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Design Optimization of Stand-Alone Hybrid Energy Systems

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Abstract

Millions of people worldwide do not have access to electricity for the most basic goods of survival. Millions of people do not have access to culture – the pleasure of reading a book because they do not have the luxury of illumination during the night.

One of the many ways to extinguish this unevenness between the developed and underdeveloped world starts from using renewable resources as a source of energy. Independently of the world's site where we stand, these sources are abundantly, free and inexhaustible. The problem inhabits in the way as this renewable resources are managed in function of a certain associated load demand.

Hybrid energy systems, namely the stand-alone or isolates ones, show an enormous weight in the path for adopting ways of giving access to energy in the most remote places of our planet. To conjugate, in an optimized way, the different forms of energy – wind, water and sun – is the course we have to adopt and implement so that motivated investors can apply their monetary resources in underdeveloped countries such as African countries.

This was the context on which this thesis was based, aimed to develop capable tools to optimize the design of stand-alone hybrid systems, concretely applied to any type of resource data and load information. However, the complexity of this problem is of an extremely high mathematical degree. Unlike the algorithms already developed, the objective was to develop a tool that could optimize continuous variables, in this case, the wind, hydro and solar resources, as well as the batteries and the diesel generator that constitute a generic hybrid system.

An innovator and powerful optimization tool was then developed – GraSO (Gradient Swarm Optimization Algorithm) – capable of efficiently answer to this kind of problems. This software is skilled at the point that it can optimized both operation (load following and cycle charging dispatch strategies) and design of the hybrid system.

This algorithm was tested in several standard evaluation functions and presented satisfactory results. Hence, his application in other kind of problems is possible and advised.

With the developed algorithm core, GraSO was then applied to the system model created in an Excel spreadsheet proving his reliability to optimize the design of stand-alone hybrid energy systems.

keywords:

Design, GraSO, Hybrid Energy Systems, Metaheuristics, Operation, Optimization Algorithms, Stand-Alone

Acknowledgments

To my Parents

To my Brother

To my Friends

To **You, Ana.**

Thanks *Boss!* See you around!

Francisco Mesquita

“We invent to persuade ourselves that events are knowable and that life has order and direction”

Calvin & Hobbes

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Abbreviations and Symbols

List of Abbreviations

AC	Alternate Current
BES	Biomass Energy System
BTU	British Thermal Unit
CAES	Compressed air energy storage
CC	Cycle Charging
CGHS	Central Grid Connect Hybrid System
DC	Direct Current
DG	Diesel Generator
DOD	Depth of Discharge
EFCE	Equivalent Full Cycles of Energy
EL	Excess Load
EPSO	Evolutionary Self-Adaptive Particle Swarm Optimization
FEUP	Faculdade de Engenharia da Universidade do Porto
FPMRT	Full Power Minimum Run Time
GRASO	Gradient Swarm Optimization
HES	Hybrid Energy System
HGS	Hybrid Generation System
HSWSO	Hybrid Solar-Wind System Optimization
IGBT	Insulated Gate Bipolar Transistor
IGHS	Isolated Grid Hybrid System
ISEL	Instituto Superior de Engenharia de Lisboa
ISHS	Isolated or Special Purpose Hybrid System
LCO	Levelized Cost of Operation
LCOE	Levelized Cost of Energy
LF	Load Following
LLP	Loss of Load Probability
LPS	Loss of Power Supply
LPSP	Loss of Power Supply Probability
MPPT	Maximum Power Point tracking
NL	Net Load
NOCT	Nominal Operating Cell Temperature
NPC	Net Present Cost
NREL	National Renewable Energy Laboratory
OC	Operation Cost
PV	Photovoltaic
REN	Rede Energética Nacional

SCR	Silicon Controlled Rectifier
SHP	Small Hydro Power
SMES	Compressed Air Energy Storage
SOC	State of Charge
SPV	Solar Photovoltaic
TC	Cells's Temperature
TES	Thermal Energy Storage
UL	Unmet Load
UREDA	Uttaranchal Renewable Energy Development Agency
VA	Volt-Ampere
WES	Wind Energy System

List of Symbols

A	Incremental diesel fuel consumption rate
Ah	Ampere hour
A_{panel}	Photovoltaic panel's area
B	Diesel generator fuel consumption at no load
B_f	Battery flow (dis)charge rate
B_{fmax}	Maximum battery flow (dis)charge rate
C_D	Diesel generator investment cost
C_{diesel}	Diesel cost
C_P	Photovoltaic generator investment cost
C_H	Hydro generator investment cost
C_W	Wind generator investment cost
F_{s1}	Inverted sigmoid activation function 1
F_{s2}	Inverted sigmoid activation function 2
h	Height
hr	Hour
h_t	Irradiation in a 30° tilt plan
i	Discount rate
it	Number of iterations
kW	Kilowatt
L_c	Critical load
LCO_D	Diesel generator levelized cost of operation
max_{it}	Maximum number of iterations
N_{bat}	Number of batteries
N_{BATmax}	Maximum number of batteries
N_{BATmin}	Minimum number of batteries
n_{swarm}	Number of particles that constitute the swarm
OC_{Dh}	Diesel generator operation cost at hour h
P_D	Diesel generator electrical power output
P_{gmax}	Maximum diesel generator power output
P_{Gmax}	Maximum renewable generator power output
P_{Gmin}	Minimum renewable generator power output
P_{HG}	Hydro generator output power
P_{PV}	Photovoltaic generator output power
P_r	Rated output power

