for aging components. After designing the best option to produce electricity by installing green energies such as photovoltaic panels and their proper devices such as inverters and batteries, this work has developed electric power reliability models to approximate the most efficient component replacement accurately. Due to the nature of the components of this study, repair time is not a substantial part of the study; however, it is essential to consider two elements that directly affect the component replacement analysis: replacement cost and maintenance cost. Replacement cost is associated directly with the market cost at the time when the asset will be replaced. Additionally, maintenance cost is associated with three elements in the planned horizon: Maintenance cost planned (budget), maintenance cost due to not time-dependent failures (exponential distribution), and maintenance cost due to time-dependent failures (Weibull distribution). This study introduces the idea to plan an economic horizon according to the maintenance cost behavior against replacement cost by analyzing the relationship between reliability index and failure mode. Once the replacement times are specified for each of the micro-grid components, it is time to select the ideal component to be replaced from a finite number of suppliers. Each particular component has a certain number of characteristics that are considered essential for its operation, which is compared between the different brands.

Acknowledgments

First, I would like to specially thank God whos without him nothing is possible. I have to thank my advisor Dr. Jose F. for his constant support and expert advice. Dr. Taboada who is very bright and smart person who shared useful advices. I am so glad for choosing Dr. Sanchez as part of my dissertation committee, thank you for your support every time. I also would like to thank Dr. Francisco O. Aguirre for his invaluable advice and help. Please do not blame me if I do not mention your name, it is just that it is almost impossible for me to mention all the people that made my life more enjoyable during my PhD studies.

During these years I would like thank to Fulbright and UTEP who gave me the first opportunity to introduce me in the doctoral studies. In the same way, thank to Dr. Lina Handam for the opportunity and her confidence.

Finally, I would like to thank my family. My wife Ruth, my daughters Isabel, Cristina and Teresa whose are part of my life and my best motivation. Thanks to my mother who's advice will be on me as long as my mi life.

List of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Nowadays, populations increase around the world. Everyday people request more and more energy to perform normal human activities to survive. Transportation, artificial light, climates, manufacturing, among others are some examples of how important is the electricity in our lives. Currently, the most common method to produce electricity is based on fossil fuel; nevertheless, this method produces many quantities of Earth pollution. Natural options are offered by the Earth to produce electricity such as photovoltaic, concentrated solar energy, wind energy, fuel cells, and many others. Not only governments around the world are worried about the climate changes but also researchers from developed countries are investing many time and money to create or improve green energy strategies. In 2015, global energy consumption increased by 1.0% and in 2014 increased by 1.1%, while in the last ten years the average energy consumption was 1.9%. This result is one of the consequences of energy savings efforts made by governments and citizens. The power grid consists of three distinct divisions namely, the generating station, transmission network, and distribution network, so the focus of this job it is after distribution network called load center. The load center is categorized by different terms such as public or private no large areas and public or private massive areas. The specific focus of this job is centered on private or public buildings. According to Dan Arvizu, director of National Renewable Lab., buildings consume 38% of the total energy produced in which 71% is electricity. For instance, the energy demand for hotels is on average higher than that of commercial buildings. A typical hotel's annual power consumption ranging from 250 to 350 kWh/m2 versus a typical commercial building at 30–152 kWh/m2. Additionally, large-scale accommodation operations have unique operational characteristics in comparison to their smaller counterparts, demanding even larger load capacities due to increased air-conditioning requirements and more extensive comfort facilities. Average annual energy consumption figures for large hotels range from 450 to 700 kWh/m2 (Dalton et al. 2008). Energy building supply is based on two distinct forms, external electricity supply, which is connected to an electric city company or by itself, which known as a micro-grid. A micro-grid into a building consists of generating enough energy for its consumption through renewable energies. The first stage is to complete the project by installing the whole elements to produce green energy based on solar photovoltaic and/or wind power. However, every system is constituted by assets that have a limited lifetime, so it is important to optimize the equipment cost replacement. Component replacement analysis consists of determining the correct time or schedules to replace certain components in the system such that some total cost function is minimized. Given a level of output or service expected from a component over some time since its installation in the system a decision is required to be made periodically to either keep that component for one more planning period. Replacing component with a new component or doing some maintenance on the existing component, as it wears out with the aging process. In general, the component replacement problem can be categorized as either serial or parallel replacement problem. Serial replacement problem considers a single component or multiple independent components to be replaced at a given point of time and it is assumed that there is no economic interdependencies exist among the components that provide the service together. On the other hand, a parallel replacement problem considers components that are economically interdependent and operate in parallel.

And with the inclusion of the constraints in this type of replacement problems, the desired solutions which include keep and replace decisions for each component over the planning period (Chenna, 2010).

1.2 Proposal Organization

In chapter one, the introduction of the proposed problem is shown. Nevertheless, it is a theoretical chapter that marks the motivation of why we present this proposal. Chapter two shows the revision of literature through articles related to environmental pollution, effects on human health, as well as related to micro-grids and renewable energies around them. How genetic algorithms and micro-grids have been related, as well as the theory of the replacement analysis of components and their relationships with stochastic programming, genetic algorithms, maintenance, and reliability. Chapter three is focused on the methodology, the Markov theory, the reliability theories and the maintenance costs associated with series-parallel connected system processes such as the case of a micro-grid. Chapter four is focused on the development of a model through the cumulative distribution function, the respective expected energy not supplied and its associated cost through Marcov's chain as well as its comparison with the annual replacement cost. In chapter five the result of a numerical example is summarized.

Chapter 2

Literature Review

Nowadays, faced with the growing demand for electric energy, the major challenge is to reduce climatic warming due in large part to emissions released by fossil fuels (Abdelkader et al. 2018). U.S. Energy consumption for generating electricity Fifty years ago was self-sufficient in its supply of petroleum. Today, it imports more than half of its petroleum and consumes 25% of the world's supply (Salameh, 2014). Oil is a limited resource that will eventually run out, at least as an economically viable energy source (Salameh, 2014 and Dawoud et al. 2018). The exponential increase in global energy demand is the primary cause of rapid depletion of fossil fuels and increased greenhouse gas emissions of conventional generators (Fahad et al. 2018, Adefarati and Bansal, 2017). Coal and natural gas are following the same trend. Figure 1 shows the percentage of electricity generated by fuel type in the U.S. Out of 3,883 billion Kwhs generate; coal was the primary fuel type used by approximately 50%. While renewable sources of energy are used to produce only 2.3% of the entire energy. Approximately 90% of the energy is being produced based on fossil fuels (Salameh, 2014 and Dawoud et al. 2018). Fossil fuels can be replaced using alternative energy resources. Specialists forecast that will be integrated and essential for multi-Hybrid Renewable Energy sources which are working together such as hydro, geothermal, Biomass (BM), Wind Turbine Generator (WTG), Solar Photovoltaic (SPV), hydrogen and nuclear at crucial part of energy generation and customer level in reorganized Renewable Energy Systems (Dawoud et al. 2018).

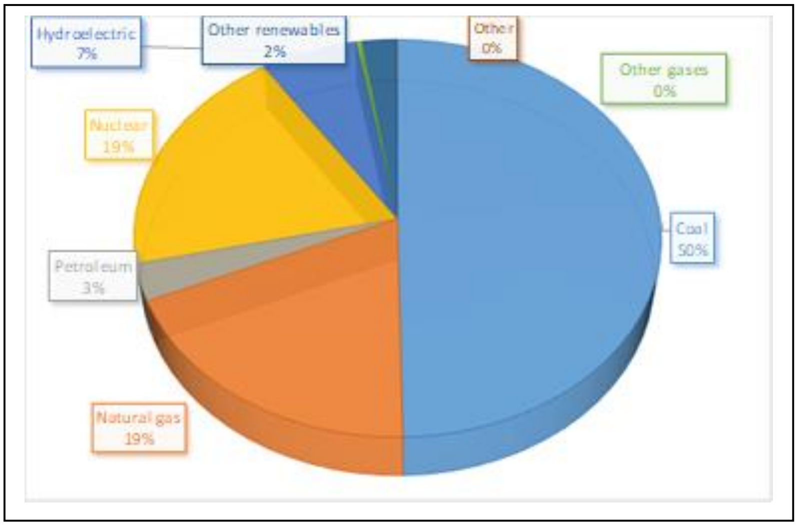

Figure 2.1 U.S electricity Generation by fuel type as of 2005.

2.1 Air Pollution

Global warming, pollution, and high oil prices forced researchers, utility companies, and the general public to pay more attention to renewable energy sources such as wind power and photovoltaic. Because of the competitive nature of the global market, the availability of energy supplies is unpredictable. Figure No. 2 shows the pollution as a result of burning fossil fuel. Atmospheric concentrations of carbon dioxide and CH4 have increased by 31% and 149% respectively, above preindustrial levels since 1750. Around 17% of emissions are accounted for by the consumption of fuel for the generation of electricity using conventional electric power plants, especially the thermal power stations (Salameh, 2014). Conventional energy sources can cause several different types of pollution. Some of the most common ones are air pollution, acid rain, and greenhouse passes. As a result of fossil fuel combustion, chemicals and particulates are released into the atmosphere. Typical examples include carbon monoxide, carbon dioxide, hydrocarbon, nitrogen oxide, and sulfur dioxide (Salameh, 2014). Although human health effects are not attributed to a specific pollutant, it is attributed to air pollution many diseases such as asthma, respiratory difficulties, even cancer. Moreover, humans and non-humans not only are facing air pollution but also soil contamination, poisonous water, and radioactive exposures. The need for more flexible electric systems, changing regulatory and economic scenarios, energy savings and environmental impact are providing impetuous to the development of Microgrids, which will play an essential role in the electric power system of the near future (Mohamed and Koivo, 2012).

Figure 2.2 Pollution from fossil fuel burning.

Image retrieved from: http://www.nationalgeographic.com/environment/global-warming/pollution/

2.2 Health

Air pollution can have several detrimental health effects on many organisms including humans. Acute and chronic exposures to hazardous air conditions are linked to a temporary decrease in lung capacity, inflammation of lung tissue, impairment the body's immune system, premature deaths, birth defects, increase of cancer's risk, asthma, cardiovascular diseases and more others against the human health and its welfares (Salameh, 2014).

2.3 Micro-Grid

A micro-grid is a discrete energy system consisting of distributed energy sources (including demand management, storage, and generation) and loads capable of operating in parallel with, or independently from, the main power grid. The primary purpose is to ensure local, reliable, and affordable energy security for urban and rural communities, while also providing solutions for commercial, industrial, and federal government consumers (Adefarati and Bansal, 2017). Fahad et al. 2018 define a micro-grid as a low-voltage distribution network of interconnected distributed energy resources, controllable loads, and critical loads. Micro-grids can operate in either grid-connected or islanded mode subject to operational characteristics of the main grid. Benefits that extend to utilities and the community at large include lowering greenhouse gas (GHG) emissions and lowering stress on the transmission and distribution system. In many respects, micro-grids are smaller versions of the traditional power grid. Like current electrical grids, they consist of power generation, distribution, and controls such as voltage regulation and switch gears. However, micro-grids differ from traditional electrical grids by providing closer proximity between power generation and power use, resulting in efficiency increases and transmission reductions. Micro-grids also integrate with renewable energy sources such as solar and wind power. Micro-grids perform dynamic control over energy sources, enabling autonomous and automatic self-healing operations. During normal or peak usage, or at times of the primary power grid failure, a micro-grid can operate independently of the larger grid and isolate its generation nodes and power loads from disturbance without affecting the larger grid's integrity. Micro-grids interoperate with existing power systems, information systems, and network infrastructure, and are capable of feeding power back to the larger grid during times of grid failure or power outages. Such a definition of microgrid confirms the substantial necessity the create energy self-sustainability buildings by producing electric energy based on renewable energies.

2.3.1 Solar Energy

Solar energy systems are categorized into two major areas such as photovoltaic (PV) and thermal solar. In terms of use in a building micro-grid, the interesting topic is photovoltaic-related. Photovoltaic cells are devices that convert light into electricity. The direct energy conversion of light to electricity was first reported in 1839 by a Becquerel, who observed a difference in electrical potential between two electrodes immersed in an electrolyte. The potential varied with light intensity (Salameh, 2014). The PV system consists of a photovoltaic array which converts the light photons falling on it to electrons, this generates a DC current which can be boosted with DC-DC converters and then inverted to deliver AC power to the loads. Thus, power electronic devices form an essential part in interfacing the PV to the grid. Also, a specific Maximum Power Point Tracking System (MPPT) is employed to enable the PV to extract maximum energy from the sun by altering the slanting angle of its rays all through the day. At last, the power is filtered with a low-pass filter to eliminate unwanted harmonics before it enters the grid (Hina and Palanisamy, 2015). Photovoltaic systems are used in many applications such as battery charging, water pumping, home power supply, satellite power systems, and so forth. A typical PV cell produces approximately 0.5 volts and a current that much depends on the intensity of the sunlight and the area of the cell. PV cells are connected in series to increase voltage, and a series of cells are connected in parallel to increase current output.

A complete system includes different components that should be selected taking into consideration your individual needs, site location, climate, and expectations. In this section, we review the components' function and several different system types. The functional and operational requirements will determine which components the system will include. It may include significant components as; DC-AC power inverter, battery bank, system and battery controller, auxiliary energy sources and sometimes the specified electrical loads (appliances).

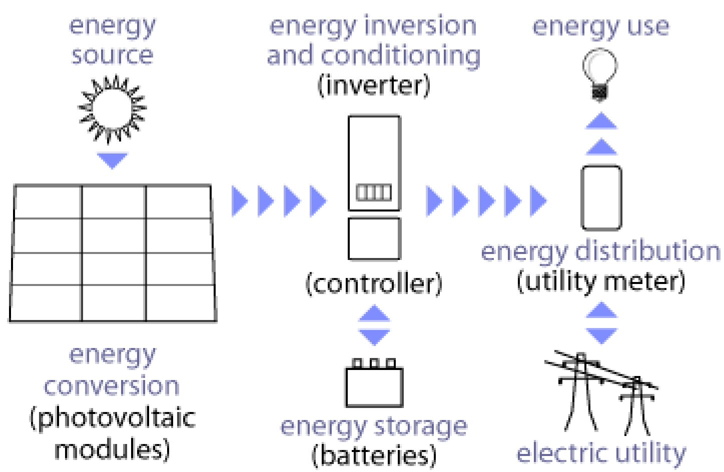

Figure 2.3 Main components of the photovoltaic system.

- PV Modules - convert sunlight instantly into DC electric power.
- Inverter - converts DC power into standard AC power for use in the home, synchronizing with utility power whenever the electrical grid is distributing electricity.
- Battery - stores energy when there is an excess coming in and distribute it back out when there is a demand. Solar PV panels continue to re-charge batteries each day to maintain battery charge.

- Utility Meter - utility power is automatically provided at night and during the day when the demand exceeds your solar electric power production.
- Charge Controller - prevents battery overcharging and prolongs the battery life of your PV system.
- Also, an assortment of a balance of system hardware; wiring, overcurrent, surge protection, and disconnect devices, and other power processing equipment.

The size of the PV system that will meet your expectations depends on your individual needs, site location and climate. Photovoltaic-based systems are generally classified according to their functional and operational requirements, their component configuration, and how the equipment is connected to the other power sources and electrical loads (appliances). The two principle classifications are Grid-Connected and Stand Alone Systems. Figure 4 shows an interconnected photovoltaic system.

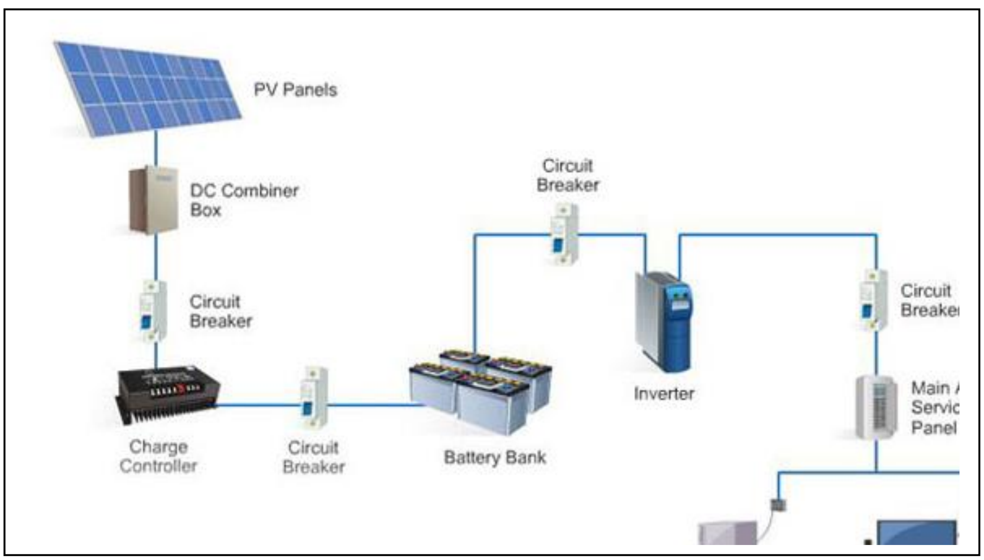

Figure 2.4 Interconnected solar panel and its components.

2.3.2 Wind Energy

Wind is the most promising source of alternate energy. Though the USA and China are the fastest-growing wind power countries in the world, European countries are the actual leaders. Germany and Spain have the highest installed wind generation capacity in the world. Wind turbines have a lifespan of about 20 years. They are most effectively used in groups known as 'wind farms' or 'wind power plants' with capacities varying from a few megawatts to few hundred megawatts in capacity. The difficulty in setting up more wind farms is the unavailability of wind forecast data as compared to solar forecast data; this is because solar energy is comparatively more predictable than wind energy. The most prominent disadvantage of renewable sources, unlike their conventional counterparts, is that they cannot be stored for later use (Hina and Palanisamy, 2015).

Wind energy conversion systems (WECS) are designed to convert the energy of wind movement into mechanical power. With wind turbine generators, this mechanical energy is converted into electricity (Salameh, 2014). In the United States, millions of windmills were erected as the American West was developed during the late nineteenth century, most of them were used to pump water for farms and ranches. By 1900, small electric wind systems were developed to generate direct current, but most of these units fell into disuse as expensive grid power was extended to rural areas during the 1930s. By 1910, wind turbine generators were producing electricity in many European countries (Salameh, 2014). As long as the sun is heating the Earth, there will always be winds because temperature differences drive air circulation. The wind blows because the heating rates of the Earth differ; therefore, as the rate of evaporation of air over one area is different from another, there is pressure differential (Salameh, 2014).

Denmark was the first country to use wind turbine generator to generate electricity in 1980. The first modern US wind turbine generator was erected and put into service in 1941 in Rutland, Vermont; it was called Grandpa's Knob. The turbine had a diameter of 55 m and was rated at 1.25 MW (megawatts) at a speed of 13.5 m/s. It was operated for 18 months before the bearings failed (Salameh, 2014).

Wind energy is the renewable energy that has increased more rapidly than the others. Current capacity installed of wind technology is 22,820 MW, so the long-term potential is 20% of the total electricity produced in the U.S. for 2030. The cost of KWH is onshore is 3.6 cents in 2012 and offshore is 7 cents in 2014. The total expectation is to produce 300 GW in which 50 GW will be produced by offshore wind farms.

The electricity can then charge batteries, be connected to a building's mains power, or connected to the national power grid. Wind turbines come in all shapes and sizes, from large-scale wind farms to small-scale wind turbines used to power a single home or business. Like solar, the European Union is leading the way with 48 percent of the world's installed wind power capacity. In 2009, wind turbines installed in the EU produced 163 TWh of electricity – avoiding 106 million tons of carbon emissions. Residential wind options include small wind turbines such as 500 W rated turbine generators – enough to run lighting or a few appliances – to larger scale turbines such as a 2 kW rated – enough to power an entire house plus sell some to the national grid depending on how much you use. Figure 5 illustrates the main elements of wind energy conversion systems (WECS).

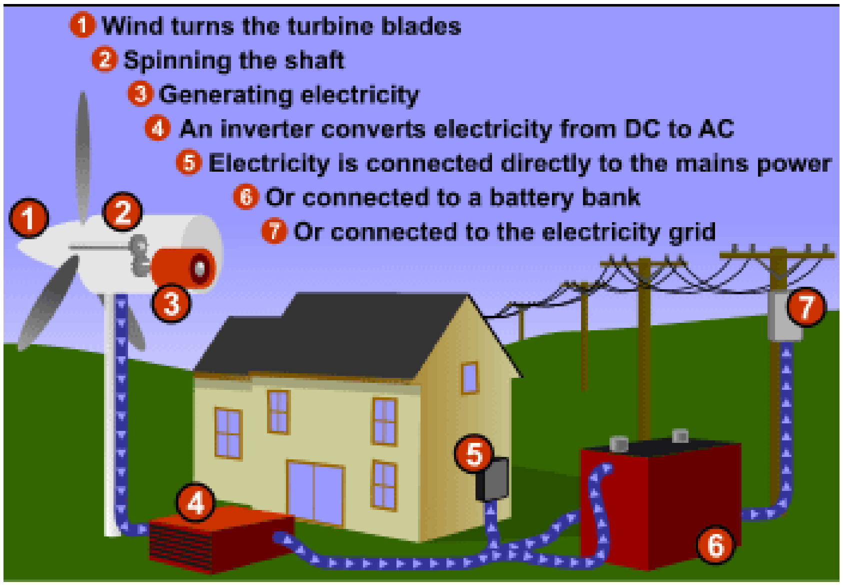

Figure 2.5 Show the main elements of the WECS

2.3.3 Fuel Cells

Fuel cells are a relatively new technology that will reform the way we produce electricity across the world. Fuel cells are a type of energy generation more efficient, lower cost, and cleaner alternative to today's conventional methods. The name fuel cell was coined in 1889 by Charles Langer and Ludwig Mond, who demonstrated a fuel cell that could develop 6 Amps at 0.73 Volts. In 1893, Friedrich Wilhelm Ostwald explained the fundamental interactions of the fuel cell. He described how Grove's "gas battery" really worked. Ostwald identified each part of the fuel cell and its function in the reaction (Salameh, 2014). Since their adoption by the space program, fuel cell technology has achieved widespread recognition by industry and government as a clean energy source for the future. Today, billions of dollars have been spent on research and the commercialization of fuel cell products.

Fuel cells convert fuel into electricity using a chemical reaction. By not using any combustion, as internal combustion engines or turbines do, fuel cells are not constrained by conventional thermodynamic efficiency limitations nor do they produce the pollution inherent with the compression and combustion of the fuel and air. Fuel cells are constructed of several parts. The electrolyte provides the medium for the migrating ions and the electrodes. Both an anode and cathode, provide an electrical path for the displacement of electrons. During the reaction, electrons are released at the anode and collected at the cathode, driving the desired electrical current. There are many types of fuel cells in the market today that have a wide range of operating temperatures, pressures and different topologies (Salameh, 2014). Figure 6 represents the chemical reaction into a fuel cell. It is clear that the fuel cell is fed with hydrogen and oxygen and its waste is clean water.

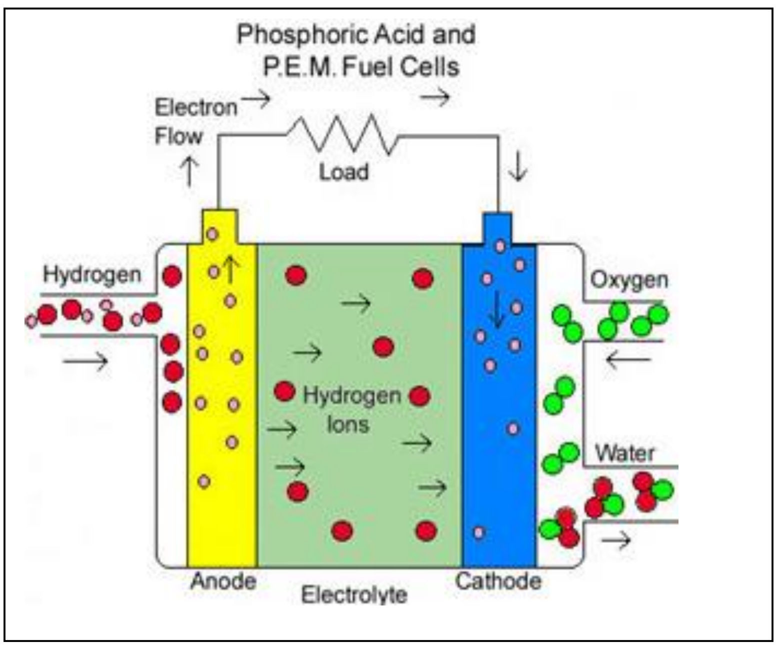

Figure 2.6. Basic fuel cell chemical reaction.

