RENEWABLE-DRIVEN MICROGRIDS
IN
ISOLATED COMMUNITIES

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ABSTRACT

This thesis presents design and planning methods for the development of microgrids in remote communities using renewable energy resources. The analysis is not only limited to the economic point of view, but also covers the social and regulatory impacts. Literature shows that the optimal sizing and location of distributed energy resources (DER) is critical for the correct operation of a microgrid. A multi-objective evolutionary optimization algorithm (MOEA) was developed for these purposes. In order to show the flexibility and applicability of the algorithm, a case study is presented. The development of microgrid brings a new paradigm in energy consumption of end-users, thus it is required to build a strong social agreement between the microgrids' stakeholders. Consequences and possible scenarios for stakeholder engagement are discussed. This thesis has two main contributions, first, the incorporation of optimization models based in MOEA to solve microgrids' planning and design problems. A second contribution is a link between the technical and the social aspects using a sustainability framework.

RESUMEN

Esta tesis presenta métodos de diseño y planificación para el desarrollo de micro-redes en comunidades remotas usando recursos de energía renovable. El análisis no solamente se limita al punto de vista económico, sino que también cubre los impactos sociales y regulatorios. La literatura indica que la óptima localización y dimensionamiento de recursos distribuidos es crítica para la correcta operación de un micro-red. Un algoritmo evolutivo de optimización multi-objetivo (MOEA) fue desarrollado para estos propósitos. Con los fines de mostrar la flexibilidad y aplicación del algoritmo, un caso de estudio es presentado. El desarrollo de micro-redes trae un nuevo paradigma en el consumo de energía para usuarios finales, por lo tanto, para su correcto funcionamiento es necesario crear un fuerte acuerdo social entre estos. Consecuencias y posibles escenarios para la compenetración de estos actores son discutidos. Esta trabajo tiene dos contribuciones principales, primero, la incorporación de métodos de optimización basados en MOEA para resolver problemas de planificación y diseño de micro-redes. Una segunda contribución es la construcción de un vínculo entre aspectos técnicos y sociales bajo el concepto de sostenibilidad.

Dedicated to Francis and Rene, my parents.

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LIST OF SYMBOLS

CHAPTER 3:

x	Decision Variable Vector
$\acute{\Omega}$	Domain of Solutions
w	Weight Vector
Z_m	Vector of Constrained Objectives
E_m	Vector Objective Constraints
n_c	SBX Distribution Index
β_i	SBX Spread Factor
P_t	Parent Population
Q_t	Offspring Population

CHAPTER 4:

R_t	Parent + Offspring Population
P^t_{DER}	Power Output of Distributed Energy Resources at Instant "t"
P^t_D	Power Demand of Loads and Losses at Instant "t"
P^t_{DRS}	Power Curtailed in Demand Response Strategies at Instant "t"
$E^{(t,t+T)}_{DRS}$	Energy from Distributed Energy Resources at Interval (t,t+T)
$E^{(t,t+T)}_D$	Energy Demand and Losses at Interval (t,t+T)
E_R	System Energy Reserve
P_n	Net Power at Node "*n*"
V_n	Voltage at Node "*n*"
E_R	Vector of Storage Energy Ratings

P_R Vector of Inverter Power Ratings

RET_R Vector of Renewable Generators Power Rating

E_{nR} Nominal Energy Rating of Storage Unit at node "*n*"

P_{nR} Nominal Power Rating of Inverter Unit at node "*n*"

RET_{nR} Nominal Power of Renewable Generation at node "*n*"

W Vector of Power Outputs for all units in the period of study

S Vector of Stored Energy for all units in the period of study

R Vector of Renewable Energy Output for all units in the period of study

F_C Fixed Cost Component

P_C Inverter Power Costs Component

E_C Energy Storage Cost Component

RET_C Renewable Energy Cost Component

P_{cf} Incremental Power Cost

E_{cf} Incremental Energy Cost

RET_{cf} Incremental Renewable Energy Cost

EM Total System Emissions

E_{NR} Non-Renewable Energy

emfac Emission Factor

H_R Average Hours of System Reserve

CHAPTER 5:

SRC Storage Reserve Capacity

IC Installation Costs

PE Particulate Emissions

NRE Non-Renewable Energy

1 INTRODUCTION

1.1 Overview

According to the World Bank, millions of people around the world do not have access to electricity because of their distance from the central grid [**1**]. Also, there are many communities which have the electric energy service, but transportation costs are high and consumption is low, making the operation of these systems not viable for the utilities. This creates low incentives for new investments, which turns into poor service quality, reduced reliability and higher prices for the customers in those isolated areas.

An affordable and adequate energy service would be a key enabler for the sustainable development of these communities. Therefore, it will be necessary to renovate existing electric delivery schemes. Considering the recent development of energy management systems and electric generation technologies, an attractive alternative nowadays is the production of electricity under the smart-grid concept, which in this case would cover generation close to the consumers, the use of local resources, modern communications, control systems and network topologies such as *microgrids* [**2**] [**3**]. However, for the massive penetration of this combined set of solutions it will be indispensable to first develop tools and applications that aid system designers and investors to assess how much resources should be allocated and where to invest [**4**]. The analysis is complex, considering that every location represents a different situation because of geographical conditions, resource availability, environmental factors and social repercussions of the adopted solutions.

This work focuses on the integration of renewable technologies to *microgrids* located on isolated areas. Nonetheless, for maximum penetration of renewable resources, which are mostly intermittent, it is vital to include distributed energy storage (DES) for balancing the power and energy requirements for the system. To address this issue, a multiobjective evolutionary algorithm (MOEA) is proposed. The algorithm is able to determine the optimum size and location of the DES resources on *microgrids*. The algorithm deals with objectives such as energy losses, installation costs of the storage units, and introduces customers with different service level requirements. The latter is based on a social and regulatory analysis which addresses the motivation of residential customers to participate in demand side management (DSM) strategies and how these strategies fit into the current regulation.

This thesis is the first work on *microgrids* at UPRM, it has a broad scope, covering both technical and economical topics as well as their related social and regulatory implications. This work is intended to become an enabler for future research in *microgrids* and smart-grid topics at UPRM and other institutions.

1.2 Topic of the Thesis

The topic of the thesis is “Renewable-Driven Microgrids on Isolated Areas”. The research covers the problem of optimum sizing and sitting of DES resources on isolated *microgrids* and its related social and regulatory repercussions. The optimization problem is solved by using a multiobjective evolutionary algorithm (MOEA).

1.3 Objectives and Contributions of the Thesis

The main purpose of this thesis is to design an optimization algorithm for distributed energy storage (DES) resources on isolated microgrids, maximizing the integration of intermittent renewable resources onto these networks. Another purpose is to addresses the motivation of residential customers to participate in demand side management (DSM) strategies and how these strategies fit into current regulations.

The specific objectives of this work are the following:

1. Compare the differences between renewable-driven microgrids and classical distribution networks.
2. Solve the optimum DES sizing and sitting problem on isolated microgrids, while maximizing renewable source integration.
3. Demonstrate the trade-offs over the customers’ electric service of the proposed algorithm.
4. Identify the sustainability dimensions on implicated communities.
5. Study the related regulatory implications of the proposed algorithm.

6. Give recommendations regarding the performance and control of the proposed algorithm.
7. Serve as a base for future research in microgrid and smart-grid topics at UPRM.

1.4 Thesis Outline

The present work is organized as follows: An introduction as well as the thesis contributions and scope are given in Chapter 1. In Chapter 2 an overview of *microgrids* and the characteristics behind this concept is given. Chapter 2 describes the optimization method to be used in this thesis (Multiobjective Evolutionary Algorithms). Chapters 3-4 are dedicated to show the general description of the DES optimum sizing/sitting problem, their general formulation, and the results and discussion of different case studies. Chapter 5 presents the social and regulatory analysis attached to the methods proposed in the thesis. Finally, Chapter 6 presents general conclusions and future work.

2 MICROGRIDS

2.1 Introduction

Traditionally, electric distribution networks have been used to deliver electricity to consumers. The development of new generation technologies, increased concern on environmental issues and the interest of moving the electrical network towards a more efficient 'smart-grid' have opened the possibility and created the incentive for transforming the distribution grids from passive to active networks, where the decision making and control is distributed among different stakeholders. As a result, an attractive alternative would be the creation of small networks 'independent' from the backbone grid, or microgrids. A microgrid is a combination of different types of loads and distributed energy resources (DER) which can autonomously meet the power, energy and quality requirements of the customers in its area. DERs could be utility or community-owned (Photovoltaic/wind farms, storage), or customer-owned (PV, wind turbines, CHP turbines, etc) [**5**]. Loads can participate in local demand side energy management strategies interacting with grid/microgrid operators through smart-metering systems. Also, the microgrid can import or export power with a main grid or between other microgrids, if connections are available.

Depending on DER penetration level, resource availability, load behavior, service quality constraints and the market structure of the microgrid, the design and planning process vary significantly compared to conventional power systems, making the problem very complex for traditional methods and tools [**6**] and urging the development of new tools for systems planners. In this section the structure and characteristics of microgrids will be studied. Also the problems in the design and planning of microgrids are formally proposed.

2.2 The Potential of Microgrids for the Smart Grid Development

The *Energy Independence and Security Act of 2007* (EISA) [**7**] defines the smart grid as "a modernization of the Nation's electricity transmission and distribution system to maintain a reliable and secure electricity infrastructure that can meet future demand growth". This law mandates federal and state agencies to implement programs that help the development of the 'Smart Grid'.

EISA states that simply adding more generators and transmission lines would not solve the energy needs of USA, but the existing grid infrastructure could be made more efficient by the use of intelligent systems, demand response strategies and new legislation that provide incentives for the efficient production, transport, and consumption of electricity [**8**]. This was corroborated by the National Electric Manufacturers Association (NEMA) and the Congressional Research Service[**9**] [**10**].

Microgrids are both *part* and *beneficiaries* of the smart-grid concept. Looking at the microgrids' benefits cited further in this Section, it is evident that there are objectives *shared* between microgrids and the smart-grid concept: reduce the costs of energy and the reliability, efficiency and security improvement. Also, there are benefits which are linked to the *use* of smart-grid technologies: the deployment of green technologies, different levels of quality and the use of demand response strategies. Figure 2.2.1 show multiple links between microgrids and the smart-grid concept.

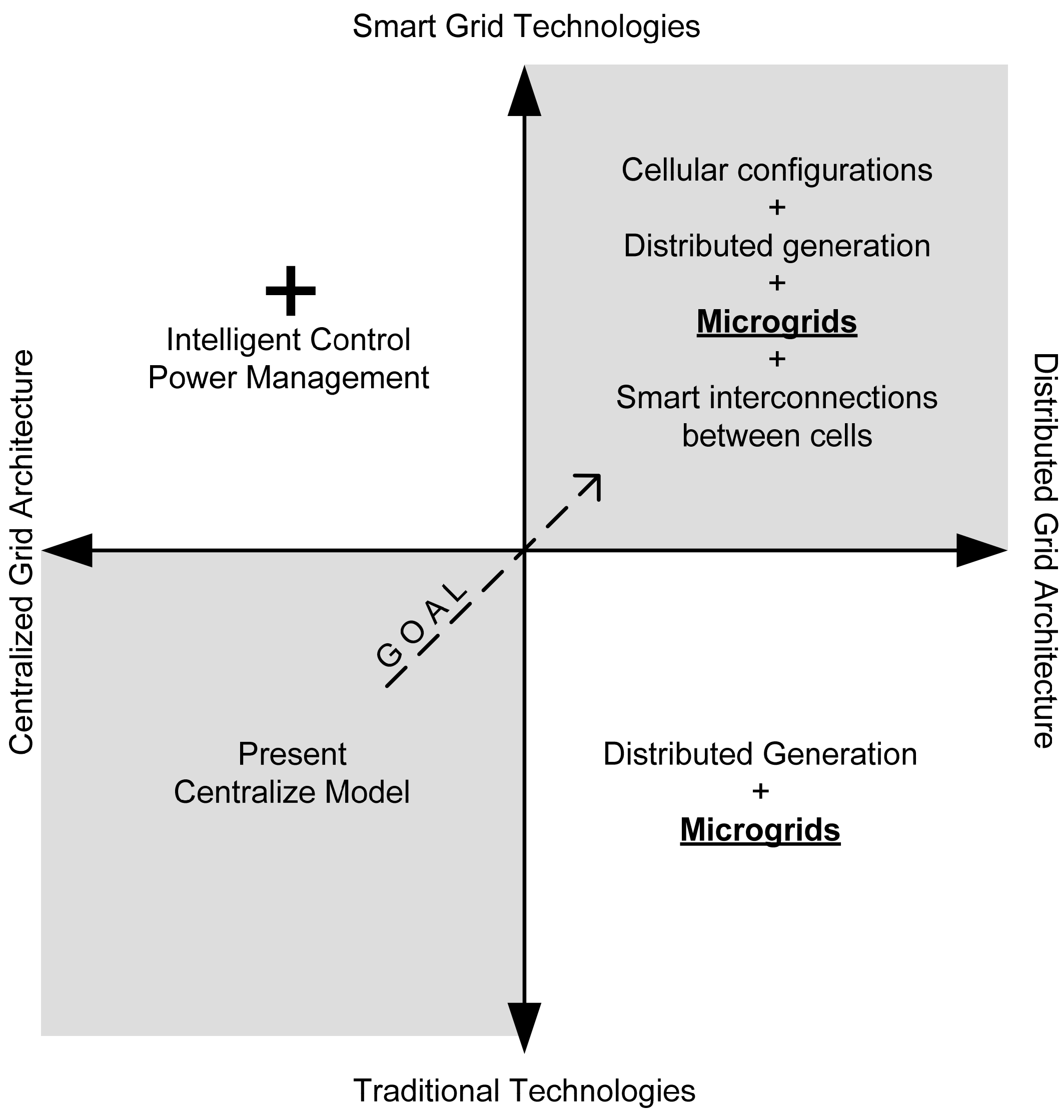


Figure 2.2.1: Conceptual Framework of Smart Grid Alternatives. Adapted from [**11**] .

These links make microgrids an essential part of the deployment and implementation of the smart-grid concept in distribution networks. A recent US Department of Energy (DOE) market research estimates that microgrids will could supply between 1GW to 13GW of connected load by year 2020, which accounts more than 550 microgrids of an average capacity of 10MW. However, for microgrids to capture this market it is necessary that they deliver the energy at favorable costs. Aside from better costs, microgrids could also deliver many different benefits and value propositions, thus the market size and public benefits can vary significantly depending in the conditions of the location. However, the same study estimates that the "cost-reduction" value proposition would generate 45 to 80% of the market, while the "reliability" and "green power" value propositions are going to generate 25% of the market each [**12**].

According to DOE, microgrids' benefits in 2020 could total \$1 billion/year, being the emissions reduction the largest benefits accounting for \$550 million/year by 2020. Also DOE estimates that microgrids would reduce 17.4 million tons of CO_2, 108,000 tons of SO_x and 18,000 tons of NO_x (Figure 2.2.2).

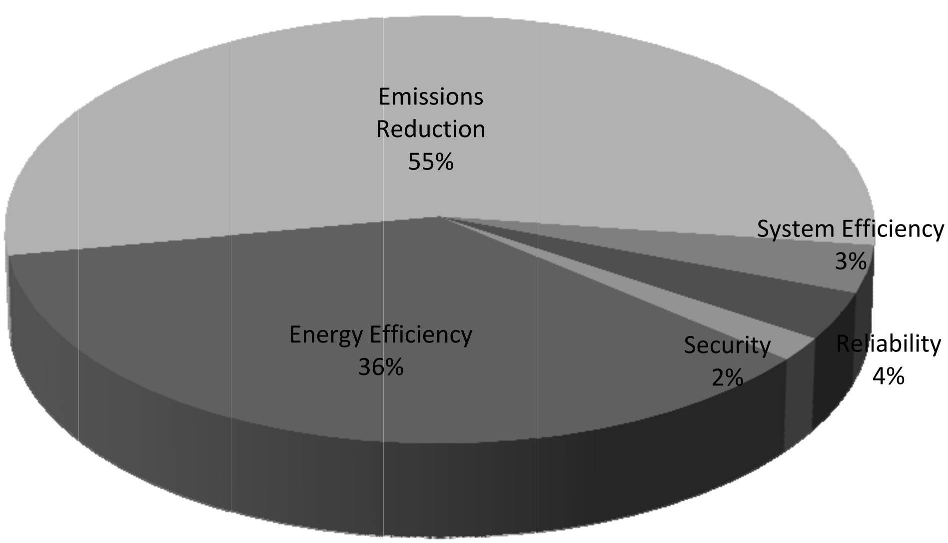


Figure 2.2.2: Microgrids will generate \$1 billion/year of benefits by 2020. Data from [**12**].

2.3 Microgrids Value

According to another study made by the DOE [**13**], microgrid systems could be implemented in a wide range of facilities and installations, which include:

- Urban development.
- Critical facilities (hospitals, military installations, police, fire, EMT, water treatment, communications).
- Services of emergency response and restoration for events such as hurricanes, terrorist attacks and earthquakes.
- **Supply of remote areas: geographical islands, rural areas, villages, and Native American reservations.**

It is important to note the importance of remote area supply in the list of microgrid applications. Another recent research work found that if technical and regulatory barriers were removed, microgrids could potentially offer six complementary benefits [**8**]:

1. Reduce the cost of energy and manage price volatility
2. Improve customer and system reliability
3. Increase the power systems' security
4. Promote the deployment and integration of green technologies
5. Make more efficient the power delivery system
6. Provide different levels and quality of service to customer

Apart from these benefits, microgrids could also bring remuneration to utilities in terms of efficiency, power quality, environment conservation and community development. Benefits for both customers and utilities are enumerated with more detail in Table 2.3.1.

Table 2.3.1: Benefits of Distributed Energy Resources.

Benefits for the Customers:	Benefits for Utilities:
• Increased reliability • Increased power quality. • Reduced outages. • More efficient use of energy • Lower energy cost. • Incentive the use of renewable energy. • Reduction of greenhouse gases.	• Loss reduction. • Increased system capacity. • Can provide reactive control. • Improves voltage profile. • Reduces investments on expansions. • Fault reduction. • Improves the customer-utility relation.

Recent studies [**11**] have shown that installation costs for communication and measurement equipment necessary for the microgrid operation at the customer side are largely inferior compared with the benefits that could bring microgrid operation. Equipment costs range between $200 per year while benefits could be ranging between $2000 per year or even more if energy and homeland security considerations are taken into account.

2.4 Microgrid Structure

In a typical distribution network the consumers are fed through a primary feeder, which is supplied by means of a distribution substation from the transmission network [**14**]. Normally, these feeders are connected radially, with lateral derivations reaching consumers. In contrast, with microgrids the distribution feeders no longer maintain their radial characteristics. In turn, the system is transformed into a meshed network. In the next sections the general structure and elements of microgrids are described.

2.4.1 General Characteristics

In general, a microgrid comprises the medium-voltage (MV) and low-voltage (LV) portion of a power distribution system. In the cases where a main-grid connection is exists, the microgrid encloses the secondary side of the substation transformer (called point of common connection or PCC) to the rest of the MV and LV system. This will include loads, and consumer- or utility-owned distributed generators, which could be of different types and technologies. The microgrid also includes all the communication equipment necessary for the operation and real-time energy management of the system. Figure 2.4.1 illustrates the general structure of a microgrid.

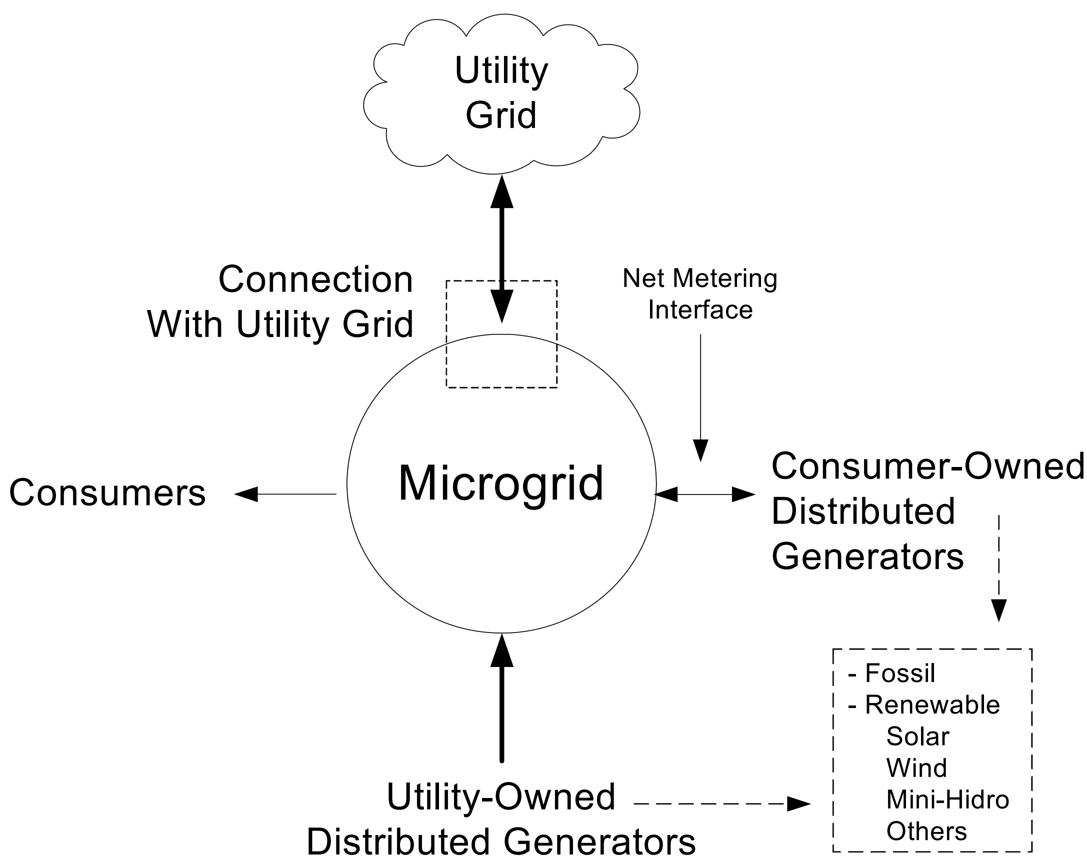


Figure 2.4.1: Typical Microgrid Structure

2.4.2 Distributed Energy Resources Types and Control Strategies

Distributed energy resources (DERs) are generation or storage units capable of supplying energy to the microgrid. In respect of their nature, DERs could be divided in distributed generators (DG), which are units that exclusively produce energy harnessed from a primary energy resource; distributed energy storage units (DES), which store energy at surplus times for later use; or hybrid units, which combine the characteristics of DG and DES. In terms of their interface with the grid they can be of two types; the ones which use a power electronics converter interface and the ones that use conventional rotating machines.

- *Power electronic converters*:

These types of generators make use of switching power electronic converters for transforming harnessed/stored energy. The efficiencies of these devices range between 90% and 98% depending on technology used and operating conditions. Common applications are for renewable energy technologies (RETs) and battery storages, photovoltaic inverters, or anywhere a power conversion is needed. Figure 2.4.2 shows the general structure of a hybrid power electronics inverter connected to a microgrid.