P_R	Renewable output power
P_{WG}	Wind generator output power
R_{swarm}^2	Particle swarm coefficient of determination
R_{φ}^2	φ coefficient of determination
SOC_{max}	Maximum state of charge
SOC_{min}	Minimum state of charge
T_{amb}	Ambient temperature
T_f	Power failure time
U_n	Battery nominal voltage
v	Wind speed at height h
v_0	Wind speed at height h_0
V_c	Cut-in speed
V_f	Cut-off wind speed
V_r	Rated wind speed
X_{queen}	Swarm queen
X_{best}	Best fitness particle
X_{swarm}	Swarm particle
α	Scale parameter internal to the algorithm
$\Delta\varphi$	Normalized variation of φ
ε	Fit curve mean error
η_{panel}	panel's efficiency , adjusted to ambient temperature
η_{MPPT}	Maximum power point tracker efficiency
$\mathcal{N}(\mu, \sigma^2)$	Gaussian distribution
μ	Mean value
∇_{φ}	φ gradient
σ^2	Gaussian distribution variance
$\sigma_{Fitness}$	Fitness standard deviation for all composing swarm particles
σ_{φ}	Distance's standard deviation between X_{queen} and X_{swarm}
τ	Power variation's coefficient at panel's cell temperature
τ_P	Photovoltaic generator annualized discount rate
τ_W	Wind generator annualized discount rate
τ_H	Hydro generator annualized discount rate
τ_D	Diesel generator annualized discount rate
τ_B	Battery annualized discount rate
φ	Distance between the queen and a random particle

Chapter 1

Introduction

This thesis was accomplished as the final scope procedure of Mestrado Integrado em Engenharia Electrotécnica e de Computadores, Faculdade de Engenharia da Universidade do Porto.

The aim of this work is to optimize the design of stand-alone hybrid systems, for any place around the world. New and powerful optimization techniques were developed working extremely well when applied to the system optimization. Moreover, this technique shows a great potential when applied in other areas than the one studied here.

This chapter contemplates an initial approach to the problem including the context as well. It presents the basic ideas that will be applied in the dissertation. The chapter's final exposes an organized abbreviated description and explication of this work.

1.1 Context

Our civilization has steadily progressed due to the energy provided from the three great fossil fuels - coal, petroleum and natural gas. The world as we know it relies on petroleum on a day to day basis for transportation, agriculture, chemicals and materials and, not trivially, for the basic needs of electricity supply. The continues extracting rates mistreat is obviously an unsustainable situation due to the fact that they grossly exceed the rate at which they are laid down [Dell e Rand \(2004\)](#).

Around two billion people world-wide do not have access to electricity services, of which the main share in rural areas in developing countries. Millions of people have hopeless dreams of a fuel source for cooking their food. It is a fact that electricity and general appliances increase the quality of life for each one of us, but in ways that we, in developed countries, take for granted. In other words, electricity is an everyday reality but for two-thirds of mankind, it is a rare and unaffordable luxury. Simple things like the purification of water needs energy and, in developing countries, people need to walk miles to the nearest clean well because they often lack well-constructed roads or simply a mean of transport. For these roads to be build, diesel fuel

powers heavy machinery is needed, electric lights for longer workdays is also essential so as to improve the buildings constructions times. Our standard of living is fully dependent on the energy we have to spend - energy makes life easier [Manwell \(2004\)](#). Energy in the poorest countries is needed because it enables irrigation and the production of chemical fertilizers, capital requirements to help feed the population. Energy keeps cities running, providing jobs for millions of people but when this becomes scarce, cities stop running, jobs disappear and those things we take like day-to-day realities become expensive. A country that provides more energy to its population can then improve their quality of life [de Vries \(2009\)](#).

Energy is not a cure for problems in undeveloped African countries. However, not having energy does make them much harder to solve. The problem in most the cases is not too little energy yet too little power. The issue remains on we humans do not effectively and efficiently use the renewable resources that are abundant in nature and available to us. We must explore how to take more advantages of these renewable energy resources that are free, for us and for all, by studying the ways to increase the efficiency on how this energy can be converted to one of the critical causes that can and, i truly believe, will save us upon the years to come.

1.2 Motivation

People who live in underdeveloped countries have to spend more than their disposable incomes on fuel for cooking food than they have to spend on food itself [Herring \(2009\)](#). These countries we are talking are mostly tropical countries. Ironically, or at least sarcastically speaking, these are countries with plenty of sunlight and wind to power many of the people's basic needs. Photovoltaic panels and wind turbines can easily capture enough energy to, say, power light bulbs or charge batteries. This could be the beginning steps to decrease starvation in poor countries where nothing or little is done to ensure the basic needs for the human right to live.

The lack of technology, at affordable prices, is one of the causes that hinder the investment in such underdeveloped countries [Herring \(2009\)](#). We need low budget solutions to high price problems. We need engineers who can develop new technologies and improve the ones that already exist. Hybrid energy systems are one of the possible solutions to this problems. Imagine a small village in the middle of Africa where people need to pump water, cook food, lights to read books and learn, where they need energy to improve the standards of their life. Transport networks do not reach such points, in Africa and in many other continents, where people still today have no means to take for granted the basic needs to live. So, it is needed to improve the ways by which these hybrid renewable systems are design, to minimize the investments to be made and make it possible to support the millions of people who, nowadays, are constantly starving and private from the craving life where we belong.

These solutions can start with the work from students around the world, who have always believed in their contributions, even if minimum. That is why this thesis contemplates ways to increase the reliability when designing hybrid energy systems. From many software that people can use to dimension this systems, a discrete base solution was always needed and so, the real

optimization of the system would not be possible. It was tried then to optimize these solutions in a continuous way, to really understand the basics of renewable sources complementarity and not to go by the assumptions on what could occur.

1.3 Objectives

In this section the thesis objectives are presented. The main objective was to develop new methodologies for design optimization of stand-alone hybrid energy systems. However, this objective can be divided in three main sub-objectives:

- Combine the dispatch strategies optimization with the design optimization of the hybrid system.
- Develop a new and innovating process that ensures the hybrid system continuous optimization.
- Develop new adequate optimization techniques that could be applied to several optimization problems.

1.4 Methodologies

The methodologies and software use in this thesis must be itemize:

- For data analysis it was used SPSS, Microsoft Excel and Matlab.
- For programming purposes it was used VBA and Matlab.
- Image processing was done with Microsoft Visio, Excel, Matlab and Acrobat Pro.
- The hybrid system model was implemented in the internal code VBA, with Microsoft Excel interface.
- It was used previous designed software to design or to simply learn about system dispatch strategies like HOMER, HYBRID2 and HOGA.
- The design interface of this thesis is $\text{\LaTeX}$ based.