2.4 Genetic Algorithm

Genetic algorithms (GA) is an optimization tool that can search optimal solutions for complex problems with discontinuities, multimodality, etc. and there are employed for system optimizations over one or more objectives (multi-objective). The multi-objective option gives, as a result, a group of solutions where each one is a better solution than another, at least in one of the objectives tested (Delgado and Dominguez, 2015).

Genetic algorithms are adaptive search and optimization approaches that work mimicking the principles of natural genetics. Gas is very different from traditional search and optimization methods used in engineering design problems. Fundamental ideas of genetics in biology are borrowed and used artificially to construct search algorithms that are robust and require minimal problem information (Koutroulios et al. 2006).

A typical constrained, the single variable optimization problem can be outlined as follows:

Maximise x: F(x)

subject to the constraint: xmin<=x<=xmax

For the solution of such a problem with Gas, the variable x is typically coded in some string structures. Binary-coded or floating point strings can also be used, while the length of the string is usually determined according to the accuracy of the solution desired (Koutroulios et al. 2006).

Michalewicz (1994), The GA, as an evolution procedure for a particular problem, must have the following components: A generic representation for potential solutions to the problem, similar to the system modeling presented in the previous section. A way to create an initial population of potential solutions. An evaluation function that plays the role of the environment, rating solutions in terms of their fitness. Genetic operators (such as crossover and mutation) that alter the composition of children.

2.4.1 Genetic Algorithm and Micro-Grids.

Hybrid energy generation that depends on renewable energies is currently widespread. Using renewable energies can mitigate the effects of greenhouse gases to meet the requirements of the Kyoto protocol, as they mainly reduce CO2, NO, NO2, and others such as particular matter. Using systems with more than one supply source; known as hybrid systems to supply power to a certain application can increase reliability and energy security compared to systems with only a single energy source (Ismail et al. 2014). The need for more flexible electric systems, changing regulatory and economic scenarios, energy savings and environmental impact are providing impetuous to the development of Microgrids, which are predicted to play an increasing role in the electric power system of the near future (Mohamed and Koivo, 2012). Koutroulis et al. Used genetic algorithm to optimize the sizes of the components making up a standalone hybrid energy system constructed of PV panels, wind turbines, and a battery bank. Dufo-Lopez and Bernal-Agustin developed a software program that uses a genetic algorithm to design PV-diesel Hybrid system. Rajkumar et al. (2011), proposed an optimization methodology for PV/Wind/battery hybrid system. Caisheng et al. Studied a microturbine/ wind turbine hybrid system. Mohamed and Koivo proposed an approach using a genetic algorithm to determine the optimal operating strategy for a microgrid, consisting of a wind turbine, PV array, diesel generator, microturbine, fuel cells, and storage battery. The load being considered was a residential application. The sources capacity was assumed to be constant, and the implemented genetic algorithm was to define the optimal setting of these different sources to minimize the cost function. Shrestha and Goel (1998), A sizing method of stand-alone PV systems which is based on energy generation simulating for various numbers of PVs and batteries using suitable models for the system devices (PVs, batteries, etc.). The selection of the numbers of PVs and batteries ensures that reliability indices such as the loss of load hours. Kellogg et al. (1998), proposed a design of a method for hybrid PV/WG system, based on energy balance using the average hourly data of wind speed, solar radiation, and consumer power demand, the difference of generated and demanded power (AP) is calculated over 24 hours. The number of PV modules in WGs are finally deleted, using an iterative procedure where the system operation is simulated for various numbers of PVs and WGs, such that AP has an average value of zero. Markvart (1996) proposed to take into consideration a seasonal variation of PV and WG power generation in the methodology. Chedid and Rahman (1997) and Yokohama et al. (1994) proposed that the optimal sizes of the PV and WG power sources and the batteries are determined by minimizing the system total cost function using linear programming techniques. Dalton et al. (2008) calculate and comparing different energy approaches in a large building (a large tourist hotel). They compared by using the software HOMER, photovoltaic, wind energy, and energy provided by the grid stand alone. Also, Renewables energies in combination such as photovoltaic and wind energy, photovoltaic energy, and grid, and wind energy and grid. An examination of the most economically viable renewable energy system (RES) component (PV or wind energy conversion system (WECS)) for large-scale accommodation. The modeling demonstrated that WECS or PV in combination with grid-supply could, in principle, meet the demand load of a large-scale resort hotel. However, the optimal net present cost was centered in the VESTA wind energy without batteries. Delgado y Dominguez

(2015) present an investigation case of renewables energies based on energy cost and reliability; however, it is focused on the methodologies used. Universal Generating Function and Monte Carlo Simulation were compared on reaching optimal results in the best time. Ismail et al. (2014), Mohamed and Koivo (2012), Moghaddam et al. (2011) and Koutroulis et al. (2006), developed different genetics algorithms based on optimization of renewables energies applied on micro-grids. Combination of photovoltaic solar panels, wind turbines, microturbines, and fuel cells, integrating not only hybrids systems but also stand-alone generating systems. Kumar Basu (2012), conducts a comparative study on a 14-bus radial micro-grid between two groups of 4-Distributed Energy Resources (DERs) each of different sizes. One group with all Diesel Generators (DGS) (i.e., All-Dg) and other with a mix of DGS and Micro Turbines (Mts) (i.e., Mix-DER). Evaluating an economical choice of deployment of technologies from an owner's investment point of view with an object to minimize fuel cost there is a noticeable gain in economic parameters like Net Present Value (NPV), Pay Back Period (PP), and Internal Rate of Return (IRR). Several options are evaluated at the best optimal fuel cost again. type of manufacturers and technology of DERs, on which fuel consumption by applying an evolutionary algorithm approach is applied. Abdelkader el al. 2018, formulated an optimization of the Total cost of Electricity (TCE) and the Loss of Power Supply Probability (LPSP) of the load, simultaneously. In this respect, a multi-objective based Genetic Algorithm approach was used to size the developed system considering all storage dynamics. Achieving an optimal system configuration, different economic analysis cases were established and the results obtained show that the minimum of LPSP is achieved according to a very low TCE. Yousefi et al. 2017, a hybrid (Combined Cooling, Heating, and Power (CCHP) micro-grid system is modeled, and optimal component sizes are determined via a multi-objective optimization approach. The system is comprised of two types of (Cooling and Heating Power (CHP) technologies; fossil fuel-fired Internal Combustion Engine (ICE) and solar photovoltaic/thermal (PV/T) panels. Two different configurations are considered for the CCHP system. The first is a system fully based on fossil fuel, i.e., a non-renewable CHP component. The second is modeled as a hybrid CCHP micro-grid using a renewable CHP component in addition to the non-renewable one. Genetic Algorithm (GA) is the most known meta-heuristic optimization algorithm which is based on the survival of the strongest and fittest creature. A CCHP micro-grid is modeled, and an optimal sizing problem is solved using NSGA-II.

2.5 Component Replacement Analysis

The conventional age replacement model assumes that a unit is replaced preventively at a certain predetermined age, or at failure, whichever comes first. The optimal preventive replacement time is usually selected to minimize the long run replacement cost per unit time, assuming fixed costs of preventive and failure replacements. The conventional age replacement model assumes that a unit is replaced preventively at a certain predetermined age, or at failure, whichever comes first. The optimal preventive replacement time is usually selected to minimize the long run replacement cost per unit time, assuming fixed costs of preventive and failure replacements (Vlok et al. 2002). Replacement analysis is a useful tool offering individuals and organizations the techniques to models economic decision-making problems, such as maintenance and replacement decisions, and determine an optimal decision. Component replacement analysis can be viewed as a configuration selection problem which assesses "if and when" a certain piece or pieces of a component or equipment should be installed in a given configuration to keep the whole system in an efficient working condition. Determining the optimal procedure of replacement of old machines or assets by new ones. Replacing components is the problem of continuing interest in the field of industrial economics, operations research, and management sciences. Many types of assets that provide a service or produce a product are replaced over time. Some examples include machines, tooling, buildings, roads, and bridges. Replacement of an asset or a component is inevitable when an asset fails and cannot be repaired or when the cost of keeping an asset in operation is prohibitive or when changes in technology make an asset inferior, outdated or obsolete or simply when a change is desired. From a monetary perspective, the objective of an asset replacement analysis is to provide the required service over some predetermined planning horizon most economically and efficiently (Chenna, 2010).

Parthanadee et al. (2012), Stasko and Oliver (2012), Bazargan and Hartman (2012), and Chang-Ing Hsu et al. (2010) agreed on developing algorithms to determine the optimal replacement decision over a time horizon. Based on cost-benefit analysis considering age, maintenance, preferences, repair cost, retrofit, purchasing, and other constraints they develop algorithms based on stochastic dynamic programming approach to optimize decisions regarding purchasing, leasing, or disposing of their components: vehicles for the first two and aircraft for the last two paper mentioned. Espiritu and Coit (2008), proposed a new replacement analysis methodology by developing and demonstrating how to determine system-level component replacement schedules for electricity distribution systems composed of sets of heterogeneous assets. The proposed model is an iterative combined dynamic programming and integer programming approach to obtain cost-efficient system-level component replacement schedules to minimize the total net present value of unmet demand (considering the system availability), maintenance, and purchase costs over a finite planning horizon. There is an annual budget limiting total expenditures for maintenance and replacement costs that limit the selection of component replacement schedules.

In general, the component replacement analysis involves the decision of whether or not to replace an existing asset with a new asset. Component replacement analysis is concerned with determining the optimal time to remove a current asset (defender), from service and election of another asset (challenger) to take its place. The performance of components within most operating systems deteriorates with the growing age thus making the equipment more expensive to be kept operational in the system hence component replacement analysis is designed to minimize operating costs by identifying the optimal periods to replace aging components with new or refurbished replacement equipment. As these components are utilized over time, they grow old with time, become worn and lead to increased operating and maintenance expenditures. Therefore, the timely replacement of these assets is necessary to assure economically efficient operations. Determining minimum cost replacement schedules requires the analysis of current and future costs over time. Given a level of output or service required from an asset over time a decision is made periodically, to either keep or replace the asset, as it wears with the aging process. This sequence of keeping and replace decisions over the given time horizon is determined, such that some total cost function is minimized. Different types of costs include capital or replacement costs (purchase costs and salvage revenues), operating and maintenance costs, and cost of unmet demand (referred to as opportunity costs). In general, a replacement problem can be categorized as either serial or parallel replacement (Chenna, 2010).

Tabriz et al. (2016) present age-based replacement models subject to shocks and failure rate to determine the optimal replacement cycle. As a result, according to system reliability, maintenance costs of the system are to be minimized. A mathematic model and Matlab programming were used to develop the age-based replacement model. Malki et al. (2015), Illustrate an investigation age-based replacement policies for a two-component parallel system with stochastic dependence. The stochastic dependence considered, is modeled by a one-sided domino effect. It was shown that a unique and finite replacement policy T* (replacement time) exists if the system's failure rate is an increasing function. "Maple solver" has been used to get the optimal policy T* for investigated policies. Golovin (2016), introduces the concept of the replacement matrix and unconditional and conditional rules. The replacement matrix facilitates the maintenance procedure in terms of content, clarity and cost structure. One of the benefits of the matrix is the ability to see quickly how and when maintenance actions are performed. Formalization of the replacement rule in the form of a matrix is a universal tool and simplifies the notation of the maintenance policy, as well as allowing the programming of a mathematical model of the repair process (renewal process) in a computer simulation. Seif and Rabbani (2014) have published based on the failure rates of the components of a machine, the life cycle cost is assessed, mathematically modeled, and incorporated to the parallel machine replacement problem with capacity expansion consideration. The problem is modeled as mixed integer programming which intends to minimize the total costs incurred during a planning horizon of several periods for the machines of the same type with different ages.

2.5.1 Maintenance and Replacement

Nodem et al. (2010), states that it is entirely reasonable to assume that successive work times will decrease and repair times will increase with the number of failures. Also, deterioration reduces the reliability of the system and increases operational risks, resulting in an undesirable penalty cost. Due to the increasing failure rate or increased repair times, the machine may eventually not be repairable after it experiences several failures. Therefore, at each failure of the machine, a decision must be made: whether to continue repairing at ever-increasing repair costs or replace the machine with a new one. Nodem et al. (2010) present in their paper the integration of preventive maintenance into the repair/replacement policy of a failure-prone manufacturing system. The system exhibits increasing failure intensity and increasing repair times the problem is formulated as a semi-Markov decision process minimizing the average cost incurred by preventive maintenance, repair, and replacement activities over an infinite planning horizon.

Tam and Price (2008) mentioned that in the management of physical assets, a particular concern is the optimization of maintenance. Complex assets such as power plants, aircraft, and production plants deteriorate with the operation and, as a result, increase the risk of failures. The cost of the failure of such assets can be significant. Maintenance is one of the key issues that companies that operate with such complex assets must take seriously. Adequate investment in maintenance can reduce this risk and ensure that the return on investment of the company is maximized. This paper consists of a mathematical model to maximize the return on maintenance investment by reducing unplanned outages through optimized planned maintenance outages.

Mathew and Kennedy (2010) state that with the age of the component, both the failure rate and the maintenance cost increase as deterioration, and it is established due to wear and aging of the components. When there is a failure, a decision must be made, either to continue to repair escalating maintenance costs and risk of failure or to replace the item. In this work, an integrated model of net present value has been developed. This model accommodates a large number of factors, such as technological change, increased maintenance costs due to equipment aging and inflation. The factors used in investment incentive schemes, such as favorable interest rates, tax concessions, accelerated depreciation, and annual subsidies, can easily be accommodated in this model. Similarly, reductions in cash flow due to the end of a product's life cycle can also be addressed.

Nakagawa (1986) observes that when a system fails, a decision must be made about whether it is economical to replace the system or repair the failed system. As the failure rate of most systems generally increases with age, it is becoming increasingly expensive to maintain a system in operation only with the repair. This paper considers periodic and sequential preventive maintenance policies for the system with minimal repair at failure. The system has a different failure distribution between preventive maintenance and replacing at the Nth preventive maintenance.

Jung et al. (2008), in this document, a replacement model was developed after the expiration of the guarantee that optimizes a value function of two attributes. As for the guarantee policies, consider two types of guarantee policies: the renewal of the guarantee and the guarantee of non-renewal. When the system fails during its warranty period, it is replaced by a new one under both warranty policies. However, the warranty is renewed each time the replacement is made under the renewal of the warranty, while the warranty is valid only during the original warranty period under the guarantee of non-renewal. When the warranty expires, the system is repaired minimally in each subsequent failure. The criterion used to determine the optimization of the maintenance period after the warranty has expired, the global value function formed by the aggregation of the expected cost rate and the expected downtime per unit of time.

Babishin and Taghipour (2016), consider the problem of finding the optimal inspection interval for a system consisting of multiple components with hard-type and soft-type failures, which are all assumed to follow a nonhomogeneous Poisson process. When a hard-type component fails, an opportunistic inspection is performed for all soft-type components. Failures of soft-type components are assumed to be hidden and revealed only at either scheduled periodic inspections, or unscheduled opportunistic inspections. Thus, the age at the failure of soft-type components is not known. At all inspections, a failure is fixed in one of two ways: failed component is minimally repaired, or it is replaced. The method proposed to find the optimal maintenance actions is divided into three stages as follows: the optimal time to replacement resulting in the minimal expected cost for the component per unit time. The optimal number of minimal repairs before replacement and the optimal periodic inspection interval for the whole system is obtained, which results in the minimal expected cost for the system over its planning horizon.

Shang et al. (2016), in this paper, it is integrated imperfect preventive maintenance at a time where the warranty expires with age replacement and proposes a maintenance–replacement policy after the expiry of the warranty for the product with two categories of competing for failure modes. The proposed maintenance–replacement policy is that imperfect preventive maintenance is performed first at a time where the warranty expires and then an aging replacement is performed. The imperfect preventive maintenance performed reduces the failure rate function of maintainable failure modes by a random variable. Compared with traditional age replacement policy after the expiry of the warranty, although the proposed maintenance–replacement policy incurs a preventive maintenance cost at the time where the warranty expires, it can improve subsequent operation time as well as decrease significantly both operation cost and failure cost.

Clavareau and Labeau (2008), this paper aims to define and model in a realistic way, possible maintenance policies of a system including replacement strategies when one type of challenger unit is available. The comparison of these possible strategies is performed based on a Monte Carlo estimation of the costs they incur. The Monte Carlo code was used to calculate the average cumulative cost incurred by the replacement strategies as a function of time.

Chang (2014), this paper proposes, from the economical viewpoint of preventive maintenance in reliability theory. As a failure occurs, the system suffers one of two types of failure based on a specific random mechanism: repairable and non-repairable failures. A modified random and age replacement policy is considered in which the system is replaced at a planned time, at a random working time, or at the first non-repairable failure, whichever occurs first. Also, as another extended model, they might consider replacing an operating system at the first working time completion over a planned time.

Fouladirad et al. (2017), this paper analyzes three time-based replacement policies when the parameters of the time-to-failure distribution are unknown. Under the hypothesis of a significant sample data, the unknown parameters are estimated via maximum likelihood method. This paper proposed general results for a sensitivity analysis of three replacement policies, namely the periodic replacement policy, the age, and the block replacement policy. The paper has aimed to quantify how uncertainty on parameters of the time-to-failure distribution (which are unknown and have to be estimated) has an impact on optimal quantities of interest for a given policy.

Nodem et al. (2011), this paper presents a method to find the optimal production, repair/replacement and preventive maintenance policies for a degraded manufacturing system. The system is subject to random machine failures and repairs. When a failure occurs, the machine is either repaired or replaced, and a replacement action renews the machine, while a repair action brings it to a degraded operational state, with the next repair time increasing as the number of repairs increases as well. The decision variables are the production rate, the preventive maintenance rate and the repair/ replacement switching policy upon machine failure. The objective of the study is to find the decision variables that minimize the overall cost, including repair, replacement, preventive maintenance, inventory holding and backlog costs over an infinite planning horizon. The proposed model is based on a semi-Markov decision process, and the stochastic dynamic programming method is used to obtain the optimality conditions.

Scarf and Cavalcante (2011), in this paper they have proposed some simple models of supplier choice in preventive maintenance, including inspection and replacement. Competing suppliers may supply replacement components of differing quality and cost. They may carry out maintenance interventions with differing quality and cost. We model component lifetimes as a mixture, with two subpopulations in the mixture, one corresponding to short lifetimes and the other to long lifetimes. In the model, a poor quality component is analogous to incorrect installation, and so the quality of replacement can be considered. The quality of inspection maintenance is modeled by allowing for the possibility of defect induction at inspection.

2.6 Distance Between Two Vectors.

Actually, one of the real challengers after defining replacing times between components in a micro-grid is choose a best supplier among a finite number of suppliers offering similar products from different brands. Product traits can be characterized in an algebraic vector considering the most important elements to be compare among different products of the same component finding the best choice related to a desired vector. Draisma et al. (2015), state that the nearest point map of a real algebraic variety with respect distance is an algebraic function. The Euclidean distance degree of a variety is the number of critical points of the squared distance to a general point outside the variety. Also they express that a real algebraic variety X C Rn, they consider the following problem: given u Є Rn, compute u*Є X that minimizes the squared Euclidean distance du(x) = n i=1(ui-xi) from the given point u. This optimization arises in huge range of applications. J. Ma. Et al. (2020), write in an interesting article that with the development of technology and sciences, data collection and processing data have become more important every day. They mention that a Support vector machine (VSM) proposed by Vapnik, has emerged as an excellent pattern recognition tool over the last decades. SVM is to seek an optimal decision boundary via maximizing the margin between two parallel support hyperplanes. SVM has been used in various real-world problems, such as fault diagnosis, least square classification and more.

Chapter 3

Methodology

On electric generation system reliability is conceptualized as the energy generation under specific demanding conditions on different consuming points. Some factors affect the electric generation drastically in a micro-grid, such as:

Not sufficient generation

Excessive user demand

System failures

In the first case, a good condition system is restricted to produce enough electricity to cover the users' demand. The second factor is referred to as micro-grid production design; it was made below of users' demand. Increasing demand over the micro-grid conditions could be another of the symptoms of this case. Our challenge is concentrated in the third case. Where the demand and generation are not an issue; however, there is another condition that affects the reliability condition directly to every micro-grid. A micro-grid is a failure condition. The failure condition is basically in two different modes: Time-dependent mode and Not time dependent mode.

Time-dependent expressions:

The reliability theory uses specific numbers of functions and variables to describe the temporary evolution of many aspects of reliability, maintenance, and energy availability.

In the first place, reliability and failure analysis expressions are specified. Time to failure, reliability function, and failure rate are specified.

3.1 Time to Failure, Tf

It is the time of the element, component or system from starting operation to fail the first time. Practically, time to failure of a system or component depend on many factors. These factors can be represented by a continuous random variable T_f with a probability density of $f(t)$ and a distribution function of $F(t)$.

$F(t)$ is the expression that defines the probability of the elements fail in the interval between 0 and t; this is:

$$F(t) = P(T_f \leq t)$$

The distribution function takes values between 0 and 1 and it being time ascendant. The distribution function is obtained by integrating its density function from an initial instant of time to "t"

$$F(t) = \int_0^t f(u)\,du$$

3.2 Reliability Function

Practically reliability function is the complementary function of failure distribution $F(t)$. $R(t)$ is the probability of a component or system failure in an interval from 0 to t.

$$R(t) = P(T_f > t)$$

Furthermore:

$$R(t)=1-F(t)$$

The tail condition of R is:

$$R(0)=1$$

$$R(\infty)=0$$

The first condition represents the initial state of every component or system working normally. The second one represents the final working time for every component or system.

Failure rate, $z(t)$

The failure rate of an element is the probability of the elements fail in an interval (t, t+Δt) when it is correctly working on the time t. The failure rate is well known as a conditioned probability of inverse time t^{-1}.

It is analytically known as:

$$z(t)=\lim_{\Delta t-0}\frac{P(t<T_f\leq t+\Delta t T_f>t)}{\Delta t}=\lim_{\Delta t-0}\frac{P(t+\Delta t>t)-F(t)}{\Delta t}.\frac{1}{R(t)}=\frac{f(t)}{R(t)}=-\frac{1}{R(t)}.\frac{dR(t)}{dt}$$

The objective is to estimate the reliability of the system that means that if the system is able to provide the waited service after a certain time or on the other hand a failure. In order to estimate the system reliability, it is necessary starting by knowing failures rates of any individual component of the system. Calculating individual reliability and knowing their interconnections, it is possible to analyze and calculate the entire system.

3.3 Maintenance Time (Sustained Shortage), T_M

Maintenance timeT_M, it is a continuous random variable that expresses the period of time since component failure until putting on service again. It could be expressed through a distribution function or maintenance probability function M(t). M(t) is the probability of accomplish repairing the element, component or system in an interval between 0 and t, where t=0 is the initial time of the failure.

$$M(\mathrm{t})=P(T_M \leq t)$$

-Repair rate, μ(t)

Repair rate is obtained from

$$\mu(\mathrm{t}) = =\lim_{\Delta \mathrm{t}-0}(\frac{1}{\Delta \mathrm{t}}.\frac{\mathrm{M(t)-M(t+\Delta t)}}{M(t)}) = -\frac{1}{M(t)}.\frac{dM(t)}{dt}$$

Reliability and maintainability represent the real availability of the system.

3.4 Probability Functions

Exponential and Weibull are the most distributions used in analyzing and explaining mathematics models about failures and maintainability in electrical systems or any others. There are elements that its common failures are random that means that are not time-dependent; on the other hand, there are elements that suffer progressive degradation through the time because its failures are time-dependent. Both cases have a different distribution. Exponential distribution. One of the most common failure distributions in reliability engineering is the exponential, or CFR, model.