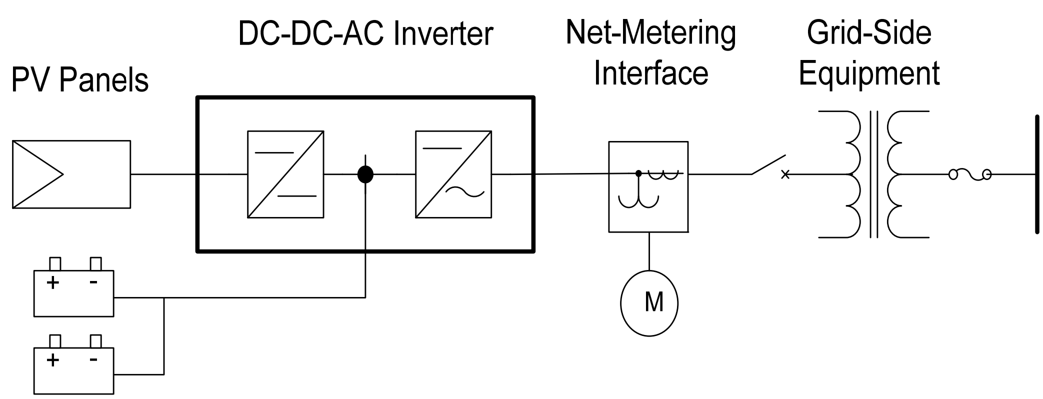


Figure 2.4.2: Power electronics interface for a hybrid system: PV inverter plus battery storage.

- *Rotating machines*:

These are the classical rotating machines used in traditional power systems. The general scheme consists in a prime mover that could be a combustion engine or turbine, coupled with a synchronous generator. The prime mover could be fossil fueled (gas or diesel), or could be renewable like mini-hydro. Also some wind technologies use rotating interfaces. Efficiency of these devices vary depending on the technology and combustible used.

Depending on the power and energy control strategy, DERs could be grid-forming, grid-supporting and grid-following DERs [**15**]. Each one of these units has a different role in the operation of the microgrid. Figure 2.4.3 illustrate these three types of DERs in a typical microgrid and Table 2.4.1 summarizes common DER types, technologies and interfaces on microgrids.

- *Grid forming DERs*: these units are the backbone of the microgrids, Being responsible of maintain stable power system conditions, these units constantly control frequency and voltage by matching the systems' generation and demand. These units could be conventional synchronous generators or Voltage Source Inverters (VSI) with battery storage.

- *Grid supporting DERs*: controllable (dispatchable) units which are dependant of bus voltage and frequency. These units could be either storage (flywheels, batteries, heat storage) or generators whose main resource is dispatchable (fuel cells, micro turbine, etc).

- *Grid following units***:** uncontrollable (grid-type) generators. These units are often designed to maximize their output by means of a Maximum Power Point Tracker (MPPT). They do not control voltage or frequency at their PCC, instead, they 'follow' the voltage and frequency signal and act as current source. The main driver for this control strategy is the uncertainty of the primary energy source of these technologies. Some examples are Photovoltaic cells and small wind turbines.

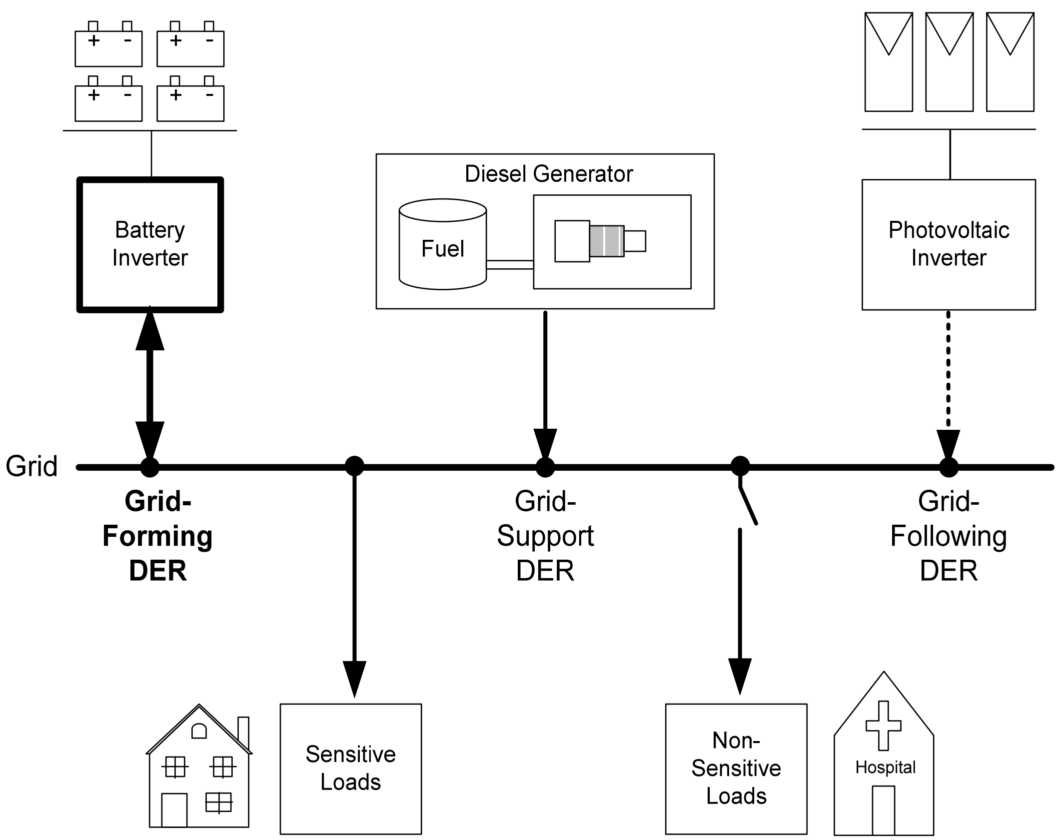


Figure 2.4.3: DERs with different control strategies.

Table 2.4.1: Common DER types, technologies and interfaces.

Type	Control	Technology	Interface
Grid-Forming	Control voltage and frequency balancing generation and demand	Reciprocating Engines Gas Turbines Battery Storage	Synchronous Generator Synchronous Generator Power Electronics
Grid-Support	Support grid-forming DERs in steady state and transient events	Fuel Cell Micro turbines Super Capacitor Storage Flywheel Storage	Power Electronics “ “ “
Grid-Following	Maximize the energy exports	Grid-tied Solar PV Wind Turbine	Power Electronics “

Being microgrids autonomous systems, it is necessary to control grid forming and grid supporting units in order to balance the active and reactive power of generators and loads, while maximizing the output of non-dispatchable units. There are mainly two types of control methods for microgrids: The ones that require communication between generators, -or a centralized control, and the ones that set the required active and reactive power autonomously.

- Microgrids with Centralized Control: Generation control, dispatch, load shedding and management of ancilliary services are acheived through a centralized controller. Means of communication needs to be provided between sources either wired or wireless. This control scheme is more aligned with the 'smart-grid' concept.

- Microgrids with Autonomous Control: Under this control scheme, the demand is shared between generators in proportion to their respective 'droops' of active and reactive power, just as in traditional power systems.

Recent research on microgrid control and smart-grids has shown that microgrids controlled via a central controller are capable of accommodating a wider range of load and generation output scenarios [**8**]. Also the study states that microgrids must integrate with the utility's or ISO's communications infrastructure.

2.4.3 Loads and Demand Response

In a microgrid loads are no longer passive elements, instead, loads can participate in demand response and shedding strategies. In isolated areas where power balance has hard limits, load control strategies play a critical role, since they have the potential of significantly reducing installation costs on additional units serving loads in peak intervals. However, these strategies should ensure that critical loads in the microgrid receive energy when needed (see Figure 2.4.3). Additional strategies include customer service differentiation, power quality and reliability enhancement of specific loads [**5**]. Demand response is covered in more detail in Section 3.1 of this work.

2.4.4 Microgrid Architectures

Depending in the interaction level between a microgrid and the main grid, a microgrid could be classified as autonomous or grid-connected. In an autonomous microgrid a connection to the main-grid is nonexistent, requiring the microgrid to be self-sustaing. In these types of microgrids the role of DES units is critical. In the other hand, grid-connected microgrids have the main grid as backup, but could also operate autonomously at certain times of the day, or when a scheduled maintenance is being performed at main-grid equipment.

- *Grid Connected Microgrids:*

These microgrid architectures could be used in utility systems to prevent outage and to maximize the integration of renewable energy sources. They also have the benefits of reducing systems' losses, expand the supply mix, manage congestion and cut the greenhouse gases emissions. Also, the grid-connected architecture is suitable for industrial or commercial facilities (university campus, industrial zones, shopping centers, buildings). In these cases the main drivers are power quality and reliability enhancement and energy independence. Other advantages include demand response management, and the possibility to operate grid-independent in response to energy prices from the main grid. Viewed from the main-grid perspective, grid-connected microgrids represent a constant or controllable load with a controllable demand profile.

- *Autonomous Microgrids:*

In this architecture the microgrid operate in isolated mode, having to self-suffice energy demand and power quality and reliability needs of local customers. This mode of operation is envisioned for systems located in geographical remote areas where access to backbone grid is difficult or too expensive. The design and planning process of an autonomous microgrid is more complex than the grid-connected counterpart because the sustainability dimensions of isolated operation. Sustainability is not limited to the energy equilibrium of the system, it extends to social and environmental balance of the communities where the microgrid is installed. It is important to note, this type of microgrid is more likely to be constructed in rural and remote areas. More details on social impact of autonomous microgrids is given in Section 3.2.

The main drivers of autonomous operation are the availability of local energy resources, energy independence and reliability. Depending on the conditions of the location, the autonomous microgrids could use different type of DGs such as small-hydro, PV panels, wind turbines and even diesel or low-emission gas turbines could also be used.

Table 2.4.2 presents the most salient differences between grid-connected and autonomous microgrids.

Table 2.4.2: Differences between grid-connected and autonomous microgrids.

Characteristic	Grid Connected	Autonomous
Mode of Operation	Isolated/Grid connected	Isolated
Main Drivers	Power quality/reliability enhancement, efficiency, costs	Sustainability of remote and rural areas, efficiency
Use of demand response strategies	Desirable	Critical
Use of Energy Storage	For responding to price signals	For self-reliance

3 SUSTAINABILITY IN MICROGRIDS

Many authors have proposed that renewable energy technologies, distributed generation (DG), and novel network topologies like *microgrids* could play an important role in the development of an integrated sustainability model, especially in developing countries and emerging economies [**16**] [**17**].

Sustainability is a multi-dimensional concept, it is difficult to define it in terms of money, tons, people, or other indexes. In 1987 the Brundtland Report defined sustainable development as "*the development that meets the needs of the present without compromising the ability of future generation to meet their own needs*" [**18**]. This term considers the social, economic and environmental aspects of development. In this aim, one of the requirements for preserving the world for future generations is the creation of a new sustainable energy model. If particularities of electrical systems are combined with the characteristics of sustainable development, a *sustainable electrical system* could be roughly defined as one that meets the following minimum conditions (Figure 2.4.1):

1. *Technically sustainable*: construction is possible within the limits of current technology; operation of critical elements of the system is not compromised.
2. *Economically sustainable*: the project is economically feasible considering environmental and social aspects.
3. *Socially sustainable:* the community accepts the system and is willing to cooperate with its development; the project promotes the social development of its users.
4. *Environmentally sustainable:* the project brings benefits to the environment in comparison with traditional power systems.

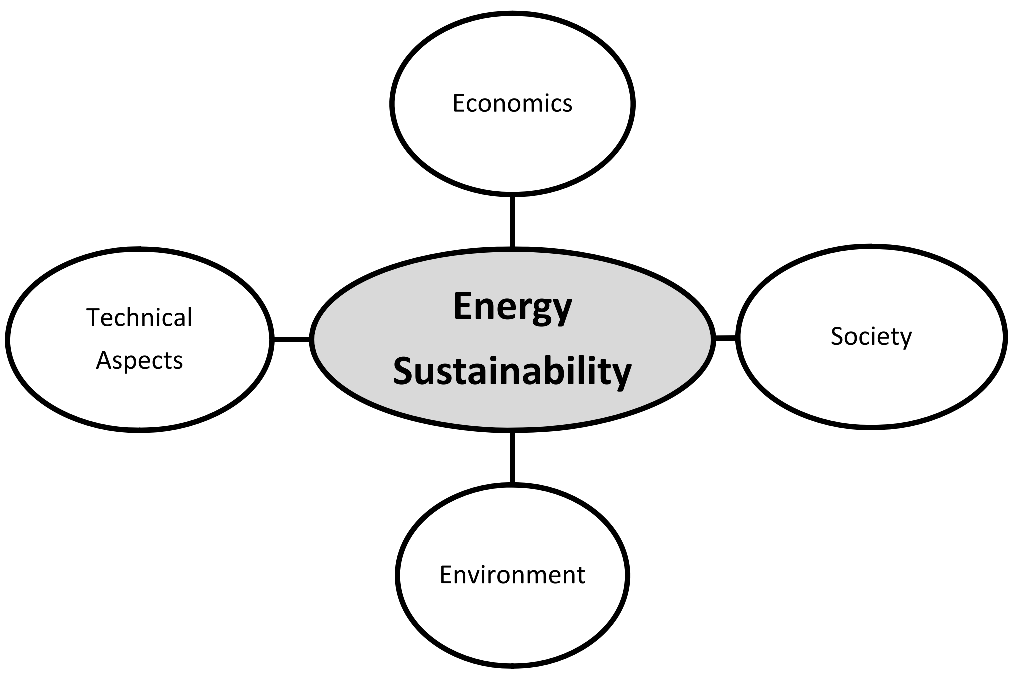


Figure 2.4.1: Components of a Sustainable Energy Model.

This section presents the different dimensions of microgrids sustainability, and the opportunities that the microgrid concept holds for both developed and developing countries. First, energy management strategies aimed at cost-diminution are described, and then social implications and environmental aspects are studied.

3.1 Energy Sustainability

One of the biggest issues that prevent massive penetration of renewable energy technologies is the variability of the primary sources of energy, mainly sun irradiance and wind [**19**]. Figure 3.1.1 depicts the numerous variations that solar irradiance could make in a period of just two hours, giving a general insight of the problem.

Several strategies have been studied for minimizing the uncertainty effects, each one having different trade-offs between costs, environmental impact and easiness of implementation. Three popular ways for overcoming intermittence and achieving energy balance in a microgrid are using fossil fuels/grid support, distributed energy storage (DES) units, or demand response strategies.

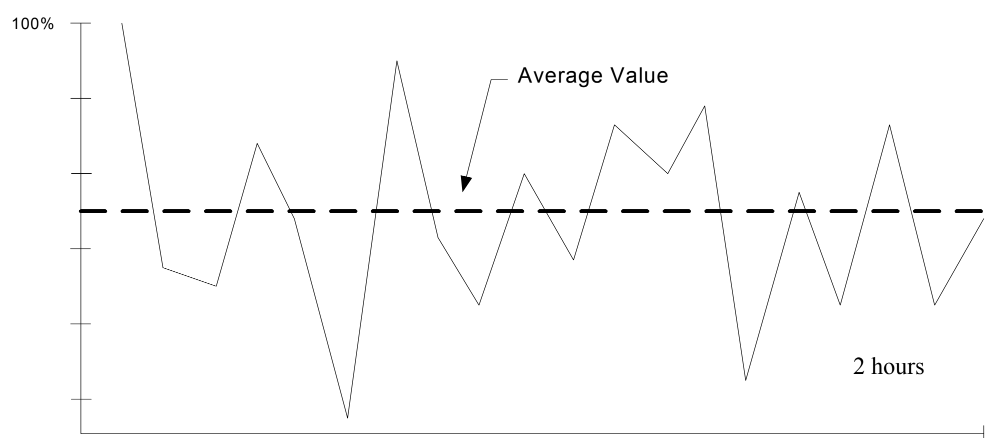


Figure 3.1.1: Typical sun irradiance profile in 2 hours. Adapted from [**20**].

1. *Using fossil fuels or main grid support:*

This approach is similar to the distribution system with distributed generation scheme. In these systems, fossil fuels from the main grid and renewable distributed generators are used to supply local energy demand.

For microgrids, several fuels could be used, the most common for this type of applications are diesel or natural gas.

- Diesel, because of the ample availability of diesel and the technological maturity of small-scale diesel generators.
- Natural Gas, because of the existent gas infrastructure in many countries and the high levels of efficiency and low emissions achieved by micro-turbines. The problems of this mode of operation are well documented in the literature [**2**] [**21**], being the most important the energy inefficiency and emissions of some fuel cycles, and the dependence on foreign resources.

2. *Adding distributed energy storage (DES) units:*

This approach consists of installing Grid-Forming and Grid-Support long-term storage units along the microgrid like the ones depicted in Section 2.4.2. These units should be strategically located and sized in order to meet the desired levels of energy demand and for achieving maximum efficiency of the system. Table 3.1.1 shows recent types of DES units and their related efficiency, power/energy rating and most common use.

Table 3.1.1: Recent distributed storage resources. Adapted from [**22**].

Type	Size	Efficiency	Use
Fuel Cells	200kW – 5MW	40-65%	Grid forming, power quality control
Battery Storage	500 – 5000 kWh	70-75%	Grid forming, power quality and voltage control.
Flywheels	2 – 20 kWh	70-80%	Transient/short-term voltage and power quality regulation

DES units tend to be very expensive, thus increasing dramatically the equipment installation costs. This makes the use of these resources very constrained by economical reasons. Also, the environmental impact of the manufacturing and disposal is significant, especially lead-acid batteries.

3. *Demand Response Strategies (DRS):*

Demand response is a new paradigm in the planning and operation of power systems. Present energy consumption patterns are leading to the unsustainability of the current energy model. The traditional power systems planning approach consists on forecasting energy demand and adjusting supply-side equipment based on these projections. This model completely ignores the possibilities that energy conservation has, i.e., control of energy demand in the consumer side, in terms of quantity and quality.

In the DRS philosophy, instead of matching the limited energy resources to the consumers' needs, the consumers' demand is adapted in the higher possible degree to the resources available, without compromising any critical activity performed by this particular user (e.g., hospitals). These energy resources could be controlled by limiting their quality, i.e. offering different power quality levels adapted to the consumers' needs, or by limiting the amount of energy flowing to the customer at certain times of the day, i.e. offering different service levels and rates to different customers.

Service differentiation could have various levels, but the most significant is between sensitive (critical) and non-sensitive customers. A sensitive customer is defined as one whose energy service should not be interrupted. This is the case of healthcare facilities, communal service buildings, communication infrastructure, and others. Non-sensitive customers could be seen as 'controllable' loads, having an interruptible nature in their total or partial demand at certain times of the day/week/month/etc. The length of the interruption intervals as well as the energy interrupted could be defined in service contracts with local microgrid operators. Table 3.1.2 summarizes the strategies of customer service differentiation DRS.

Table 3.1.2: Customer service differentiation strategies.

Load Type	Strategy
Sensitive	Not-Controllable
Non-sensitive	Controllable – when needed Controllable - scheduled

Application of demand response strategies may seem appealing and straight-forward, however it is complex and requires a strong social agreement among the microgrids' stakeholders. Before the application of such strategies, it is fundamental to evaluate the knowledge, ideas and aptitudes that the communities have about the implementation, with the objective of taking decisions that guarantee its success. The most important social indicators to study are [**23**]:

- Level of energy culture that makes people aware of the different energy options available.
- The level of conscience about energy conservation.
- The consumption behavior of the individuals.
- The willing of the individual to change its habits.

Depending on the results of this analysis, the weaknesses that the community presents must be dealt with before the implementation of the demand response strategies. Possible methods to handle this usually include the creation of campaigns, training programs, and other educational methods. Reducing the energy consumption patterns of people is linked with a change of lifestyle which is very difficult to achieve. These strategies could be aided by government regulations like pricing or taxation of inefficient equipment, discourage of the use of energy-intensive device, or encouraging the use of energy-saving devices and the implementation of DSR strategies. These strategies must be backed with technology capable of regulating and controlling these consumption patterns. This is being done nowadays by the introduction of the smart-grid concept and their related communications and control infrastructure [**8**]. In the other hand, these strategies must also be translated into policies and regulations controlled by the government energy agencies and international energy conservation institutions. These strategies are what is usually done to deal with power system planning and also other public-related services. Nevertheless, in order to be truly sustainable, these processes need a broader and more inclusive participation from all stakeholders. Otherwise, these strategies could be seen as imposed by a government, with very little ownership from stakeholders; top-down strategies usually face strong opposition from stakeholders that might feel left out of the decision-making process on ideas and plans that directly affect them. There are various participatory options for stakeholder engagement available in literature. Although this approach is less common than top-down options, it is more likely to get support from those affected and will be more sustainable in all dimensions [**24**] [**25**].

3.2 Microgrids as Tools for Sustainable Development

Energy is a crucial actor in the evolution of society, and its accessibility is indispensable for the socio-economic development of a nation. Due to the wide availability of energy resources, developed countries enjoy a lifestyle unattainable if these resources were not available. However, the reality is that this lifestyle is only accesible by a small fraction of the human population.

The energy dimension of poverty is defined as ‘energy poverty’, or the absence of sufficient choice in accessing an adequate, affordable, reliable, high-quality, safe, and environmental benign energy service that serves as a support for the economic and human development [**26**]. The reasons for this energy poverty are diverse, in many cases controversial, and are beyond the scope of this work. Many international forums have tried to address this issue, being the most important the 1992 United Nations Conference on Environment and Development in Rio de Janeiro, or the ‘Earth Summit’. In this conference, 178 heads of state gathered to make a consensus in policies aimed at sustainability and world conservation, named Agenda 21. Agenda 21 dictates courses of actions for governments and major groups aimed at the creation of sustainable, secure, socially harmonious and environmental safe societies. For meeting these goals, A. Reddy [**26**] identifies five crucial components:

1. Economic efficiency
2. Equity for the poor, women, ethnic minorities and remote areas inhabitants
3. Empowerment of self-reliance
4. Environmental soundness
5. Peace

Because of the linkages between social issues and energy, the latter could serve as an enabler for the development of solutions aimed at dealing with poverty and other social realities in an integrated way. But an increased access to energy resources will not by itself bring economical and social benefits to communities, which is the way that current governments deal with the poverty problems. They do not directly address the energy and poverty linkage. Traditional policy-making or increased education would not effectively alleviate poverty problems because the main problem – lack of adequate energy resources is still there. People still have to use biomass and expensive fuels for satisfying energy needs. In contrast, developing new energy strategies and technologies that directly improve the energy consumption patterns of communities – *like microgrids* – in combination with new, more inclusive policymaking would allow wider access to short and long term benefits of new energy sources, technologies and strategies. There are poor people in both industrialized and developing countries, but the reality is very different for the two types of economies because the nature of the energetic problems is also different:

Industrialized Economies:

In industrialized countries the problem of poor citizens is not the lack of access to energy resources, the problem is that energy is too expensive and therefore a large proportion of the monthly income has to be spent on fulfilling energy needs. In contrast with developing countries, the problem in industrialized and mid-income countries is not having access to energy resources, but maintaining the service. This makes the choice of citizens limited to expensive energy or no energy at all.

In these economies, microgrids could help by reducing the costs of electricity in parts of the electric system where infrastructure or geographical conditions make the system operation not feasible for utilities or consumers. Also, with the implementation of demand response strategies within the microgrid, consumers have different choices of energy services and can find one that they can afford while fulfilling entirely or most of their energy needs.

A good example of this type of microgrids is being tested since summer 1997 in Sendai City, Japan. This purpose of this project is to evaluate the possibility that the microgrid can create "value" to the consumers, by using different customer service levels in the area. The microgrid is comprised of two 350 kW gas engines and one 250 kW molten-carbonate fuel cells. The different service levels include interruption, voltage-drop, and wave differentiation. Although this microgrid is still in the testing phase, developers say it has improved the power quality of the consumers at the site [**27**].