1.5 Thesis Structure

Beyond the scope of this chapter 1, with an introductory nature, this thesis contains six more chapters, divided by the concepts that should be studied.

In chapter 2 begins the state of the art regarding the principles that constitute the basics of this thesis. The components of several hybrid systems are presented as well as their functions to the system. Some applications are still referred. It is also described a brief review of the renewable resources that will be studied in this work and the hybrid system economics.

In chapter 3 the state of the art continues. In this chapter, the literature about unit sizing, optimization dispatch and design, is reviewed. Some of the most known software for design optimization of hybrid systems are also briefly described.

In chapter 4 this thesis base is constructed. The system is assembled with all renewable and fossil generators performance models, the storage, and the load diagrams. Several dispatch strategies are defined concerning the ways on which the optimization will occur.

In chapter 5 the novel optimization algorithm is presented. It will be explained how does the Gradient Swarm Optimization (GraSO) algorithm works, what are its principles and how the idea to look for a new and innovating optimization algorithm occur. Several test functions are presented to ensure the algorithm's good behavior.

In chapter 6 the results of applying GraSO to the optimization of hybrid energy systems are discuss. First it is explained the aggregation between GraSO, developed in chapter 5, and the system model, developed in chapter 4. Secondly, several case studies are applied to better understand how can the resources complementarity improve the hybrid system.

In chapter 7 the conclusions of this work are presented, as well as the thoughts on how this work can be further developed.

1.6 Data and Information

During this thesis, several information data was used. This data is of an extremely importance to this work so it seems like an obligation to be reference.

- Load diagrams, wind and solar data, from HOMER's sample website
- Historical hydro data from 2007 to 2008 from a generic small hydro and wind plant, gently ceded by SmartWatt.
- Information about investment costs on renewable generators, gently ceded by Professor Cláudio Monteiro, Faculdade de Engenharia da Universidade do Porto, and Professor Cristina Camus, Instituto Superior de Engenharia de Lisboa.
- Hydro run-of-the-river data retrieved from Rede Energética Nacional (REN)

Chapter 2

Hybrid Energy Systems - Principles

2.1 Introduction

The term hybrid energy system refers to those applications in which multiple energy conversion devices are used together to supply an energy requirement. These systems are often used in isolated applications and normally include at least one renewable energy source in the configuration. Hybrid energy systems are used as an alternative to conventional systems, which typically are based on a single fossil fuel source. Hybrid energy systems may also be used as part of distributed generation application in conventional electricity grid [Manwell \(2004\)](#).

As already said in chapter 1, the use of renewable energy sources presents a tremendous potential for many applications and especially off-grid stand-alone systems. In this context, one of the most promising applications of renewable energy technology is the installation of hybrid energy systems (HES) in remote areas, where the grid extension is costly and the cost of fuel increases drastically with the remoteness of the location. Recent research have shown that HES have an excellent potential, as a form of supplementary contribution to conventional power generation systems [Belfkira et al. \(2008\)](#). In figure 2.1, one of the most common hybrid renewable system implemented and studied until the present date is described.

2.2 Applications

There are numerous possible applications for hybrid power systems. The most common examples are:

- Central grid connected hybrid systems (CGHS)
- Isolated grid hybrid systems (IGHS)
- Isolated or special purpose hybrid systems (ISHS)

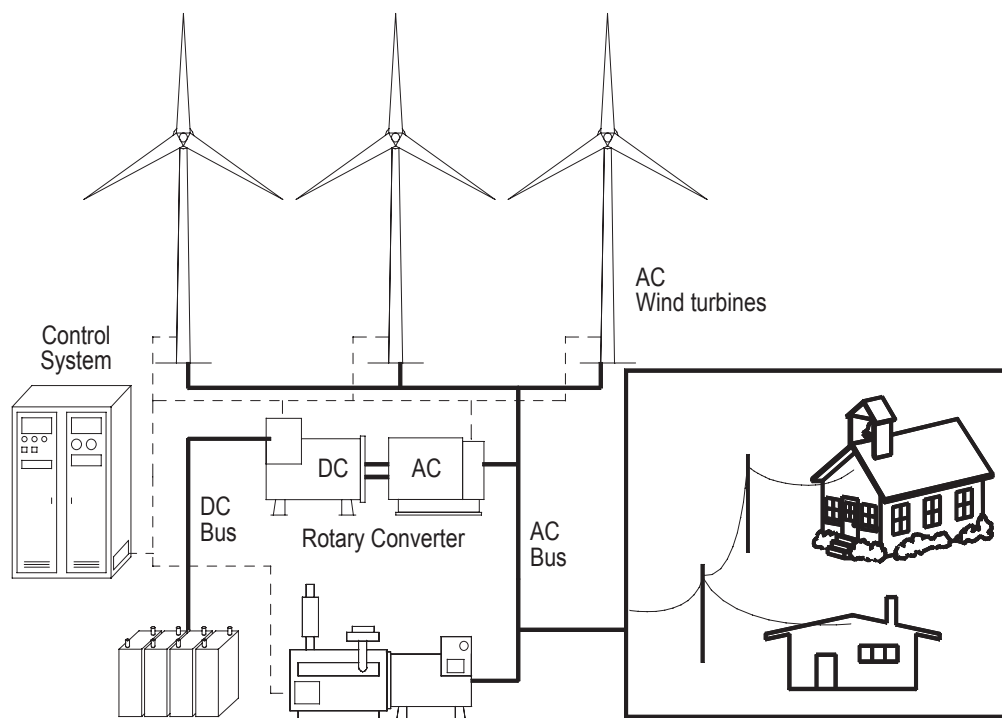


Figure 2.1: Schematic of a typical wind diesel hybrid system with storage [Corbus \(2006\)](#)

The classic example of the hybrid energy system is the remote, diesel-powered AC network (IGHs). The basic goal is to decrease the amount of fuel consumed by diesel generators and to decrease the number of hours that they operate [Manwell \(2004\)](#).