Failures due to completely random or chance events will follow this distribution. It should dominate during the useful life of a system or component. It is also one of the easiest distributions to analyze statistically. A well-known characteristic of the exponential model, one not shared by other failure distributions, is its lack of memory. That is, the time to failure of a component is not dependent on how long the component has been operating. There is no aging or wear out effect. The probability that the component will operate for the next 1000 hours is the same regardless of whether the component is brand new, has been operating for several hundred hours, or has been operating for several thousand hours. The basic expressions of exponential distribution are showed in table 3.1.

Table 3.1 Basic expressions of reliability from an exponential distribution

Concept	Mathematics expression
Distribution function	F(t) = 1 - $e^{-\lambda t}$
Probability density	f(t) = λ $e^{-\lambda t}$
Reliability function	R(t) = $e^{-\lambda t}$
Failure rate	Z(t)= λ = constant

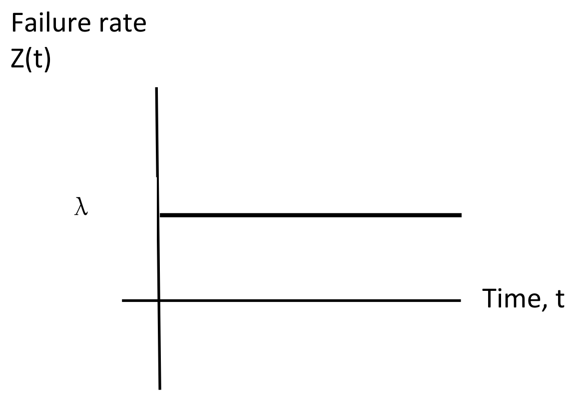

Figure 3.1 Failure rate, not time-dependent

3.4.1 Weibull Distribution:

One of the most useful probability distribution in reliability is the Weibull. The Weibull failure distribution may be used to model both increasing and decreasing failures rates. The basic expressions of Weibull distribution are showed in table 3.2.

Table 3.2 Basic expressions of reliability from Weibull distribution

Concept	Mathematics expression
Distribution function	$F(t) = 1 - e^{-(\lambda t)^{\alpha}}$
Probability density	$f(t) = (\alpha\lambda)(\lambda t)^{\alpha-1}e^{-(\alpha\lambda)^{\alpha}}$
Reliability function	$R(t) = e^{-(\lambda t)^{\alpha}}$
Failure rate	$Z(t) = (\alpha\lambda)(\lambda t)^{\alpha-1}$

Alpha (α) is referred to as the shape parameter: Its effect on the distribution can be seen in figure 3.2 for several different values. For α<1, the Weibull is similar in shape to de exponential. Summarizing for different values of α :

α < 1 Early failure,
α = 1 Constant failure rate (exponential distribution), Random failures,
α > 1 Wearout failures

An essential form of the hazard rate function is shown in figure (x). Because of its shape, it is commonly referred to as the bathtub curve. System is having this hazard rate function experience decreasing failure rates early in their life cycle (infant mortality), followed by a nearly constant failure rate (useful life), and followed by an increasing failure rate (wear out).

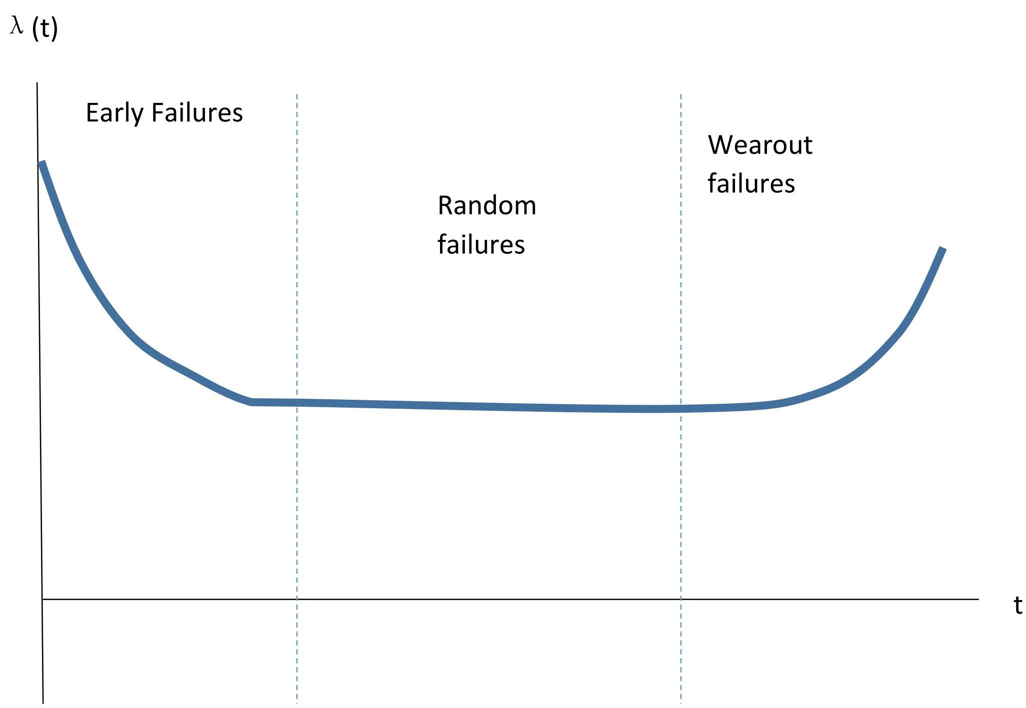

Figure 3.2 Flexible failure rate (Bathtub curve)

This figure usually called bathtub graph, there are three different stages, initial phase (infant mortality) with a significant failure rate because of manufacturing defects no detected, defects due to transportation, installation or design. After fixing or repairing the initial phase, the second phase is starting. The second phase is well known as the random failure rate phase or useful life phase. The last phase starts with increasing failures due to degradation. Material fatigue or other failure causes that increase failures time-dependent; at this point, it is important to be prepared to replace components. Some components suffer degradation through its entire life such us mechanical components. Those cases pass directly from the first phase to the third phase immediately.

3.4.2 Mean Value Expressions

The mean value expressions are associated and useful for exponential distributions. The basic variables of the mean value for repairable electric generation systems are showed as follow.

-MTTF or MTFF (Mean Time To Failure or Mean Time to First Failure)

The mean time until the first failure of an element is obtained integrating the reliability function:

$$\text{MTTF} = \int_0^\infty R(t)dt$$

It is an important parameter because of represents the meantime while the component is working normally; thus, this is an indicator of its reliability. In the case of non-repairable elements, this concept represents the mean lifetime of the component or system. In figure 3.3, the mean value variables are showed how they interact through the time.

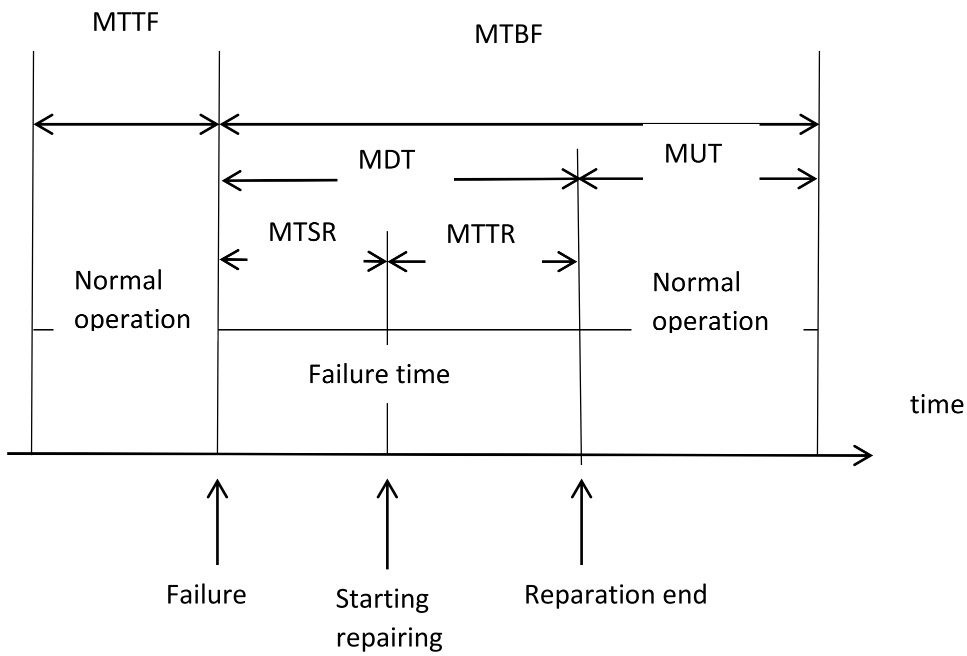

Figure 3.3 Mean value functions interacting in a repairable system.
(Figure retrieved from the doctoral thesis of Pablo Diaz Villar, 2003)

Recalling the exponential expression of reliability

$$\text{MTTF} = \int_0^t e^{-\lambda t} = \frac{1}{\lambda}$$

In this case, MTTF is the inverse of the failure rate. If the reliability is calculated in t=MTTF:

$$\text{R(MTTF)} = e^{-\lambda MTTF} = e^{-\frac{MTTF}{MTTF}} = \frac{1}{e} \approx 0.36$$

Thus, in an exponential distribution represents the time for which the probability that the element has not failed is 36%, or, for a large set of equal elements, the estimated time for which 2/3 of the elements have failed.

MTBF (Mean Time Between Failures)

Mean time between failures is the time between starting the failure and starting the next failure. MTBF integrate the maintenance time, a basic parameter in order to know the quality and integration of every element through the system and its availability.

MDT (Mean Down Time)

Mean downtime is the time in which the system is not operating. This time is between the failure and startup after being repaired.

MTSR (Mean Time to Start Repairing)

It is the Meantime since the beginning of the failure until the repair is starting.

MTTR (Mean Time to Repair)

Mean time to repair is the appropriate name for its description. It is the average of the repair time for any component or system.

MUT (Mean Up Time)

It is the average time during which the system is able to operate correctly, since the system is started after the failure and repairing, until the next failure. Therefore, it is the complement of MDT.

According to definitions above:

$$MTBF = MUT + MDT$$

$$MDT = MTSR + MTTR$$

Finally, the mean availability of the system could be defined as

$$A = \lim_{t \to \infty} \frac{MUT}{MDT + MUT} = \frac{MUT}{MTBF}$$

3.5 Markov Chain

Espiritu, 2007 states that using Markov processes, the state probabilities are calculated and the optimal value of the mean time to preventive maintenance was obtained by maximizing the availability of a single component concerning the mean time to minimal preventive maintenance.

3.5.1 Markov Model for Two Repairable Components

From Espiritu, 2007 a Markov model is presented for sustained outages overlapping component sustained outages for two components; each component can be in either the up-state or the downstate. Letλ_1, λ_2 μ_1, and μ_2 be the sustained outage rates and repair rates for components 1 and 2. Outages and repairs occur as a homogeneous Poison process. The Markov chain model assumes constant outage and repair rates and exponentially distributed time between failures and repair times.

In this case, each of the components can be in one of two states, either working or failed. There are two components, and thus, there are 2^2 or 4 possible states in which the system can exist. These are enumerated in Table 3.3.

Table 3.3 Space diagram states

State	Component 1	Component 2
1	Up	Up
2	Down	Up
3	Up	Down
4	Down	Down

The corresponding state space diagram is shown in Figure 3.4. It is important to mention that in the model, a transfer from state 1 and 4 or between states 2 and 3, is not possible because such transfers require two simultaneous changes in the states of the components involved. The probabilities of such simultaneous occurrences are assumed to be negligibly small.

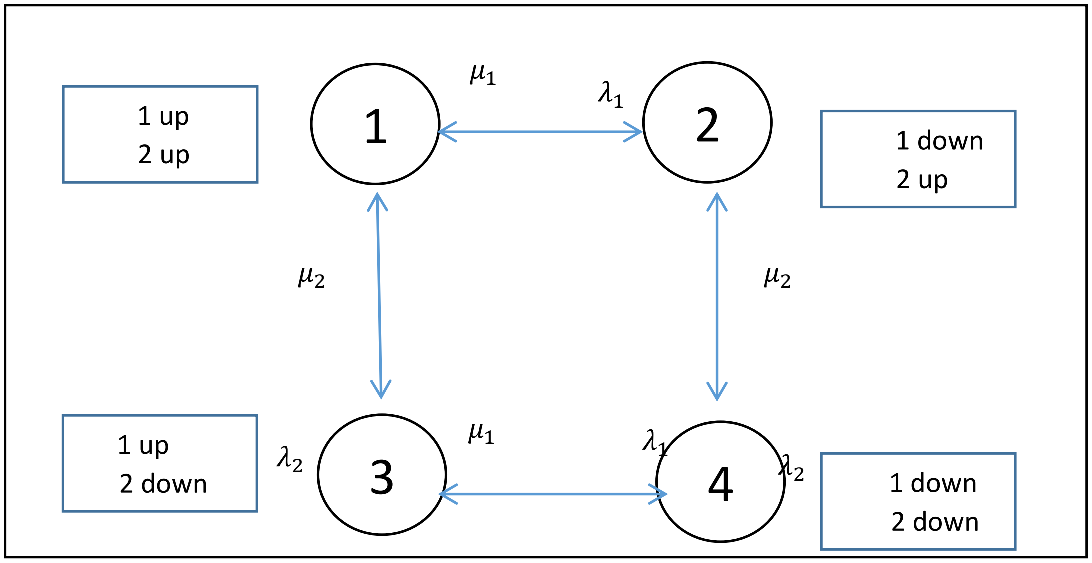

Figure 3.4 State-space diagram for two different repairable components

Retrieved from: Espiritu, 2007.

For this case, the ρ-matrix, stochastic transitional probability matrix (P) and the

Markov differential equations, in vector-matrix notation, are as follows:

$$\rho = \begin{array}{c} \\ S_1 \\ S_2 \\ S_3 \\ S_4 \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & S_3 & S_4 \end{array} \\ \begin{pmatrix} 0 & \lambda_1 & \lambda_2 & 0 \\ \mu_1 & 0 & 0 & \lambda_2 \\ \mu_2 & 0 & 0 & \lambda_1 \\ 0 & \mu_2 & \mu_1 & 0 \end{pmatrix} \end{array}$$

$$
\mathbf{P} = \begin{pmatrix} 1-(\lambda_1+\lambda_2) & \lambda_1 & \lambda_2 & 0 \\ \mu_1 & 1-(\lambda_2+\mu_1) & 0 & \lambda_2 \\ \lambda_2 & 0 & 1-(\lambda_1+\mu_2) & \lambda_1 \\ 0 & \mu_2 & \mu_1 & 1-(\mu_1+\mu_2) \end{pmatrix}
$$

$$
\begin{pmatrix} P_1'(t) \\ P_2'(t) \\ P_3'(t) \\ P_4'(t) \end{pmatrix} = \begin{pmatrix} -(\lambda_1+\lambda_2) & \mu_1 & \mu_2 & \mathbf{0} \\ \lambda_1 & -(\lambda_2+\mu_1) & \mathbf{0} & \mu_2 \\ \lambda_2 & \mathbf{0} & -(\lambda_1+\mu_2) & \mu_1 \\ \mathbf{0} & \lambda_2 & \lambda_1 & -(\mu_1+\mu_2) \end{pmatrix} \begin{pmatrix} \boldsymbol{P_1(t)} \\ \boldsymbol{P_2(t)} \\ \boldsymbol{P_3(t)} \\ \boldsymbol{P_4(t)} \end{pmatrix}
$$

Then it is having the following set of equations:

$$P_1'(t) = -(\lambda_1+\lambda_2)P_1(t) + \mu_1 P_2(t) + \mu_2 P_3(t)$$

$$P_2'(t) = \lambda_1 P_1(t) - (\lambda_2+\mu_1)P_2(t) + \mu_2 P_4(t)$$

$$P_3'(t) = \lambda_2 P_2(t) - (\lambda_1+\mu_2)P_3(t) + \mu_1 P_4(t)$$

$$P_4'(t) = \lambda_2 P_2(t) + \lambda_1 P_3(t) - (\mu_1+\mu_2)P_4(t)$$

The steady-state probabilities can be computed by the simultaneous of $\alpha P = \alpha$

Where $\alpha = [P_1 \quad P_2 \quad P_3 \quad P_4]$, and $P_1 + P_2 + P_3 + P_4 = 1$

3.5.2 Components Connected in Series

Considering the case when two repairable components are connected in series as in Espiritu (2003). The steady-state probability of both components being in operating condition is given by the equation (3.2). To obtain the outage rates and repair rates for the system it is necessary first to obtain the outage rates and repair rates of a single component that is equivalent to the two components connected in series in the diagram shown in Figure 3.5. Thus, the probability of the single component being in the up-state can be obtained.

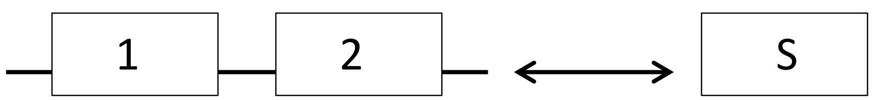

Figure 3.5 Components connected in series (Retrieved from Espiritu, 2003).

For the equivalent component, the steady-state probability of being in the proper state is,

$$P_1 = \frac{\mu_s}{\lambda_s + \mu_s} \tag{3.1}$$

For the single component to be equivalent to the two series components, according to Espiritu (2007), Thus,

$$\frac{\mu_s}{\lambda_s + \mu_s} = \frac{\mu_1 \mu_2}{(\lambda_1 + \mu_1)(\lambda_2 + \mu_2)} \tag{3.2}$$

Rearranging and solving for μ_s yields,

$$\mu_s = \frac{\lambda_s \mu_1 \mu_2}{\lambda_1 \lambda_2 + \lambda_1 \mu_2 + \lambda_2 \mu_1} \tag{3.3}$$

Expressing the equation (x), in terms of mean repair timesr_1, $r_2, and\ r_s$, where

$r_1 = \frac{1}{\mu_1}$, $r_2 = \frac{1}{\mu_2}$ and $r_s = \frac{1}{r_s}$

And substituting equations, it is obtaining the average repair time p[or two components connected in series

$$r_s = \frac{\lambda_1 r_1 + \lambda_2 r_2 + \lambda_1 r_1 \lambda_2 r_2}{\lambda_1 + \lambda_2} \tag{3.4}$$

From de above equation, it can say that for component 1, the number of outages per unit is λ_1, and every time the component is down, it takes on average, r_1 time units to repair. $\lambda_1 r_1$ is also an approximation of the fraction of the time the component 1 is down for $\lambda_1 r_1$ << 1. When $\lambda_1 r_1$ and $\lambda_2 r_2$ is small ($\lambda_1 r_1$ << 1 and $\lambda_2 r_2$ << 1). Equation (x) reduces to:

$$r_s = \frac{\lambda_1 r_1 + \lambda_2 r_2}{\lambda_1 + \lambda_2} \tag{3.5}$$

The system outage rate for two components connected in series is:

$$\lambda_s = \lambda_1 + \lambda_2 \tag{3.6}$$

The expected system downtime can then be approximated, as in Billington & Allan (1983) as.

$$U_s = \lambda_1 r_1 + \lambda_2 r_2 \tag{3.7}$$

3.5.3 Components Connected in Parallel

In the case where the components are connected in parallel, the system fails if both components fail. From the equations derived from the Markov model (Espiritu, 2007) correspond to the case when the system is down. The steady-state probability can be set equal to the unavailability for the parallel two-component systems as follows,

$$P_p = \frac{\lambda_p}{\lambda_p + \mu_p} \tag{3.8}$$

Therefore

$$\frac{\lambda_p}{\lambda_p + \mu_p} = \frac{\lambda_1 \lambda_2}{(\lambda_1 + \mu_1)(\lambda_2 + \mu_2)} \tag{3.9}$$

$$\lambda_p = \frac{\mu_p \lambda_1 \lambda_2}{\lambda_1 \mu_2 + \lambda_2 \mu_1 + \mu_1 \mu_2} \tag{3.10}$$

Since repairing either component brings up the system to the working state, the equivalent repair rate is equal to the sum of the two individual repair rates (for exponentially distributed repair times). That is,

$$\mu_p = \mu_1 + \mu_2 \tag{3.11}$$

Combining equations (3.10 and 3.11)

$$\lambda_p = \frac{(\mu_1 + \mu_2)\lambda_1 \lambda_2}{\lambda_1 \mu_2 + \lambda_2 \mu_1 + \mu_1 \mu_2} = \frac{(r_1 + r_2)(\lambda_1 \lambda_2)}{1 + \lambda_1 r_1 + \lambda_2 r_1} = \frac{\lambda_1 \lambda_2 r_1 + \lambda_1 \lambda_2 r_2}{1 + \lambda_1 r_1 + \lambda_2 r_2} \tag{3.12}$$

In the case of two components connected in parallel, for component 1, the number of failures per unit time is λ_1, and every time the component is down, it takes an average, $r_1$time units to repair. Therefore, $\lambda_1 r_1$ is a close approximation to the fraction of time the component is down. For highly reliable components, as in the case of electricity generation systems, this number is very small. Similarly, $\lambda_2 r_2$ is also small ($\lambda_1 r_1$<<1 and $\lambda_2 r_2$<< 1), Then it can be expressed equation (x) as the following approximation to obtain the system outage rate.

$$\lambda_p \approx \lambda_1 \lambda_2 r_1 + \lambda_1 \lambda_2 r_2 = \lambda_1 \lambda_2 (r_1 + r_2) \tag{3.13}$$

The average repair time and the system downtime can be computed as,

$$r_p = \frac{1}{\mu_p} = \frac{1}{\mu_1 + \mu_1} = \frac{r_1 r_2}{r_1 + r_2} \tag{3.14}$$

$$U_p = \lambda_p r_p \tag{3.15}$$

Elements

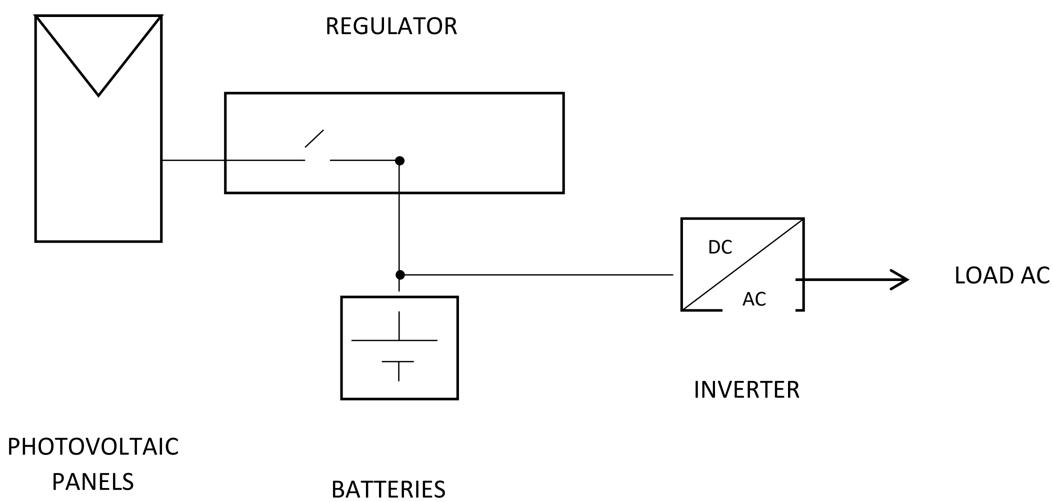

Figure 3.6 A single-line diagram of a photovoltaic generation system.

3.3 Reliability Model

Photovoltaic Panels

The photovoltaic module is usually the most reliable element of the system, with a low number of failures compared to the rest of the elements. Usually, sudden or accidental causes (vandalism, rays or own random failures) are considered as sole causes of failure. Under these conditions, the failure rate can be estimated as a constant over time. It is possible to model, then, the time until the generator failure, T_G, by an exponential distribution with scale parameters λ_{pv1}. Its failure rate is:

$$Z_{pv1}(t) = \lambda_{pv1}$$

For this study, photovoltaic module failure is considered when the peak power is less than 80% of its rated power. It is true that in practice no periodic power controls are carried out on the modules in operation, but their malfunction is inferred from the effect on other elements of the system and on the final electrical supply. However, in a study that claims to be systematic and advance in technical quality, this fact cannot be ignored, since reduced modulus powers influence the correct functioning of systems, with increasingly frequent power cuts. The loss of power due to progressive degradation can be modeled by an increasing failure rate since the more time passes, the more likely a module reaches 80% of its rated power.