Developing Economies

Four out of five people without electricity live in areas of the developing world, especially in peripheral urban and isolated rural areas. Thus, the principal challenge of developing countries in energy matters is the expansion of the electric service to the rural and remote areas. Table 3.2.1 and Figure 3.2.1 presents data of the International Energy Agency (IEA) electricity access for developing countries in year 2005. It could be clearly seen the extremely low level of electrification in rural areas, in special in Africa. Although Latin America has the highest level of rural and urban electrification in all developing countries, numbers like 34.4% of the rural population without energy access are still too elevated and a source of concern for countries in the 21st century.

Table 3.2.1: Electricity Access in Developing Countries, 2005. Adapted from [**28**].

		Africa	**Asia**	**Latin America**	**Middle East**
Total	Total Population (million)	891	3418	**449**	186
	Population in Urban Areas (million)	343	1063	**338**	121
	Population in Rural Areas (million)	548	2355	**111**	65
Rural	With Access (%)	19	65.1	**65.6**	56.4
	Without Access (%)	81	34.9	**34.4**	43.6
Urban	With Access (%)	67.9	86.4	**98**	86.7
	Without Access (%)	32.1	13.6	**2**	13.3

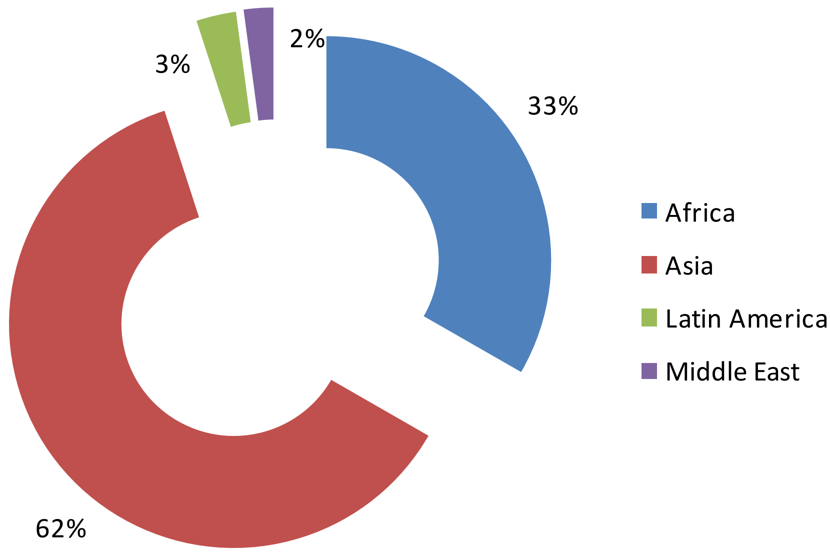


Figure 3.2.1: Electricity Access for Developing Countries in Absolute Values, Year 2005. Adapted from [**28**].

The rural electrification problem is linked to rural-urban migrations, which are one of the principal causes of cities overpopulation. Rural-urban migration is a complex problem which is out of the scope of this work; however, there is a potential contribution of rural microgrids in improving the life quality in rural areas, including the creation of local economies that could help to reduce migration to cities. Perhaps an increment of urbanized areas is inevitable, it could be of less impact if innovative energy policies are implemented in rural areas.

On the other hand, the financial implications of lack of proper energy access are high in developing countries. Some countries spend up to 50% of their trade surpluses on energy imports [**28**]. In others, as much as 10% of the country's GDP is spent on subsidizing the electric sector. Of the 47 countries with per capita incomes of less than 2 dollars a day, 80% are net importers of oil, while 53% import all of their oil. The situation is expected to worsen in the future since electrical demand is expected to double for year 2030, the biggest share occurring in developing countries [**29**].

Another interesting effect of microgrids is their ability of becoming vehicles for economic development. It is understood that under the sustainability concept, when the economic viability of a project is studied the whole global and macro economical repercussions must also be included into the analysis. In contrast to conventional generation technologies where jobs are too specialized and concentrated, distributed generation and microgrids have a great potential for local job creation, as well as the expected expansion of the economic activity in the places where they are installed. Also, children and women of villages in developing countries could have access to media and modern methods of education. In general, the installation of these technologies could be a vehicle for solidarity for communities where some of today's modern equipment is not accessible.

Electricity in remote areas enables the use of electric tools and equipment, increasing the productivity of workers and creating more and diverse types of occupations in communities. Increasing productivity could result in more economic activity, which is equivalent to an increase in business revenues. Today, many projects in Africa serve as examples of the impact of microgrids in remote zones. This is the case of the community of Mpeketoni in sub-Saharan Africa, where electricity has contributed to the mechanization of agriculture, facilitated trade and commerce, and most important, has created more jobs and added more value to the goods produced in the community. Field data gathered from the village artisans and carpenters shows that the productivity of the workers increased between 50 to 200% with the use of electricity, and gross revenues per day between 20 to 70% [**30**]. Also, access to electricity brings other unexpected benefits, as is the case of the introduction of diesel tractors for agricultural use, that apparently do not relate to electricity but the villagers explain in very clear words [**30**]:

> *‘‘Without electricity, very few people would dare bring their tractors out here because in the event of a major breakdown, welding repair services could only be obtained in Witu or Mombasa (100 km and 450 km away, respectively)”*

Also, children of Mpeketoni are now able to compete with students of more developed all thanks to the benefits of electricity. Better education methods, more flexible schedules, and less time spent on energy-gathering (biomass) have translated into a considerable increase in the education of Mpeketoni villagers [**30**].

3.3 Financial Models and Market Development

While developments like distributed generation, microgrid, and net-metering aim to make renewable energies more competitive, government incentives are still required for matching against the unbalances introduced by unpaid externalities of conventional generation technologies. In general, a microgrid project based on renewable energy could be an economical sustainable project if it is backed with an adequate financial model and with correct government support. However, even a renewable energy project could not be sustainable if it does not address environmental or social issues related to the project.

Many people use much higher discount rates when making energy-related decisions [**31**]. This means that people usually think in terms of initial costs of equipment rather than the whole life cycle costs, preferring inefficient energy sources which initial prices are lower. The reasons for this behavior are diverse and out of the scope of this work. Market entry in remote, rural or isolated microgrid markets is still considered of ‘high risk’, opening the need for the creation of market rules that allow investors to make profits beyond the short term [**32**]. There are other alternatives that could be generated inside governments for the promotion of microgrids, like subsidies, tax credits, carbon taxes, among others. Apart from government aid, there are other service delivery mechanisms that support the development of microgrids and renewable energies, being the most important [**33**]:

1. *Electric Utilities:* In cases where electric service is available at the locations, this is one of the best alternatives. Utilities already have a close relationship with customers, and have numerous incentives with the system conversion. The utility option could be combined with other financial alternatives.

2. *Commercial Banks:* DER technologies like biomass, mini-hydro, wind and in some cases solar photovoltaic are considered as low-risk investment by commercial banks. One of the principal obstacles for obtaining these loans is the valuing of the system revenues. The reason is that since the output of renewable resources is intermittent, a constant project cash flow could not be established. Despite all of these issues, bank loans are a possible financing alternative that should be studied.

3. *External Financing:* This is one of the most suited alternatives for remote communities in developing countries. International institutions like the Inter-American Development Bank (IDB), The United Nations Development Programme (UNDP), World Bank, and others support and finance projects aimed at energy efficiency and renewable energy. Examples of rural off-grid electrifications in the

World Bank portfolio include solar home system projects in India and Indonesia, various projects in Argentina, rural electrifications in Uganda and Sri-Lanka, and a number of small loans to PV companies [**32**]. Despite the financial support these institutions offer, their contribution is not enough for the demand of the rural electrification market.

Successful microgrids projects will have to develop viable business plans for both consumers and service suppliers. The World Bank has experimented with different service delivery mechanisms through the world, identifying the principal types [**32**] [**34**] :

- *Decentralized virtual utilities:* This approach consists on charging fixed month payments to consumers, or through pre-paid cards. This approach is convenient because of the structure is similar to the popular mobile communication structure, that the majority of the people are used to.
- *Local electricity retailers:* Cooperatives establish an electricity retail business. The driver of this model is the capability that gives a formal institution like a cooperative to obtain financing, institutional help, or backing from stronger partner.
- *Concessions:* This is one of the most promising alternatives for service delivery. Bidders are invited to concessions to supply electricity in remote areas The concessionary obtains the monopoly of a determined area in turn for the duty to serve customers, and to maintain its continuity over the duration of the concession. An interesting aspect is that contracts are awarded through a competitive bidding process, minimizing the subsidies from the government. The same approach is currently being tested in South Africa, Benin, Bolivia Cape Verde and Togo. Although this scheme separates of the 'free-market' theory, believed to bring

efficiency in power systems, there are benefits such a risk reduction, creation of sufficient customer base, and scale economies that make this approach more suited for remote applications. The experience with concessions is still limited, so there is still a long path to go in the evolution of these mechanisms.

4 MULTIOBJECTIVE OPTIMIZATION

4.1 Introduction

Optimization is the procedure in which a decision maker seeks to obtain the best value (either minimum or maximum) of an objective. A general multiobjective optimization problem could be proposed as:

$$\begin{cases} \text{Optimize } Z(x) = \text{ Optimize } ([z_1(x), z_2(x)\ , \ldots . z_n(x)]^T) \\ x \in \Omega \\ \\ \textit{Subject to:} \\ h(x) = 0 \\ c(x) \leq 0 \end{cases} \tag{4.1.1}$$

where Z is the vector of objective functions to optimize (minimize or maximize), n is the number of objectives, *x* is the decision vector, Ω is the domain of solutions (search space), *h* and *x* are equality and inequality constraints, respectively.

The objective to optimize could be an economic cost, a weight, a length, or any other factor or index. However, most problems in engineering and science involve more than one conflictive objective, which translates into more than one optimal solution to the problem. Classically, these kinds of problems have been treated as single-objective problems, requiring the decision maker to make early preferences on one objective over another before seeing the full range of alternatives -or trade-off- between them. With classical methods, for visualizing the full range of trade-offs it was necessary to iteratively change the preference information, thus, obtaining a different point of the trade-off curve in each run.

The classical working principle was motivated by the reality that early optimization methods only allowed to find a single solution (or point in the trade-off curve) at a time. However, with the recent evolution in the field of optimization there are numerous methods available which make it possible to obtain a *population* of solutions in each run, allowing capturing multiple optimum solutions of a multiobjective problem in a single run. Of these novel methods, the Evolutionary Algorithms (EA's) stands out. It imitates the Darwinian natural selection and natural genetics. The use of EAs will allow the decision maker to make more accurate choices without the need of any a-priori preference information about objectives.

In this section the salient features and fundamentals of Evolutionary Algorithms and Multiobjective Evolutionary Algorithms Optimization (MOEA) are discussed. Next, the concepts behind "Elitist MOEAs" are discussed as well as different methods of achieving elitism in Multiobjective Optimization (MOO). Lastly, the different methods for representing the output data of MOEAs will be described.

4.2 Single-objective vs. Multiobjective Optimization

Traditionally, optimization problems have been treated as single objective problems, even though most optimization problems in science and engineering consist on different conflicting objectives. These problems are solved by 'combining' all objective functions into a representative set of weight factors or constraints. This approach is simple and useful when the decision-maker knows the preferences between conflicting objectives, or at least know certain ranges where these objectives are acceptable.

However, there are other cases where the decision-maker does not clearly know what the preferences are, and reaching an 'optimal decision' accounting for all objectives requires evaluation of different trade-offs among objectives could be clearly seen. For these cases, multiobjective optimization is the best alternative. In multiobjective optimization all objectives are treated equally, and the different correlations and trade-offs between them are shown to the decision maker *before* making preferences over objectives.

Multiobjective optimization methods should be used when information about objectives is not known by the decision maker. In the case this information is available, it is always simpler to rely on single optimization and classical methods. Section 4.3.3 discuss in more detail classical methods and their principal drawbacks. Further, in Section 4.5, multiobjective optimization methods using evolutionary algorithms are presented.

4.3 Multiobjective Optimization

When multiple objectives are optimized, there is no single solution which satisfies all objectives; instead the result is a "trade-off" curve, or a set of optimal solutions which are better or worse depending of the objective. The goal of MOO is to find all of these solutions.

4.3.1 Dominance and Pareto Optimality

To compare candidate solutions in MOO problems, the concepts of dominance and Pareto Optimality [**35**] are frequently used [**36**]. A solution x^1 is said to dominate other solution x^2 if the following conditions hold true [**37**]:

1. The solution x^1 is *no worse* than x^2 in all objectives.
2. The solution x^1 is *strictly better* than x^2 in at least one objective.

If any of the above conditions is violated it means that solution x^1 *does not dominate* solutionx^2. If the opposite, solution x^1 *dominates* solutionx^2, or ($x^1 \preccurlyeq x^2$). It is good to clarify that if $x^1 \preccurlyeq x^2$ does not means that $x^2 \preccurlyeq x^1$, thus the dominance relation is *not symmetric.*

Figure 4.3.1 shows the trade-off curve for two conflicting objectives: the Maximum Travel Distance and the Minimum Cost of a mean of transport. From the graph it can be seen that traveling by foot is cheaper than by scooter, and longer distances could be achieved. The 'foot' alternative is said to dominate the 'scooter' alternative. The same can be said about bicycle-horse case. The group of all dominant solutions (foot, bicycle and car) form the pareto optimal front of this problem. The second front is represented by the horse, which is worse than the members of the first front but at the same time better than the scooter solution, which forms the third front.

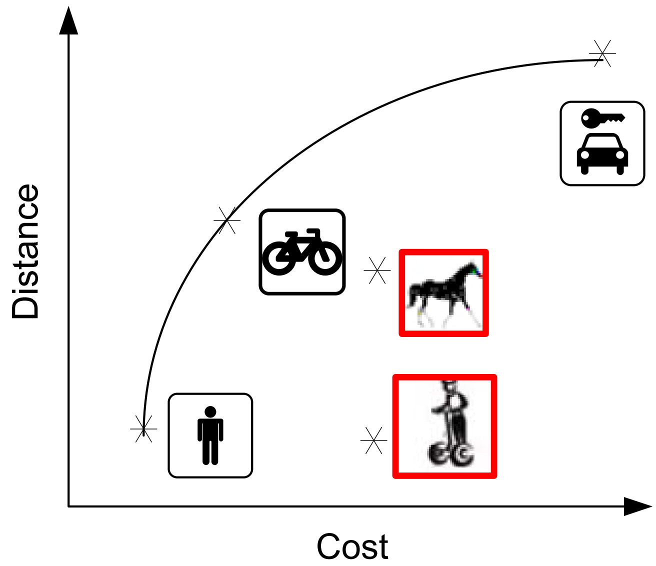


Figure 4.3.1: Trade-off curve between two objectives: Maximum Travel Distance and Cost of transportation means.

When all solutions are compared for dominance, and dominated results are eliminated, the result will be a set of solutions which are not dominated in respect to each other, and constitute the 'non-dominated' set. This set has the property of dominating all solutions which are outside of it, thus, the elements of this set are said to be "better" than all the others. When a non-dominated set is obtained for all the solutions of the search space, this set is referred as the Pareto-optimal set, and the corresponding objective vectors are said to be in the Pareto Optimal Front (POF)[**36**]. Figure 4.3.2 shows different POF for different two objective minimization and maximization problems. Because nearly all problems in power systems optimization are minimization problems, optimize will refer to minimize for now on, unless otherwise stated.

4.3.2 Goals of MOO

After having defined the concepts of dominance and Pareto Optimality, it is possible to formally define the goals of MOO. Kalyanmoy Deb [**37**] mentions the following as the principal goals in MOO:

1. To find a set of solutions as close as possible to the Pareto-optimal front.
2. To find a set of solutions as diverse as possible.

The first goal is required for any optimization algorithm: it is strictly necessary that the solutions obtained are close to the true solutions of a problem. It is important to note that in single objective optimization this is the only goal to achieve.

Patrick Ngatchou et al [**36**] divided the second goal into two sub-objectives:

2b. Ensure a good distribution of solutions along the approximation set

2c. Maximize the range covered by solutions along each of the objectives.

In general, this goal ensures that the solutions in the POF are diverse enough for getting a good set of trade-off solutions between objectives.

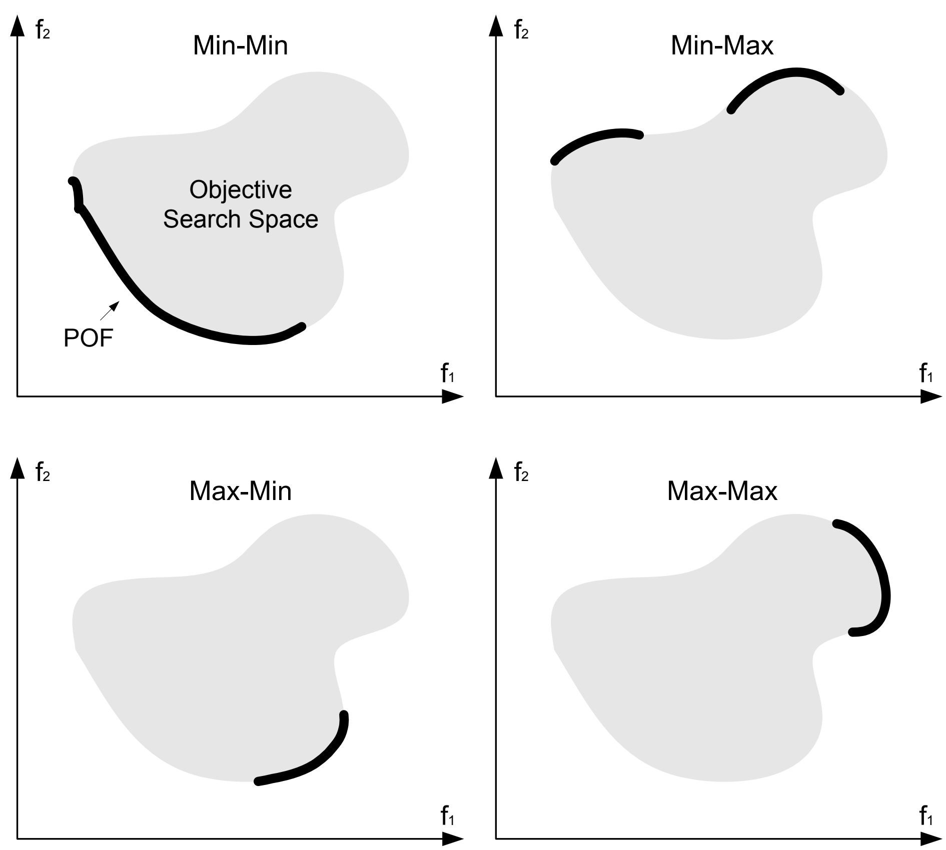


Figure 4.3.2: Different Pareto Optimal Fronts for two objective minimization and maximization problems. Adapted from [**37**].

4.3.3 Classic Methods of MOO

Classic methods aim at solving the MOO problem by converting it into a SO problem, and then, solving it by one of the numerous traditional methods available. It is important to note that these methods are intended to find a single point of the POF, based on a-priori preference information over objectives. Although many classical methods exist, the weighted sum and the E-constraint are the more popular and simple.

Weighted Sum Method

This is the most popular method for solving MOO. It consists of aggregating all the objectives and applying a 'weight' to each one, which resembles the importance of an objective over another. The sum of all weights should be equal to one, that is:

$$\begin{aligned} &Minimize\ Z = \sum_{i=1}^{N} w_i \cdot z_i(x) \\ &where\ \ w_i > 0 \\ &and\ \ \sum_{i=1}^{n} w_i = 1 \end{aligned} \tag{4.3.1}$$

where w is the weight vector and n is the number of objectives of the problem. To obtain a full POF using this method it would be necessary to repeat the process with different weight vectors w. This method faces difficulties, mainly because in nonlinear MOO a set of uniformly distributed weight vectors may not produce a uniformly distributed POF. Also, the weighted sum method is not compatible with non-convex problems [**37**].

E-Constraint Method

The E-constraint method alleviates the issues with non-convex problems of the weighted sum approach. The method consists on optimizing for one objective while treating the remaining objectives as constraints in a range defined by E. Formally, it was proposed by Haynes et al. [**38**] as:

$$\begin{aligned} &Minimize\ Z = z_a(x) \\ &subject\ to\colon\ z_m(x) \leq \epsilon_m \end{aligned} \tag{4.3.2}$$

where z_a is the optimized objective, z_m is the vector of constrained objectives, and Ɛ is the vector of objective constraints. The value Ɛ is repeatedly changed for getting the problems' POF. Again, the problem of this method is the need of a-priori information from the decision maker.

Limitations of Classical Methods

While classical methods are simple and facilitate the use of traditional optimization techniques for solving the problems, they have a number of difficulties when the user is interested in finding the POF. Kalyanmoy Deb summarizes them as follow [**37**]:

1. *Only one Pareto-optimal solution can be expected to be found in one simulation run of a classical algorithm.* – This makes the methods computational expensive.

2. *Not all Pareto-optimal solutions can be found by some algorithms in nonconvex MOO problems*. – This makes some methods not compatible with all problems.

3. *All algorithms require some problem knowledge, such as suitable weights or E values.* – This makes the methods entirely dependent of the chosen weight or E values.

4.4 Evolutionary Algorithms

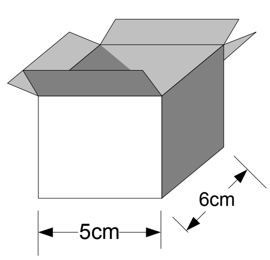
EA imitate the Darwinian natural selection and natural genetics process, in which individuals of a population go through stochastic operations such as selection, mutation, and crossover in order to achieve a better objective value, called ‘fitness’ value in genetic terms. Different types of EA exist, such as Genetic Algorithms (GA), Evolutionary Programming (EP), Differential Evolution (DE), Simulated Annealing (SA), and others. Of these, GA are the ones that have been more extensively used over the last decade as search and optimization tools for MOO problems [**37**]. The primary reasons for their success are their broad applicability, ease of use and global perspective [**39**].

4.4.1 Genetic Algorithms

Genetic Algorithms were first introduced by John Holland of the University of Michigan, Ann Arbor. Subsequently he and his student have continued the work on the field and developed the initial concept to what it is nowadays. In the next sub-chapters the operation of GA will be explained.

Encoding

The first step to apply GA is to select a correct *encoding* for the faced problem. The encoding refers to the way that the decision variables of the problem are mapped into a string of symbols, which could be binary numbers, characters, real numbers, or any other alphabet (Figure 4.4.1**)**.



Encoding	Binary	Real	Char
Lenght	101	5	a
Width	110	6	b

Figure 4.4.1: Different encodings for a box sizing problem.

At the early stages of GA the binary encoding was the most popular encoding because of its highest degree of implicit parallelism. However, new studies have found problems with binary-encoding when handling problems having continuous search spaces and where high precision is required [**37**]. Also other studies have found that real-encoding could be more effective when handling crossover operations [**40**]. Since real decision variable parameters could be used directly for the calculation of fitness function values, the real-encoding approach is easier when compared with binary-encoding. However, difficulties arise when using the genetic operators and special methods need to be applied (such as 'blending' operators instead of crossover). In this work the real encoding will be used for representing decision variables, thus operators discussed will be aimed at real-encoding problems.