Isolated grid hybrid systems differ in many ways from most of those connected to a central grid. First, they must be able to provide for all the energy that is required at any time on the grid or find a graceful way to shed load when they cannot. They must be able to set the grid frequency and control the voltage. The latter requirement implies that they must be able to provide reactive power as needed. Under certain conditions, renewable generators may produce energy in excess of what is needed. This energy must be dissipated in some way so as not to introduce instabilities into the system [Peças Lopes \(2006\)](#).

There are basically two types of isolated grid hybrid systems which include a renewable energy generator among their components. These are known as low penetration or high penetration, depending on the ratio of renewable production by the total electrical load being served. Low penetration, which is on the order of 20% or less, signifies that the impact of the renewable generator on the grid is minor, and little or no special equipment or control is required. High penetration, which is typically over 50% and may exceed 100%, signifies that the impact of the renewable generator on the grid is significant and special equipment or control is almost certainly required [Manwell \(2004\)](#). High-penetration systems may incorporate supervisory control, so-called dump loads, short-term storage, and load management systems [Nema et al. \(2009\)](#). Two important considerations in an isolated system are whether the system can at times run totally on the renewable source (without any diesel generator on) and whether the renewable source can run in parallel with (i.e.,

at the same time as) the diesel generator.

2.3 Technology used

A wide range of technology may be used in a hybrid energy system. Some say that part of the system's steadiness is lost due to the large number of components. However, manufactures have been studying several ways to increase this reliability [Morea et al. \(2007\)](#). Another issue will relate to the reliability of operation and sizing of the HES, which will be discussed later in this work. Devices to be discussed include energy consuming devices (loads), renewable energy converters, fossil fuel generators, energy storage devices, power converters, control systems, and load management devices. Some of the various possible devices and arrangements that may be found in HES are illustrated in figure 2.2. The primary focus here is on isolated network hybrid systems, but much of the technology applies to other types of HES as well.

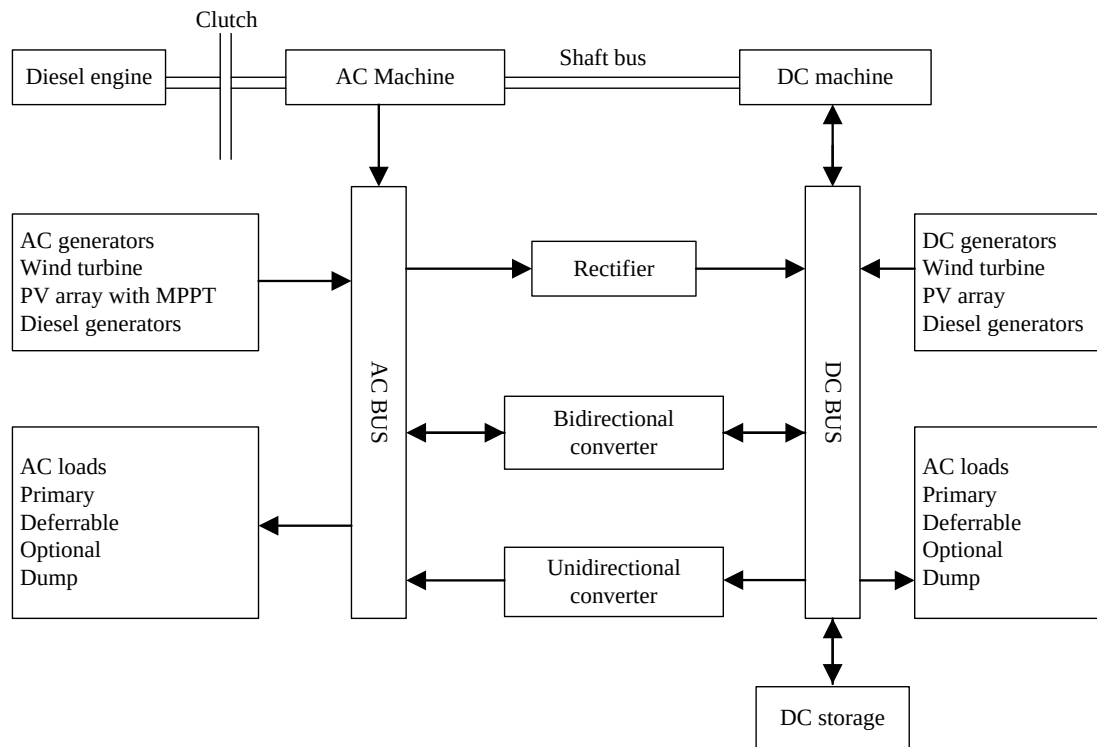


Figure 2.2: Possible devices and arrangements in HES [Manwell \(2004\)](#)

2.3.1 Renewable Energy Generators

Renewable energy generators are devices that convert energy from its original form in the renewable energy source into electricity. Renewable energy generators that are most likely to be found in hybrid energy systems include wind turbines and photovoltaic panels [Gupta et al. \(2007b\)](#). Some hybrid energy systems use hydroelectric generators [Gupta et al. \(2008a\)](#), biomass

fueled generators [Gupta et al. \(2008b\)](#), or fuel cells [Zahedi \(2007\)](#). These references are only one of the multiple cases that could be taken as an example for each type of application. At this point, it would be unreasonable to expose all the references searched. Consequently, there have been chosen the most complete and incisive articles with the highest factor rates [kn: \(2009\)](#).

2.3.2 Fossil Fuel Generators

Fossil fuel generators are commonly used in hybrid energy systems. Actually, most isolated power systems are based on fossil fuel, using internal combustion engines as prime movers. It is common to see diesel engine/generators in medium-sized and larger isolated systems. The smallest systems sometimes use gasoline and some very large isolated power systems occasionally use conventional oil-fired steam power plants. Diesel generators typically consist of three main functional units: a diesel engine, a synchronous generator with voltage regulator, and a governor (device which automatically regulates speed). The diesel engine is normally connected directly to a synchronous generator. A voltage regulator ensures the proper voltage is produced. The frequency of the AC power is directly proportional to the engine speed, which in turn is controlled by the governor [Zoulias e Lymberopoulos \(2008\)](#).