From this point of view, the time to failure, T_G, can be expressed by means of a Weibull distribution, with scale parameter λ_{pv2} and shape parameter α_{pv2}> 1, that is, linearly increasing. The failure rate is presented as

$$Z_{pv2}(t) = (\alpha_{pv2}\lambda_{pv2})(\lambda_{pv2}t)^{\ \alpha_{pv2}-1}$$

Since the effect of the degradation of the modules does not modify the risk of accidental failure, both types of failures, random and by degradation (not dependent on time and dependent on time) must be considered together. As shown in the figure 3.7, the failure rate of the photovoltaic module is, Z_{pv} is the sum of the non-time-dependent and time-dependent failure rate.

$$Z_{pv}(t) = Z_{pv1} + Z_{pv2} = \lambda_{pv1} + (\alpha_{pv2}\lambda_{pv2})(\lambda_{pv2})^{\ \alpha_{pv2}-1}$$

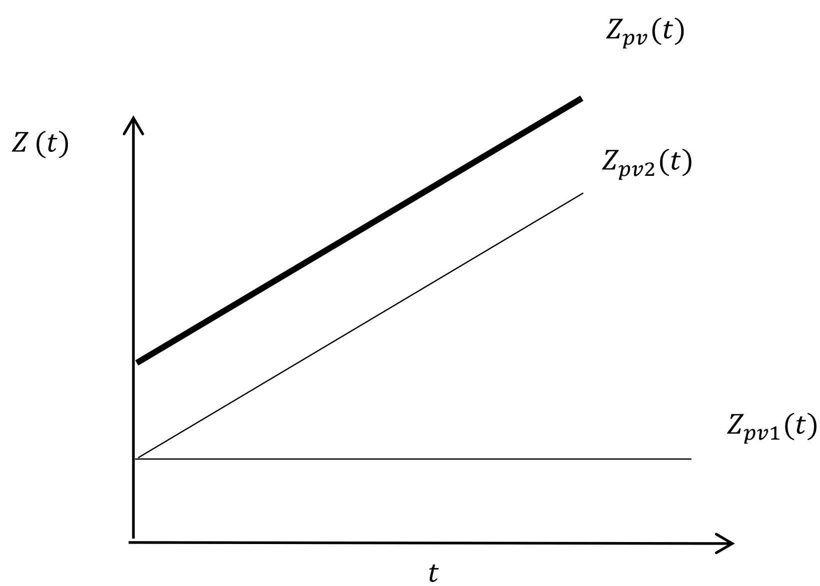

Figure 3.7 Failure rate due to random causes, degradation and joint

The reliability R_{pv} is obtained by the product of the reliability due to each one of the factors:

$$R_{pv}(t) = R_{pv1}(t)R_{pv2}(t) = e^{-(\lambda_{pv1}t+(\lambda_{pv2}t)^{\ \alpha_{pv2}})}$$

Batteries

The influence of batteries on the long-term operation of photovoltaic installations is crucial. Their real-life time presents notable differences depending on their manufacturing characteristics, but also, on the external operating conditions. In this sense, although the battery can fail due to random causes: breakage of the box, short circuit, the sudden failure of the regulator with total discharge, lack of water, etc., in reality, the loss of capacity due to degradation with time of use predominates. First of all, the case of a constant failure rate (no time-dependent, Exponential distribution), is proposed; however, it is advisable to use a model with a Weibull distribution of scale parameter λ_B and linearly increasing failure rate α_B to adequately represent the effects of loss of capacity of the battery. From this factor, the increase in the risk of failure with the elapsed time is derived.

$$R_B(t) = e^{-(\lambda_B t)^{\alpha_B}}$$

$$Z_B(t) = (\alpha_B \lambda_B)(\lambda_B t)^{\alpha_B - 1}$$

Regulator

This section deals only with the reliability of the regulator itself in its function of interruption or transmission of current. It is assumed that the faults that affect the regulator have, in general, random causes, once the initial quality control has been carried out to avoid a malfunction due to a common cause. It can be assumed, therefore, that within the expected useful life period the time until the regulator failure, T_R, follows an exponential distribution, with constant failure rate λ_R. Thus:

$$R_R(t) = e^{-\lambda_R t}$$

$$Z_R(t) = \lambda_R$$

Inverter

This section deals only with the reliability of the inverter itself in its function of transforming DC current into AC current in order to be used by the consumer. It is assumed that the faults that affect the inverter have, in general, random causes, once the initial quality control has been carried out to avoid a malfunction due to a common cause. It can be assumed, therefore, that within the expected useful life period the time until the inverter failure, T_I, follows an exponential distribution, with constant failure rate λ_I. Thus:

$$R_I(t) = e^{-\lambda_I t}$$

$$Z_I(t) = \lambda_I$$

System

The reliability of the system is obtained by the product of the reliability of each of its components since it has been assumed that the failure of any of them causes a general failure.

$$R\,(t) = R_{pv}(t)R_B(t)R_R(t)R_I(t)$$

While the failure rate is the sum of the failure rates of each of the elements of the system

$$Z\,(t) = Z_{pv}(t) + Z_B(t) + Z_R(t) + Z_I(t)$$

Giving values to t gives the probability that the system has not failed during its normal operation and the associated failure rate at each instant.

3.7 Maintenance Costs

According to the above, maintenance is firmly associated with the reliability of the systems. Because each failure in a component responds to a repair cost, we can differentiate the maintenance costs for random failures and the maintenance cost for failures due to the use or degradation of the components. Also, it is important to consider the costs of fixed maintenance already established in an annual budget, where there is a response to preventive maintenance, skilled labor, in short, fixed costs that arise whether or not there are failures in a system.

Annual Scheduled budget ……………….. B_{ij} (Component I, period j)
Annual Cost of Random failures …………………. Fr_{ij}
Annual Cost by Degradation failures ………….. Fd_{ij}
Replacement Cost …………………….. RP_{ij}
Annual Maintenance Cost …… AMC_{ij}

PV Modules

$$R_{pv}(t) = R_{pv1}(t) + R_{pv2}(t)$$

$$R_{pv}(t) = e^{-\lambda_{pv1}t} + e^{-(\lambda_{pv2}t)^{\alpha_{pv2}}}$$

$$AMC = B_{ij} + Fr_{ij}\left(1 - e^{-\lambda_{pv1}t}\right) + Fd_{ij}(1 - e^{-\left(\lambda_{pv2}t\right)^{\alpha_{pv2}}})$$

Considering that not all components in a system are brand new τ is considered a variable that represents the year in the use of any component.

So, this change likes this:

$$AMC = B_{ij} + Fr_{ij}\left(1 - e^{-\lambda_{pv1}[t+\tau]}\right) + Fd_{ij}(1 - e^{-\left(\lambda_{pv2}[t+\tau]\right)^{\alpha_{pv2}}})$$

For each component of the system, the only difference is whether the maintenance costs caused by time-dependent failures and random failures or only one of the two are integrated.

3.8 Reliability Evaluation in Electric Power Systems

Literature in the area of electric power system reliability has focused on obtaining outage rates for series and parallel configurations when considering different outage cases. Billington & Allan

(1984), Billington & Li (1994) and Billington & Zang (2000) discuss the reliability evaluation of power systems. Particularly, they describe approximation techniques for the reliability analysis of series and parallel system configurations (with two or three components). Moreover, Billington & Allan (1983) and Billington & Li (1994), note that for complex systems, a series-parallel transformation to the actual system reliability metric.

The main objective is to develop electric power system reliability equations to accurately estimate the system outage rate, average repair time and expected downtime, for a micro-grid system. The mathematical expressions developed, consider just the component sustained outages overlapping component sustained outages. If the system is a series-parallel system, then each cut-set represents each parallel structure, called a subsystem. If another configuration is appropriate, then cut-sets are initially determined.

The following notation is used.

λ_{ij} = Sustained outage rate for component *j* in subsystem *i*
$\lambda_{s_i}^{m_i}$ = Sustained outage rate for a subsystem *i* with m_i components
λ_{s-p} = Sustained outage rate for series-parallel system
r_{ij} = Average repair time for component *j* in subsystem *i*
$r_{s_i}^{m_i}$ = Average repair time for subsystem *i* with m_i components
r_{s-p} = Average repair time for series-parallel system
$U_{s_i}^{m_i}$ = Expected downtime for subsystem *i* due to sustaa ined outage with m_i components
U_{s-p} = Expected Downtime for series-parallel system

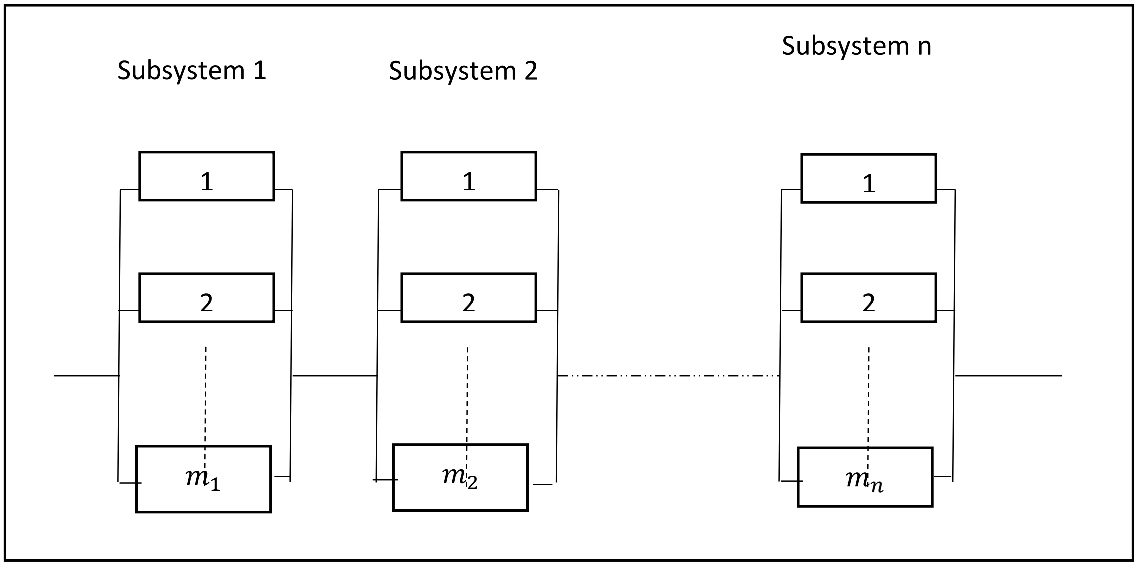

Figure 3.8 Series-parallel System

Figure 3.8 Presents a series-parallel system with *n* subsystems connected in series, and each of these subsystems has m_i components connected in parallel.

Sustained outages overlapping component sustained outages

System outage rate

Billington & Allan (1983, 1984) and Billington & Li (1994) present an outage rate equation for systems with a series configuration:

$$\lambda_{s-p} = \sum_{i=1}^{n} \lambda_{s_i}^{m_i} \qquad (3.16)$$

That is, the outage rate for series-parallel design is the sum of the outage rates associated with each for the parallel subsystems. Based on the equations presented by Billington & Allan (1983, 1984) and Billington & Li (1994) a general formulation for subsystem *i* can be given as:

$$\lambda_{s_i}^{m_i} = \left[\prod_{j=1}^{m_i} \lambda_{ij}\right] \sum_{j_1<j_2<\cdots<j_{m_i}} r_{j_1} r_{j_2} \dots r_{j_{m_i}} = \left[\prod_{j=1}^{m_i} \lambda_{ij}\right] \sum_{j=1}^{n} \prod_{k\neq i} r_{ik} \qquad (3.17)$$

Equation 3.17 is a direct extension of the approach presented by Billington & Alla (1983) for two and three component parallel subsystems. According to Espiritu (2007) for two components Equation 3.18 yields:

$$\lambda_{s_1}^{2} = \lambda_{11}\lambda_{12}(r_{11} + r_{12}) = \lambda_{11}(r_{11}\lambda_{12}) + \lambda_{12}(r_{12}\lambda_{11}) \qquad (3.18)$$

Espiritu (2007) mentions to Billington & Allan (1983): "a two-component parallel systems fails if the first system component fails, at rate λ_{11}, and during the repair time of such component, r_{11}, the second systems component fails, at rate λ_{12}, or if the second system component fails, at rate λ_{12}, and during the repair time of such component, r_{12}, the first system component fails, at rate λ_{11}."

A set of recursive equations has been developed to obtain the system outage rate (Espiritu 2007). This recursive approach is applied to most of the metrics proposed. A recursive formula for $\lambda_{s_i}^{m_i}$, a parallel subsystem is given by:

$$\lambda_{s_i}^{m_i} = \lambda_{s_i}^{m_i-1} \lambda_{im_i}\left(r_{s_i}^{m_i-1} + r_{im_i}\right) \qquad (3.19)$$

Equation 3.19 follows from the idea that a parallel system with m_1 components can be regarded as a new parallel system with two components. The first "component" of this new system has associated the failure rate of $\lambda_{s_i}^{m_i-1}$.

The recursion consists of exactly m_i computations or recursions. The first recursion considers only the first component and its outage rate is computed, i.e. $\lambda_{s_i}^1 = \lambda_{i1}$. The second recursion considers only the first two components its outage rate computed, i.e., $\lambda_{s_i}^2$. Thus,

$$\lambda_{s_i}^2 = \lambda_{s_i}^{m_i-1}\lambda_{im_i}\left(r_{s_i}^{m_i-1} + r_{im_i}\right) = \lambda_{s_i}^1\lambda_{i2}\left(r_{s_i}^1 + r_{i2}\right) = \lambda_{i1}\lambda_{i2}(r_{i1} + r_{i2}) \qquad (3.20)$$

In the same form, the remaining recursions can be used to obtain

$$\lambda_{s_i}^{m_i} = \lambda_{s_i}^{m_i-1}\lambda_{im_i}\left(r_{s_i}^{m_i-1} + r_{im_i}\right) \qquad (3.21)$$

3.8.1 Expected Outage Duration (Average Repair Time)

Espiritu (2007) mentions direct approximation equations for systems with a series configuration proposed by Billington & Allan (1983, 1984) and Billington & Li (1994) as:

$$r_{s-p} = \frac{\sum_{i=1}^{n} \lambda_{s_i}^{m_i} r_{s_i}^{m_i}}{\lambda_{s-p}} \qquad (3.22)$$

A general formulation for subsystem I can be given as:

$$r_{s_i} = \frac{\prod_{i=1}^{n} r_{ij}}{\sum_{j=1}^{n} \prod_{k \neq j} r_{ik}} \tag{3.23}$$

A recursive formula for $r_{s_i}^{m_i}$ can be obtained by:

$$r_{s_i}^{m_i} = \frac{r_{s_i}^{m_i-1} r_{im_i}}{r_{s_i}^{m_i-1} + r_{im_i}} \tag{3.24}$$

The first recursion considers only the first component and its outage duration is computed, i.e., $r_{s_i}^{1} = r_{i1}$. The second recursion considers only the first two components and its outage duration is computed, i.e.,

$$r_{s_i}^{2} = \frac{r_{s_i}^{1} r_{i2}}{r_{s_i}^{1} + r_{i2}} = \frac{r_{i1} r_{i2}}{r_{i1} + r_{i2}} \tag{3.25}$$

The same process can be applied to the remaining recursions to determine:

$$r_{s_i}^{m_i} = \frac{r_{s_i}^{m_i-1} r_{im_i}}{r_{s_i}^{m_i-1} + r_{im_i}} \tag{3.26}$$

System Outage Time

Average system outage time for the series-parallel system is given by:

$$U_{s-p} = \lambda_{s-p} r_{s-p} = \sum_{i=1}^{n} U_{s_i}^{m_i}$$

Where:

$$U_{s_i}^{1} = \lambda_{s_i}^{1} r_{s_i}^{1}$$

$$U_{s_i}^{2} = \lambda_{s_i}^{2} r_{s_i}^{2}$$

$$U_{s_i}^{3} = \lambda_{s_i}^{3} r_{s_i}^{3}$$

$$U_{s_i}^{m_1} = \lambda_{s_i}^{m_i} r_{s_i}^{m_i}$$

3.9 Expected Energy Not Supplied

The probability of customers being disconnected can be reduced by increased investment during the planning phase, operating phase, or both. Over-investment can lead to excessive operating costs which must be reflected in the tariff structure. Consequently, economic constraints can be violated even though the system may be highly reliable.

On the other hand, under-investment can lead to the opposite situation. It is evident therefore that the economic and reliability constraints can be quite competitive, and this can lead to extremely difficult managerial decisions at both the planning and operating phases.

It is 0important to conjecture at this point on what can be done regarding reliability assessment and why it is necessary. Failures of components, plant, and systems occur randomly; the frequency, duration, and impact of failures vary from one year to the next. Generally, all utilities record details of the events as they occur, and produce a set of performance measures, such as:

system availability
estimated unsupplied energy
number of incidents
number of hours of interruption
excursions beyond set voltage (and frequency) limits

The basic methodology for evaluating generating system reliability is to develop probability models for capacity on the outage and load demand and calculate the probability of loss of load by a convolution of the two models. This calculation can be repeated for all the periods (e.g., weeks) in a year considering the changes in the load demand, planned outages of units, and any unit additions or retirements, etc.

3.9.1 Probabilistic Criteria and Indices

An understanding of the probabilistic criteria and indices used in generating capacity reliability (HLI) studies is important. These include

loss of load probability (LOLP)
loss of load expectation (LOLE)
loss of energy expectation (LOEE)/expected energy not supplied (EENS)
frequency & duration (F&D) indices
energy index of reliability (EIR)
energy index of unreliability (EIU), and
system minutes (SM).

LOLP,

This is the oldest and the most basic probabilistic index. It is defined as the probability that the load will exceed the available generation. Its weakness is that it defines the likelihood of encountering trouble (loss of load) but not the severity; for the same value of LOLP, the degree of trouble may be less than 1 MW or greater than 1000 MW or more. Therefore it cannot recognize the degree of capacity or energy shortage.

This index has been superseded by one of the following expected values in most planning applications because LOLP has less physical significance and is difficult to interpret.

LOLE,

This is now the most widely used probabilistic index in deciding future generation capacity. It is generally defined as the average number of days (or hours) on which the daily peak load is expected to exceed the available capacity. It, therefore, indicates the expected number of days (or hours) for which a load loss or deficiency may occur. This concept implies a physical significance not forthcoming from the LOLP, although the two values are directly related.

It has the same weaknesses that exist in the LOLP.

LOEE,

This index is defined as the expected energy not supplied (EENS) due to those occasions when the load exceeds the available generation. It is presently less used than LOLE but is a more appealing index since it encompasses the severity of the deficiencies as well as their likelihood. It, therefore, reflects risk more truly and is likely to gain popularity as power systems become more energy-limited due to reduced prime energy and increased environmental controls.

EIR and EIU,

These are directly related to LOEE which is normalized by dividing by the total energy demanded. This ensures that large and small systems can be compared on an equal basis and chronological changes in a system can be tracked.

Frequency & Duration (F&D) Indices,

The F&D criterion is an extension of LOLE and identifies expected frequencies of encountering deficiencies and their expected duration.

It, therefore, contains additional physical characteristics but, although widely documented, is not used in practice. This is due mainly to the need for additional data and greatly increased the complexity of the analysis without having any significant effect on the planning decisions.

3.9.2 Reliability Measures (Conventional),

System indices (sometimes appearing under different names)
LOLP = Loss of load probability
LOLE = Loss of load expectation (h/year)
EPNS = Expected power not supplied (MW)
EENS = Expected energy not supplied (MWh/year)
LOLF = Loss of load frequency (occ./year)
LOLD = Loss of load duration (h)
LOLC = Loss of load cost (US$/year)
etc.

Load Point Indices,

failure rate, λ

average outage time, r

average annual unavailability, U = λ.r

average load disconnected, L

expected energy not supplied, E = U.L

-Series Structure, n Components

Interruption frequency $\mathbf{f_s} = \sum_{i=1}^{n} \boldsymbol{\lambda_i}$ [Interruptions/year]

Interruption duration $\boldsymbol{r_s} = \frac{\sum_{i=1}^{n} \lambda_i r_i}{\sum_{i=1}^{n} \lambda_i}$ [hours/interruption]

Annual downtime $\boldsymbol{U_s} = \boldsymbol{f_s r_s} \sum_{i=1}^{n} \boldsymbol{\lambda_i}\, \boldsymbol{r_i}$ [hours/year]

-Parallel Structure, n (independent) Components

Interruption frequency $\mathbf{f_s} = \mathbf{8760}\left[\prod_{i=1}^{n}\left(\frac{\lambda_i r_i}{8760}\right)\right]\sum_{i=1}^{n}\left(\frac{1}{r_i}\right)$ [Interruptions/year]

Interruption duration $\boldsymbol{r_s} = \frac{1}{\sum_{i=1}^{n}\frac{1}{r_i}}$ [hours/interruption]

Annual downtime $\boldsymbol{U_s} = \mathbf{8760}\prod_{i=1}^{n}\left(\frac{\lambda_i r_i}{8760}\right)$ [hours/year]

-System-Oriented Reliability Indices, Number of Interruptions

Weighting by the number of customers

System Average

Interruption Frequency Index:

$SAIFI = \frac{\sum_{i-1}^{n} \mathrm{f}_i N_i}{\sum_{i=1}^{ntot} N_i}$ [Interruptions/year]

f_i = number of interruptions at load point i

N_i= number of customers connected to load point i

n = number of load points interrupted

n_{tot} = total number of load points

-System-Oriented Reliability Indices, Annual Interruption Time,

Weighting by number of customers

System Average

Interruption Duration Index:

$$SAIDI = \frac{\sum_{i=1}^{n} U_i N_i}{\sum_{i=1}^{ntot} N_i} = \frac{\sum_{i=1}^{n} \mathrm{f}_i r_i N_i}{\sum_{i=1}^{ntot} N_i}$$

U_i= $\mathrm{f}_i r_i$= annual outage for load point i

r_i= average outage duration for load point i

-System-Oriented Reliability Indices, Average Interruption Duration,

Weighting by the number of customers

Customer Average Interruption Duration Index:

$$CAIDI = \frac{\sum_{i=1}^{n} U_i N_i}{\sum_{i=1}^{ntot} \mathrm{f}_i N_i}$$

$$\boldsymbol{SAIFI\ x\ CAIDI = SAIDI}$$

-System-Oriented Reliability Indices, Unavailability, Energy Not Supplied,

Energy Not Supplied: $\boldsymbol{ENS = \sum_{I=1}^{N} P_{av(i)} U_i}$ (kWh/year)

Pav(i) = Average load connected to load point i

Cost of energy Not Supplied: $\boldsymbol{CENS = ENS(cost[dlls]\frac{kwh}{year})}$

The theoretical basis for the measurement of outage cost is the loss of consumer welfare as a consequence of an outage. Several approaches have emerged in the literature over the past few decades. One approach is to estimate outage costs on the basis of estimated willingness-to-pay for planned electricity consumption. In another approach, electric supply rates (tariffs) are used to derive the Value-based reliability (VBR) estimates. Many attempts are made on the use of a ratio of gross economic measure (e.g., GNP) and a suitable energy consumption measure to yield a $/kWh value that is assumed to be the cost of unsupplied energy during interruptions. While most of these approaches are reasonably straightforward to apply, their disadvantages are that they are based on severely limiting assumptions.

Chapter 4

Modeling

Figure 4.1 represents a micro-grid system in which have been installed five photovoltaic panels in parallel following a regulator in series, following two batteries in parallel finalizing just one inverter in series, producing a certain amount of energy.