Fitness

The fitness function is the one that models and characterizes the problem to be solved. The fitness of an individual population is the result of its evaluation on the fitness function of the problem. The fitness function of GA is different from the objective function of traditional optimization methods in the fact that the fitness of an individual is defined with respect to the other members of current population, while the objective function is a measure of performance of a particular individual [**40**].

Constraint Handling

GA has to face the constraints that most real-world problems have. The GA operators (crossover, mutation) in their basic form do not take into account the feasibility of the solutions they generate. Therefore, there is a high probability of generating offspring that is not feasible for the problem. There are basically two different techniques for constraint handling:

1. Restricting the problems' search space: These methods modify the crossover and mutation operators in order to make them only produce offspring in the feasible region of the problem.
2. Using penalty functions: This approach allows the exploration of the entire search space, and if an unfeasible solution is found the algorithm penalizes it. The penalty can be applied in two ways:
    1. By a multiplication factor: $g(x) = f(x) * p(x)$.
    2. By an addition factor: $g(x) = f(x) + p(x)$.

    where *g(x)* is the penalty factor, *f(x)* the constraint violation and *p(x)* the penalty term. Also, it is desirable that the penalty function varies with the constraint violation and with the GA iteration count.

It has been suggested [**40**] that the use of penalty functions is better suited for constraint handling in power systems problems, where the optimal solution are usually on the boundaries of feasible regions. The reason is that an unfeasible point close to the optimum solution contains more information than a feasible point far from the optimum, in terms of the GA.

GA Operators

In this section the selection, crossover and mutation operators are discussed. These operators have the responsibility of maintaining the population in good fitness, and creating diversity within it.

Selection

The selection operator is the responsible of creating new populations by preserving fitted individuals from the old population and eliminating those whose fitness is inferior. Since the selection operator deals with the objectives' fitness function, there is no difference between selection operators for binary- or real-encoded decision variables. There are different selection methods, the tournament selection and the roulette wheel selection being the most popular.

Proportional Selection or Roulette Wheel Selection

In Roulette Wheel Selection (RWS) the probability that an individual is selected to be in the mating pool is proportional to its fitness. Recent investigations have shown that the RWS method, despite its popularity inside the power system research community, is usually an inferior approach [**40**]. However, there exists many workarounds for improving the RWS methods such as Linear Scaling, Sigma Truncation, Power Scaling, and with major modifications the Stochastic Universal Sampling (SUS).

Tournament Selection

In this selection method, 'tournaments' are played between individuals and the better ones are placed in the 'mating pool', where other operators are then applied. The process is illustrated in Figure 4.4.2**,** and is as follow:

1. Pairs of solutions are randomly selected and the better solutions are placed in the mating pool.
2. A different pair of solutions is chosen, better solutions are placed in mating pool.
3. In this way, the better solution will have at least two occurrences in the mating pool, and the worst solutions will be eliminated from the tournament.

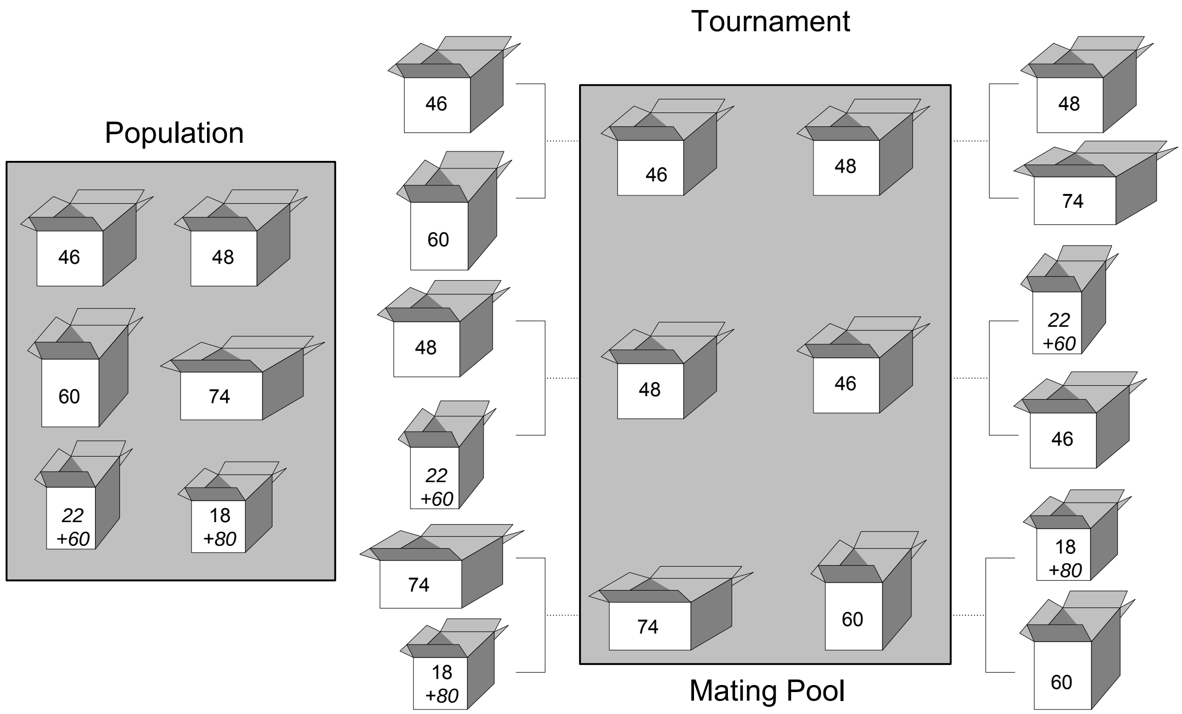


Figure 4.4.2: Two tournaments are played with population members, the winning individuals are placed in the mating pool. Adapted from [**37**].

The tournament selection process could be made either with or without replacement. In the tournament with replacement (TWR) the candidates selected for a tournament are eligible for participating in further tournaments. In the other hand, in tournament without replacement (TWOR), individuals could not participate in more than one tournament [**41**].

Crossover

The crossover operator could be seen as an interchange of information between individuals. Crossover methods used for binary- and real-encoding are different. Because in real-encoding the 'crossover' action is not evident as in binary-encoding (where two bits are exchanged), the term 'blending' is often used to describe the crossover operator in real-encoded problems. However, because most blending operators are known as crossover operators we will continue using that notation in this work. More information about crossover operators can be found in [**42**] and [**37**].

A Binary-like Crossover

This crossover operator is similar to the crossover operators used in binary-encoded GAs. A position $i \in \{1, 2, 3 \ldots nvars\}$ is randomly chosen, producing two new offspring:

Parent 1:	$p_1 = [\, v_1^1,$	$v_2^1,$		$v_3^1,$	$v_4^1,$	...	$v_n^1]$
Parent 2:	$p_2 = [\, v_1^2,$	$v_2^2,$		$v_3^2,$	$v_4^2,$	...	$v_n^2]$
Offspring 1:	$o_1 = [\, v_1^1,$	$v_2^1,$	...	$v_i^1,$	$v_{i+1}^2,$	...	$v_n^2]$
Offspring 2:	$o_1 = [\, v_1^2,$	$v_2^2,$	...	$v_i^2,$	$v_{i+1}^1,$	...	$v_n^1]$

Single-point, two-point, n-point or uniform crossover operators could also be built in this manner, just with minor modifications of the *i* vector. In real-encoding this operator does not have sufficient search power, thus its use is not adequate for real-encoded variables [**37**].

Simulated Binary Crossover (SBX)

The simulated binary crossover (SBX) was developed by Kalyanmoy Deb and his student in 1995 [**43**]. The purpose of SBX, as it name implies, is to translate the concept of single-point crossover operator of binary strings to the continuous search spaces. SBX works as follows [**43**][**37**]:

1. A probability density function (PDF) with distribution index η_c is defined. This probability function is also a function of the "spread factor" β_i, which is defined as the ratio of the absolute difference in offspring values to that of the parents:

$$\beta_i = \left| \frac{x_i^{(2,t+1)} - x_i^{(1,t+1)}}{x_i^{(2,t)} - x_i^{(2,t)}} \right| \tag{4.4.1}$$

and the PDF is:

$$\wp(\beta_i) = \begin{cases} 0.5(\eta_c + 1) * \beta_i^{n_c}, & if\ \beta_i \leq 1; \\ 0.5(\eta_c + 1) * \dfrac{1}{\beta_i^{n_c+2}}, & otherwise. \end{cases} \quad (4.4.2)$$

A large value of η_c will produce a higher probability for creating near-parent solution, while a small value of η_c will more likely produce solutions distant to the parents.

2. A random number $u_i \in [0,1)$ is generated.
3. The ordinate β_{qi} is found so that the area under the PDF curve from 0 to $\beta_{qi} = u_i$, or:

$$\beta_{qi} = \begin{cases} (2u_i)^{\frac{1}{n_c+1}}, & if\ u_i \leq 0.5; \\ \left(\dfrac{1}{2(1-u_i)}\right)^{\frac{1}{n_c+1}}, & otherwise. \end{cases} \quad (4.4.3)$$

4. Next offspring is computed by:

$$x_i^{(1,t+1)} = 0.5\left[\left(1+\beta_{qi}\right)x_i^{(1,t)} + \left(1-\beta_{qi}\right)x_i^{(2,t)}\right], \quad (4.4.4)$$

$$x_i^{(2,t+1)} = 0.5\left[\left(1-\beta_{qi}\right)x_i^{(1,t)} + \left(1+\beta_{qi}\right)x_i^{(2,t)}\right]. \quad (4.4.5)$$

This method will produce two offspring which are symmetric about the parent solutions. Also, for a fixed η_c the offspring will have a spread proportional to that of the original parents, introduced by the β_{qi} factor. This has an advantage: for initial populations (where solutions are distant - randomly placed) the offspring can get virtually any value, but for near-parents (when problem is converging) the offspring is not allowed to separate too much from them (Figure 4.4.3).

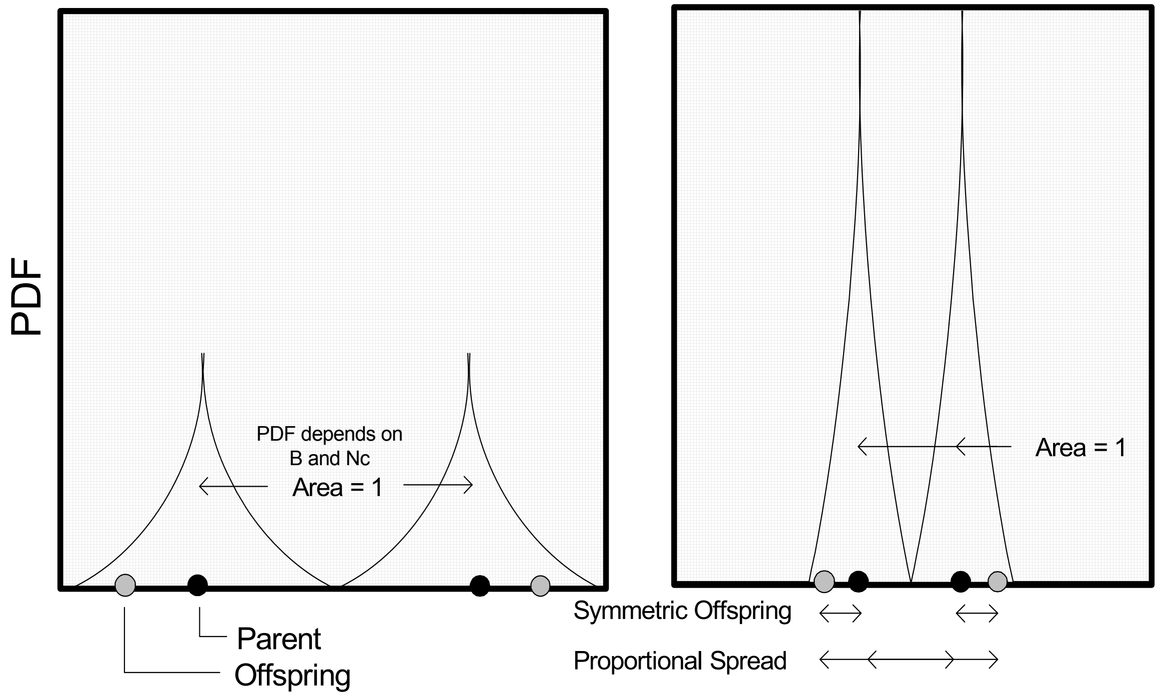


Figure 4.4.3: PDF of offspring with distant and with closely spaced parents. Also offspring symmetry and proportional spread is shown. Adapted from [**37**].

Mutation

The mutation operator introduces perturbations to create a more diverse offspring. While the crossover operator adaptively introduces perturbations within the diversity of the parent individuals, the mutation operator create perturbations within a predefined range using one parent.

Uniform (Selective) Mutation

An offspring is created randomly from the entire search space:

$$y_i^{(1,t+1)} = r_i(x_i^{(U)} - x_i^{(L)}) \tag{4.4.6}$$

where $r_i = [0,1]$ and $x_i^{(U)}$, $x_i^{(L)}$ are the upper and lower bounds of the search space, respectively.

Gaussian Mutation

A random offspring is generated, taken from a zero-mean Gaussian probability distribution:

$$y_i^{(1,t+1)} = x_i^{(1,t+1)} + N(0, \sigma_i) \tag{4.4.7}$$

where σ_i is the standard deviation of the distribution. σ_i can be either user-specified or adaptively changed as generations advance.

Polynomial Mutation

The probability distribution is a polynomial function instead of a normal distribution, like in SBX:

$$y_i^{(1,t+1)} = x_i^{(1,t+1)} + \left(x_i^{(U)} - x_i^{(L)}\right) \bar{\delta}_i \tag{4.4.8}$$

where $\overline{\delta}_i$ is calculated from the polynomial probability distribution:

$$\wp(\delta) = 0.5(\eta_m + 1)(1 - |\delta|)^{n_m} \tag{4.4.9}$$

$$\bar{\delta}_i = \begin{cases} (2r_i^{\frac{1}{(n_m+1)}} - 1, & if\ r_i < 0.5 \\ 1 - [2(1 - r_i)]^{\frac{1}{(n_m+1)}}, & if\ r_i \geq 0.5 \end{cases} \tag{4.4.10}$$

A fixed value of the parameter n_m is suggested by [**37**].

4.5 Multiobjective Evolutionary Algorithms

The greatest advantage of EA as a method for MOO is its capability of processing an entire population per iteration. Because of this characteristic, EAs with minor modifications are capable of capturing a population of Pareto-optimal solutions in a single run. This will also eliminate the need of any a-priori information such as weight vector or ϵ vectors.

There are two types of multiobjective evolutionary algorithms (MOEA), the ones which use an elite-preserving operator (Elitist MOEA), and the ones which do not (Non-Elitist MOEA). An elite-preserving operator works by favoring the elites (best individuals) of a population by giving them an opportunity to be directly carried as new offspring to the next generation. This ensures that a good solution found early in the run does not deteriorate due to the effect of the crossover and mutation operators.

Because of the proven importance of elitism to the EA [**37**], this work will only focus on Elitist MOEA. There are a number of Elitist MOEA, namely NSGA-II [**44**], Strength Pareto EA, and others. However, for the simulations in this work NSGA-II was chosen, for the following reasons:

1. Proven strength and performance of the algorithm [**44**].
2. Vast documentation and support available in the literature.
3. Availability of a number of free and paid toolboxes and programs in MATLAB and C [**45**] [**46**] [**47**].

4.5.1 Non-dominated Sorting Genetic Algorithm II (NSGA-II)

NSGA-II was developed in the 2000 by Kalyanmoy Deb and his students [**44**]. NSGA-II features an elite-preservation strategy as well as an explicit diversity-preserving mechanism.

NSGA-II works by creating a population R_t of size 2N result of a combination of the parent (P_t) and offspring (Q_t) populations. This population R_t is then non-dominated sorted, i.e. non-dominated solutions are put first, creating various non-dominated ‘fronts’ (groups of solutions which are non-dominated between each other). Once this sorting is over, a new population is created by filling it with the individuals of the sorting, starting with the best non-dominated ones, one at a time. However, because the new population size is N and R_t is 2N a part of the population could not be accommodated. Instead of arbitrarily deleting these remaining solutions, a crowding strategy is used where more sparse solutions are preferred over niched solutions. The NSGA process is illustrated in Figure 4.5.1.

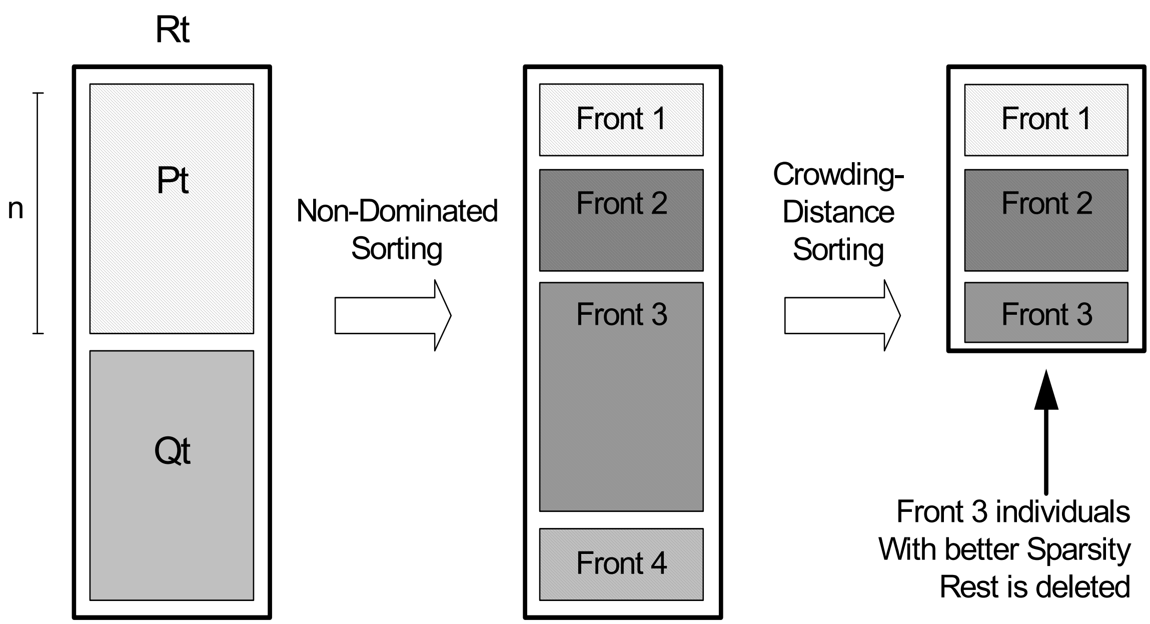


Figure 4.5.1: The procedure of NSGA-II. Adapted from [**37**]

Formally, the NSGA-II works as follows [**37**]:

1. Parent (P_t) and offspring (Q_t) population are combined, creating $R_t = P_t \cup Q_t$. A non-dominated sorting is performed to vector R_t, making possible to identify different 'fronts'.
2. A new population $P_{t+1} = 0$ is set, and a counter is initialized at $i = 1$, and until $|P_{t+1}| + |\mathcal{F}_i| < N$; $P_{t+1} = P_{t+1} \cup \mathcal{F}_i$ and $i = i + 1$ is performed.

3. A Crowding-sort ($\mathcal{F}_i < c$) procedure is performed, including the most widely spread ($N - |P_{t+1}|$) solutions by using the crowding distance values in the sorted $\mathcal{F}_i$ to P_{t+1}. The crowding distance concept is explained in detail in [**37**].
4. Offspring population Q_{t+1} is created from P_{t+1} by applying crowded tournament selection, crossover, and mutation operators.

4.5.2 Representation of Results in MOEA

To represent the information obtained from the MOEA two approaches will be used in this work. The first will be for the cases when two objectives are optimized for illustration purposes. The second will be for the cases when multiple objectives are optimized.

The Pareto-optimal Front Plot

In the cases when only two objectives are optimized the POF plot will be used. This plots represents the trade-offs between two objectives functions. The curve represented will be the POF of the first non-dominated front Figure 4.5.2.

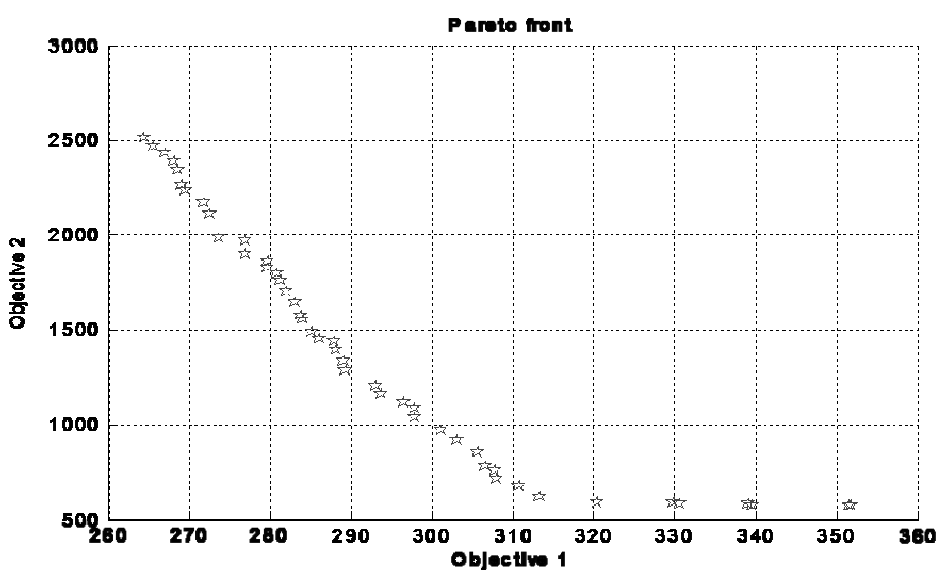


Figure 4.5.2: Example of a POF plot.

The Scatter-Plot Matrix

This plot method consists of plotting all $\binom{f}{2}$ pairs of plots among, if f objective functions are optimized. The diagonal sub-plots mark the axis for the off-diagonal plots (Figure 4.5.3). Also, in the diagonal sub-plots the user could observe objective range and discontinuities. Depending on the simulation several fronts could be plotted in a single graph. Scatter-plot matrix is useful for analyzing the correlations between objectives.