Diesel engine generators are often called on to follow the load. That means that their output must be equal to the system load less the production of any other generators that might be producing energy - net load. As the load may go up and down, so must the electricity generated. This is known as part load operation. Generally, the conversion efficiency is less at part load than at full load. Fuel consumption over the full range of operation is summarized in fuel curves. In these curves, fuel consumption is graphed against engine loads (see figure 2.3). Regardless of efficiency considerations, manufacturers normally recommend that diesel generators not be run below some specified minimum power level, known as the minimum load. Typically, the minimum recommended load is between 25% and 50% of rated. Engines run for long periods at levels below the minimum recommended can experience a number of problems [Zoulias e Lymberopoulos \(2008\)](#).

2.3.3 Energy Storage

Energy storage is often used in hybrid energy systems. It can be useful for ruling a mismatch between the electrical load and the renewable energy resource, and nevertheless to facilitate the control and operation of the overall system by being capable of smoothing out load fluctuations and making up for seasonal variations in renewable sources. Energy storage technologies are classified according to the energy, time, and transient response required for their operation [Farret \(2006b\)](#). In terms of energy requirements, energy storage capacity can be classified regarding the density needs, for medium and long-term needs, or relatively to power density, for short and very short-term needs. In an hybrid energy system, energy storage can provide the required constant and stable output of the system, despite load fluctuations and maintenance services. It is able to provide energy for ride through lacks of primary energy resources such as wind, solar and hydropower. Energy storage as the capability of supplementing a diesel generator or a fuel cell, providing load

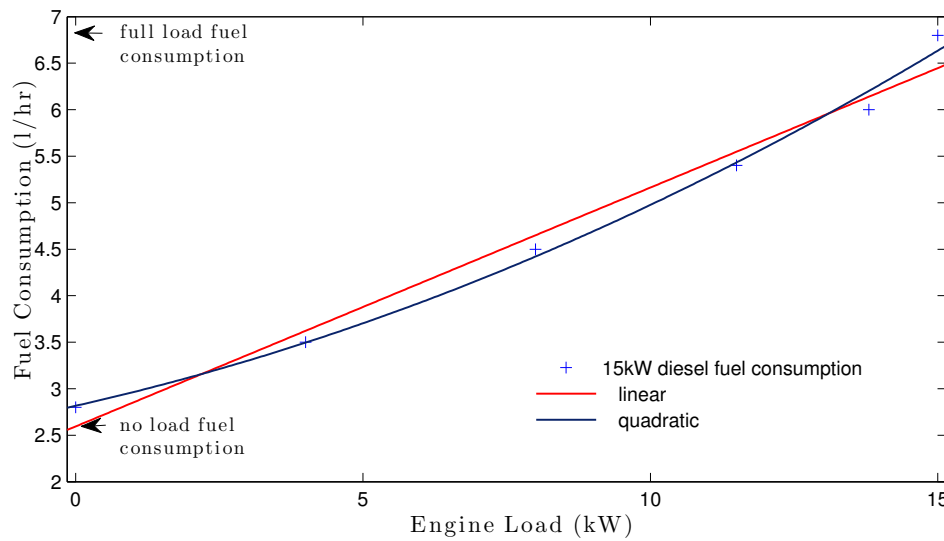


Figure 2.3: A typical diesel engine fuel curve [Farret \(2006a\)](#)

following services and increasing the generator efficiency, reducing fuel consumptions as well. A storage unit can operate in parallel with a generating unit to meet temporary higher peaks of demand than the rated generator capacity. In figure 2.4, it is possible to see both mature and emerging storage technologies organized in categories of ride-through, power quality and energy management.

Energy storage can be classified in two main applications, which is convertible use and end-use. The first one is that which can be converted back to electricity. End-use storage can be applied to a particular end-use requirement but may be, or not, converted back to electricity. There are many convertible storage media, although only a few of them are used frequently in the system configuration. Batteries are the most commonly used form in hybrid energy systems. Nevertheless, many studies have been performed for different (or emergent) forms of convertible storage. These are the less usually used, but often discussed forms, like pumped hydroelectric [Anagnostopoulos e Papantonis \(2007\)](#); [Katsaprakakis et al. \(2008\)](#), flywheels [Bolund et al. \(2007\)](#); [Leclercq et al. \(2003\)](#), compressed air [Denholm e Sioshansi \(2009\)](#); [Lund e Salgi \(2009\)](#) and hydrogen [Shakya et al. \(2005\)](#); [Zhou e Francois \(2009\)](#).

In a pumped hydroelectric system, the water is pumped from one reservoir at a low elevation up to one at a higher elevation. The amount of energy that can be stored is a function of the size of the reservoir and the difference in elevation. The overall efficiency of the storage is a function of the efficiency of the pumps and turbines (which may be the same devices) and the hydraulic losses in the pipes connecting the two reservoirs. The use of pumped storage is limited by the lack of sites where such facilities can be installed at a reasonable price [Manwell \(2004\)](#). The typical overall efficiency of pumped hydro systems is bounded in 65% and 77%, while the maximum depth of discharge is up to 95% without affecting their considerable (up to 50 years) service period [Kaldellis et al. \(2009\)](#).