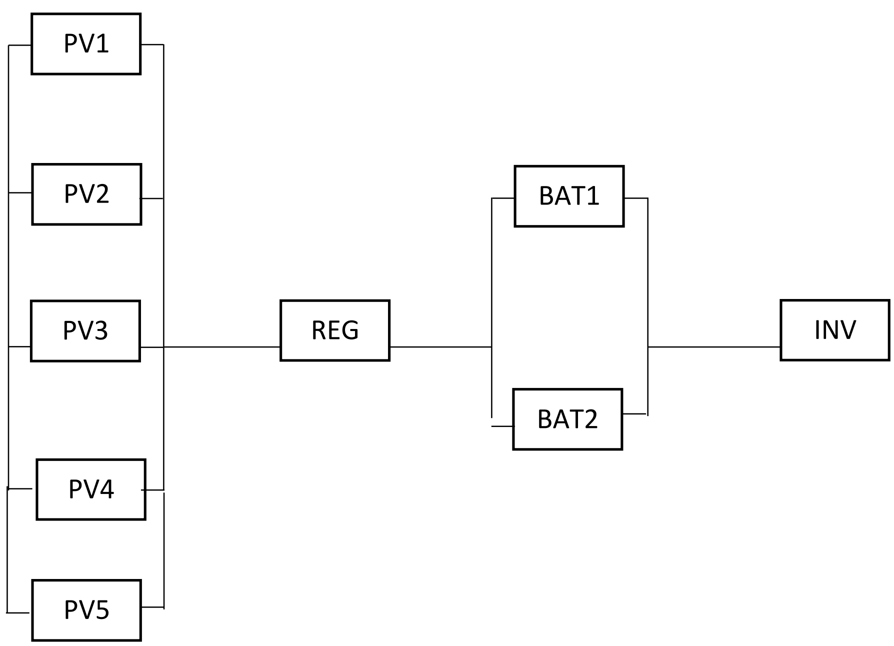

Figure 4.1 System is representing a residential micro-grid.

4.1 Maintenance Cost

PV1………………… Panel photovoltaic 1
PV2………………… Panel photovoltaic 2
PV3………………… Panel photovoltaic 3
PV4………………… Panel photovoltaic 4
PV5………………… Panel photovoltaic 5
REG………………… Regulator

BAT1………………. Battery 1

BAT2………………. Battery 2

INV…………………. Inverter

Photovoltaic Panels (pv's)

$$AMC = [1 + I]^j \left[B_{ij} + Fr_{ij}\left(1 - e^{-\lambda_{pv_1[t+\tau]}}\right) + Fd_{ij}\left(1 - e^{-\left(\lambda_{pv_2}[t+\tau]\right)^{\alpha pv_2}}\right)\right]$$

B_{ij} ……………………………..Annual scheduled maintenance budget, component i, period j

Fr_{ij} ……………………………. Annual maintenance cost associated to random failures

Fd_{ij} ……………………………..Annual maintenance cost associated to degradation failures

$\left(1 + e^{-\lambda_{pv_1}[t+\tau]}\right)_{ij}$ …………Failures associated to random failures

$\left(1 + e^{-\lambda_{pv_2}[t+\tau]^{\alpha pv_2}}\right)_{ij}$……Failures associated to degradation failures

$[1 + I]^j$ …………………………Economic index associated to period j

$$RC = [RC_i][1 + I]^j$$

RC………………………. Replacement cost

RC_i ……………………. Replacement cost component i

$[1 + I]^j$ …………….. Interest applied to period j

AMC ≥ RC -------------- Optimal replacement time.

Figure 4.2 represents how maintenance cost is increasing over time reaching the equilibrium point when annual maintenance cost reaches the replacement cost.

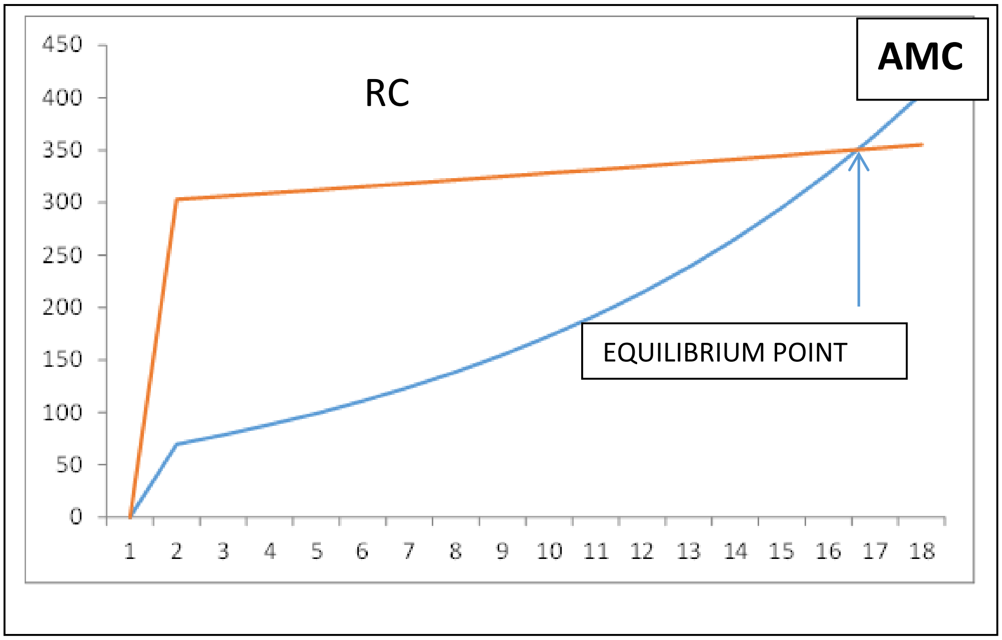

Figure 4.2 Equilibrium point between Annual Maintenance Cost and Replacement Cost.

Regulator

$$AMC = [1+I]^j\left[B_{ij} + Fr_{ij}\left(1 - e^{-\lambda_{R[t+\tau]}}\right)\right]$$

B_{ij} ....Annual scheduled maintenance budget, component i, period j

Fr_{ij} .... Annual maintenance cost associated to random failures

Fd_{ij} ....Annual maintenance cost associated to degradation failures

$\left(1 + e^{-\lambda_R[t+\tau]}\right)_{ij}$ ....Failures associated to random failures

$[1+I]^j$ .... Economic index associated to period j

$$RC = [RC_i][1+I]^j$$

RC............................ Replacement cost

RC_i .... Replacement cost component i

$[1+I]^j$ .... Interest applied to period j

AMC ≥ RC -------------- Optimal replacement time.

Batteries

$$AMC = [1+I]^j\left[B_{ij} + Fr_{ij}\left(1-e^{-\lambda_{B1[t+\tau]}}\right) + Fd_{ij}\left(1-e^{-(\lambda_{B2}[t+\tau])^{\alpha_{B2}}}\right)\right]$$

B_{ij} ……………………………..Annual scheduled maintenance budget, component i, period j

Fr_{ij} …………………………….. Annual maintenance cost associated to random failures

Fd_{ij} ……………………………..Annual maintenance cost associated to degradation failures

$\left(1+e^{-\lambda_{B1}[t+\tau]}\right)_{ij}$ ………..Failures associated to random failures

$\left(1+e^{-\lambda_{B2}[t+\tau]^{\alpha_{B2}}}\right)_{ij}$……Failures associated to degradation failures

$[1+I]^j$ ……………………… Economic index associated to period j

$$RC = [RC_i][1+I]^j$$

RC………………………. Replacement cost

RC_i ……………………. Replacement cost component i

$[1+I]^j$ …………….. Interest applied to period j

AMC ≥ RC -------------- Optimal replacement time.

Inverter

$$AMC = [1+I]^j\left[B_{ij} + Fr_{ij}\left(1-e^{-\lambda_{I[t+\tau]}}\right)\right]$$

B_{ij} ………………………………..Annual scheduled maintenance budget, component i, period j

Fr_{ij} ……………………………. Annual maintenance cost associated to random failures

Fd_{ij} ……………………………Annual maintenance cost associated to degradation failures

$\left(1+e^{-\lambda_I[t+\tau]}\right)_{ij}$ …………..Failures associated to random failures

$[1+I]^j$ …………………………Economic index associated to period j

$$RC = [RC_i][1+I]^j$$

RC………………………. Replacement cost

RC_i ……………………. Replacement cost component i

$[1+I]^j$ …………….. Interest applied to period j

AMC ≥ RC -------------- Optimal replacement time.

4.2 Expected Energy Not Supplied (EENS)

$$\lambda_{s_i}^{m_i} = \left[\prod_{j=1}^{m_i} \lambda_{ij}\right] \sum_{j_1<j_2<\cdots<j_{m_i}} r_{j_1} r_{j_2} \dots r_{j_{m_i}} = \left[\prod_{j=1}^{m_i} \lambda_{ij}\right] \sum_{j=1}^{n} \prod_{k\neq i} r_{ik}$$

$$U_{s-p} = \lambda_{s-p} r_{s-p} = \sum_{i=1}^{n} U_{s_i}^{m_i}$$

$$EENS = U_{s-p} L$$

L ………………….. Total load

EC ………………… Energy cost.

EXPECTED LOSSES = $[EENN][L][EC]$

4.3 Expected Downtime

Photovoltaic Panels

Table 4.1 Data for photovoltaic panels

Panel	Failure Rate	Average Repair Time
PV1	λ_1	r_1
PV2	λ_2	r_2
PV3	λ_3	r_3
PV4	λ_4	r_4
PV5	λ_5	r_5

$$\lambda_{pv}^5 = \lambda_1\lambda_2\lambda_3\lambda_4\lambda_5[(r_1r_2r_3r_4) + (r_1r_2r_3r_5) + (r_1r_2r_4r_5) + (r_1r_3r_4r_5) + (r_2r_3r_4r_5)]$$

$$r_{pv}^5 = \frac{1}{\frac{1}{r_1} + \frac{1}{r_2} + \frac{1}{r_3} + \frac{1}{r_4} + \frac{1}{r_5}}$$

$$U_{pv}^5 = \lambda_{pv}^5 r_{pv}^5$$

Regulator

Table 4.2 Data for Regulator

Regulator	Failure Rate	Repair Time
R	λ_1	r_1

$$\lambda_R^1 = \lambda_1$$

$$r_R^1 = r_1$$

$$U_R^1 = \lambda_R^1 r_R^1$$

Batteries

Table 4.3 Data for Batteries

Battery	Failure Rate	Repair Time
B1	λ_1	r_1
B2	λ_2	r_2

$$\lambda_B^2 = \lambda_1 \lambda_2 (r_1 + r_2)$$

$$r_B^2 = \frac{r_1 r_2}{r_1 + r_2}$$

$$U_B^2 = \lambda_B^2 r_B^2$$

Inverter

Table 4.4 Data for Inverter

Inverter	Failure Rate	Repair Time
I	λ_1	r_1

$$\lambda_I^1 = \lambda_1$$

$$r_I^1 = r_1$$

$$U_I^1 = \lambda_I^1 r_I^1$$

4.3.1 System's Expected Downtime

$$U_{s-p} = \lambda_{s-p} r_{s-p} = \sum_{i=1}^{n} U_{s_i}^{m_i}$$

$$U_S = U_{pv}^{5} + U_R^{1} + U_B^{2} + U_I^{1}$$

4.3.2 Cost of Expected Losses

$$COST\ OF\ EXPECTED\ LOSSES = [U_S][L][EC]$$

Where

L .... Total load

EC .... Energy cost.

Optimal component replacement,

$$AMC + EXPECTED\ LOSSES\ \geq RC$$

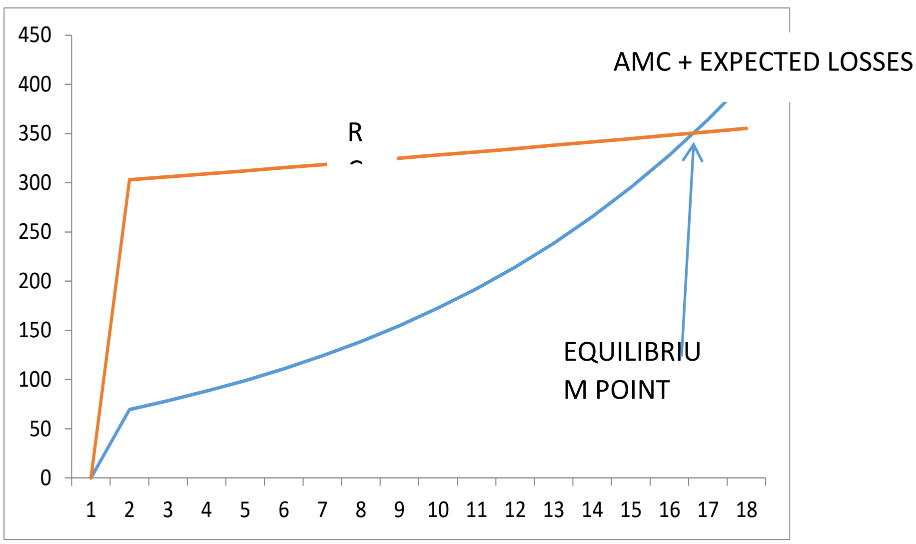

Figure 4.3 Equilibrium point between Annual Maintenance Cost Plus Expected Energy not Supplied versus Replacement Cost.

Chapter 5

5.1 Numerical Example: Case of Study No. 1

Table 5.1 Numerical data of the example.

Component	Age (τ) (years)	λ_1	λ_2	α_2	Inflation (%)	Interest (%)	AMS (Dlls)	RC (Dlls)	NSMC (Dlls)
PV1	0	.125	.067	3.5	6	1	40	300	150
PV2	5	.125	.067	3.5	6	1	40	300	150
PV3	10	.125	.067	3.5	6	1	40	300	150
PV4	6	.125	.067	3.5	6	1	40	300	150
PV5	15	.125	.067	3.5	6	1	40	300	150
REG	4	.125	--	--	6	1	200	1500	400
BAT1	0	.125	.067	3.5	6	1	50	500	500
BAT2	0	.125	.067	3.5	6	1	50	500	500
INV	5	.125	--	--	6	1	300	2500	800

Results:

Table 5.2 Results of the example.

	PV1	PV2	PV3	PV4	PV5	REG	BAT1	BAT2	INVERTER
REPLACEMENT COST	341.43	344.84	328.11	334.70	315.30	1848.59	541.43	541.43	3050.48
YEAR	13.00	14.00	9.00	11.00	5.00	21.00	8.00	8.00	20.00
MAINTENANCE COST	344.39	496.31	370.87	345.35	336.42	1941.23	583.46	583.46	3317.24
EENS COST	0.90	0.98	0.60	0.74	0.33	1.70	0.53	0.53	1.57
MC+EENSC	345.29	497.29	371.47	346.09	336.75	1942.93	583.99	583.99	3318.82

Results show maintenance and replacement cost information through the time of use of the elements of the system, in the case of figure 5.1, the photovoltaic panel is new. The break-even point is around 17 years; the total cost considers the maintenance cost and energy not generated cost during the system's downtime. Figures 5.2, 5.3, 5.4 and 5.5 are the specific cases of solar panels, the difference between them is in the years of operation before being installed in the system (i.e., they are second-hand elements), in the case of figure 5.2, it is five years, case 5.3, 10 years, case 5.4, 6 years and in case 5.5 it is 15 years. The other graphs speak for themselves. In the case of figure 5.6 the regulator with an age of 4 years, should be replaced in year 24 of continuous use. Figures 5.7 and 5.8 compare the same case of seven years with the replacement and, finally, in Figure 5.9, which was five years old at the time of installation, it is suggested that it be replaced after 24 years of service. This system is a simple system to compare the probability of failure based on its Cumulative Failure Distribution, the expected cost of energy not supplied together versus the direct replacement cost through an immediate future horizon in units of years elapsed.