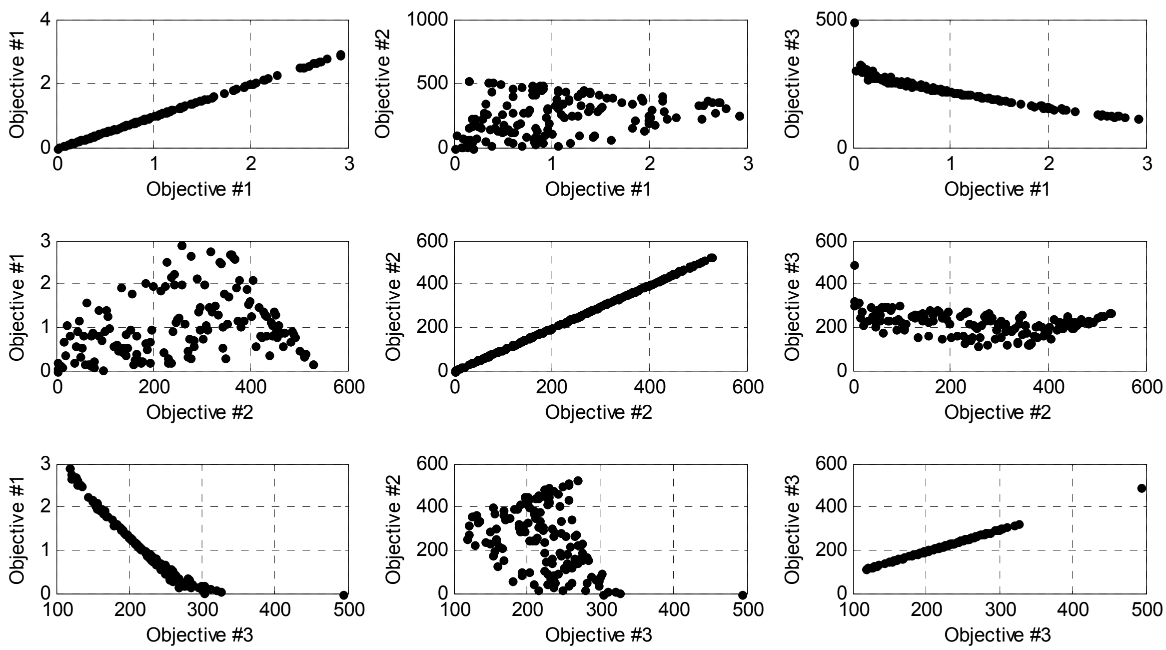


Figure 4.5.3: Scatter-Plot for a MOO with 3 objective functions.

5 METHOD

5.1 Introduction: Optimum DER Sizing and Sitting Using MOEA

The DER sizing is a critical issue in the design process of autonomous microgrids. Of special importance is the correct sizing of storage (DES) units, which will serve to compensate for the variability of renewable DGs. The DER sizing problem has two dimensions: the energy balance and the power balance. In general, the DERs should be sized to fulfill the entire systems' power demand and energy consumption. Because of the variability of renewable DGs, load pattern changes or other contingencies, is also desirable to have good levels of reserve capacity. Formally, the DERs size should satisfy:

$$\sum P_{DER}^{t} = \sum P_{D}^{t} - \sum P_{DRS}^{t} \tag{5.1.1}$$

And under normal operation:

$$\sum E_{DER}^{(t,t+T)} - \sum E_{D}^{(t,t+T)} \geq E_{R} \tag{5.1.2}$$

where P_{DER}^{t} is the power produced by DER units at instant t, P_{D}^{t} is the power demanded by the system at instant t, and P_{DRS}^{t} is the demand that could be reduced at instant t result of demand response strategies. $E_{DER}^{(t,t+T)}$ is the net energy contribution from DGs in the interval $(t,t+T)$, $E_{D}^{(t,t+T)}$ is the energy consumed by customers and losses in the interval $(t,t+T)$, and E_R is the systems' reserve capacity. Under abnormal situations E_R could vary.

Additional to the DER sizing problem lays the DER sitting problem. Load dispersion and high impedance lines, -very common in remote locations- could affect the efficiency of the DERs, making some locations better than others for the resource sitting. Driesen and Katiraei have suggested in [**48**] design guidelines to overcome the sizing and sitting problems:

- Advanced power sharing and unit commitment among a set of multiple-size generation sources to select appropriate combination of DER based on load change.
- Utilization of optimal-sized energy storage units.
- Prioritization and advanced control of load.

The DER sizing/sitting problem is a mixed integer, mixed discrete-continuous, non-convex optimization. An optimal configuration should not only fulfill economical objectives but also others related to the energy independence and sustainability of the microgrid. In the case of electrification of remote and rural areas, decisions regarding financial costs are more difficult to assess because of parameters like: willingness to pay (WTP) and tariffs for different customer service levels, demand growth rate, generation technologies used and availability of resources and potential integration of productive use into the microgrid (industries, commerce). Because of these reasons, a general recommendation for the optimal microgrid topology cannot be given. Solutions will vary significantly depending on the remote zone location and their interest over specific objectives.

In [**49**] authors developed a methodology for the optimum sizing and sitting of distributed generators in a distribution feeder using the Pareto-Strength MOEA approach. This work tackles the planning problem for intermittent resources such as solar-photovoltaic and combined heat and power (CHP) generators. The method gives good results for the minimization of losses, grid exports and installation costs on distribution feeders, but do not have tools for the microgrid analysis, where multi-dimensional problems such as storage scheduling and demand response management play important roles in the resource allocation process. In another work [**50**] the authors tried to overcome the problem of power system planning in presence of intermittent distributed by nesting Montecarlo simulations in a multiobjective evolutionary algorithm. Other approaches [**51**] have included energy storage, but have focused in the market interactions of the system leaving apart other objectives necessary for microgrid sustainability. In [**52**] and [**53**] the authors studied the effects of distributed energy storage, designing an optimization algorithm for the optimum resource allocation on distribution feeders. This work also concentrated in the response of storage units to price signals and economic performance, not in energy sustainability.

In summary, it could be seen that almost all literature available and methods developed for the optimum sizing and sitting of distributed generators on distribution feeders' do not effectively comply with their objectives when the microgrids scenario is considered. These methods lack the necessary tools for assessing optimal resource allocation in microgrids, where self-reliance, social and environmental aspects play important roles in the decision making process.

The algorithm proposed in this thesis tackles the DER sizing and sitting problem in microgrids, with special attention to the sustainability of the system. The algorithm uses a multi-objective evolutionary approach, following the guidelines for a microgrid design benchmark suggested by Driesen and Katiraei [**48**]. Renewable generators, storage units and demand response strategies are included in the multiobjective algorithm, which uses the *de facto* standard in elitist multiobjective optimization, NSGA-II. System constraints such as voltage and thermal limits of equipment are also considered. As output, the decision maker will have numerous different network topologies each one representing objective preferences in different levels. With this information, the decision maker is capable of making more accurate choices based on the particular characteristics of communities and locations.

5.2 Assumptions and Limitations

The problem worked in this thesis is deterministic, i.e., system parameters such as load profiles, resource availability and equipment efficiency are known *a priori* for the period of study. Instead of using probabilistic deviations, typical operation cases are used for the simulations. These cases represent common operation conditions for the system in specified time intervals. For the simulations it is assumed that the contributions from conventional generators (diesel, gas) occur at a single node of the system, which is previously identified as an input. Possible locations for renewable generation must also be specified as inputs. After these locations are defined the algorithm always considers these nodes for DES sitting even if their specific contribution is determined to be small.

Distributed energy resources are modeled as hybrid units (Section 2.4.2), consequently renewable generation is connected directly to the storage (i.e., not injecting energy directly to the microgrid).

Current injections from distributed sources and load demand at each node *n* are modeled as constant power:

$$I_n = \left(\frac{P_n}{V_n}\right)^* \tag{5.2.1}$$

Since the main objective of the algorithm is the long-term assessment of resource allocation, reactive power is not considered. Similar approaches have been used in the literature [**52**] [**53**]. However, is important to note that power electronic converters are capable of supplying reactive power within the limits of their capability curve. Liu and Bebic have shown that by increasing inverter size by 10% the reactive power can be increased from zero to nearly 46% at maximum capacity [**54**].

Another important assumption is that non-renewable energy has zero impact on costs, and renewable energy zero impact on pollutants. It would be unfair for some renewable energy sources like solar photovoltaic to use non-renewable generation prices without internalizing the costs associated with the environmental impact of these technologies. The approach used was to consider installation costs and environmental impact as two separated objectives. Since renewable energy sources have a larger impact on costs rather than on environmental impact, these technologies were modeled as full cost, zero emissions. The opposite was done to the non-renewable energies, because of their significantly lower costs (compared to renewables) and larger environmental impact. However, by using this assumption the algorithm is unable to include technologies which do not fit with this supposition, such as CHP turbines and solar thermal generators. The algorithm was tested with good results for solar photovoltaic and wind generators. To include other generation technologies it would be necessary to assess if the assumption holds, or develop a method that overcomes this limitation. The latter is mentioned in the future work section of this thesis.

The algorithm only considers installation costs of technologies, not including all costs and benefits associated with the microgrid operation. Future additions should not be limited to fuel and maintenance costs. All economical, environmental and social benefits in the microgrid life cycle must also be included (see Section 3). The life cycle analysis was out of the scope of this work, and is left as future work.

5.3 Steps of the Optimization Process

The algorithm starts by generating a number of random solutions (decision vectors) which are evaluated and then introduced into the NSGA-II algorithm. After NSGA-II, crossover and mutation operators are applied to the offspring, forming a new generation of solutions. In the case that some of the solutions violate the defined constraints, these are eliminated from the solution pool. The process is repeated iteratively until a number of generations have passed or after a pre-determined goal (objective value) is achieved. Because of the heuristic nature of MOEA, a global optimum cannot be guaranteed. The algorithm flowchart is illustrated in

Figure **5.3.1**.

5.3.1 Time Model

The time period is divided into *t=1,2,3…, T* discrete time intervals. These intervals must be pre-defined as inputs to the algorithm. Lengths of time intervals depend on the availability of accurate data and could range between 15 minutes to one hour. All variables are assumed constant during each time interval.

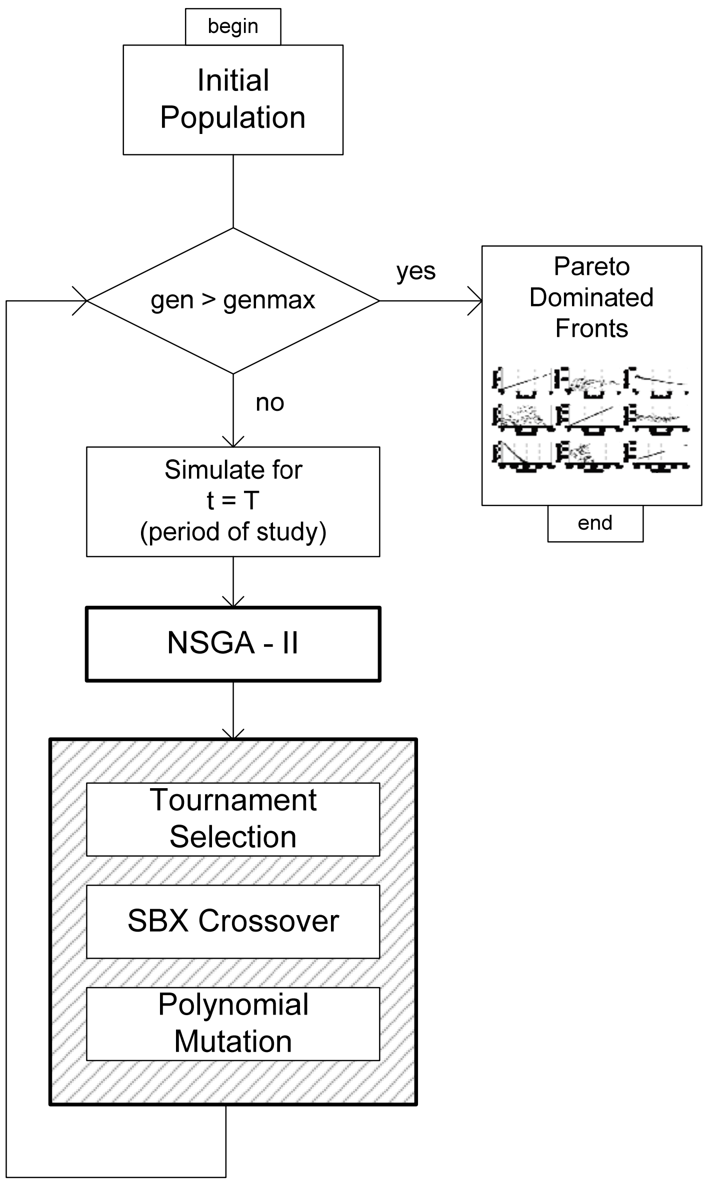


Figure 5.3.1: Flowchart of the Optimization Algorithm.

5.3.2 Distributed Energy Storage Model

The power output of each DES at time interval *t* is defined by its rated power and stored energy. Because energy storage could only be charged by renewable energy (see assumptions, Section 5.2), the level of stored energy is defined by the quantity of energy flowing from renewable resources to the unit at previous intervals. Figure 5.3.2 illustrates two architectures of DES unit. In the first, a renewable energy generator is connected in hybrid mode to a battery inverter, which converts the DC voltage into AC and injects it to the system. This configuration eliminates the problem of intermittence and sudden variation of renewable sources. The second configuration shows a storage unit connected to the system, and a renewable generator connected at the same point. In both configurations the stored energy at the end of interval *t* will be the result of the net sum of storage and renewable contributions, minus power conversion losses. The hybrid scheme used through this work is the one in the left part of the figure (hybrid). From now on, the terms DES and hybrid DES units will have the same meaning.

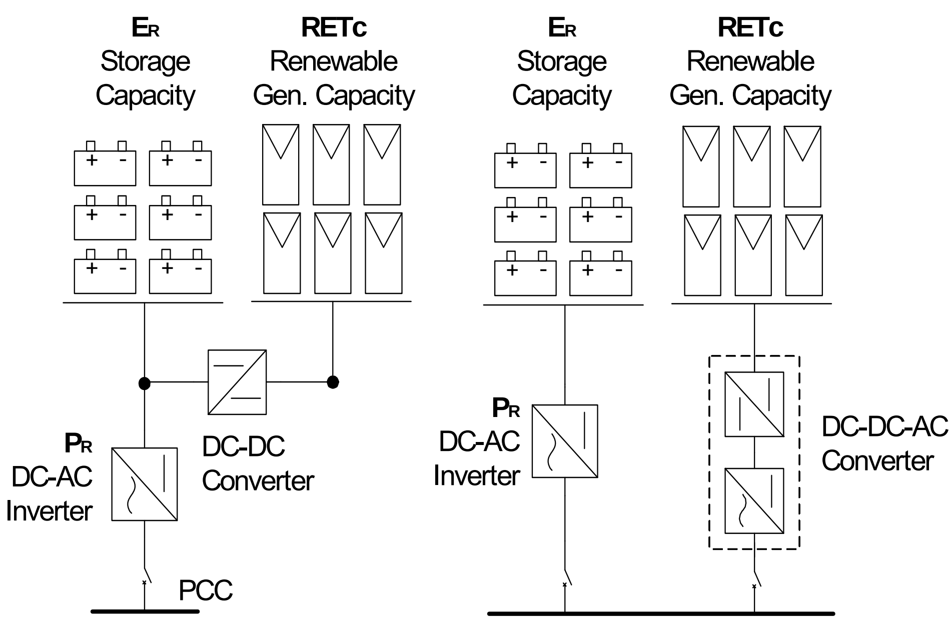


Figure 5.3.2: Two types of Architectures for a hybrid DES unit.

For each DES unit $n=1,2,\ldots,N$, we define:

En_R = nominal energy storage rating of DES unit n. It is defined as the electrical capacity in megawatt-hour (MWh) of the battery bank.

E_{n0} = initial energy stored at time $t=0$ (MWh).

$E_n(t)$= stored energy in DES unit n at the end of time interval t (MWh).

Pn_R = nominal power rating of DES unit n. It is defined as the capacity of the DC-AC inverter in megawatts (MW).

$P_n(t)$= power output of DES unit n at time interval t (MW).

$RETn_R$= nominal power rating of renewable energy generator connected at DES unit n (MW).

$RET_n(t)$= power output of renewable energy connected at DES unit n at time interval t (MW).

Let E_R, P_R and RET_R be the vector of DES energy, power, and renewable energy ratings, respectively; W the vector of power outputs, S the vector of stored energy and R the vector of renewable energy outputs, then:

$$0 \leq W(t) \leq P_R \tag{5.3.1}$$

$$W(t+1) \leq S(t) \tag{5.3.2}$$

$$0 \leq S(t) \leq E_R \tag{5.3.3}$$

$$0 \leq R(t) \leq RET_R \tag{5.3.4}$$

Equations 5.3.1 to 5.3.4 ensure that the power outputs of DES units and renewable energy, and the energy stored at battery banks at each time interval lies within the nominal ratings specified for the manufacturers. For simplicity, Equations 4.3.1 to 4.3.4 are defined for one-hour intervals; however they could be adapted for other time intervals by properly adjusting the time increment.

Each interval gets the information of stored energy at the previous interval *E(t-1)* as an input and calculates the appropriate power output of DES units for this time frame according to load sharing equations 4.3.5 and 4.3.6. With these power outputs relevant parameters for the objective functions calculation are stored for each interval. These values are DES unit outputs, total system losses, non-renewable energy contributions, reserve status. Then, this information is processed for the evaluation of the objectives functions. The process is illustrated in Figure 5.3.3.

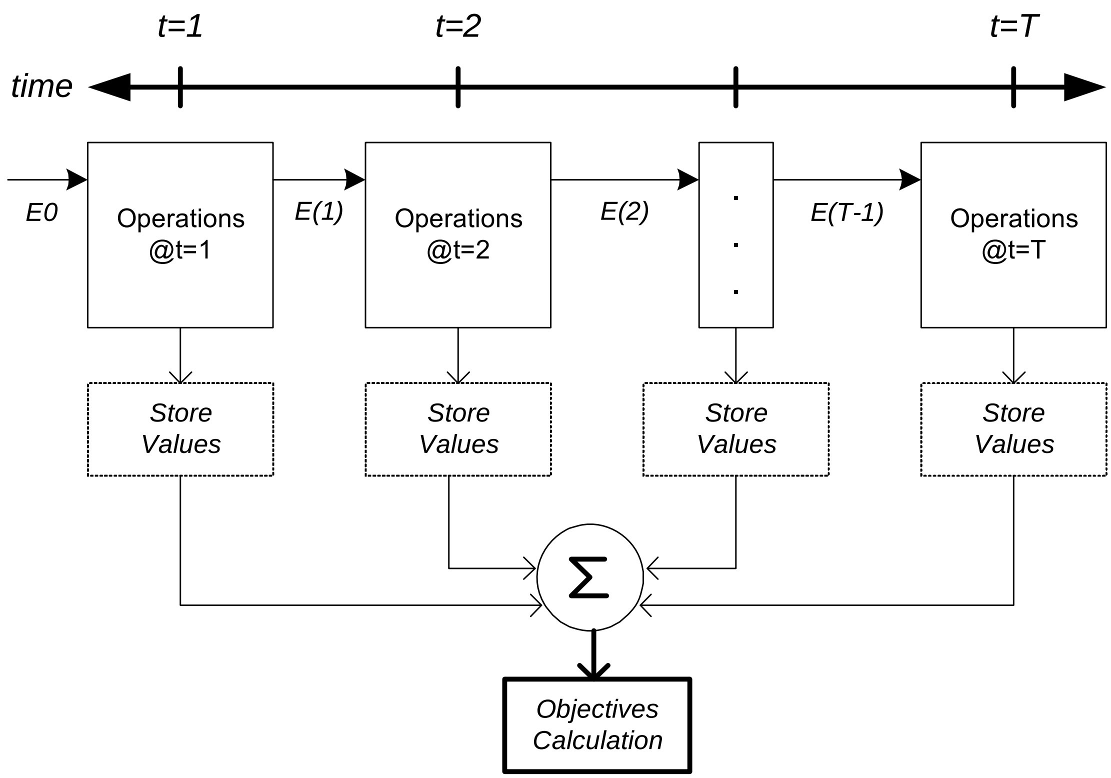


Figure 5.3.3: Calculation of Objective Functions.

The load sharing control is based on the level of stored energy in DES units. The output of a DES unit at time *t* is given by:

$$Pn(t) = P_D(t) * \frac{Pn_{max}(t)}{\sum P_{max}(t)} \tag{5.3.5}$$

where $P_{max}(t)$ is the vector of $Pn_{max}(t)$:

$$Pn_{max}(t) = \begin{cases} Pn_R & if\ E_n(t) > Pn_R \\ E_n(t) & otherwise \end{cases} \tag{5.3.6}$$

5.3.3 Demand Response Model

The algorithm is capable of distinguishing between different types of customers and apply demand response strategies based on this information. Three different service levels could be defined:

A – Sensitive Customers: These types of costumers need to have a continuous energy supply.

B – Interruptible Customers: These customers could lack of part or their total electricity demand during certain hours of the day.

C – Controllable Customers: These customers could lack of part or their total electricity demand when the system requires it. The maximum interruption time must be specified.

The demand response strategy works as follow:

1. If the systems demand $P_L(t)$ is greater than the maximum possible output of DES units $P_{max}(t)$ at time *t*, the system is eligible for demand response.
2. The algorithm evaluates all possible load curtailments P_{DRS} from Interruptible and Controllable Customers who have not completed their daily interruption quota.
3. The alternative that makes $P_L(t) - P_{max}(t) - P_{DRS}$ closer to zero is selected.

4. Customers selected in step -2- are partially or fully disconnected for time interval t, depending on their contracts with microgrid operator.

5.3.4 The Decision Variable Vector

The possible placement alternatives are represented as a vector of values of fixed length, called the decision variable vector. This vector is comprised of the rated power, rated energy and rated distributed generation connected at each DES (P_R, E_R and RET_R). Figure 5.3.4 shows the structure of the decision vector.

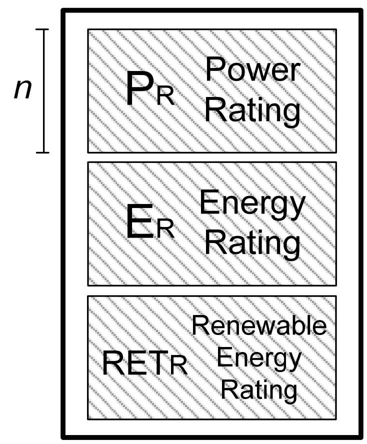


Figure 5.3.4: Decision Vector for the optimum DER sizing/sitting problem.

The length of the decision vector is 3*n + 1

Each parameter on the decision vector is pre-defined with an upper and a lower bound. These numbers define the range of values the MOEA will consider in the optimization process. The selection of reasonable upper and lower bounds is essential for the algorithm convergence and speed. For example, when selecting the limits of the power rating P_R, the maximum intervals should be between zero and a value slightly higher than the total system demand, in case all generation is desired at one node. The energy ratings should be sized in accordance with the desired hours of reserve, and so on.

5.3.5 Objective Functions

The main goal of the algorithm developed in this thesis is to determine good location and capacities for DES units for achieving a ‘sustainable’ microgrid. This is accomplished by minimizing different objective functions aimed at the sustainability of the mcirogrid. However, the mathematical formulation of objectives aimed at sustainability is not an easy task, and requires the representation of these objectives as indexes or other factors. In this work, three objective functions are defined: the first, Minimize Installation Costs, which takes into account the economical aspects of the microgrid sizing and sitting. The second, Minimize Particulate Emissions, is a representation of the environmental impact of the project. The third, Minimize Average Hours of System Reserve optimizes the quantity of distributed energy storage in the system, and the fourth, Minimize Non-Renewable Energy Penetration, minimizes the penetration of non-renewable generators in the microgrid (the last two address both social and economical impacts). Although these indexes are a good approach for optimizing the desired objectives, the algorithm is flexible for upgrading or incorporating new ones. In the following, each objective function is described in more detail.

Minimize Installation Costs

This objective takes into account investments necessary for the installation of DES equipment in the microgrid. The DES units have two cost dimensions: the power rating and energy capacity. The power rating cost P_c +RET_c is represented by the DC-AC inverter interface plus the size of the RET generators feeding the DES units. The energy cost E_c is represented by the size of the battery arrays. There is also a fixed cost F_c associated with the construction and conditioning of the power plant site, legal and administrative work, and other miscellaneous activities which are independent of the size of the power plant.

$$Cost = F_c + P_c + RET_c + E_c \quad (\$) \tag{5.3.7}$$

$$P_c = \sum_{i=1}^{n} Pn_R * P_{cf} \tag{5.3.8}$$

$$E_c = \sum_{i=1}^{n} En_R * E_{cf} \tag{5.3.9}$$

$$RET_c = \sum_{i=1}^{n} RETn_R * RET_{cf} \tag{5.3.10}$$

P_{cf} , E_{cf} and RET_{cf} represent the incremental power and energy costs. P_{cf} and RET_{cf} are defined in \$/MW, while E_{cf} in \$/MWh.