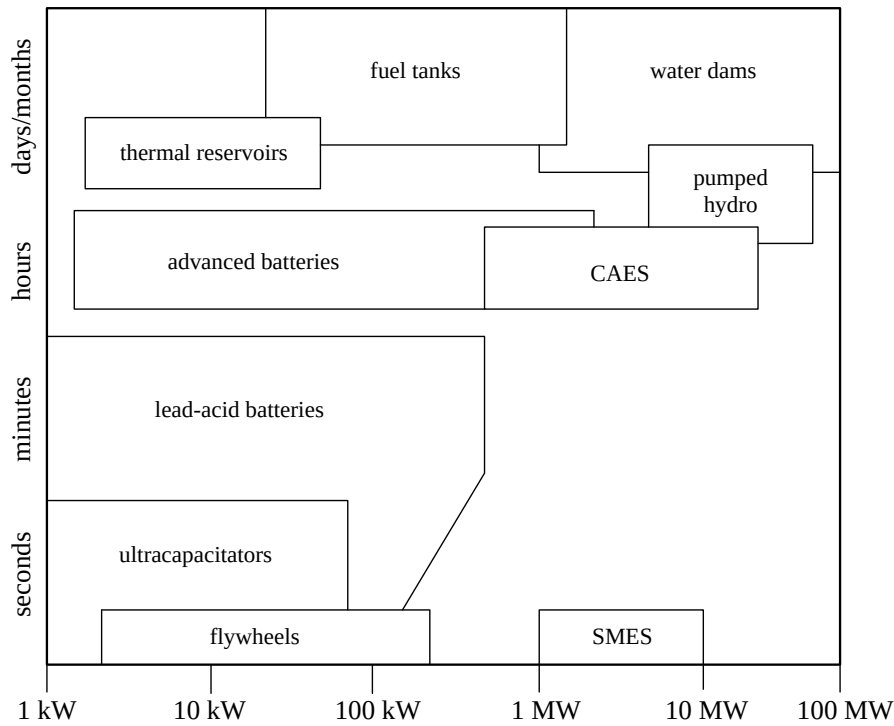


Figure 2.4: Energy storage devices and corresponding time capacity [Farret \(2006b\)](#)

Flywheels are kinetic energy storage devices, and store energy in a rotating mass (rotor), with the amount of stored energy (capacity) dependent on the mass and form (inertia), and rotational speed of the rotor. An accelerating torque causes a flywheel to speed up and store energy, while a decelerating torque causes a flywheel to slow down and regenerate energy [Ruddell \(2003\)](#). Flywheels typically store relatively small amounts of energy, but they can absorb or release the energy at high rates. Thus in hybrid power systems they can be used to smooth short term fluctuations in power (on the order of seconds or minutes) and they can facilitate system control [Kaldellis et al. \(2009\)](#).

Compressed Air Energy Storage (CAES) systems store energy by compressing air within an air reservoir, using a compressor powered by off-peak/low cost electric energy. Three reservoir types are generally considered: naturally occurring aquifers (such as those used for natural gas storage), solution-mined salt caverns, or mechanically formed reservoirs in rock formations. During discharge, the plant's generator operates to produce power using a conventional natural gas combustor and the stored air. During charging the turbine operates in reverse (as a motor) to provide mechanical energy to the air compressors. A special clutch is required to allow the turbine/generator to operate in two directions [Schoenung e Burns \(1996\)](#). CAES is an available technology for large-scale (1MW-100MW) energy storage [Kaldellis et al. \(2009\)](#).

Similar to electricity, hydrogen is a high-quality energy carrier, which can be used with a high efficiency and zero or near-zero emissions at the point of use. Hydrogen can be used for power generation, and could replace current fuels in all their present uses. Hydrogen can be produced using a variety of starting materials, derived from both renewable and nonrenewable

sources, through many different process routes. In an hybrid system, the electrolysis of water is widely used. The process of producing hydrogen from renewable sources is, more precisely, the hydrogen production by the electrolysis of water, where the main power input is electrical power produced from the conversion of the renewable sources [Gupta \(2008\)](#).

End-use storage, as opposed to convertible storage, refers to the situation in which some product is created through the use of electricity when it is available. The product is then stored and made available when it is needed. Load management schemes often incorporate some end-use storage.

Thermal energy storage (TES) is the concept of generating and storing energy in the form of heat or cold for use during peak periods. Thermal energy storage has been used for centuries, but only recently have large electrical users taken advantage of the technique for cost management. The process involves storing Btu's (or lack of Btu's) for use when either a heat source or a heat sink is required. The use of eaves, root cellars, ground coupled heat pump systems, and adobe type thermal mass could all be considered forms of thermal storage [Turner \(2006\)](#). Pumped water and pure water technologies are other types of end-use storage. The first one is quite similar to the pumped hydroelectric with the difference that, when the storage is elevated, the water flows by gravity to the point of use, so no further inputs of externally produced energy are required. The second one is a less common form of energy storage, bases on the production and then storage of pure water from salty or brackish water. This process can involve ultrafiltration, reverse osmosis, or vapor compression evaporation to produce pure water [Hadjipaschalis et al. \(2009\)](#).

2.3.4 Power Converters

For any hybrid energy system to function properly, it is common that one or more power converter to be incorporated into the system. These are either electromechanical or electronic devices.

Within electromechanical power converters, there are at least two types that have been used in hybrid energy systems - rotary converter and the synchronous condenser. A rotary converter is an electromechanical device that converts AC to DC or vice versa. When it is converting AC to DC it is a rectifier. When operating the other way it is an inverter. The rotary converter consists of two rotating electrical machines that are directly connected together. One of them is a DC machine; the other is an AC machine. Either of them can run as a motor or generator depending on the intended direction of power flow. The AC machine can be either an induction machine or a synchronous machine. The one which will be used depend on the requirements of the system.

Rotary converters have the advantage that they are a rugged and well-understood technology that has been around for many years. Their disadvantage is that their costs are higher and their efficiencies are lower than are electronic devices that can serve the same purpose [Greenberg \(1999\)](#).

A synchronous condenser, or compensator, is a synchronous motor that is not attached to any driven equipment. Its field is controlled by a voltage regulator to either generate or absorb reactive power as needed to support a system's voltage or to maintain the system power factor at a specified level. Synchronous condensers are used in hybrid energy systems when there are, for at least some

of the time, no other synchronous machines connected. This is often the case in those systems that include diesel generators but that are intended to allow all the diesels generators to be turned off under some circumstances [Weedy \(1972\)](#).

Many of the electronic converters serve similar functions to the electromechanical devices described previously, but have a number of advantages, such as lower cost, higher efficiencies, and greater controllability. The devices of greatest interest include rectifiers, inverters, dump loads, and maximum power point trackers [Manwell \(2004\)](#).