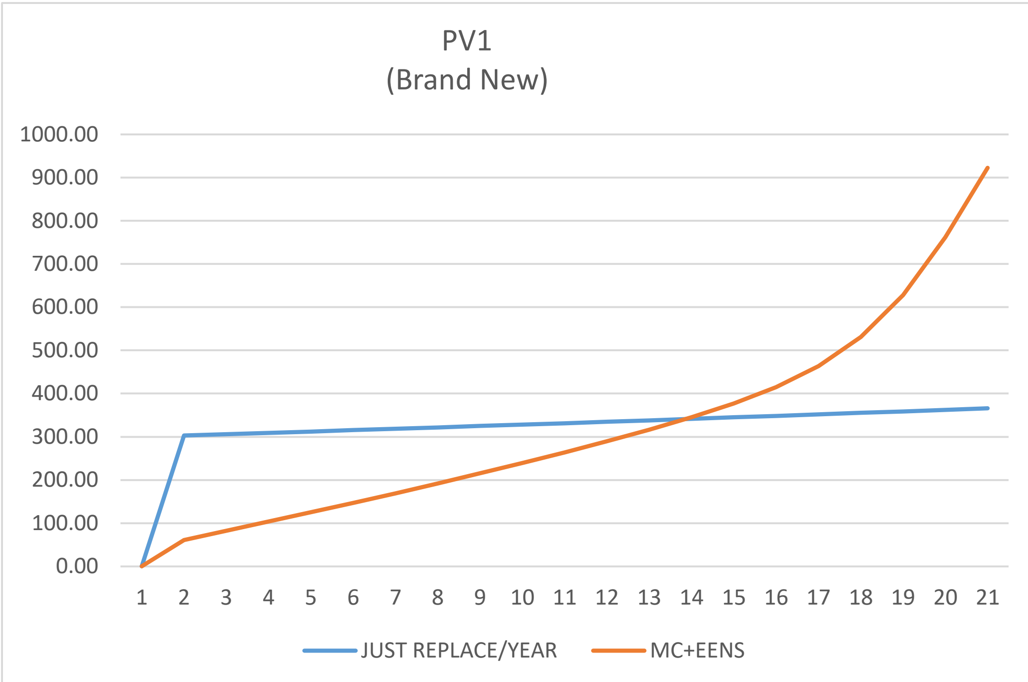

Figure 5.1 Equilibrium point for solar panel 1

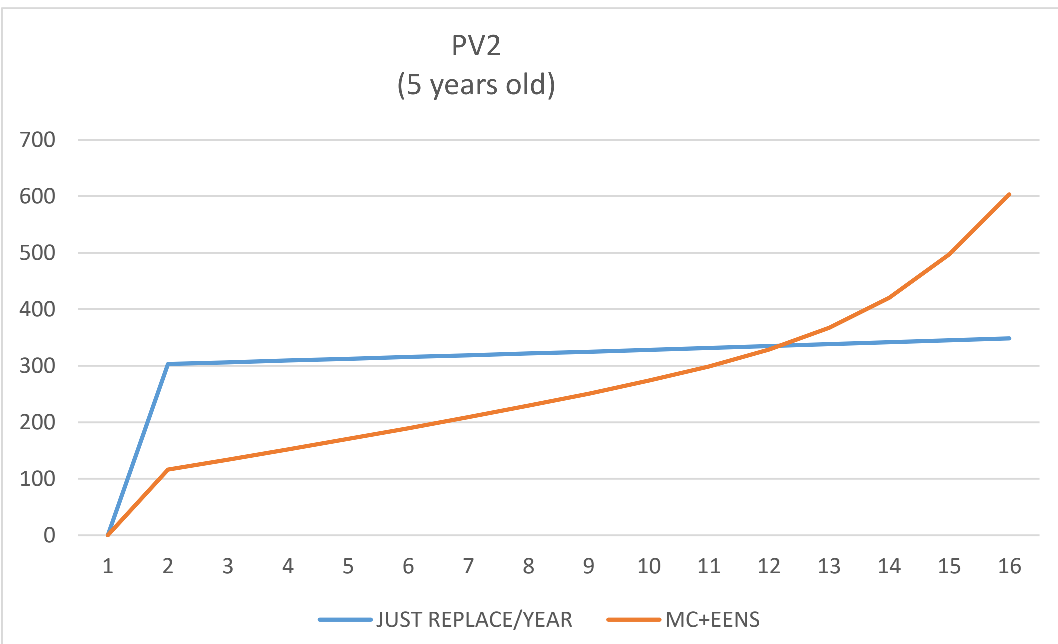

Figure 5.2 Equilibrium point for solar panel 2

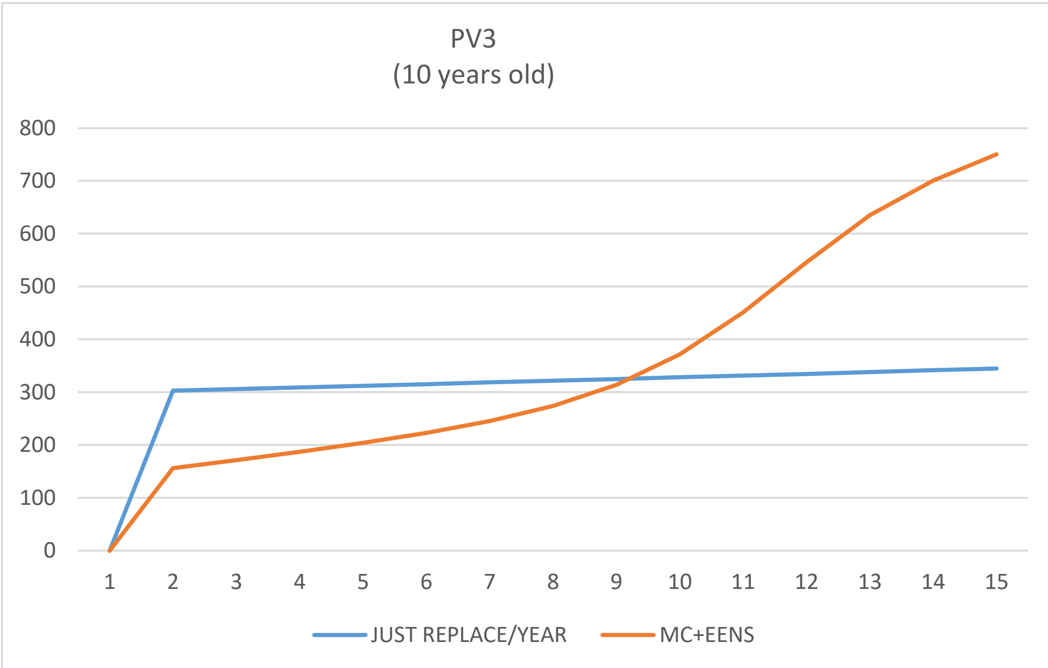

Figure 5.3 Equilibrium point for solar panel 3

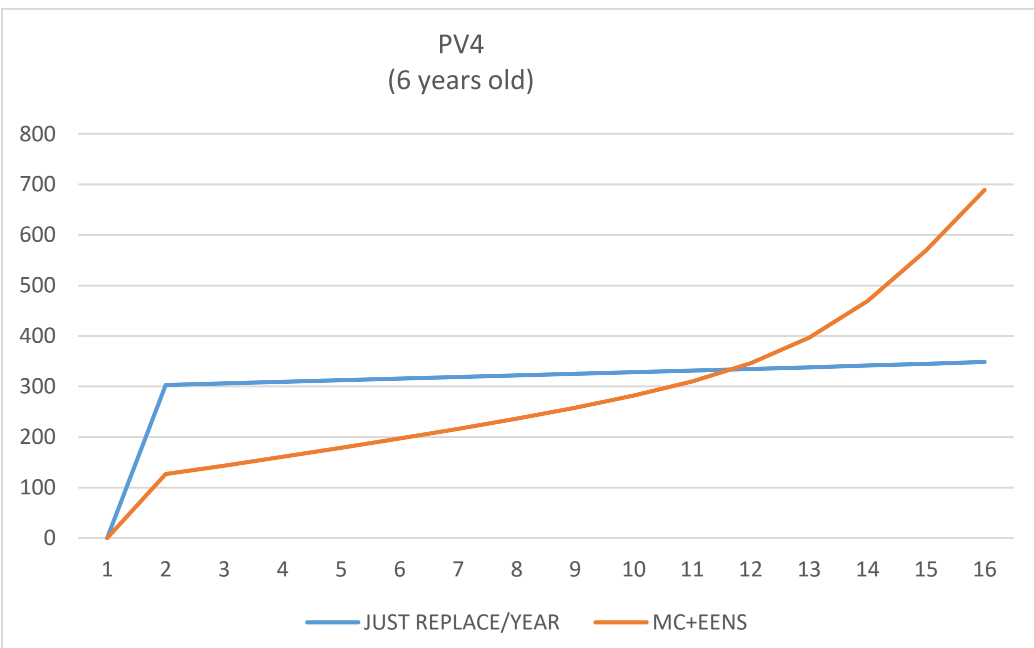

Figure 5.4 Equilibrium point for solar panel 4

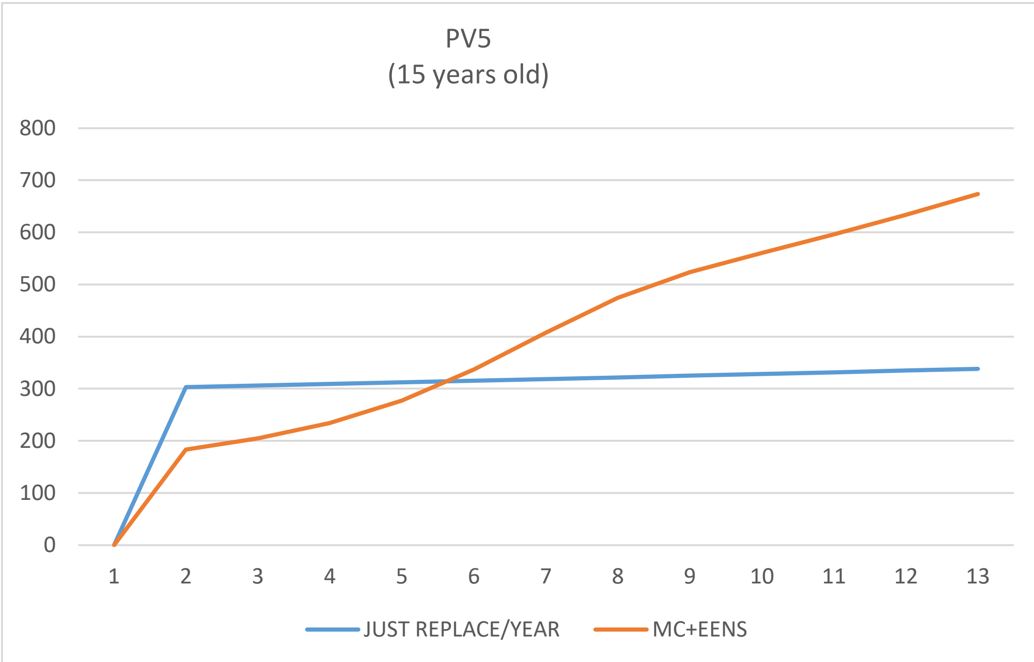

Figure 5.5 Equilibrium point for solar panel 5

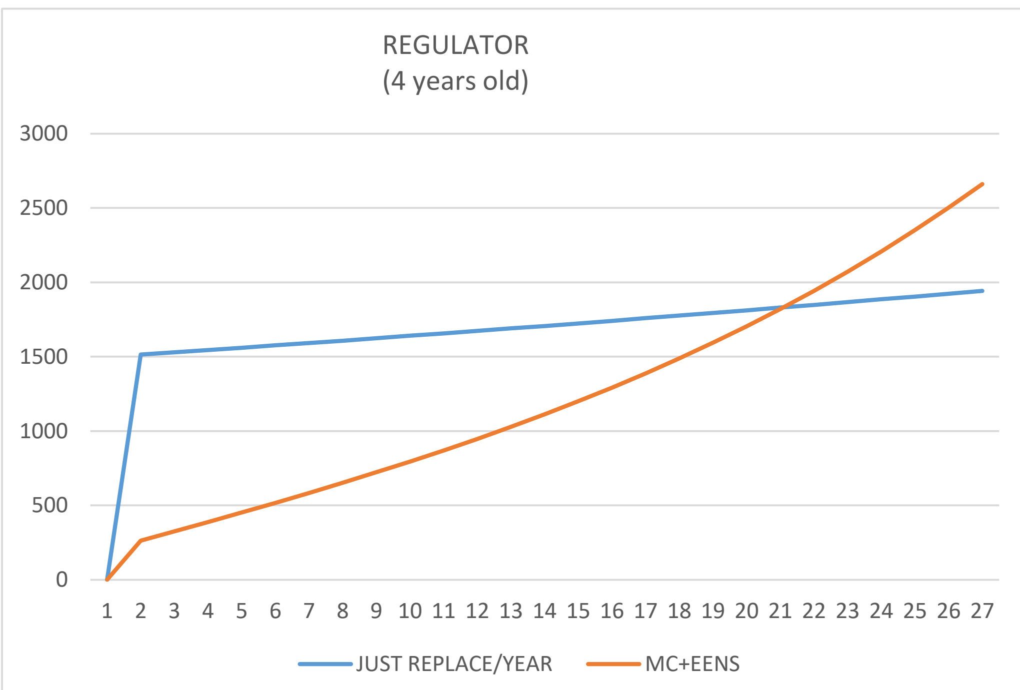

Figure 5.6 Equilibrium point for regulator

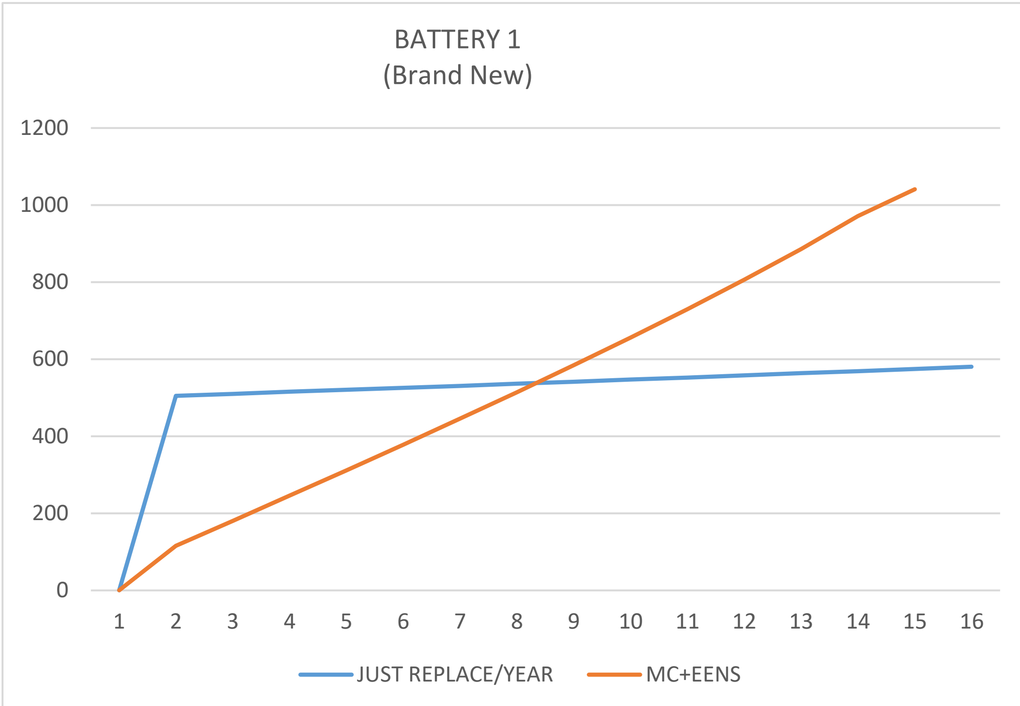

Figure 5.7 Equilibrium point for solar battery 1

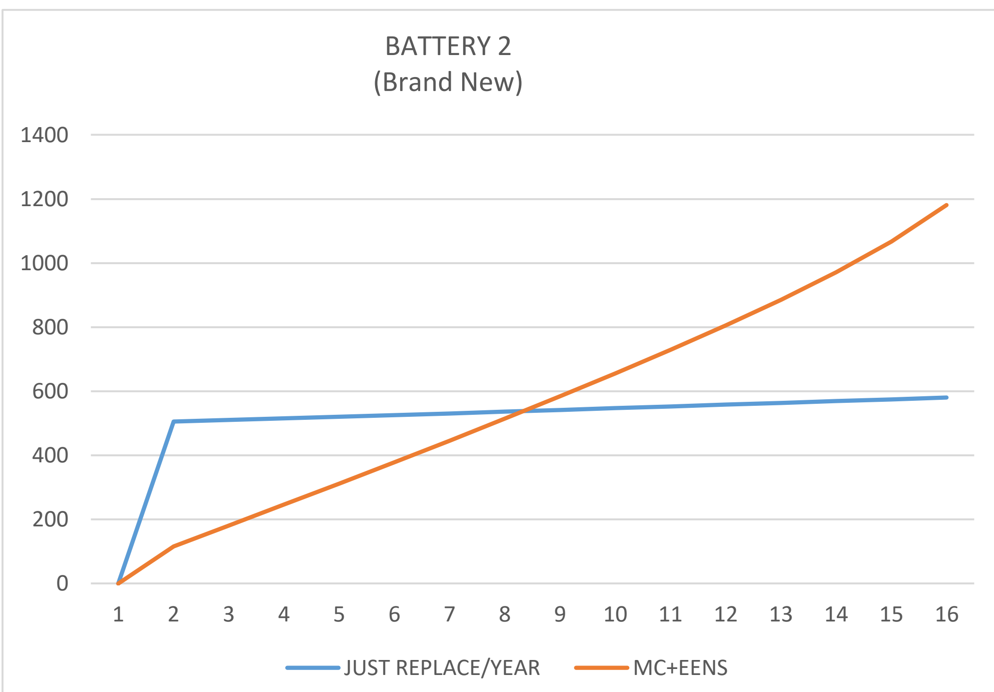

Figure 5.8 Equilibrium point for solar battery 2

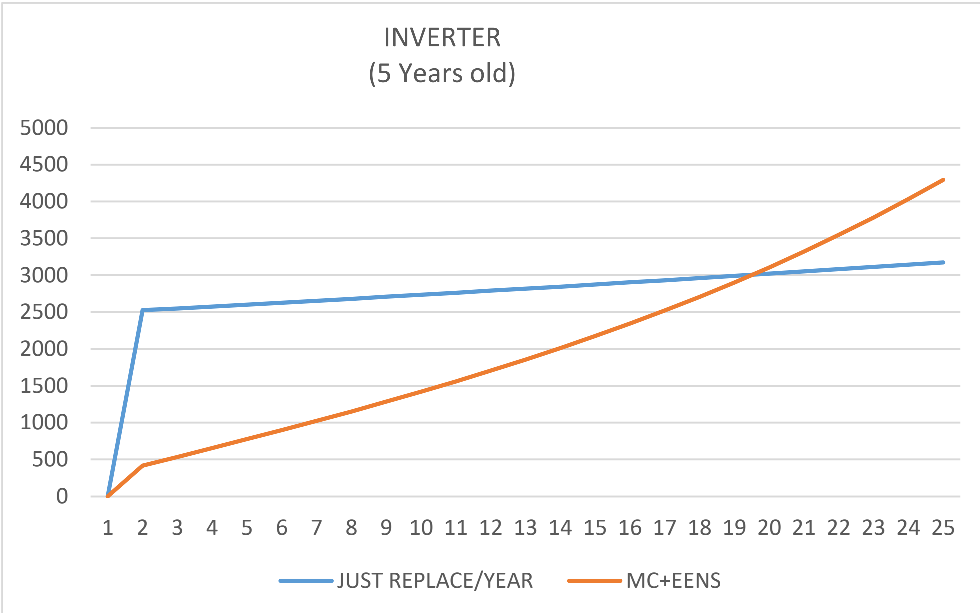

Figure 5.9 Equilibrium point for solar inverter

After a first analysis of the first case of study, we discovered that the Expected Cost of Energy Not Supplied was not significant. The next step is to analyze the allocation system as a whole. Figure 5.10 shows the replacement allocation system considering all components in the same line of time. Overlapping in the same chart all components are allocated in the period of time to be replaced or just keeping in maintenance cost.

Every peak on the curve is the replacement proposal time recommended by the probabilistic system considering accumulated distribution function Weibull and Exponential.

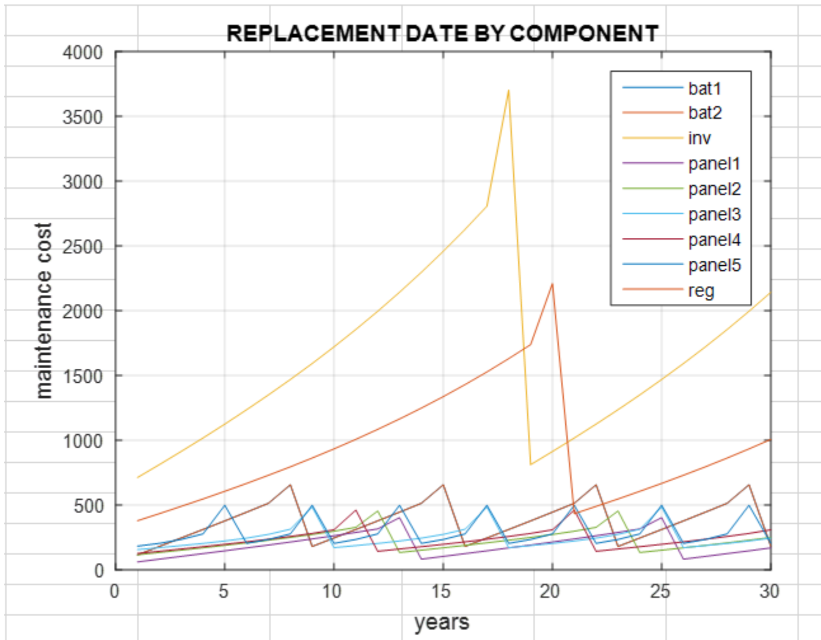

Figure 5.10 Replacement allocation system.

In the same way, every year was evaluated considering replacement cost and maintenance cost. Lowest value and highest values can be considered as a constraint in case of a specified budget, leave replace of components depending of budget analysis.

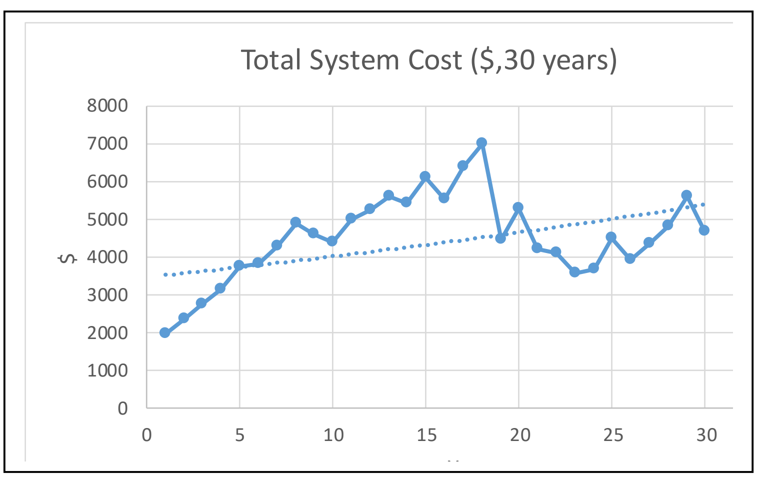

Figure 5.11. Total system cost lower and higher values.

Likewise, a display by component of the proposed replacement dates is shown in the following figure (5.12). Each component shows a 30-year cycle and possible replacement times generated by the probabilistic failure cost and replacement system.

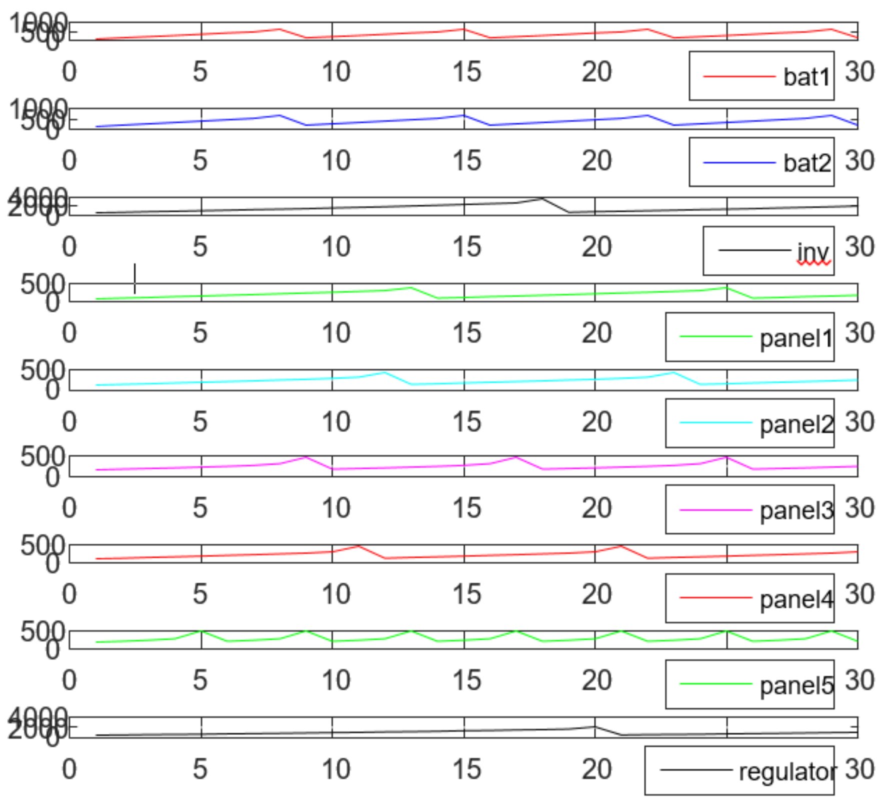

Figure 5.12 Replacement guide trough next 30 years by component

5.2 Case of Study No. 2

In the first case were tested components in a micro-grid based on solar panels using different ages between elements of the same class. Replacing times were deducted using a probabilistic method based on Exponential and Weibull distribution comparing maintenance versus replacing costs. In the second case, bigger micro-grid is considered having the same restriction such as micro-grid based on solar panels stand alone and same age for every component (brand new).

The second study case has a peculiarity against the first. The second study case is based on the load needs of a particular consumer. Data such as total load and installed load in the specific case of the consumer. Geographic data such as irradiance in the case of the place and of course data such as each of the electrical components that make up the microgrid. After a basic calculation of components, the need is reached for 15 solar panels, one regulator, four battery banks and one inverter. This configuration is shown in the figure 5.10

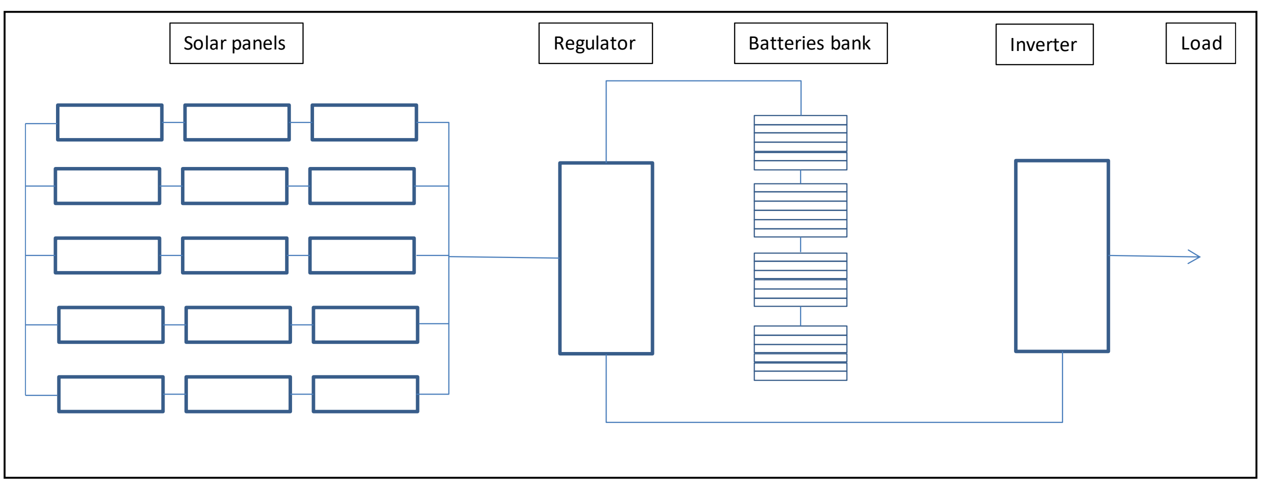

Figure 5.13 Second case of study. Micro grid solar panel stand alone.

A multi-objective GA was developed to determine the best components based on "n" number of suppliers, there were two objectives considered in the study, the first objective (Ftss1, 5.2.1) is based on the solar panel efficiency, and the second objective considers the minimization of the total annualized component cost (5.2.2), the objectives considered were to maximize the Average Solar Panel Efficiency subject to a nominal efficiency (13%)and to minimize the total annualized component cost

$$\text{Average Solar Panel Efficiency} = \sum_{i=1}^{n} \frac{Eff_{pi}}{n} \tag{5.2.1}$$

$$\text{Annualized Component Cost} = \sum_{i}^{n} \frac{C_i}{Ul_i} + Cm_i \tag{5.2.2}$$

$$Eff = \frac{I_{nom} x\, V_{nom}}{G\; x\; A} \tag{5.2.3}$$

Subject to:

Ftss1 >= X

Ftss2 >= Budget

Where:

Eff ------------------ Solar panel efficiency

G ------------------ Irradiance Kwh/m2

A ------------------ Area of solar panel m2

Inom ---------------- Nominal current

Vnom --------------- Nominal voltage

C_i ------------- Cost of element *i*

Ul_i ------------- Useful life in years of component *i*

Cm_i ------------ Maintenance cost of element *i*

After running 30 iterations the algorithm shows through a pareto set (Figure 5.11) different options of supplier combinations. As it can be observed, higher solar panel efficiency solutions are seen in the right upper corner while lower cost solutions are shown in the left lower corner. According Figure 5.11 (pareto set) micro-grid solar panel stand alone has been completed, maximizing solar panel efficiency and minimizing annualized total cost. This configuration was structured by 15 solar panels, 1 regulator, 4 batteries and just one inverter.

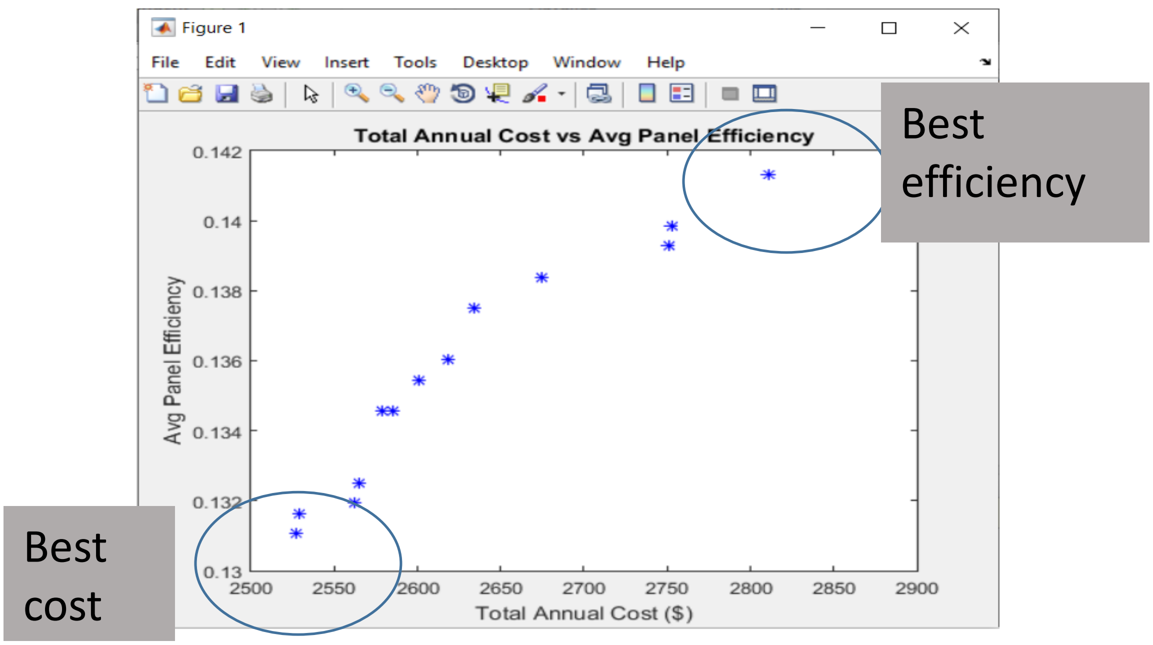

Figure 5.14 Pareto Optimal Solution for micro-grid configuration

Once the Pareto-Optimal solutions have been obtained, a solution for system implementation has to be obtained, in the present example, one solution to design the micro-grid is selected and the replacement algorithm is running to allow to establishing probabilistic replacement dates for each of its components.