Minimize Particulate Emissions

This objective accounts for the environmental impact of the thermal generation in the microgrid for the period of study. Emissions are represented in proportion of the total energy from non-renewable sources. The total emissions are calculated by:

$$EM = E_{NR} * emfac \tag{5.3.11}$$

where E_m is the total system emissions, and *Emfac* is the emission factor for the used combustible. A piecewise emission curve could also be specified for this *Emfac*.

Minimize Average Hours of Energy Reserve

This objective is defined as the average hours of supply that energy storage units have in reserve at each time interval. The energy reserve is important for achieving sustainability in microgrids with large penetration of intermittent resources. The objective is defined as:

$$H_R = average[\frac{S}{P_{D(base)}}] \tag{5.3.12}$$

where H_R is the average hours of system reserve, and S and P_D were previously defined as the vector of energy stored and system demand, respectively.

Non-renewable Energy Penetration

Although renewable generation brings many environmental, quality and security benefits, non-renewable generation is also required for keeping sustainability in economic-constrained microgrids. The visualization of this objective is useful because allows the decision maker to watch the effects of different levels of non-renewable generation (E_{NR}).

In another perspective, this objective could be seen as the energy injections from a main grid, or the potential loss of load (PLL) of the system, defined as the demand that cannot be satisfied by the microgrid.

$$E_{NR} = \sum_{t=0}^{T} \frac{P_D(t) - W(t)}{P_D(t)} \tag{5.3.13}$$

While a set of objective functions is defined in this thesis, the algorithm proposed is easily expandable for handling others. Some interesting objectives that could be integrated are mentioned in the Future Work chapter.

5.3.6 Constraints

The MOEA objective space is restricted by a set of constraints. These constraints ensure that the system work under acceptable operation ranges. Also, by constraining the objective space these constraints help the algorithm to achieve better results in less time. While a set of constraints is defined in this thesis, the algorithm proposed is easily expandable for handling others.

Consider only long-term storage

This constraint ensure that the algorithm only consider solutions that aim for long-term storage. For this purpose, solutions with an energy rating smaller than its corresponding power rating are eliminated:

$$En_R \geq Pn_R \tag{5.3.14}$$

DER integrity

This constraint ensures that the algorithm does not consider solutions that involve *only* storage, or *only* distributed generation. This is done to ensure the presence of hybrid DES units throughout the system. The following two conditions satisfy the constraint:

$$\begin{cases} P_R > 0 \\ E_R > 0 \\ RET_R > 0 \end{cases} \quad \text{or} \quad \begin{cases} P_R = 0 \\ E_R = 0 \\ RET_R = 0 \end{cases} \tag{5.3.15}$$

Exploit Renewable Resources

This constraint prevents the creation of configurations where renewable energy could not be fully harnessed. This could occur, for example, when batteries are full at peak hours of sun irradiance, in case of solar photovoltaic generation.

$$\sum_{t=1}^{T} R \leq \sum_{t=1}^{T} S \tag{5.3.16}$$

System Constraints

1 *Voltage Constraint:* The voltage at all nodes is kept under normal range.

$$V_{min} \leq V_n \leq V_{max} \tag{5.3.17}$$

2 *Line Thermal Limits:* Line flows are kept under nominal range.

$$S_{min} \leq S_n \leq S_{max} \tag{5.3.18}$$

5.3.7 Mathematical Formulation of the Problem

If optimization objectives and constraints are substituted in Equation 3.1.1 the optimization problem could be expressed mathematically as:

$$\textbf{Minimize } \boldsymbol{F(x)} = \textbf{ Minimize } ([\boldsymbol{f_1(x)}, \boldsymbol{f_2(x)}, \boldsymbol{f_3(x)}, \boldsymbol{f_4(x)}]^{\boldsymbol{T}})$$
$$\boldsymbol{x \in \Omega}$$

<u>*Installation Costs:*</u>

$$minimize\ f_1(x) = \sum_{i=1}^{n} Pn_R * P_{cf} + \sum_{i=1}^{n} En_R * E_{cf} + \sum_{i=1}^{n} RETn_R * RET_{cf}$$

<u>*Particulate Emissions:*</u>

$$minimize\ f_2(x) = E_{NR} * emfac$$

<u>*Average Hours of Reserve:*</u>

$$minimize\ f_3(x) = average[\frac{S}{P_{D(base)}}]$$

<u>*Non-Renewable Energy Penetration:*</u>

$$minimize\ f_4(x) = \sum_{t=0}^{T} \frac{P_D(t) - W(t)}{P_D(t)}$$

Subject to:

$$En_R \geq Pn_R$$

$$\begin{cases} P_R > 0 \\ E_R > 0 \\ RET_R > 0 \end{cases} \quad \text{or} \quad \begin{cases} P_R = 0 \\ E_R = 0 \\ RET_R = 0 \end{cases}$$

$$\sum_{t=1}^{T} R \leq \sum_{t=1}^{T} S$$

$$V_{min} \leq V_n \leq V_{max}$$

$$S_{min} \leq S_n \leq S_{max}$$

5.3.8 Solutions

The solution of the MOEA is a set of pareto-optimal solutions with respect to each objective. This set of solutions is obtained after the algorithm achieves a pre-specified number of generations or after a number of individuals achieve acceptable objective values. Each solution is represented as a Decision Variable Vector (see Section 5.3.4), which must satisfy the following conditions:

- The solution must be a member of the pareto-optimal front.
- The solution must be in the range within the Decision Variable Vector limits.
- The solution must not violate any of the problem constraints (Section 5.3.6).

5.4 Case Study: 6-bus Remote Village

The following case study consists on a hypothetical remote village, consisting in one radial feeder. More details are given next.

- *Time Model*: The system is modeled for a time period of one year. The data is sampled in intervals of one hour.

- *Characteristics*: The system modeled is a village separated from the main electric system. It is located in a region where a vast solar resource is available. Non-renewable generation is acceptable, but the use of renewable energy is desired. The network is a portion of a distribution feeder [**55**], and consists of 6 nodes, in which 4 loads with different characteristics are present. DES units of any size could be placed in the shown locations. There is one location where non-renewable generation (a diesel engine or gas turbine) could be installed. The system is illustrated in Figure 5.4.1.

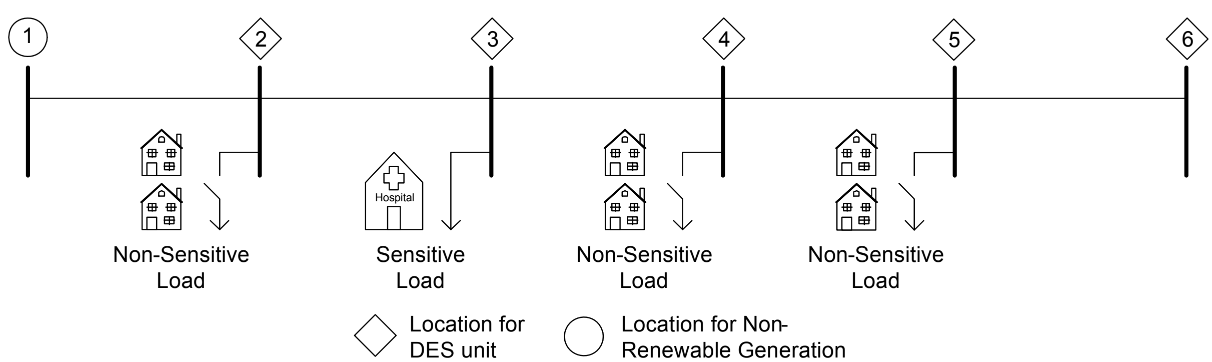


Figure 5.4.1: 6 Bus System for Case Study I.

– *Line Data:* The system is radial and is comprised of 5 branches. Nominal voltage is 6.6kV and base power is 10MVA. Line data is shown in Table 5.4.1.

Table 5.4.1: Line Data.

Sending Node	Receiving Node	R (p.u.)	X (p.u.)
1	2	0.003145	0.075207
2	3	0.000330	0.001849
3	4	0.006667	0.030808
4	5	0.005785	0.014949
5	6	0.014141	0.036547

Base Voltage=6.6kV ; BaseMVA = 10MVA

– *Load Data:* The system has 4 loads with different characteristics of size and sensitivity. Also, three levels hours of load control in demand response strategies will be considered. Since the system is predominantly residential, loads are considered with power factor equal to unity. Information is shown in Table 5.4.2.

Table 5.4.2: Load Data.

Node	Type	Power (kW)	Controlled Hours/day
2	Sensitive	49.5	0
3	Non-Sensitive	95.8	3
4	Non-Sensitive	44.2	3
5	Non-Sensitive	11.3	3

A typical load shape for residential customers is considered in the study (Figure 5.4.2). This daily pattern is fixed for all the time of analysis; this means that neither demand growth nor seasonality is considered.

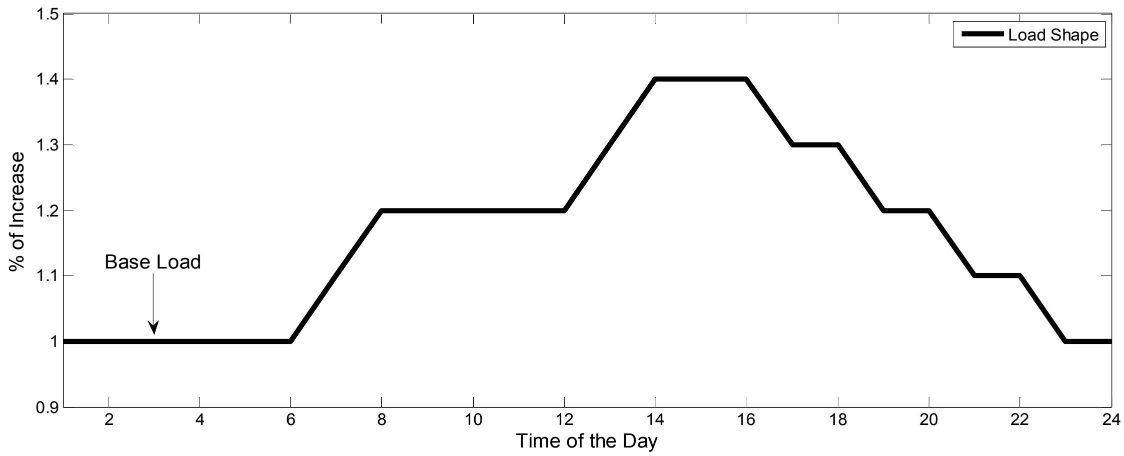


Figure 5.4.2: Daily Load Shape.

– *Solar Resource*: The solar resource is very abundant in the area. For the modeling, the Typical Meteorological Year 3 of the National Solar Radiation Database for the western Puerto Rican area (TMY3) was used [**56**]. TMY3 is a data set of typical hourly values of solar radiation for a 1-year period. While this data set represent typical rather than extreme conditions, it is still useful for the quantification of the resource availability. Figure 5.4.3 shows four typical days in TMY3.

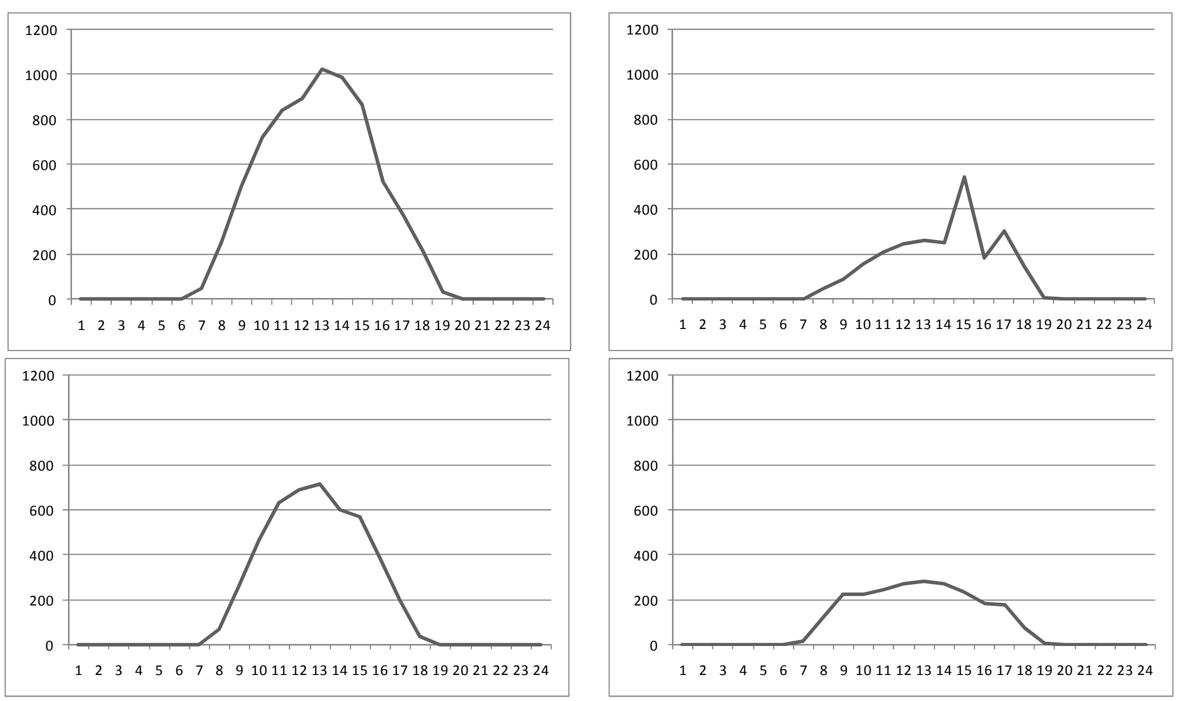


Figure 5.4.3: Four typical days in TMY3: High irradiance (left) and Low irradiance (right).

– *Costs*: Costs for this case study are typical incremental costs per MW or MWh found in the industry. Table 5.4.3 summarizes these costs.

Table 5.4.3: Unitary Costs.

Cost	Description	Value
$\mathbf{F_C}$	Fixed Cost for installing a DES unit at node *n*. ($)	500,000.00
$\mathbf{P_C}$	Cost for power rating of DES unit. ($/W)	0.60
$\mathbf{E_C}$	Cost for energy rating of DES unit. ($/Wh)	0.15
$\mathbf{RET_C}$	Cost for renewable energy equipment ($/W)	4.50

– *MOEA Parameters:* The parameters for the Multiobjective Evolutionary Algorithm are summarized in Table 5.4.4. The decision variable vector is in Table 5.4.5.

Table 5.4.4: MOEA Parameters.

Setting	Type	Parameters
GA Type	NSGA-II	-
Population Size	-	Size = 150
Maximum Generations	-	Max Gen = 2000
Selection	Tournament w/o Replacement	Size = 2
Crossover	SBX	Crossover probability = 0.9 Swap probability = 0.7 Order of polynomial = 10
Mutation	Polynomial	Mutation probability = 12% Order of polynomial = 20

Table 5.4.5: Decision Variable Vector for Values at Each Node.

Variable	Type	Lower Bound	Upper Bound
$\mathbf{P_R}$	Integer	0	200 kW
$\mathbf{E_R}$	Integer	0	3,800 kWh
$\mathbf{RET_R}$	Integer	0	800 kW

6 RESULTS AND DISCUSSION

6.1 Introduction

Figure 6.2.1 shows the optimization algorithm results for a run of 1600 generations. MOEA parameters for this case study are presented in Appendix A, and the output data for the last population is presented in Appendix B. Line losses were neglected in this case study for the sake of computational burden. A worst-case power flow (all energy flowing from one node) shows that losses for this system account for less than 0.5% of total energy consumption, making the assumption realistic.

6.2 Analysis of Correlations

The scatter-plot matrix shows important information about the characteristics of the problem. Each optimal solution in respect to each objective is represented as a red dot in the scatter-plot. Also, the black line gives more clear information about the trend of the graphic. It is important to note that all incremental cost factors associated with the power and energy rating of equipment are linear, thus the non-linear characteristic observed in the graphs are a result of the correlation between these objectives.

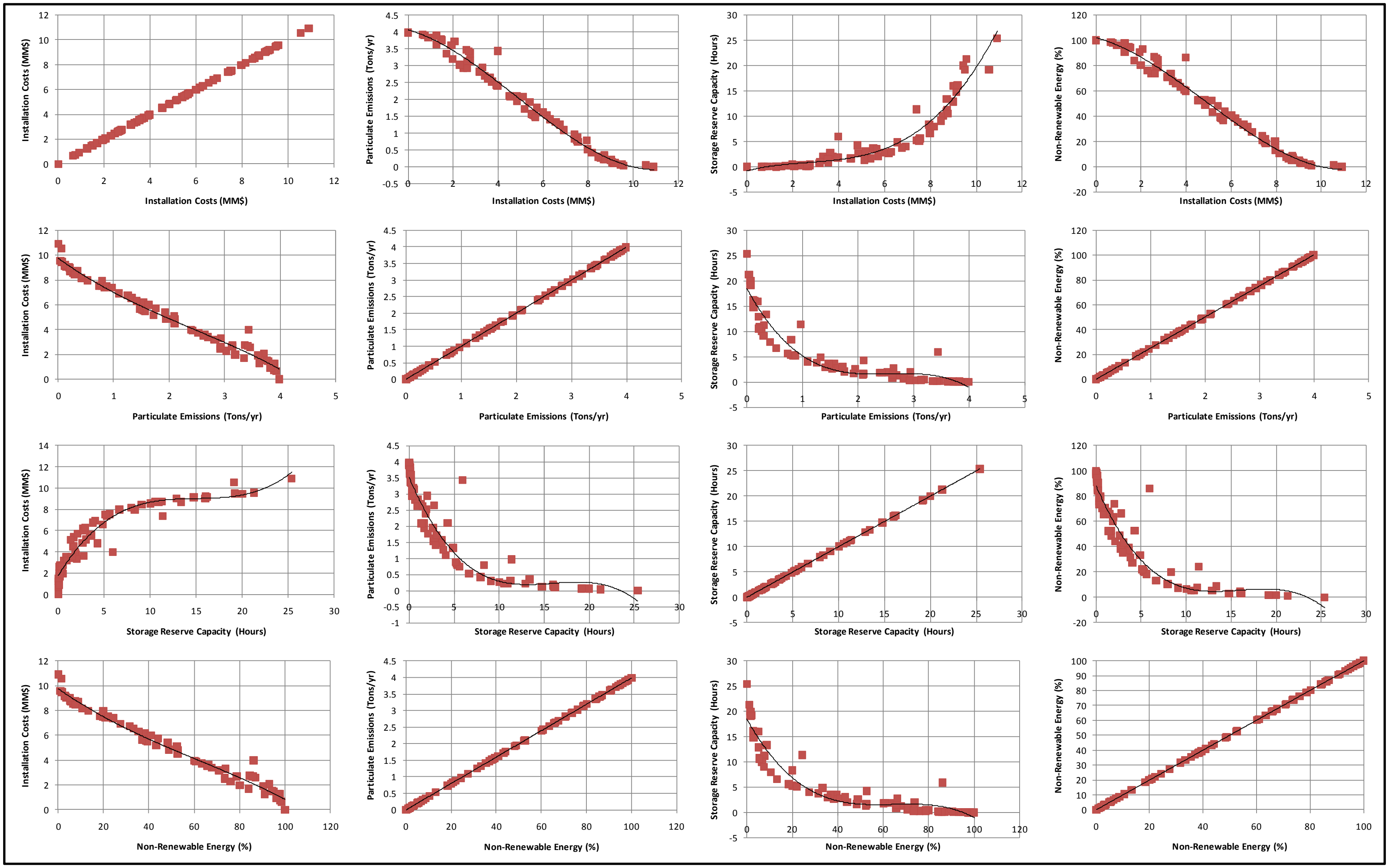


Figure 6.2.1: Scatter-Plot Matrix.
Each point represents a solution.

In the case of Installation Costs and Storage Reserve Capacity (SRC), both objectives are said to be 'positively correlated', because as one rises the other does as well. In this case, the correlation is present since the expansion of the SRC requires capital investments accounted in the Installation Costs (IC). However, it could be seen that the relationship is not linear. This behavior occurs because of two reasons: first, SRC does not represent all the system costs, and second, for small configurations expansion of SRC also requires expansion of other system elements, making the impact of SRC on costs less significant as the capacity rises. The penetration of Non-Renewable Energy (NRE) is strongly positively correlated with Particulate Emissions (PE). This is because Diesel engines accounts for all emissions in the microgrid. The linear relationship between these objectives is linear because of the nature of the emission factors.

In the other hand, IC and NRE penetration are strongly negative correlated. If a system with higher energy losses is considered, the correlation would be less linear. IC and PE are also negatively correlated. This relation could be justified because of the positive relation between PE-NRE and the characteristics of the emission factors.

Although the previous relationships are at some degree conceivable, there are others that are not evident by the simple inspection of the trade-off curves. This is the case of the SRE and the penetration of NRE, for example. For the analysis of this scenario, more information between the two objectives is needed. For this purpose, in Figure 5.2.2 solutions with NRE penetration lower than 20% are highlighted with blue dots in all graphics. In this range of solutions, the NRE is very low (meaning high penetration of renewables) and the Storage Reserve Capacity is very sparsed ranging from 5 to 30 hours of independence.

Observing the different scenarios for *PE* in Figure 6.3.1 is clear that this objective occurs fully in accordance with the non-renewable penetration, product of the strong correlation between these objectives. If the *SRC* vs. *IC* plot is observed, it is evident that the costs for this range vary from medium-high to high, despite the contribution from non-renewable resources is kept very low. This information tells that energy storage is needed when the renewable energy dominates the systems' supply. In addition, it could be seen that at this penetration level increasing *SRC* do not dramatically increase the *IC* of the system. It should be noted that the higher cost for the system occurs because of a large reserve capacity. In summary, the relationship between *Non-Renewable Energy* and *Storage Reserve Capacity* is product of their different correlation with the *Installation Costs* objective*:* negative for the first and positive for the latter.

The same analysis could be performed between remaining objectives and other interesting relationships could be discovered. This exercise is beneficial for the decision maker because valuable insight into the problem is gained. It is important to note at this point that this type of analysis is not possible with classical optimization techniques.

6.3 Decision-making Process

After having a deep understanding about the relationship and trade-offs between objectives, the next step consists in selecting the best solution in accordance with the decision maker preferences. For this purpose, 4 topologies from the solutions population are chosen in Table **6.3.2**. The selection of these topologies was made by choosing different levels of *IC*; however, other criteria could be used for this purpose. This includes de use of decision-making methods and other techniques.