A rectifier is a device that converts AC to DC, commonly used to charge batteries from an AC source. Single-phase diode rectifiers require a rather high transformer VA rating for a given DC output power. Therefore, these rectifiers are suitable only for low to medium power applications. For power output higher than 15kW, three-phase or polyphase diode rectifiers should be employed [Rashid \(2001\)](#).

An inverter is a device that converts DC to AC, used to supply individual AC loads from a DC source or a battery bank.. The primary switching elements are either silicon controlled rectifiers (SCRs) or power transistors (IGBTs). They are arranged in a bridge circuit and switched on (and off, in the case of transistors) in such a way that an oscillating waveform results. Some inverters operate in conjunction with other devices that set the system frequency. These are referred to as line commutated. Other inverters have the capability to set frequency themselves (self-commutated) [Rashid \(2001\)](#).

One component that may be required in hybrid power systems but is uncommon in conventional isolated systems, is a dump load. A dump load is used to protect against an excess of power in the network. Such an excess could arise during times of high renewable contribution and low load. Excess energy could lead to grid instability. The dump load may be a real device, based on power electronics or switchable resistors. In some cases, dissipation of excess power may be accomplished without the use of a dump load. An example is the dissipation of excess wind power by furling the rotor or blade pitch control [Farret \(2006a\)](#).

In systems using PV cells, the array voltage is given by the match voltage of the connected load. It is sometimes useful to use power conditioning equipment to match the load with the characteristics of the PV cell. One method of carrying this in practice is to use a maximum power point tracker (MPPT) to maximize the PV system output. MPPT are devices that keep the impedance of the circuit of the cell at levels corresponding to best operation, and also convert the resulting power from the PV array so that its voltage is the one required by the load [Duffie \(1991\)](#)

2.3.5 Supervisory Controller

Many hybrid systems, especially the more complex ones, have a supervisory controller to ensure proper operation of all the devices within the system. The possible functions of a supervisory controller are illustrated in figure [2.5](#).

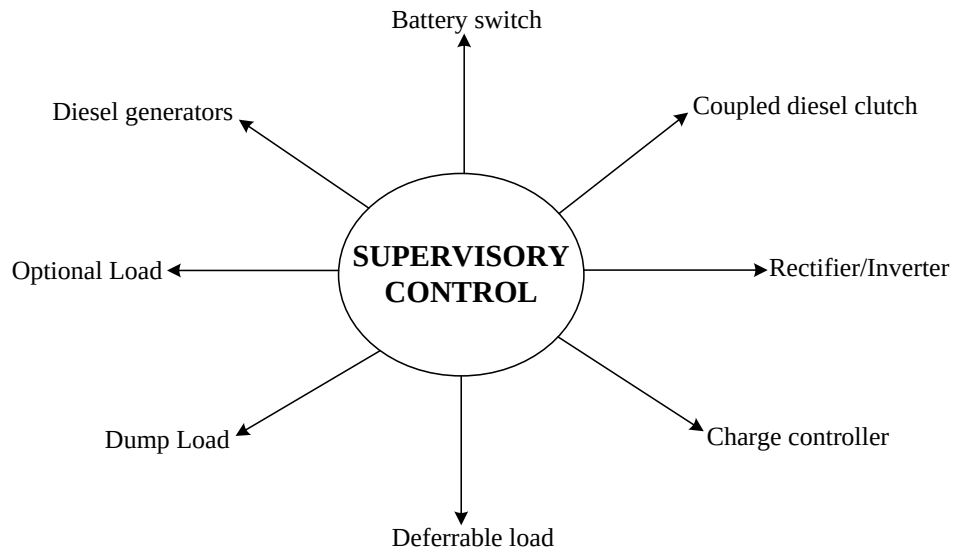


Figure 2.5: Supervisory control functions [Manwell \(2004\)](#)

2.4 Energy Loads

The energy supplied by a hybrid system can be categorized in a variety of ways. The first has to do whether the energy supplied is electricity or heat (thermal load). Within the electrical category, electricity loads are often divided into primary and secondary loads.

Primary loads are those that must be served immediately, at a specific time. Demand associated with lights, TV, household appliances are examples of primary energy loads [Farret \(2006a\)](#).

Secondary loads are associated with load management, and they may be further divided in what are known as deferrable and optional loads. Deferrable loads have some flexibility in when they are served (within a defined time interval). The inherent storage ability of battery-charging stations and water pumps, as well as the flexibility as to when the system can serve them, classifies them as deferrable loads. Optional loads, as the name refers, are only served if there happens to be sufficient excess energy available to do so [Farret \(2006a\)](#).

Regardless of the load type, it may be noted that loads frequently vary significantly from one season to the next as well as over the week and over the day.

2.5 Renewable Energy Resources

2.5.1 Wind

Ultimately wind resources are driven almost entirely by the sun's energy, causing differential surface heating, but they tend to be very dependent on location. Over most of the earth, the average wind speed varies from one season to another. It is also likely to be affected by general weather patterns and the time of day. It is not uncommon for a site to experience a number of days of relatively high winds and for those days to be followed by others of lower winds,

strongly interfering with the operation planing of an hybrid system comprehending wind turbines. The wind also exhibits short term (seconds to minutes) variations in speed and direction, known as turbulence [Burton \(2001\)](#).

2.5.2 Solar Radiation

The solar radiation resource is fundamentally determined by the location on the earth's surface, the date, and the time of day. Those factors will determine the maximum level of radiation. Other factors, such as height above sea level, water vapor or pollutants in the atmosphere, and cloud cover, decrease the radiation level below the maximum possible. Solar radiation does not experience the same type of turbulence that wind does, but there can be variations over the short term. Most often, these are related to the passage of clouds [Rosa \(2005\)](#).

2.5.3 Hydropower

The hydropower resource at a site is a function of the amount of flowing water available in a river or stream and the change in elevation. The head is usually relative constant (affected only by high water during storms), but the amount of water available can vary significantly over time. The average discharge is determined by rainfall and the drainage area upstream of the site on which the rain falls. Discharge will increase after storms and decrease during droughts. Soil conditions and nature of the terrain can also affect the discharge. Short term fluctuations are normally insignificant [Rosa \(2005\)](#).