Table 5.3. Numerical data for example number two.

Component	Age (τ) (years)	λ_1	λ_2	α_2	Inflation (%)	Interest (%)	AMS (Dlls)	RC (Dlls)	NSMC (Dlls)
PV	0	.05	.0606	3.5	6	1	22	220	100
PV	0	.05	.0606	3.5			22		100
PV	0	.05	.0606	3.5			22		100
PV	0	.05	.0606	3.5			22		100
PV	0	.05	.0606	3.5			22		100
REG	0	.05	--	--			70	687	300
BAT	0	.05	.067	3.5			160	1600	300
BAT	0	.05	.067	3.5			160		300
INV	0	.05	--	--			170	1700	800

After evaluating this system in Matlab® following results were found.

The results show maintenance and replacement cost information through the time of use of the elements of the system, in the case of figure 5.11 represent all photovoltaic panels due to they are same brand and same age. The break-even point is around 19 years. in the case of figure 5.12 represent the case of the regulator, it is 21 years, case of figure 5.13 (Batteries), 21 years was calculated as the year in which the maintenance cost is higher than replacement cost. Inverter Fig. 5.14, it is suggested that it be replaced after 25 years of service. This system is a simple system to compare the probability of failure based on its Cumulative Failure Distribution, the expected cost of energy not supplied together versus the direct replacement cost through an immediate future horizon in units of years elapsed. Fig. 5.15 represents the system cost compared trough the time horizon. Fig 5.16 shows expected energy not supplied cost during the down times.

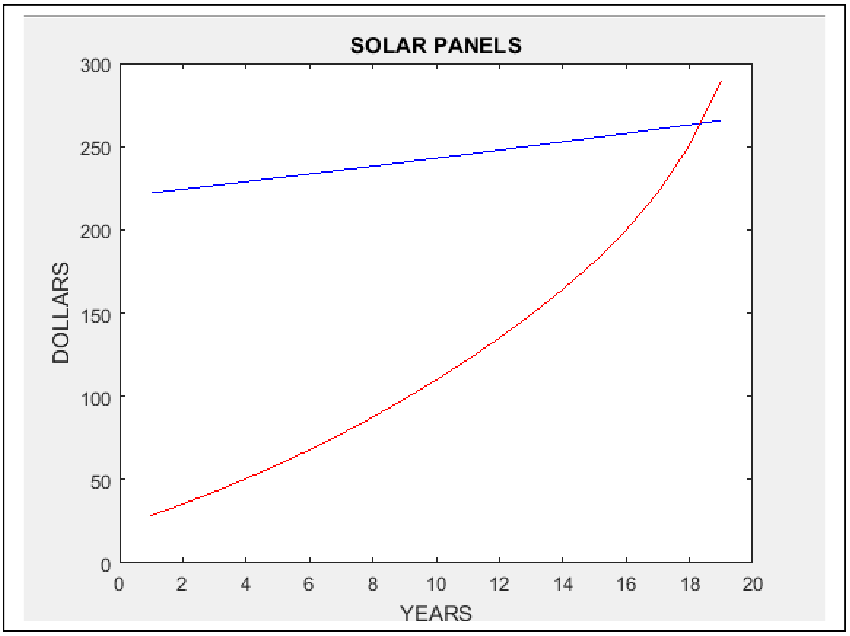

Figure 5.15 Solar panels break point.

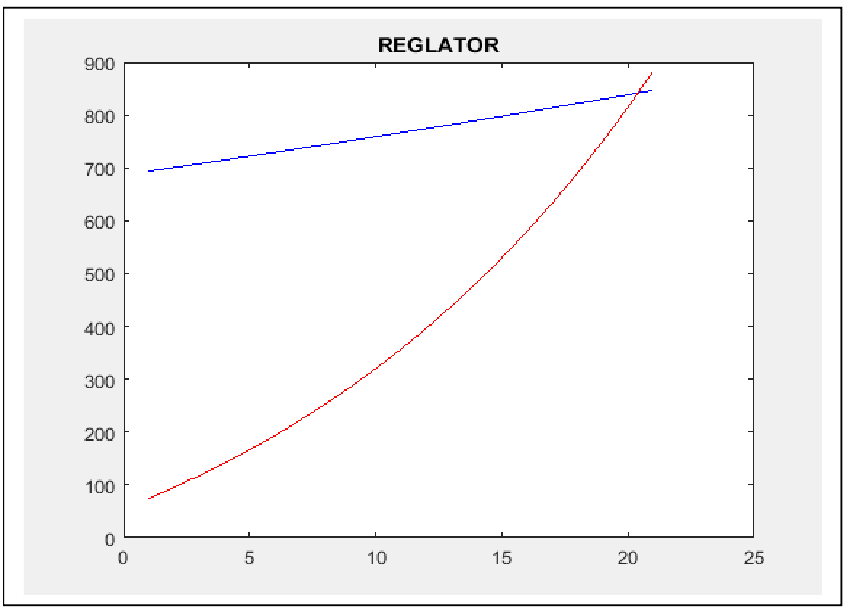

Figure 5.16 Regulator maintenance cost vs replacement cost.

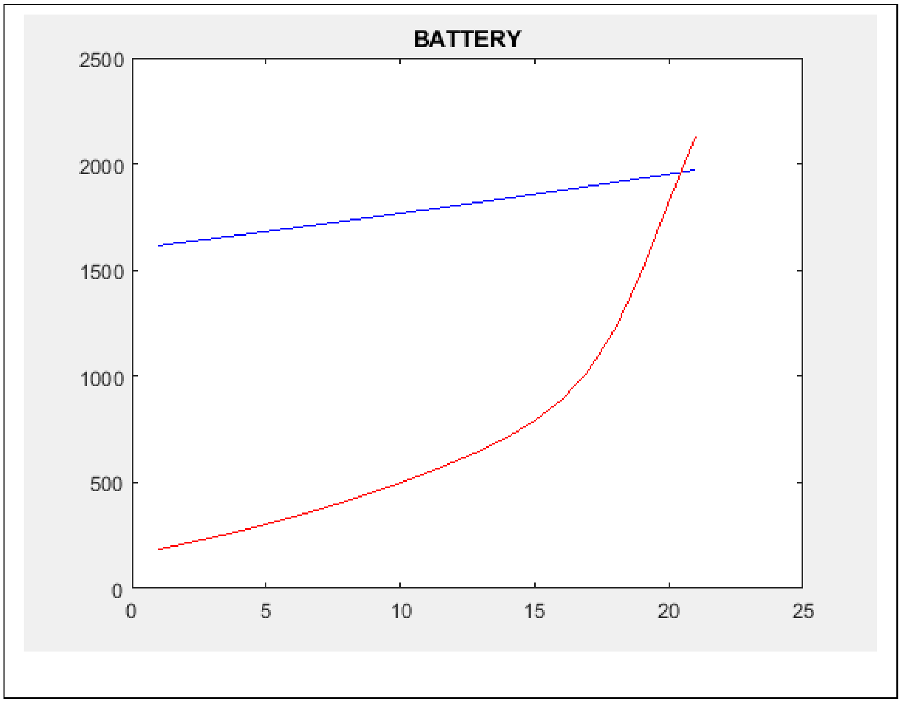

Figure 5.17 Batteries break point.

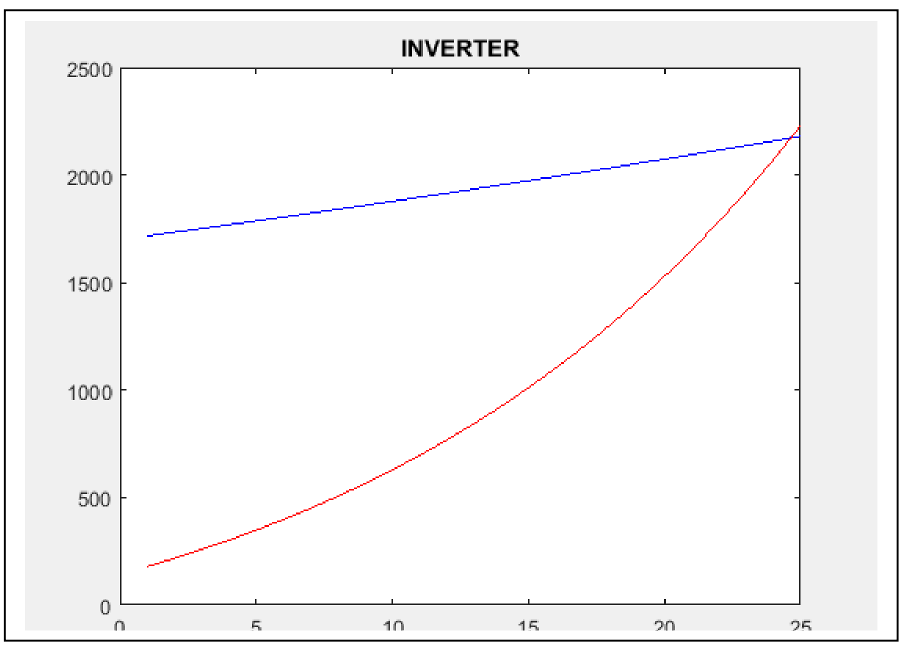

Figure 5.18 Inverter maintenance cost vs replacement cost.

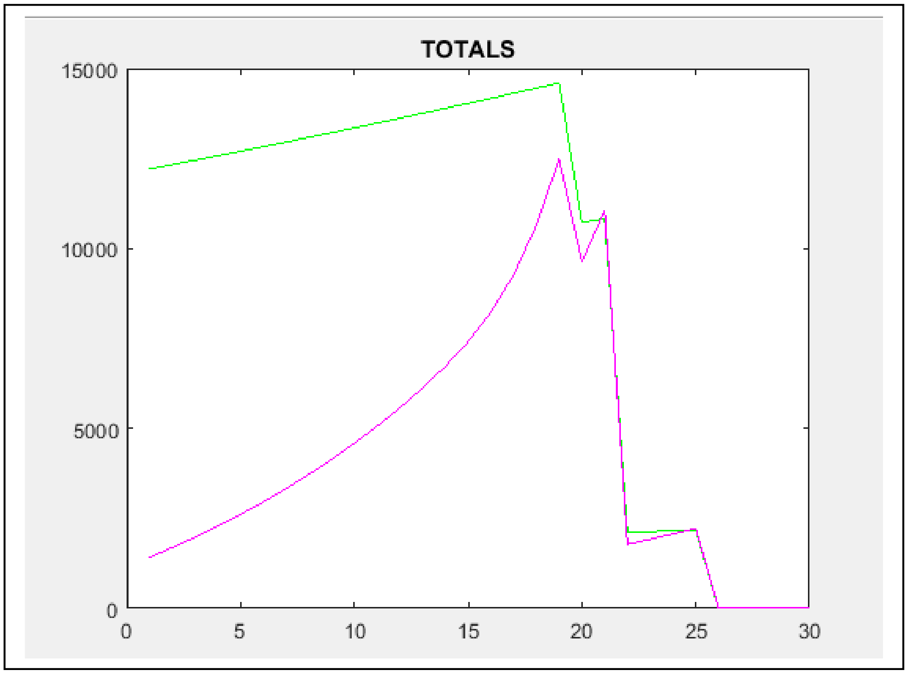

Figure 5.19 System total costs comparison.

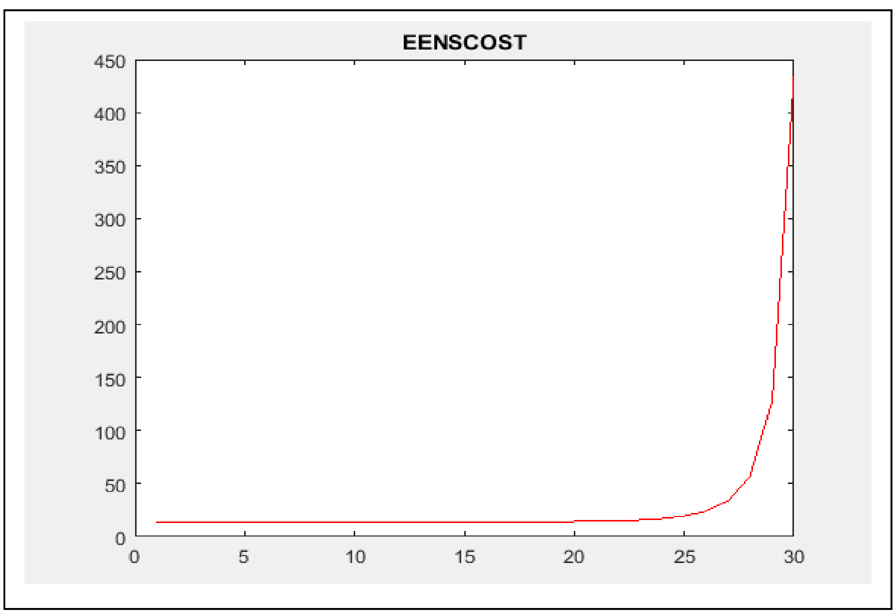

Figure 5.20 Expected Energy Not Supplied Cost due to down times.

5.3 Selecting Best Supplier

After determining breakpoint in which maintenance cost is higher than replacing cost to probability distributions Weibull and exponential representing maintenance cost of time-dependent and no time-dependent fees respectively, the next step is determining the best option among different suppliers offering a diverse number of components to be implemented in the micro-grid solar panels stand alone. Two different methods were tested to develop this step. One of them is relative to Euclidean distance vectors; on the other hand, a better methodology representing values whit positive trends and the negative tendency is better.

5.3.1 Euclidean Distance.

Some characteristics are considered for every component, for example:

Table 5.4 Characteristic for micro-grid component

Solar panels	Maximum power S. C. power Efficiency Cost Warranty time Maintenance cost Useful life
Regulator	Maximum power input Own energy consumption Efficiency Cost Maintenance cost Warranty time
Batteries	Useful life Deep discharge Cost Maintenance cost
Inverter	Nominal power Peak power Efficiency Cost Maintenance cost Warranty time

Those elements create a vector for every supplier i compared with the desired vector finding the shorter distance between vectors. The best vector to consider is who is to nearest vector to the desired vector.

Supplier vector:

$$vi = (x_1 + x_2 + x_3 + \cdots + x_n) \tag{5.3.1}$$

Desired vector:

$$vbi = (x_{b1} + x_{b2} + x_{b3} + \cdots + x_{bn}) \tag{5.3.2}$$

Euclidean distance:

$$di = \sqrt{\sum_{i=1}^{n} \left(1 - \frac{v_i}{v_{bi}}\right)^2} \tag{5.3.3}$$

5.3.2 Numerical Example

Solar Panels

Table 5.5 shows the numerical example for solar panels. Three different suppliers were considered jus for this example; however, it can be regarded as n number of suppliers.

Table 5.5 Solar panel main traits.

Solar Panel	Desired	SUP1	SUP2	SUP3
Maximum power (w)	250	250	250	250
S.C. power (kw)	335	326	350	335
Eficiency (%)	15.34	16	14.87	16
Cost (Dlls)	220	222	280	200
Warranty (years)	10	4	6	15
Maintenance cost (Dlls)	22	22	28	20
Useful life (years)	25	40	15	25

Evaluating those vector using the formula 5.3.3:

Table 5.6 Results for solar panels

SOLAR PANEL	DESIRED	SUP1	SUP2	SUP3	VALUE PU1	VALUE PU2	VALUE PU3	(base-data)^2	(base-data)^2	(base-data)^2
Maximum power (w)	250	250	250	250	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000
S.C. power (kw)	335	326	350	335	0.9731	1.0448	1.0000	0.0007	0.0020	0.0000
Eficiency (%)	15.34	16	14.87	16	1.0430	0.9694	1.0430	0.0019	0.0009	0.0019
Cost (Dlls)	220	222	280	200	1.0091	1.2727	0.9091	0.0001	0.0744	0.0083
Warranty (years)	10	4	6	15	0.4000	0.6000	1.5000	0.3600	0.1600	0.2500
Maintenance cost (Dlls)	22	22	28	20	1.0000	1.2727	0.9091	0.0000	0.0744	0.0083
Useful life (years)	25	40	15	25	1.6000	0.6000	1.0000	0.3600	0.1600	0.0000
								0.7227	0.4717	0.2684
								0.8501	0.6868	0.5181

According to this methodology, the best solar panels' supplier has been option number three, resulting in the number nearest to zero with 0.5181.

Regulator:

Table 5.7 shows the numerical example for the regulator. Three different suppliers were considered jus for this example; however, it can be regarded as n number of suppliers.

Table 5.7 Results for the regulator

REGULATOR	DESIRED	SUP1	SUP2	SUP3	VALUE PU1	VALUE PU2	VALUE PU3	(base-data)^2	(base-data)^2	(base-data)^2
Maximun power input (w)	4850	4850	5000	4500	1.0000	1.0309	0.9278	0.0000	0.0010	0.0052
Own energy consumption (w)	1	1.5	1	2.5	1.5000	1.0000	2.5000	0.2500	0.0000	2.2500
Efficiency (%)	97.5	97	98	96	0.9949	1.0051	0.9846	0.0000	0.0000	0.0002
Cost (Dlls)	687	750	690	750	1.0917	1.0044	1.0917	0.0084	0.0000	0.0084
Maintenance cost (Dlls)	70	75	70	80	1.0714	1.0000	1.1429	0.0051	0.0000	0.0204
Warranty (years)	5	4	6	5	0.8000	1.2000	1.0000	0.0400	0.0400	0.0000
								0.3035	0.0410	2.2843
								0.5509	0.2025	1.5114

According to this methodology, the best regulator’s supplier has been option number two, resulting in the number nearest to zero with 0.2025.

Batteries:

Table 5.8 shows the numerical example for batteries. Three different suppliers were considered jus for this example; however, they can be regarded as n number of suppliers.

Table 5.8 Results for Batteries

BATTERIES	DESIRED	SUP1	SUP2	SUP3	VALUE PU1	VALUE PU2	VALUE PU3	(base-data)^2	(base-data)^2	(base-data)^2
Useful Life (years)	20	8	12	18	0.4000	0.6000	0.9000	0.3600	0.1600	0.0100
Deep discharge (%)	20	15	12	25	0.7500	0.6000	1.2500	0.0625	0.1600	0.0625
Cost (Dlls)	1600	1400	1500	1600	0.8750	0.9375	1.0000	0.0156	0.0039	0.0000
Maintenance cost (Dlls)	160	140	180	160	0.8750	1.1250	1.0000	0.0156	0.0156	0.0000
								0.4538	0.3395	0.0725
								0.6736	0.5827	0.2693

According to this methodology, the best battery supplier has been option number three, resulting in the number nearest to zero with 0.2693.

Inverter:

Table 5.9 shows the numerical example for the inverter. Three different suppliers were considered jus for this example; however, it can be regarded as n number of suppliers.

Table 5.9 Results for inverter

INVERTER	DESIRED	SUP1	SUP2	SUP3	VALUE PU1	VALUE PU2	VALUE PU3	(base-data)^2	(base-data)^2	(base-data)^2
Nominal power (w)	4500	4500	5000	4000	1.0000	1.1111	0.8889	0.0000	0.0123	0.0123
Peak power (w)	10000	10000	12000	8000	1.0000	1.2000	0.8000	0.0000	0.0400	0.0400
Efficiency (%)	95	95	94	92	1.0000	0.9895	0.9684	0.0000	0.0001	0.0010
Cost (Dlls)	1600	1600	1800	1500	1.0000	1.1250	0.9375	0.0000	0.0156	0.0039
Maintenance cost (Dlls)	160	160	180	150	1.0000	1.1250	0.9375	0.0000	0.0156	0.0039
Warranty time (years)	5	5	4	4	1.0000	0.8000	0.8000	0.0000	0.0400	0.0400
								0.0000	0.1237	0.1012
								0.0000	0.3517	0.3180

According to this methodology, the best inverter's supplier has been option number one, resulting in the number nearest to zero with 0.0000. In this example, supplier number one offered components with the same level for every characteristic. This example is an excellent example to prove that the method works correctly. It was the same point as the desired vector.

5.3.3 Ideal Vector System

Some characteristics are considered for every component, for example:

Table 5.10 Characteristic for micro-grid component

Solar panels	Maximum power S. C. power Efficiency Cost Warranty time Maintenance cost Useful life
Regulator	Maximum power input Own energy consumption Efficiency Cost Maintenance cost Warranty time
Batteries	Useful life Deep discharge Cost Maintenance cost
Inverter	Nominal power Peak power Efficiency Cost Maintenance cost Warranty time

Those elements create a vector for every supplier i compared with the desired vector finding the more positive number between vectors. The best vector to considered is the nearest vector to the desired vector.

Supplier vector:

$$v_i^{+,-} = \left(x_1^{+,-} + x_2^{+,-} + x_3^{+,-} + \cdots + x_n^{+,-}\right) \tag{5.3.4}$$

Desired vector:

$$vb_i^{+,-} = \left(x_{b1}^{+,-} + x_{b2}^{+,-} + x_{b3}^{+,-} + \cdots + x_{bn}^{+,-}\right) \tag{5.3.5}$$

Maximum and minimum values as better:

x_i^{+}-----------------------------→ A characteristic that high value is better.

x_i^{-}-----------------------------→ A characteristic that low value is better.

$$v_{si}^{+} = [v_i^{+} - v_{bi}^{+}] \quad \text{or} \quad v_{si}^{-} = [v_{bi}^{-} - v_i^{-}] \tag{5.3.6}$$

$$vw_i = \sum_{i=1}^{n} vw_i = 1 \tag{5.3.7}$$

Where:

vw_i-------→ Is the weigh vector, values given according to the importance of each characteristic.

$$d_1 = \sum_{i=1}^{n} vw_i \left(\frac{v_{si}^{+}}{v_{bi}^{+}}\right) \tag{5.3.8}$$

$$d_2 = \sum_{i=1}^{n} vw_i \left(\frac{v_{si}^{-}}{v_{bi}^{-}}\right) \tag{5.3.9}$$

$$f_n = d_1 + d_2 \tag{5.3.10}$$

f is the final result for every supplier, those numbers are compared among them, and the best product will be the most positive number.

5.3.4 Numerical Example.

Solar Panels

Table 5.11 shows the numerical example for solar panels. Three different suppliers were considered jus for this example; however, it can be regarded as n number of suppliers.

Table 5.11 Solar panel main traits.

Solar Panel	Desired	SUP1	SUP2	SUP3
Maximum power (w)	250	250	250	250
S.C. power (kw)	335	326	350	335
Eficiency (%)	15.34	16	14.87	16
Cost (Dlls)	220	222	280	200
Warranty (years)	10	4	6	15
Maintenance cost (Dlls)	22	22	28	20
Useful life (years)	25	40	15	25

Evaluating those vector using the formulas (5.3.6), (5.3.7), (5.3.8), (5.3.9), and (5.3.10) it is obtained:

Table 5.12 Results for solar panels

SOLAR PANEL	DESIRED	SUP1	SUP2	SUP3	Vs	Vs	Vs								
Maximum power (w)	250	250	250	250	0	0	0	0.0000	0.0000	0.0000	IGUAL				
S.C. power (kw)	335	326	350	335	-9	15	0	-0.0269	0.0448	0.0000	HIGH BETTER	0.0500	-0.0013	0.0022	0.0000
Eficiency (%)	15.34	16	14.87	16	0.66	-0.47	0.66	0.0430	-0.0306	0.0430	HIGH BETTER	0.1000	0.0043	-0.0031	0.0043
Cost (Dlls)	220	222	280	200	-2	-60	20	-0.0091	-0.2727	0.0909	LOW BETTER	0.4000	-0.0036	-0.1091	0.0364
Warranty (years)	10	4	6	15	-6	-4	5	-0.6000	-0.4000	0.5000	HIGH BETTER	0.2000	-0.1200	-0.0800	0.1000
Maintenance cost (Dlls)	22	22	28	20	0	-6	2	0.0000	-0.2727	0.0909	LOW BETTER	0.1000	0.0000	-0.0273	0.0091
Useful life (years)	25	40	15	25	15	-10	0	0.6000	-0.4000	0.0000	HIGH BETTER	0.1500	0.0900	-0.0600	0.0000
												1			
								0.0162	-0.7859	0.5430	HIGH BETTER		-0.0270	-0.1408	0.1043
								-0.0091	-0.5455	0.1818	LOW BETTER		-0.0036	-0.1364	0.0455
								0.0071	-1.3313	0.7248			-0.0307	-0.2772	0.1498

According to this methodology, the best solar panels' supplier has been option number three, resulting in the most positive number with 0.1498. The other two suppliers mean it loses.