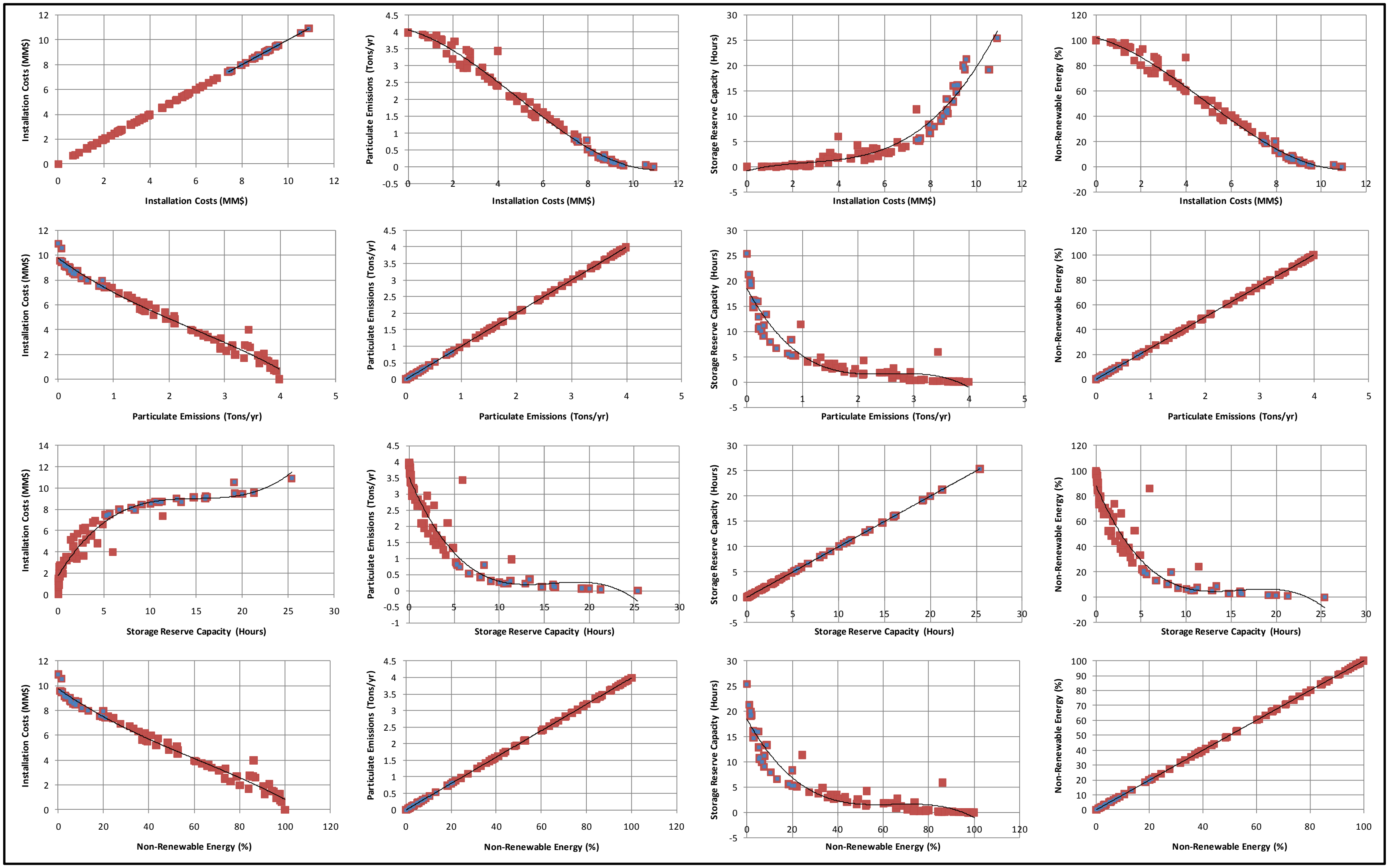


Figure 6.3.1: Scatter-Plot Matrix with Highlighted Solutions.
Each point represents a solution. Blue dots represent solutions with *Non-Renewable Energy* penetration lower than 20%.

All objective values are normalized in respect of solutions considered 'good' for each objective. This is done in order to make comparisons in consistent units. With this conversion, a high normalized value represents a good solution in respect to that objective. The normalized objectives are in

Table 6.3.1 and illustrated in Figure 6.3.2. The decision maker should be cautious when making comparisons between topologies expressed in relative terms, because the normalizations are made in terms of the importance of objectives in the same topology.

Table 6.3.1: Normalized Topologies.

	Topologies			
Objectives	**1** **Ref: 1**	**2** **Ref: 12**	**3** **Ref: 31**	**4** **Ref: 75**
Installation Costs (MM$)	1.0000	0.1972	0.4500	0.0000
Particulate Emissions (Tons/yr)	0.0000	0.9461	0.5914	1.0000
Storage Reserve Capacity (Hours)	1.0000	0.5839	0.8894	0.0000
Non-Renewable Energy (%)	0.0000	0.9461	0.5914	1.0000

Table 6.3.2: Selected Topologies.

	Topologies			
Objectives	**1** **Ref: 1**	**2** **Ref: 12**	**3** **Ref: 31**	**4** **Ref: 75**
Installation Costs (MM$)	10.9078	8.7572	5.9988	0.0000
Particulate Emissions (Tons/yr)	0.0000	0.2149	1.6283	3.9849
Storage Reserve Capacity (Hours)	25.3828	10.5624	2.8062	0.0000
Non-Renewable Energy (%)	0.0000	5.3934	40.8621	100.0000

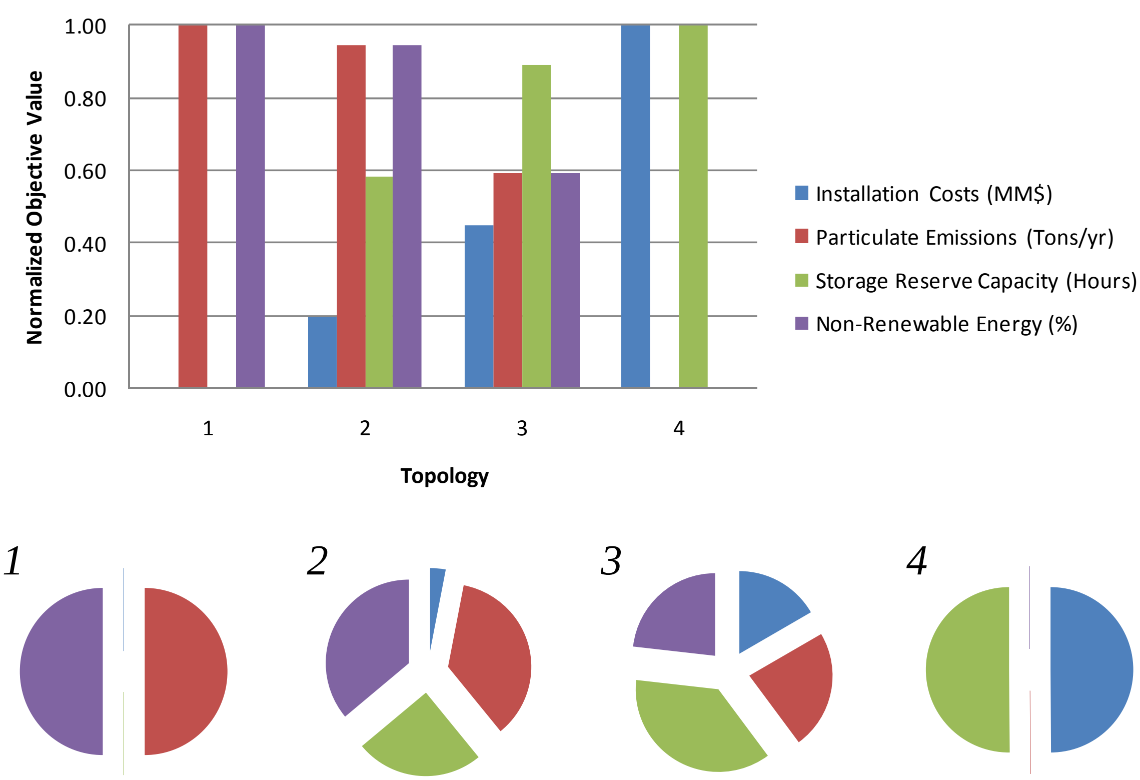


Figure 6.3.2: Graphic Representation of the 4 Chosen Topologies.

Topology 1 is a system high NRE and low SRC, much the same as a normal distribution feeder in the classical representation of power systems. This low renewable penetration is reflected by the low IC and insignificant SRC through the year. NRE is very high because it is used for supplying base and peak demand. PE is at its peak because of the large quantity of energy supplied by the diesel generator. This topology must be considered if the concern for environmental aspects is not an important issue, and if energy sustainability of the microgrid is not pursued. The detriment of these objectives will translate into minimum (good) IC. It is important to note that this analysis does not take into consideration the costs associated to greenhouse gas emissions.

Topology 2 represents a system with still a large dependence on NRE, but with a small portion of its demand supplied by renewable resources. Also, SRC is available in case of any contingencies. This topology should be chosen if the decision maker is interested in small penetration of renewable resources with high-reliance on non-renewable generators. It should be noted that installation costs are low for this system because of the low penetration of renewables.

In Topology 3 the system is largely dominated by renewable resources and high levels of storage are present. Because of this, IC has also risen. As could be seen in the pie-charts, the importance of NRE of Topology 2 is now diminished by the presence of more SRC. It is evident that the hours of reserve for this topology are far more than in Topology 2. Since NRE is present at a medium level, PE behaves accordingly. This solution should be chosen if the decision maker wishes to have a system with renewable generation but does not want to make investments in a large SRC, serving part of the demand by the use of fossil generation.

In Topology 4 installation costs are elevated as well as SRC. This system is entirely supplied by renewable energy, making PE and NRE zero for this case. This topology should be chosen if the decision maker wishes to have a system with large renewable penetration, vast storage from DES resources, and large interest on environment conservation or energy independence. The decision making process now translates into defining the importance of each objective and selecting an appropriate solution from the population generated by the optimization algorithm. If the decision maker wishes to have a considerable penetration of renewable resources, but does not want to incur into large capital costs associated with installing vast SRC, the topology that best suited is Topology 3, illustrated in Figure 6.3.3.

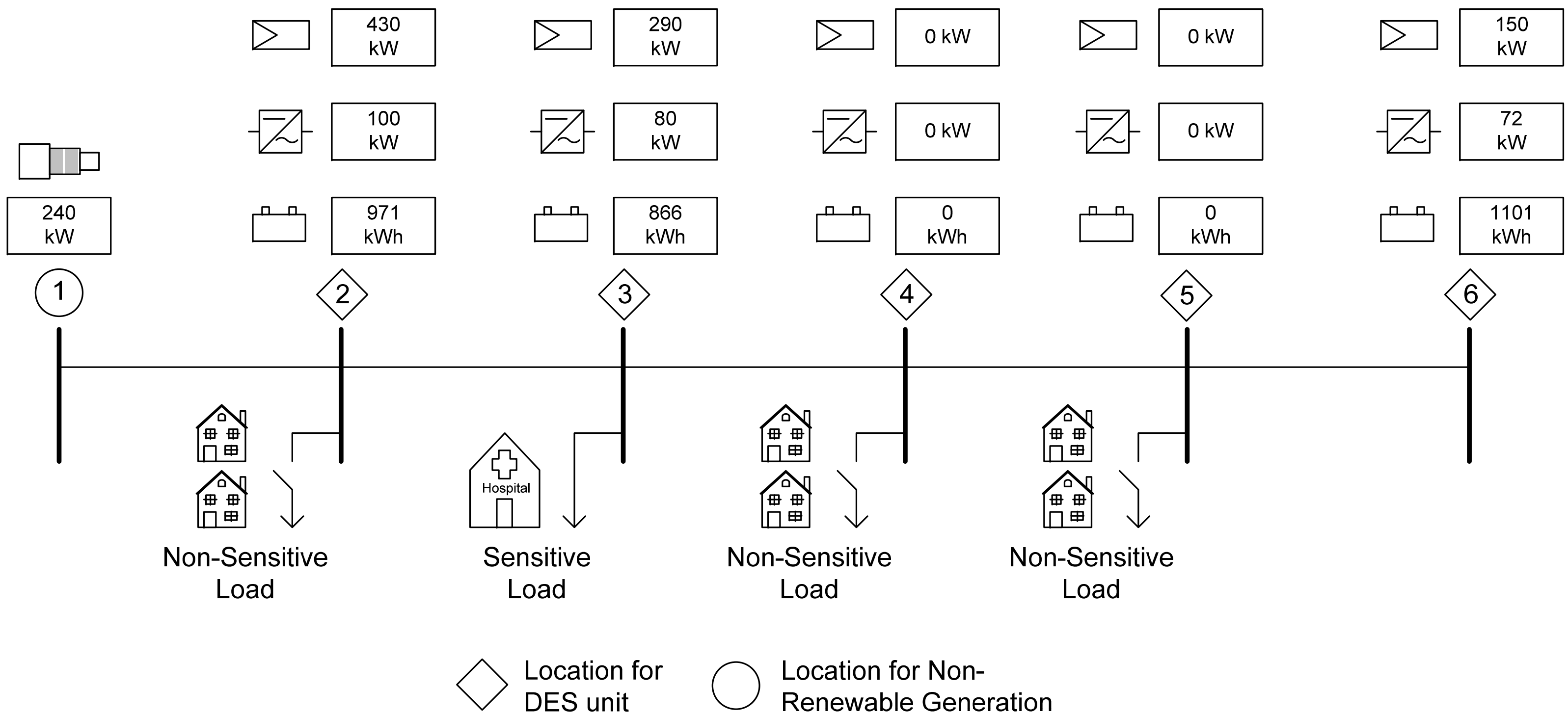


Figure 6.3.3: Power and Energy Ratings for Topology 3

Figure 6.3.4 and **Figure 6.3.5** show power flows of Topology 3 for two days of simulation. The first, is a day which happens after various days of good solar irradiance, hence the stored energy is at its peak. The second is a day with poor irradiance during previous days. In the first it could be seen that the hybrid DES are capable of supplying the base demand of the system while NRE serves as support for peak periods of demand. In the latter, the need for NRE is larger because of the lack of stored energy.

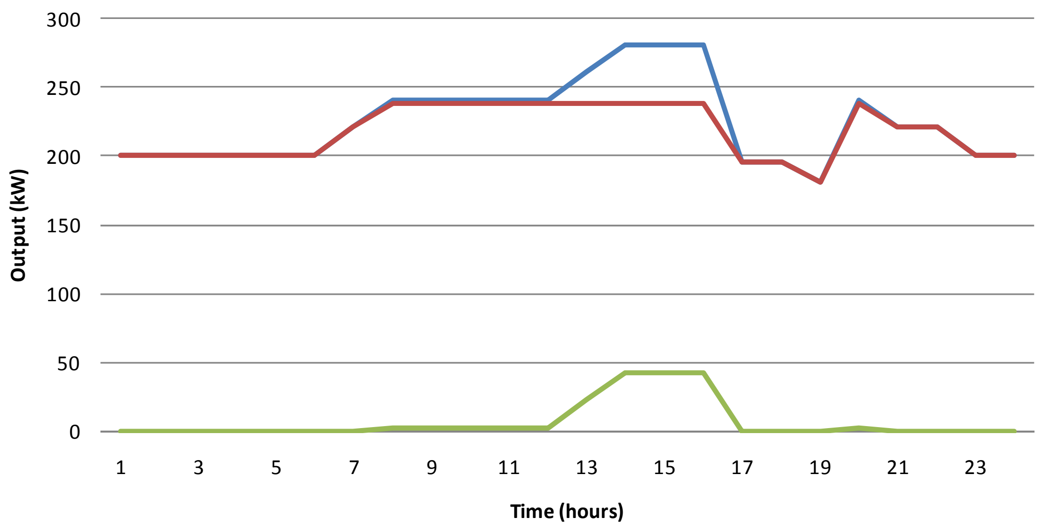


Figure 6.3.4: One-Day Power Flow for Topology 3 – high storage level

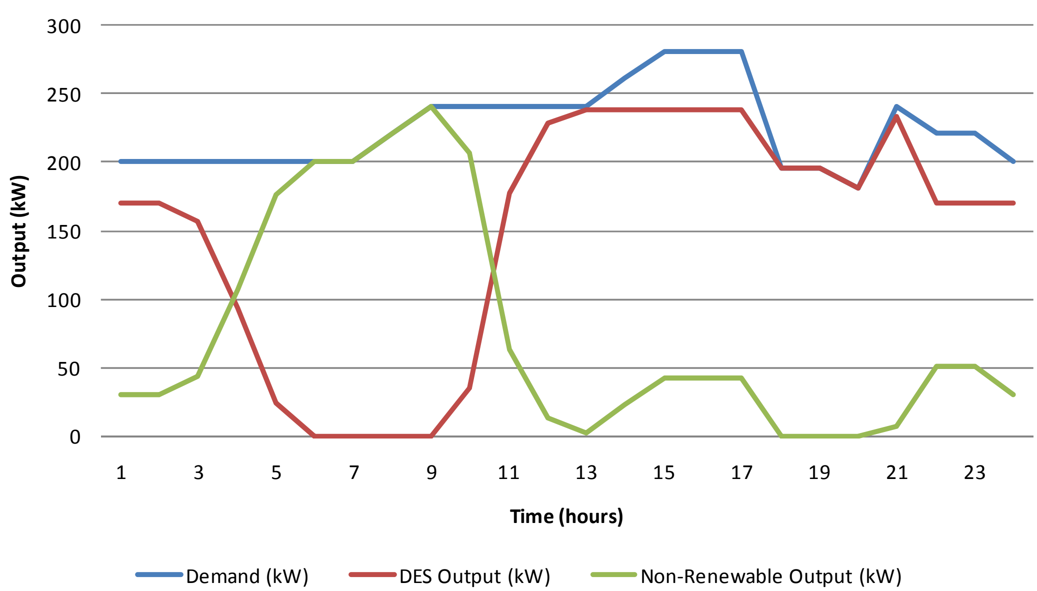


Figure 6.3.5: One-Day Power Flow for Topology 3 – low storage level

6.4 Impact of Demand Response Strategies

Demand response introduced by different customer differentiation levels in the network are an additional resource for the diminution of microgrid installation costs and use of non-renewable generation. The shaded area in Figure 6.4.1 represents the energy involved in demand response strategies for Topology 3 in a typical day. It could be clearly seen that with this energy diminution at peak hours, the energy necessary from non-renewable resources is decreased, thus, also decreasing particulate emissions.

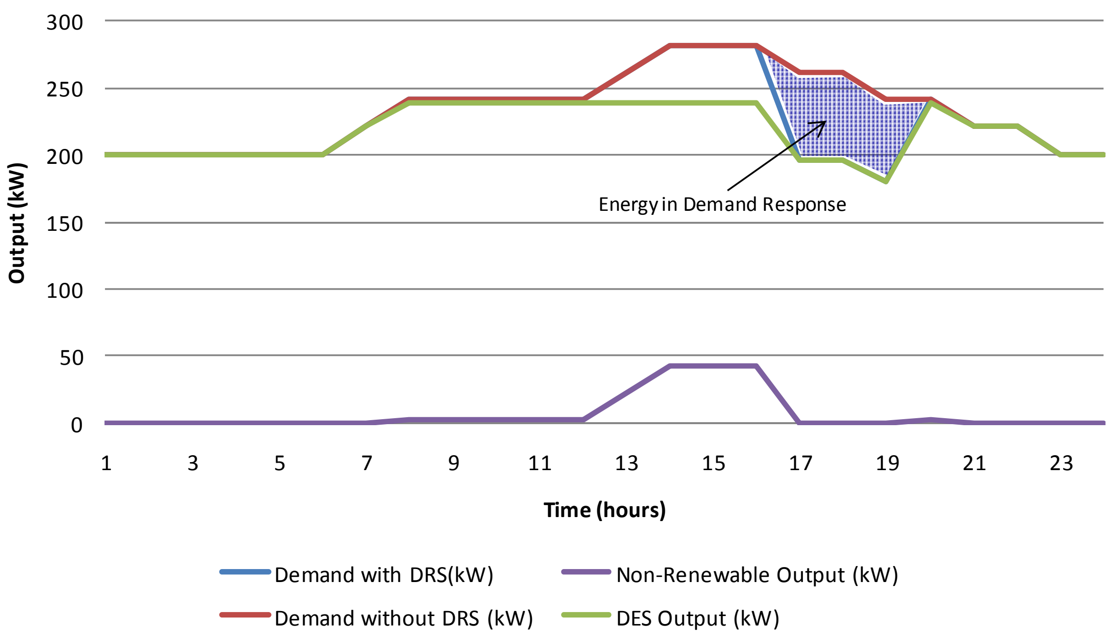


Figure 6.4.1: One-Day Power Flow for Topology 3 - effects of Demand Response

Figure 6.4.2 shows the diminutions in NRE by increasing the levels of demand response in the network. This figure illustrates the effects of different levels of demand response in the NRE and PE necessary for the energy sustainability of the system. While demand response may bring benefits in terms of these two objectives (plus expected diminutions on IC), when analyzing the maximum level of energy that could be involved on these strategies the decision maker should bear in mind the social impacts and the peoples' will to accept and promote these measures. Consequences of failing in the assessment of social repercussions could compromise the long-term sustainability of the microgrid. For example, if a system is planned and dimensioned counting on the contributions of demand response, and then the people reject the strategies, the system would not be sustainable from the social and technical point of view and is likely to collapse.

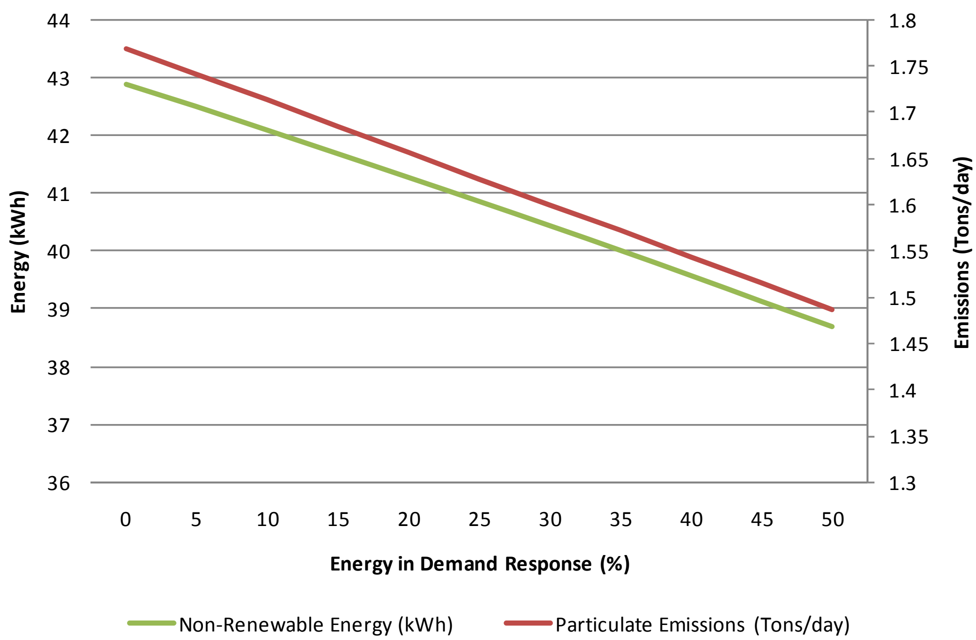


Figure 6.4.2: Effects of Demand Response in One Day for Topology 3

An extra two-objective simulation was made for finding the optimal level of demand response in the system. For demonstration purposes, the simulations were made for a time interval of 5 days. An extended time interval would be far more accurate and is needed for making planning decisions, the results obtained are still useful for watching trends and correlations.

Figure 6.4.3 show the trade-off curve between the Energy in DRS and Non-Renewable energy penetration. The solutions with larger quantity of energy curtailed in DRS are highlighted. The negative correlation of these two objectives could be easily appreciated. It demonstrates that for higher levels of demand response, the dependence on non-renewable energy is diminished. The relation between the two objectives is obscured by the energy ratings of DES units, which are forced to diminish because of the pressure of the installation costs objective. This effect makes the system more dependent on non-renewable energy for some cases.

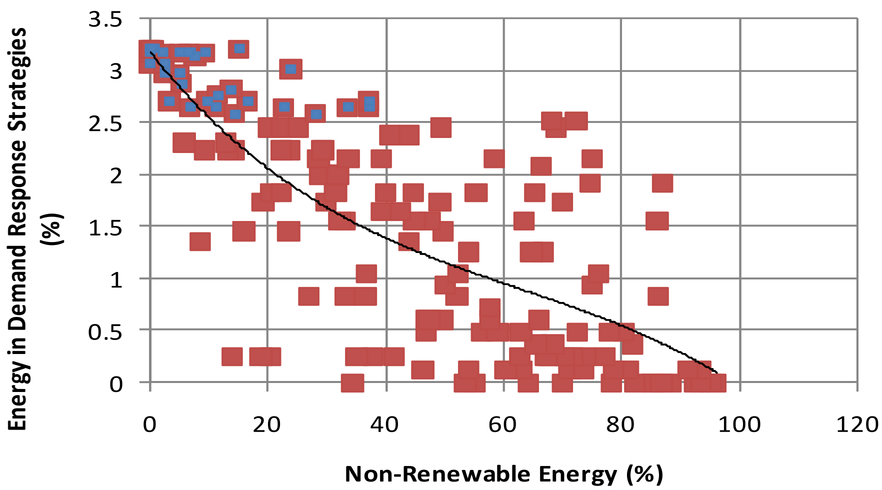


Figure 6.4.3: Non-renewable Energy vs. DRS.

6.5 Experience with MOEA Control Parameters

After numerous testing simulations were performed, it was found that population size is important for the convergence and diversity of the algorithm results. Large populations are more likely to find optimal solutions since the search space is better covered. The system was simulated for populations ranging between 100 and 300 individuals, finding better results (in terms of convergence and diversity) for populations bigger than 150 members. However, the computational time is dramatically increased by large populations.

Another important parameter is the constraint-handling technique used in the algorithm. Three different approaches for constraint handling were tested:

1. Constraints in Section 5.3.6 were defined for each node and introduced into the MOEA as penalty functions – Good results but large computational time.
2. Constraint violations for all nodes were added into a global constraint factor (for each constraint at all nodes). This approach yield bad results. The algorithm got stalled numerous times in non-feasible regions.
3. The search space was restricted of achieving prohibited zones delimited by the constraints. This approach was used with the 'DER integrity' constraint defined in Section 5.3.6, achieving average results. Sometimes the algorithm got stalled in the P_R=E_R=RET_R=0 alternative for a large number of generations, but in general the results were fair good. Another advantage was the decreased computational time in comparison with method 1. Improvements for this method are suggested in the Future Work section.

7 CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

Governments in developing countries require solutions to provide electricity access for more than 1.5 billion of people that currently do not have. The largest portion of these people live in rural and isolated areas, making off-grid energy solutions like microgrids ideal for these zones. The microgrid concept could also be applied in rural and isolated areas of developed countries. A microgrid is a combination of different types of loads and distributed energy resources (DER) which can autonomously meet the power, energy and quality requirements of the customers in its area. Microgrids have proven to give benefits to both customers and utilities in terms of efficiency, power quality, environment conservation and community development. Current challenges for the development of microgrids include the design of solutions that combine demand side and supply side alternatives aimed at the achievement of sustainability for particular locations.

In this work a method for the optimal sizing and location of distributed generators in usually isolated or stand-alone microgrids was presented. The proposed algorithm tackles the resource allocation problem in microgrids with special interest in the microgrid sustainability and self-reliance. These two aspects are very important in the microgrid planning process, especially for isolated areas. Various strategies for the achievement of sustainability and self-reliance have been analyzed in this work and incorporated into the algorithm, including the use of non-renewable energy, installation of distributed storage units, and application of consumption reduction strategies at the customer side. All of the previous sustainability strategies have related social, economical and environmental issues that are also presented.

For the optimization process, The Non-dominated Sorting Genetic Algorithm II (NSGA-II) was selected. NSGA-II is one of the leader methods in the field of elitist multiobjective evolutionary algorithms (MOEAs). MOEAs imitate the Darwinian natural selection and natural genetics process, in which individuals of a population go through stochastic operations such as selection, mutation, and crossover in order to achieve better objective values. The greatest advantage of MOEA for the proposed method is the capability of processing entire populations on a single iteration. Because of this characteristic, different system topologies could be optimized in a single run of the algorithm, eliminating the need of any a-priori information about objectives such as weights or ϵ-constraint vectors. A drawback of MOEAs is that an optimal solution could not be guaranteed because of its stochastic nature; however, with the accurate tuning of its control parameters very successful results can be obtained.

The algorithm was successful when finding different optimal system topologies with respect to different pre-defined objectives. A case study of a microgrid in a remote village was presented in which the algorithm was tested with four different objectives aimed at the assessment of microgrid sustainability: Installation costs, energy involved in demand response strategies, average system reserve, and contributions of non-renewable energy. Results showed that total installation costs are largely dominated by the storage reserve capacity making this alternative expensive from the economic point of view. In the other hand, alternatives which relied on the use of non-renewable energy showed the lowest installation costs but caused large quantities of particulate emissions, elevating the environmental impact of the project. The relationship between non-renewable energy penetration and storage reserve capacity was also analyzed. An interesting association between these two objectives is produced by the different correlation between the two and their respective installation costs. After analyzing different relationships between objectives, the decision-making process was continued until an 'optimal' configuration was selected, based on the objectives' preferences of an imaginary decision maker. Lastly, the importance of demand response strategies in cost reduction and non-renewable dependence was demonstrated by simulating the case study for different demand response levels and watching the effects on the aforementioned objectives.

Regarding to the MOEA performance, different simulations were performed until a good set of control parameters was found. It was found that population size is important for the convergence and diversity of the algorithm results. Large populations are more likely to find optimal solutions since the search space is better covered. However, these benefits are at the expense of computational time, which is dramatically increased by large populations especially when power flow calculations are needed for the quantification of losses, voltage, and thermal constraints. Another important parameter is the constraint handling technique used in the algorithm. Different constraint strategies were studied, first, different constraints were defined for each node and introduced into the MOEA as dynamic penalty functions, second, constraint violations for all nodes were added into a global constraint factor (for each constraint); and third, the search space of restricted of achieving prohibited zones delimited by the constraints. Using the first approach computational time for each generation increased significantly because of the augmented number computations. However, the algorithm achieved better solutions in fewer generations, compared with the other approaches. Using the second approach the algorithm did not presented good convergence characteristics because a clear understanding of the violation is not given to the algorithm. Using the third approach computational time decreased significantly because fewer calculations were needed, but at the expense of a larger number of generations needed for the algorithm to achieve good results.

According to the successful implementation of the developed models for the microgrid planning problem, we can summarize that the method developed in this work represents a valuable contribution to the modern heuristics research applied to new tendencies in energy technologies, and constitutes an additional tool for the promotion of energy sustainability and social development in isolated areas.

7.2 Future Work

In this thesis a method for the optimal allocation of distributed generation resources in isolated microgrids is developed. The proposed algorithm deals with the optimization problem with special interest on the sustainability and self-reliance of the microgrid. As a general recommendation, it is suggested to further study other implementations of MOEAs in the field of microgrids and smart-grid technologies. Future upgrades should include the construction of better mutation and crossover operators that could distinguish connections between energy storage, inverter capacity and renewable generation connected at each node. This addition will improve convergence of the algorithm and would significantly lower the execution time of the program.

The developed algorithm tackles the microgrid long term planning problem, but there are still much work to do in methods for assessing optimal operation and unit scheduling of microgrids with distributed energy storage, considering resource availability, price signals from main grids and interconnections with other microgrids.

A good addition would be the incorporation of other demand response strategies into another objective function in the optimization algorithm, either as an index, or parameter. Also, it would be important to enhance the current work with different objective functions that deal with more robust environmental indicators, such as the ecological footprint of the project. Another useful improvement would be the inclusion of life cycle analysis of the proposed solutions taking into account more detailed information about hidden revenues, costs and externalities of renewable and non-renewable technologies.

For the case of rural projects in developing countries, an interesting addition will include ways of comparing installation costs with the willingness to pay (WTP) of the customers in the service area and other methods for assessing optimal rate structures that promote social development as well as capital recovery.

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APPENDIX A: INPUT FILE FOR THE MOEA

```
# Input file for the GA Toolbox
# Author: Kumara Sastry
# Date: April, 2006
#

#
# GA type: SGA or NSGA
#
NSGA

#
# Number of decision variables
#
15

#
# For each decision variable, enter:
#      decision variable type, Lower bound, Upper bound
# Decision variable type can be double or int
#
double 0 20
double 0 20
double 0 20
double 0 20
double 0 20
int 0 3800
int 0 3800
int 0 3800
int 0 3800
int 0 3800
int 0 80
int 0 80
int 0 80
int 0 80
int 0 80



#
# Objectives:
#      Number of objectives
#      For each objective enter the optimization type: Max or Min
#
4
Min
Min
Min
Min

#
# Constraints:
#      Number of constraints
#      For each constraint enter a penalty weight
#
2
1.0
1.0

#
# General parameters: If these parameters are not entered default
#                      values will be chosen. However you must enter
#                      "default" in the place of the parameter.
#      [population size]
#      [maximum generations]
#      [replace proportion]
#
150
2000
default

#
# Niching (for maintaining multiple solutions)
```

```
# To use default setting type "default"
#  Usage: Niching type, [parameter(s)...]
#  Valid Niching types and optional parameters are:
#       NoNiching
#       Sharing [niching radius] [scaling factor]
#       RTS [Window size]
#       DeterministicCrowding
#
#  When using NSGA, it must be NoNiching (OFF).
#
NoNiching

#
# Selection
#  Usage: Selection type, [parameter(s)...]
#  To use the default setting type "default"
#
#  Valid selection types and optional parameters are:
#       RouletteWheel
#       SUS
#       TournamentWOR [tournament size]
#       TournamentWR [tournament size]
#       Truncation [# copies]
#
#  When using NSGA, it can be neither SUS nor RouletteWheel.
#
TournamentWOR 2

#
# Crossover
#  Crossover probability
#  To use the default setting type "default"
#
#  Usage: Crossover type, [parameter(s)...]
#  To use the default crossover method type "default"
#  Valid crossover types and optional parameters are
#       OnePoint
#       TwoPoint
#       Uniform [genewise swap probability]
#       SBX [genewise swap probability][order of the polynomial]
#
0.9
SBX 0.7 10

#
# Mutation
#  Mutation probability
#  To use the default setting type "default"
#
#  Usage: Mutation type, [parameter(s)...]
#  Valid mutation types and the optional parameters are:
#       Selective
#       Polynomial [order of the polynomial]
#       Genewise [sigma for gene #1][sigma for gene #2]...[sigma for gene #ell]
#
0.15
Polynomial 20

#
# Scaling method
#  To use the default setting type "default"
#
#  Usage: Scaling method, [parameter(s)...]
#  Valid scaling methods and optional parameters are:
#       NoScaling
#       Ranking
#       SigmaScaling [scaling parameter]
#
NoScaling

#
# Constraint-handling method
# To use the default setting type "default"
#
# Usage: Constraint handling method, [parameters(s)...]
# Valid constraint handling methods and optional parameters are
#       NoConstraints
#       Tournament
#       Penalty [Linear|Quadratic]
#
Tournament
```

```
#
# Local search method
# To use the default setting type "default"
#
# Usage: localSearchMethod, [maxLocalTolerance], [maxLocalEvaluations],
#              [initialLocalPenaltyParameter], [localUpdateParameter],
#              [lamarckianProbability], [localSearchProbability]
#
# Valid local search methods are: NoLocalSearch and SimplexSearch
#
# For example, SimplexSearch 0.001000 20 0.500000 2.000000 0.000000 0.000000
default

#
# Stopping criteria
# To use the default setting type "default"
#
# Number of stopping criterias
#
# If the number is greater than zero
#    Number of generation window
#    Stopping criterion, Criterion parameter
#
# Valid stopping criterias and the associated parameters are
#       NoOfEvaluations, Maximum number of function evaluations
#       FitnessVariance, Minimum fitness variance
#       AverageFitness, Maximum value
#       AverageObjective, Max/Min value
#       ChangeInBestFitness, Minimum change
#       ChangeInAvgFitness, Minimum change
#       ChangeInFitnessVar, Minimum change
#       ChangeInBestObjective, Minimum change
#       ChangeInAvgObjective, Minimum change
#       NoOfFronts (NSGA only), Minimum number
#       NoOfGuysInFirstFront (NSGA only), Minimum number
#       ChangeInNoOfFronts (NSGA only), Minimum change
#       BestFitness (SGA with NoNiching only), Maximum value
#
default
```

APPENDIX B: TABULATED RESULTS FOR THE MOEA

**Solutons with constraint violations not included*

** Highlighted solutions belong to topologies analyzed in Section 6.3*

	DECISION VARIABLES															OBJECTIVES			
	PR					ER					RETR								
REF	2	3	4	5	6	2	3	4	5	6	2	3	4	5	6	Instalation Costs ($)	Particulate Emissions (Tons/yr)	Energy Reserve (hours)	Non-renewable Energy (%)
1	9.8	4.4	8.7	1.9	4.8	2725	1116	2582	1523	1082	52	22	45	7	27	10.907834	0	25.382794	0
2	9.8	4	8.6	2.1	4.8	2725	601	2135	1524	880	52	18	45	7	27	10.551675	0.063107	19.131783	1.583676
3	13	8.2	0	0	8.2	3794	2505	0	0	1341	66	41	0	0	43	9.563718	0.039159	21.278424	0.982695
4	12	8.1	0	0	8.9	3262	2849	0	0	1651	68	38	0	0	42	9.49072	0.076218	19.193509	1.912692
5	13	8.1	0	0	8.3	3218	2868	0	0	1634	68	39	0	0	40	9.441048	0.064793	19.988507	1.625974
6	13	8.1	0	0	7.4	3444	1675	0	0	1343	66	38	0	0	42	9.202094	0.130108	16.052877	3.265048
7	13	8.1	0	0	8.2	3374	1757	0	0	1141	63	42	0	0	41	9.177092	0.112318	16.178317	2.818606
8	13	8.1	0	0	8.2	2709	1628	0	0	1343	69	38	0	0	40	9.134729	0.118604	14.754082	2.97636
9	13	8.6	0	0	7.5	3252	1762	0	0	1341	67	41	0	0	35	9.054613	0.143487	16.011442	3.600791
10	13	8.1	0	0	8.4	3398	2692	0	0	1195	68	40	0	0	31	9.015616	0.198477	15.992546	4.980764
11	12	8.2	0	0	8.1	3366	1465	0	0	923	61	38	0	0	45	9.005832	0.208846	12.891144	5.240984
12	13	8.5	0	0	7.1	1900	1458	0	0	1051	65	41	0	0	37	8.757188	0.214918	10.562448	5.393351
13	12	8.1	0	0	8.4	3387	410	0	0	1608	66	29	0	0	44	8.730569	0.304768	11.239133	7.648126
14	13	9.8	0	0	6.3	3561	1762	0	0	1138	70	42	0	0	23	8.709291	0.346993	13.373334	8.707763
15	13	8.3	0	0	8.2	1891	1803	0	0	1128	63	39	0	0	38	8.691337	0.220372	10.899142	5.530212
16	13	8.6	0	0	7.5	1825	1631	0	0	1045	62	41	0	0	35	8.550847	0.263589	10.043338	6.614752
17	13	8.4	0	0	7.4	1729	1512	0	0	949	63	40	0	0	34	8.454999	0.301192	9.078488	7.558383
18	13	8.2	0	0	6.5	1839	1269	0	0	913	63	40	0	0	28	8.155225	0.418959	7.933903	10.513743
19	13	8.2	0	0	7.7	1715	786	0	0	861	61	31	0	0	37	7.972136	0.52886	6.659267	13.271692
20	13	8	0	0	8.4	3363	2906	0	0	1654	68	40	0	0	5	7.940565	0.794233	8.333019	19.931217
21	12	8.3	0	0	7.9	1526	1040	0	0	933	57	30	0	0	32	7.541207	0.736014	5.60445	18.470203
22	12	8.1	0	0	7.4	1667	410	0	0	625	66	29	0	0	26	7.509718	0.876034	5.143391	21.984005
23	13	9.2	0	0	7.8	1724	1224	0	0	1098	51	37	0	0	28	7.494903	0.792765	5.324569	19.894361
24	13	7.5	0	0	8.3	1971	914	0	0	872	62	22	0	0	31	7.402388	0.830981	5.265172	20.853393
25	8.5	4.3	0	0	9.1	3004	1278	0	0	1104	50	25	0	0	35	7.382431	0.968295	11.373502	24.299296
26	12	9.2	0	0	7.8	1504	570	0	0	871	47	30	0	0	30	6.923399	1.092838	4.030775	27.424676
27	11	7.8	0	0	7.5	1742	425	0	0	629	48	29	0	0	27	6.746991	1.25751	3.80189	31.557116
28	14	8.2	0	0	0.5	1884	1314	0	0	846	54	41	0	0	1	6.553418	1.326795	4.864628	33.295806
29	13	8.3	0	0	8	989	720	0	0	991	38	30	0	0	26	6.300357	1.414376	2.948577	35.493656
30	13	8.3	0	0	8	1312	893	0	0	1124	33	30	0	0	26	6.169707	1.530396	2.683839	38.405173
31	9.9	8	0	0	7.2	971	866	0	0	1101	43	29	0	0	15	5.998766	1.628302	2.806212	40.862119
32	12	8.2	0	0	7.5	1040	802	0	0	959	36	29	0	0	16	5.723016	1.756477	2.093533	44.07866
33	13	8.5	0	0	0	1308	973	0	0	0	55	38	0	0	0	5.649677	1.472386	3.607186	36.949406
34	12	8.5	0	0	0	1320	844	0	0	0	55	38	0	0	0	5.628963	1.517168	3.545197	38.0732
35	12	8.9	0	0	0	1308	909	0	0	0	55	36	0	0	0	5.547039	1.536571	3.482549	38.560113
36	12	8	0	0	0	1600	1231	0	0	0	51	37	0	0	0	5.499379	1.568956	3.617823	39.372831
37	12	8.3	0	0	6.7	974	839	0	0	646	39	20	0	0	16	5.398051	1.924751	1.688111	48.301466
38	11	8.5	0	0	0	1224	909	0	0	0	47	36	0	0	0	5.168555	1.72308	3.051333	43.240561
39	12	8.2	0	0	7.4	974	413	0	0	947	38	15	0	0	16	5.112351	2.08785	1.373307	52.394437
40	12	7.1	0	0	0	1511	1178	0	0	0	41	33	0	0	0	4.842889	1.945954	2.63987	48.83355
41	6.8	8.1	0	0	0	3366	1732	0	0	0	28	38	0	0	0	4.819398	2.102011	4.266119	52.749784
42	14	8.1	0	0	0	1176	860	0	0	0	43	26	0	0	0	4.534094	2.094955	1.684413	52.572735
43	14	8.7	0	0	0	1014	860	0	0	0	42	27	0	0	0	4.514026	2.098818	1.592041	52.669663
44	13	4.7	1.6	0	0.1	1931	1325	1954	0	922	10	3	2	0	6	3.976487	3.435121	5.951073	86.204077
45	6.6	9.3	0	0	0	946	854	0	0	0	28	30	0	0	0	3.970514	2.394134	1.832695	60.080605
46	11	5.5	0	0	0	1263	398	0	0	0	45	12	0	0	0	3.906078	2.424135	1.864955	60.833468
47	6.8	6.3	0	0	0	1054	766	0	0	0	29	24	0	0	0	3.732835	2.52709	1.945164	63.417124
48	7.2	7	0	0	0	1308	78	0	0	0	41	11	0	0	0	3.628926	2.63981	2.769074	66.245812
49	14	5.3	0	0	0	1028	286	0	0	0	39	11	0	0	0	3.555034	2.619214	0.878336	65.728963
50	7.2	6.5	0	0	0	857	510	0	0	0	27	23	0	0	0	3.533381	2.621886	1.489891	65.796017
51	7.2	6.5	0	0	0	761	650	0	0	0	27	20	0	0	0	3.404887	2.696961	1.302355	67.680017
52	0	0	0	18	2.2	0	0	0	438	3123	0	0	0	36	1	3.31332	2.939662	2.012541	73.770587
53	7.2	6.5	0	0	0	761	650	0	0	0	22	20	0	0	0	3.179887	2.830394	0.953036	71.028502
54	13	0	0	0	4.5	621	0	0	0	281	32	0	0	0	11	3.167647	2.815862	0.648286	70.66384
55	10	4.7	0	0	0	154	280	0	0	0	16	6	0	0	0	2.757234	3.365054	0.176173	84.445758
56	12	5.1	0	0	0	1171	763	0	0	0	29	1	0	0	0	2.735465	3.138163	0.510777	78.751947
57	10	0	6.5	0	3.5	198	0	423	0	165	18	0	2	0	1	2.678742	3.419049	0.166738	85.800768
58	13	0	0	0	4.4	761	0	0	0	228	20	0	0	0	11	2.639832	3.134007	0.330416	78.647658

59	0	0	0	20	0	0	0	0	438	0	0	0	0	43	0	2.613124	2.928623	0.346841	73.493563
60	10	5.8	0	0	3.8	198	406	0	0	165	17	1	0	0	1	2.583234	3.465019	0.153802	86.954377
61	0	0	0	19	0	0	0	0	651	0	0	0	0	39	0	2.459434	2.928573	0.41668	73.492313
62	0	0	0	19	0	0	0	0	448	0	0	0	0	36	0	2.293984	3.028366	0.315942	75.996592
63	8.4	4.7	0	0	0.3	130	62	0	0	28	6	3	0	0	1	2.059262	3.71276	0.101366	93.1714
64	11	0	0	0	0	755	0	0	0	0	29	0	0	0	0	1.980441	3.192959	0.48944	80.127058
65	11	0	0	0	2.2	1747	0	0	0	37	9	0	0	0	4	1.925924	3.605181	0.199787	90.471722
66	12	0	0	0	0	300	0	0	0	0	24	0	0	0	0	1.694562	3.349082	0.216412	84.044945
67	6.8	3.2	0	0	0	437	144	0	0	0	2	6	0	0	0	1.504104	3.757526	0.078281	94.294803
68	7.2	6.5	0	0	0	343	134	0	0	0	3	4	0	0	0	1.464838	3.786692	0.057615	95.026724
69	14	0	0	0	2.8	201	0	0	0	46	2	0	0	0	1	1.267665	3.898922	0.023063	97.843125
70	0	0	0	19	0	0	0	0	495	0	0	0	0	13	0	1.266034	3.626143	0.100452	90.997773
71	0	5.1	0	0	3.7	0	159	0	0	46	0	3	0	0	1	1.26083	3.873237	0.03128	97.198557
72	0	6	0	0	0	0	979	0	0	0	0	5	0	0	0	0.905836	3.828096	0.096237	96.065764
73	7.6	0	0	0	0	362	0	0	0	0	3	0	0	0	0	0.732705	3.89618	0.027329	97.774319
74	0	0	7.9	0	0	0	0	113	0	0	0	0	2	0	0	0.651812	3.928803	0.01524	98.592996
75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.98487	0	100