Regulator:

Table 5.13 shows the numerical example for the regulator. Three different suppliers were considered jus for this example; however, it can be regarded as n number of suppliers.

Table 5.13 Results for the regulator

REGULATOR	DESIRED	SUP1	SUP2	SUP3	Vs	Vs	Vs								
Maximun power input (w)	4850	4850	5000	4500	0	150	-350	0.0000	0.0309	-0.0722	HIGH BETTER	0.1000	0.0000	0.0031	-0.0072
Own energy consumption (w)	1	1.5	1	2.5	-0.5	0	-1.5	-0.5000	0.0000	-1.5000	LOW BETTER	0.0500	-0.0250	0.0000	-0.0750
Efficiency (%)	97.5	97	98	96	-0.5	0.5	-1.5	-0.0051	0.0051	-0.0154	HIGH BETTER	0.1000	-0.0005	0.0005	-0.0015
Cost (Dlls)	687	750	690	750	-63	-3	-63	-0.0917	-0.0044	-0.0917	LOW BETTER	0.4000	-0.0367	-0.0017	-0.0367
Maintenance cost (Dlls)	70	75	70	80	-5	0	-10	-0.0714	0.0000	-0.1429	LOW BETTER	0.2500	-0.0179	0.0000	-0.0357
Warranty (years)	5	4	6	5	-1	1	0	-0.2000	0.2000	0.0000	HIGH BETTER	0.1000	-0.0200	0.0200	0.0000
												1.0000			
								-0.2051	0.2361	-0.0875	HIGH BETTER		-0.0205	0.0236	-0.0088
								-0.6631	-0.0044	-1.7346	LOW BETTER		-0.0795	-0.0017	-0.1474
								-0.8683	0.2317	-1.8221			-0.1001	0.0219	-0.1562

According to this methodology, the best regulators' supplier has been option number two, resulting in the most positive number with 0.0219. The other two suppliers mean it loses.

Batteries:

Table 5.14 shows the numerical example for batteries. Three different suppliers were considered jus for this example; however, it can be regarded as n number of suppliers.

Table 5.14 Results for Batteries

BATTERIES	DESIRED	SUP1	SUP2	SUP3	Vs	Vs	Vs								
Useful Life (years)	20	8	12	18	-12	-8	-2	-0.6000	-0.4000	-0.1000	HIGH BETTER	0.25	-0.1500	-0.1000	-0.0250
Deep discharge (%)	20	15	12	25	-5	-8	5	-0.2500	-0.4000	0.2500	HIGH BETTER	0.1000	-0.0250	-0.0400	0.0250
Cost (Dlls)	1600	1400	1500	1600	200	100	0	0.1250	0.0625	0.0000	LOW BETTER	0.4000	0.0500	0.0250	0.0000
Maintenance cost (Dlls)	160	140	180	160	20	-20	0	0.1250	-0.1250	0.0000	LOW BETTER	0.2500	0.0313	-0.0313	0.0000
												1			
								-0.8500	-0.8000	0.1500	HIGH BETTER		-0.1750	-0.1400	0.0000
								0.2500	-0.0625	0.0000	LOW BETTER		0.0813	-0.0063	0.0000
								-0.6000	-0.8625	0.1500			-0.0938	-0.1463	0.0000

According to this methodology, the best batteries'' supplier has been option number three, resulting in the most positive number with 0.000. The other two suppliers mean it loses.

Inverter:

Table 5.15 shows the numerical example for the inverter. Three different suppliers were considered jus for this example; however, it can be regarded as n number of suppliers.

Table 5.15 Results for inverter

INVERTER	DESIRED	SUP1	SUP2	SUP3	Vs	Vs	Vs								
Nominal power (w)	4500	4500	5000	4000	0	500	-500	0.0000	0.1111	-0.1111	HIGH BETTER	0.1	0.0000	0.0111	-0.0111
Peak power (w)	10000	10000	12000	8000	0	2000	-2000	0.0000	0.2000	-0.2000	HIGH BETTER	0.0500	0.0000	0.0100	-0.0100
Efficiency (%)	95	95	94	92	0	-1	-3	0.0000	-0.0105	-0.0316	HIGH BETTER	0.1000	0.0000	-0.0011	-0.0032
Cost (Dlls)	1600	1600	1800	1500	0	-200	100	0.0000	-0.1250	0.0625	LOW BETTER	0.4000	0.0000	-0.0500	0.0250
Maintenance cost (Dlls)	160	160	180	150	0	-20	10	0.0000	-0.1250	0.0625	LOW BETTER	0.2500	0.0000	-0.0313	0.0156
Warranty time (years)	5	5	4	4	0	-1	-1	0.0000	-0.2000	-0.2000	HIGH BETTER	0.1000	0.0000	-0.0200	-0.0200
												1			
								0.0000	0.1006	-0.5427	HIGH BETTER		0.0000	0.0001	-0.0443
								0.0000	-0.2500	0.1250	LOW BETTER		0.0000	-0.0813	0.0406
								0.0000	-0.1494	-0.4177			0.0000	-0.0812	-0.0036

According to this methodology, the best inverter's supplier has been option number one, resulting in the most positive number with 0.0000.

Table 5.16 shows methodology comparison in this specific numerical problem.

Table 5.16. Selecting proper supplier

Component	Method 1	Method 2
Solar panel	Supplier three	Supplier three
Regulator	Supplier two	Supplier two
Batteries	Supplier three	Supplier three
Inverter	Supplier one	Supplier one

This example concludes that both methodologies found same result.

5.4 Solar Panel Micro-Grid Allocation System Genetic Algorithm

Throughout this study, one of the main parts is to obtain a solar panel stand-alone micro-grid to develop replacement algorithm and supplier selection algorithm for replacement electrical components based on the characteristics offered by current market suppliers. Now, a genetic algorithm is developed with the objective of obtaining a result through multiple evolutions that minimizes the cost of implementation and operation of a micro-grid. The objective is to minimize the total cost of implementation prorated according to the useful life of the component and its annual maintenance cost. This example is based on a solar panel stand-alone micro-grid that in its configuration is composed of 15 solar panels, one regulator, four batteries and one inverter. This procedure can be applied to 'n' number of suppliers; however, this specific example applies to seven suppliers of electrical components. Tables from 5.17 to 5.20 show data considered in this example. Information obtained from different suppliers' electrical component-related such as solar panel, regulator, batteries and inverter

Table 5.17 Solar Panels

Solar Panel	P1	P2	P3	P4	P5	P6	P7
Initial cost ($)	220	222	280	200	250	300	350
Maintenance cost ($)	50	80	70	80	85	110	130
Inom (Amps)	4.71	4.89	4.96	4.45	5.02	4	4.18
Vnom (Volts)	18.04	17.4	17.1	19.1	16.93	18	18
Isc (Amps)	5.04	5.32	5.89	5.02	5.32	5	5
Voc (Volts)	21.92	21.7	21.62	21.98	21.7	18.1	19
G (Kw/m2)	1000	1000	1000	1000	1000	1000	1000
Area (m2)	0.65	0.7	0.55	0.65	0.7	0.55	0.5
Useful life (years)	20	20	18	15	20	15	13

Table 5.18 Regulator

Regulator							
Initial cost ($)	687	750	690	750	810	900	1000
Maintenance cost ($)	100	105	100	110	120	200	240
Useful life (years)	20	18	20	16	20	15	16
Efficiency (%)	97.5	97	98	96	95	94	93

Table 5.19 Batteries

Battery							
Initial cost ($)	1600	1400	1500	1600	1200	1800	2000
Maintenance cost ($)	160	140	180	160	180	200	300
Disarche Eff (%)	0.8	0.85	0.8	0.85	0.7	0.6	0.8
Chemmical Eff (%)	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Useful life (years)	20	8	12	18	16	8	7

Table 5.20 Inverter

Inverter							
Initial cost ($)	1600	1600	1800	1400	1500	1900	2000
Maintenance cost ($)	160	160	180	150	200	300	400
Efficiency (%)	95	95	94	92	92	90	92
Useful life (years)	15	16	15	12	10	8	8

Single objective

$$\text{Annualized Component Cost} = \sum_{i}^{n} \frac{C_i}{Ul_i} + Cm_i \qquad (5.2.2)$$

Subject to:

Ftss2 >= Budget

Where:

C_i ------------- Cost of element *i*

Ul_i ------------- Useful life in years of component *i*

Cm_i ------------ Maintenance cost of element *i*

After running the genetic algorithm, several evolutionary populations were created and evaluated according the objective considered in the figure 5.17

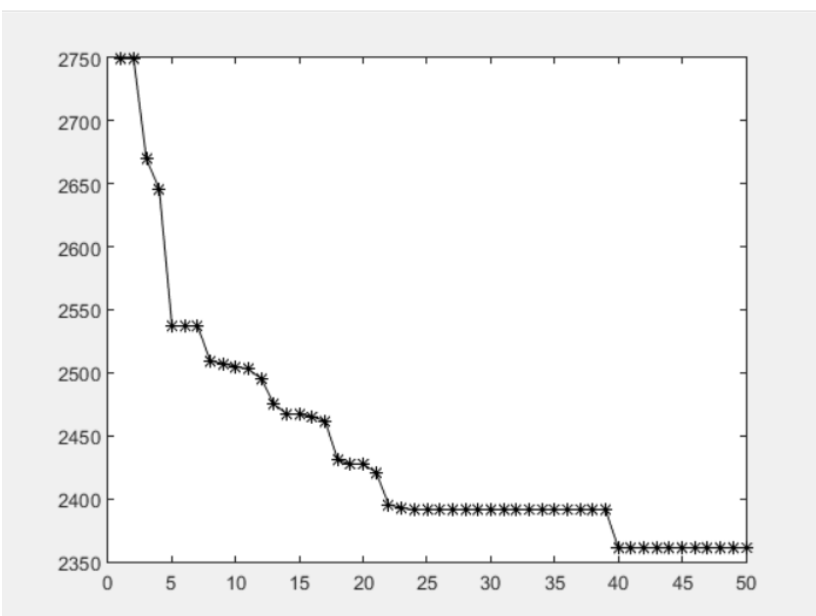

Figure 5.21 Genetic Algorithm evolutionary pareto set

Approximately, 40 evolutions were necessary to obtain a potential best solution in the solar panel stand-alone micro-grid based on seven different suppliers to complete the configuration of 15 solar panels, one regulator, four batteries and one inverter.

Conclusions

This work attempts to calculate a probabilistic maintenance cost based on the cumulative failure distribution of a component that presents random (exponential) failures, degradation failures (Weibull), or both. It is considered a fixed maintenance cost that can be based on personnel costs, space costs, or costs that regardless of failure or not in the system are commonly given — the cost associated with random failures experiencing an exponential distribution with its associated cost over the years. In the same way, the degradation of a component associated with an accumulated distribution of failure of the type Weibull affected by the cost of maintenance over the years. These elements are summarized and affected by annual inflation that costs usually affect. Following the Marconian developments taken from Espiritu (2007), it is possible to obtain the results of expected energy loss of the components, but as a system as a whole, that is, as a micro-grid. These downtimes that are also related to possible faults caused by their behavior (exponential or Weibull) are connected at a cost due to the energy not generated during the down times. This total cost generated is compared with the replacement cost displayed in a future horizon, which is compared year to year until the break-even point is identified. From then on it would be assumed that maintenance is more expensive than replacement of the component. This system can serve so that at a point in time the people responsible for making decisions define on the horizon possible investments that as a system are required to continue operating continually and efficiently. The distributions can change as well as the structures of the systems, each system is unique and independent, and so each problem should be adapted to your particular situation.

References

Abdelkader, A., Rabeh, A., Ali, D. M., & Mohamed, J. (2018). Multi-objective genetic algorithm based sizing optimization of a stand-alone wind/PV power supply system with enhanced battery/supercapacitor hybrid energy storage. Energy, 163, 351- 363. doi:10.1016/j.energy.2018.08.135

Adefarati, T., & Bansal, R. (2017). Reliability and economic assessment of a microgrid power system with the integration of renewable energy resources. Applied Energy, 206, 911-933. doi:10.1016/j.apenergy.2017.08.228

Basu, A. K. (2013). Microgrids: Planning of fuel energy management by strategic Deployment of CHP-based DERs – An evolutionary algorithm approach. International Journal on Electrical Power & Energy Systems, 44(1), 326-336. doi:10.1016/j.ijepes.2012.07.059

Bazargan, M., & Hartman, J. (2012). Aircraft replacement strategy: Model and analysis. *Journal of Air Transport Management,25*, 26-29. doi:10.1016/j.jairtraman.2012.05.00

Babishin, V., & Taghipour, S. (2016). Optimal maintenance policy for multicomponent systems with periodic and opportunistic inspections and preventive replacements. *Applied Mathematical Modelling,40*(23-24), 10480-10505. doi:10.1016/j.apm.2016.07.019

Chang, C. (2014). Optimum preventive maintenance policies for systems subject to random working times, replacement, and minimal repair. *Computers & Industrial Engineering,67*, 185-194. doi:10.1016/j.cie.2013.11.011

Hsu, C.-I., Li, H.-C., Liu, S.-M., & Chao, C.-C. (2011). Aircraft replacement scheduling: A Dynamic Programming Approach. Transportation Research Part E: Logistics and Transportation Review, 47(1), 41–60. https://doi.org/10.1016/j.tre.2010.07.006

Chedid, R., & Rahman, S. (1997). Unit sizing and control of hybrid wind-solar power systems. *IEEE Transactions on Energy Conversion,12*(1), 79-85. doi:10.1109/60.577284

Chenna, V. D. (2010). *Component replacement analysis for electricity distribution systems using evolutionary algorithms* (Unpublished master's thesis).

Clavareau, J., & Labeau, P. (2009). Maintenance and replacement policies under technological obsolescence. *Reliability Engineering & System Safety,94*(2), 370-381. doi:10.1016/j.ress.2008.03.033

Dalton, G., Lockington, D., & Baldock, T. (2009). Feasibility analysis of renewable energy supply options for a grid-connected large hotel. *Renewable Energy,34*(4), 955-964. doi:10.1016/j.renene.2008.08.012

Draisma, J., Horobeţ, E., Ottaviani, G., Sturmfels, B., & Thomas, R. R. (2015). The euclidean distance degree of an algebraic variety. Foundations of Computational Mathematics, 16(1), 99–149. https://doi.org/10.1007/s10208-014-9240-x

Dawoud, S. M., Lin, X., & Okba, M. I. (2018). Hybrid renewable microgrid optimization techniques: A review. Renewable and Sustainable Energy Reviews, 82, 2039-2052. doi:10.1016/j.rser.2017.08.007

Delgado, C., & Domínguez-Navarro, J. A. (2015). Multi-objective design optimization of hybrid renewable systems using UGF. *COMPEL - The international journal for computation and mathematics in electrical and electronic engineering,34*(6), 1825-1844. doi:10.1108/compel-11-2014-0326

Dufo-López, R., & Bernal-Agustín, J. L. (2008). Multi-objective design of PV–wind–diesel–hydrogen–battery systems. *Renewable Energy,33*(12), 2559-2572. doi:10.1016/j.renene.2008.02.027

Espiritu, J. F., & Coit, D. W. (2008). A Component Replacement Model for Electricity Distribution Systems. *The Engineering Economist,53*(4), 318-339. Doi:10.1080/00137910802482279

Fouladirad, M., Paroissin, C., & Grall, A. (2018). Sensitivity of optimal replacement policies to lifetime parameter estimates. *European Journal of Operational Research,266*(3), 963-975. doi:10.1016/j.ejor.2017.10.055

Golovin, S. (2016). Representation of replacement rules in the form of a matrix. *Journal of Quality in Maintenance Engineering,22*(2), 164-179. doi:10.1108/jqme-06-2015-0022

Malki, Z., Ait-Kadi, D., & Ouali, M. (2015). Age replacement policies for two-component systems with stochastic dependence. *Journal of Quality in Maintenance Engineering,21*(3), 346-357. doi:10.1108/jqme-03-2014-0013

Heymann, B., & Martinon, P. (2018). Optimal Battery Aging: An Adaptive Weights Dynamic Programming Algorithm. Journal of Optimization Theory and Applications. doi:10.1007/s10957-018-1371-9

Ismail, M., Moghavvemi, M., & Mahlia, T. (2014). Genetic algorithm based optimization on modeling and design of hybrid renewable energy systems. *Energy Conversion and Management,85*, 120-130. doi:10.1016/j.enconman.2014.05.064

Jung, K. M., Han, S. S., & Park, D. H. (2008). Optimization of cost and downtime for replacement model following the expiration of warranty. *Reliability Engineering & System Safety,93*(7), 995-1003. doi:10.1016/j.ress.2007.05.005

Kellogg, W. D., Nehrir, M.H., Venkataramanan, G., Gerez, V., (1998). Generation unit sizing and cost analysis for stand-alone wind, photovoltaic and hybrid wind/PV systems. IEEE Transacrions on Energy Conversion 13 (1), 70-75.

Koutroulis, E., Kolokotsa, D., Potirakis, A., & Kalaitzakis, K. (2006). Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms. *Solar Energy,80*(9), 1072-1088. doi:10.1016/j.solener.2005.11.002

Nakagawa, T. (1986). Periodic and sequential preventive maintenance policies. *Journal of Applied Probability,23*(02), 536-542. doi:10.2307/3214197

Nodem, F. D., Kenné, J., & Gharbi, A. (2010). Preventive Maintenance and Replacement Policies for Deteriorating Manufacturing Systems. *IFAC Proceedings Volumes,43*(3), 98-103. doi:10.3182/20100701-2-pt-4012.00018

Nodem, F. D., Kenné, J., & Gharbi, A. (2011). Simultaneous control of production, repair/replacement and preventive maintenance of deteriorating manufacturing systems. *International Journal of Production Economics,134*(1), 271-282. doi:10.1016/j.ijpe.2011.07.011

Ma, J., Yang, L., & Sun, Q. (2020). Capped L1-norm distance metric-based fast robust twin bounded support vector machine. Neurocomputing, 412, 295–311. https://doi.org/10.1016/j.neucom.2020.06.053

Markvart, T. (1996). Sizing of hybrid photovoltaic-wind energy systems. *Solar Energy,57*(4), 277-281. doi:10.1016/s0038-092x(96)00106-5

Mathew, S., & Kennedy, D. (2003). A strategy for optimal equipment replacement. *Production Planning & Control,14*(6), 571-577. doi:10.1080/09537280310001613740

Michalewicz, Z. (2011). *Genetic algorithms data structures = evolution programs*. Berlin: Springer.

Moghaddam, A. A., Seifi, A., Niknam, T., & Pahlavani, M. R. (2011). Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source. *Energy,36*(11), 6490-6507. doi:10.1016/j.energy.2011.09.017

Mohamed, F. A., & Koivo, H. N. (2012). Online management genetic algorithms of microgrid for residential application. *Energy Conversion and Management,64*, 562-568. doi:10.1016/j.enconman.2012.06.010

Parthanadee, P., Buddhakulsomsiri, J., & Charnsethikul, P. (2012). A study of replacement rules for a parallel fleet replacement problem based on user preference utilization pattern and alternative fuel considerations. *Computers & Industrial Engineering,63*(1), 46-57. doi:10.1016/j.cie.2012.01.011

Rajkumar, R., Ramachandaramurthy, V., Yong, B., & Chia, D. (2011). Techno-economical optimization of hybrid pv/wind/battery system using Neuro-Fuzzy. *Energy,36*(8), 5148-5153. doi:10.1016/j.energy.2011.06.017

Salameh, Z. (2014). *Renewable Energy System Design*. Academic Press.

Scarf, P. A., & Cavalcante, C. A. (2012). Modelling quality in replacement and inspection maintenance. *International Journal of Production Economics,135*(1), 372-381. doi:10.1016/j.ijpe.2011.08.011

Seif, J., & Rabbani, M. (2014). Component based life cycle costing in replacement decisions. *Journal of Quality in Maintenance Engineering,20*(4), 436-452. doi:10.1108/jqme-08-2013-0053

Shang, L., Si, S., & Cai, Z. (2016). Optimal maintenance–replacement policy of products with competing failures after expiry of the warranty. *Computers & Industrial Engineering,98*, 68-77. doi:10.1016/j.cie.2016.05.012

Shrestha, G., & Goel, L. (1998). A study on optimal sizing of stand-alone photovoltaic stations. *IEEE Transactions on Energy Conversion,13*(4), 373-378. doi:10.1109/60.736323

Stasko, T. H., & Gao, H. O. (2012). Developing green fleet management strategies: Repair/retrofit/replacement decisions under environmental regulation. *Transportation Research Part A: Policy and Practice,46*(8), 1216-1226. doi:10.1016/j.tra.2012.05.012

Sternberg, S. P. (2015). *Air pollution: engineering, science, and policy*. Glen Allen, VA: College Publishing.

Tabriz, A. A., Khorshidvand, B., & Ayough, A. (2016). Modelling age based replacement decisions considering shocks and failure rate. *International Journal of Quality & Reliability Management,33*(1), 107-119. doi:10.1108/ijqrm-11-2014-0168

Tam, A. S., & Price, J. W. (2008). A generic asset management framework for optimizing maintenance investment decision. *Production Planning & Control,19*(4), 287-300. doi:10.1080/09537280802034042

Vlok, P. J., Coetzee, J. L., Banjevic, D., Jardine, A. K., & Makis, V. (2002). Optimal component replacement decisions using vibration monitoring and the proportional-hazards model. *Journal of the Operational Research Society,53*(2), 193-202. doi:10.1057/sj/jors/2601261

Wang, C., Li, J., Colson, C. M., & Nehrir, M. H. (2009). Power management of a stand-alone hybrid wind-microturbine distributed generation system. *2009 IEEE Power Electronics and Machines in Wind Applications*. doi:10.1109/pemwa.2009.5208375

Yousefi, H., Ghodusinejad, M. H., & Kasaeian, A. (2017). Multi-objective optimal component sizing of a hybrid ICE PV/T driven CCHP microgrid. Applied Thermal Engineering, 122, 126-138. doi:10.1016/j.applthermaleng.2017.05.017

Zia, M. F., Elbouchikhi, E., & Benbouzid, M. (2018). Microgrids energy management systems: A critical review on methods, solutions, and prospects. Applied Energy, 222, 1033-1055. doi:10.1016/j.apenergy.2018.04.103

Vita

Jose T. Reyes**,** is a Ph.D. student in the Environmental Science and Engineering program at the University of Texas at El Paso. He studied his M.S. degree in Industrial Engineering at the Tecnologico Nacional de Mexico campus Cd. Juarez. Engineering course in electrical engineering at the Tecnologico Nacional de Mexico campus Cd. Juarez. He is the recipient of the Fullbright scholarship which allowed him to pursue his Ph.D. studies in the USA. He has participated in international conferences such as Academia Journals International. He is currently an Associate Professor at El Tecnologico Nacional de Mexico Campus Cd. Juarez. He served as the head of the graduate school at El Tecnologico Nacional de Mexico Campus Cd. Juarez from 2014 to 2015. Moreover, he worked for 18 years in the Manufacturing industry in positions such as manufacturing manager, continuous improvement and leading quality improvement projects as Master Black Belt.