2.6 Economics

The choice on whether or not a HES is in fact used, and what components constitute him, is forcefully related to the economics of the system. The cost of a hybrid system is primarily determined by two factors: the cost of the system and the amount of useful energy that is produced, i.e. not the energy production but the energy truly used for consumption. Other factors are concerned when talking about the economics of an HES, like the cost of conventional energy, lifetime of the system, maintenance costs, and financial costs [Manwell \(2004\)](#).

The cost of the system is primarily affected by the individual's components cost that make up the system, and generally the renewable energy generators themselves. Diesel generators are also costly, but considerably less so than wind turbines [Manwell \(2004\)](#).

Economics of hybrid energy systems are typically evaluated by a technique known as life cycle costing. This method takes account of the fact that HES have relatively high initial costs but long lifetimes and low operating costs. These factors, together with various financial parameters, are used to predict present value costs, which can then be compared with costs from the conventional alternatives [Farret \(2006a\)](#).

Chapter 3

Hybrid Energy Systems - Design Considerations

3.1 Introduction

After a pre-feasibility study about the climacteric conditions and load profiles, the proper sizing of system components is made based on specific location weather data and maximum capacity. Being the unit sizing one of the most important factors when designing the HES, it is common sense that it will play an important part deciding the economic and reliability of the system.

The literature on this subject is very wide but limited. From the references studied, it is a fact that photovoltaic-wind hybrid systems are the most frequently analyzed. Very complete and with a remarkable explanatory factor articles were present by authors like Ajai Gupta [Gupta et al. \(2008b\)](#), [Gupta et al. \(2008c\)](#), [Gupta et al. \(2008d\)](#), simply making references to more complex studies on other renewable sources hybrid mixed such as hydro, biomass and others.

From this point on, an elucidative analysis of various unit sizing methods will be reviewed, specifically about the means by which the renewable energy generators capacity is determined as well as the capacity of the diesel generator and the number of batteries to guarantee load's imposed autonomy.

3.2 Brief Review on Design Techniques

In 1983, Borowy and Salameh [Ofry e Braunstein \(1983\)](#) proposed the loss of power supply probability as a technique for designing stand-alone solar electrical photovoltaic systems. Hongxing Yang and Lin Lu [Yang et al. \(2007\)](#) have presented a hybrid solar-wind system Optimization Sizing (HSWSO) model, to optimize the capacity sizes of different components of hybrid solar-wind power generation systems employing a battery bank. The application was based on the loss of power supply probability (LPSP) concept and the levelised cost of energy (LCE) concept, being

the LPSP considered the criteria for sizing the system. This technique represents the probability that an insufficient power supply results when the hybrid system is unable to satisfy the load demand. Others have used the LPSP approach to design hybrid systems [Borowy e Salameh \(1996\)](#).

Some differences can be seen from a probability method with LPSP, which is shown at paragraph above, and an analytical method with LPSP [Abouzahr e Ramakumar \(1991\)](#)

Francesco Bonanno et al. [Bonanno et al. \(1998\)](#) developed a logistical model for performance evaluation of hybrid generation systems (HGS). The special feature consisted in an auxiliary fictitious source introduced to the hybrid system in order to obtain the power electric balance at the busbars during the simulation stage in any case of ill-sized components. The auxiliary source represented a compensatory source of any power imbalance of the power plant during the power load request, and it allowed performing the simulation runs without interruptions. The observed imbalance powers were then used to update, in each iteration, the optimal system design.

Another sizing method is explained in [Chedid et al. \(2005\)](#). Here, a multi-objective design methodology was proposed based on the ϵ -constraint method to minimize the cost of the HES, taking in account gas emission minimization as a constraint of the problem. In a first stage, linear programming was used to minimize the total system cost while satisfying the energy demand, reliability, stability and battery constraints. The result of this first stage pointed to an optimum design of the system. Secondly, a same approach was used with the purpose to minimize CO₂ emissions as the main function of the multi-objective problem. The multiple results of the n-1 constraint equations form a multi-objective problem which is solved by the ϵ -constraint.

A simple but effective approach was developed by Pradeep K. Katti and Mohan K. Khedkar [Katti e Khedkar \(2007\)](#). The authors fixed first an energy flow strategie for the HES. The second step was selecting commercially available unit sizes for wind turbines, PV panel, as per site matching strategy and battery storage. Since the rating for the wind turbine far exceeded the ones of a single PV panel, they keep the number of turbines constant and increased the number of PV panel until the system was balanced. Next step consisted in experimenting different number of wind turbines as needed. For last, the LPSP was calculated for each combination that satisfied that the curve of ΔP vs. time had an average zero value over a given period of time.

B. Ai et al. [Ai et al. \(2003\)](#) developed a different approach to unit sizing PV-wind hybrid systems components. By fixing the capacity of wind generators, the whole year's LPSP values of the hybrid systems with different capacity of PV array and battery bank were calculated. Given the LPSP value, the trade-off curve between the PV array and battery bank capacity of the system meeting this load demand was drawn, then the optimum system configuration could be uniquely identified by drawing a tangent to the trade-off curve with the slope representing the relationship between PV module and battery costs. The authors include sensitivity factors in this mathematical models, like the surplus energy (Esurp), the loss of power supply (LSP), power failure time (Tf), loss of load probability (LLP) and the already used by others [Yang et al. \(2007\)](#) loss of power supply probability. By ensuring one initial configuration for the system, those parameters where constantly changing so the best design could be meet. This looks like a time consuming work but the results were very satisfying. In [Beyer e Langer \(1996\)](#), a trade-off method was used as

well. The author used this approach because of the conflicting objectives and the uncertainties evolving the problem. The objective aimed not to pretend to find a unique optimal solution, rather an organized way of evaluating the relationship between the attributes and the uncertainties, eliminating many plans that were inferior and, what as left, were plans which represented a reasonable compromise. The attributes to minimize were the capital investment and the loss of load probability and the uncertainties under which the design should be carried were associated with the load demand and the renewable energy sources availability. The solutions were chosen by the decision theory of the trade-off method, in which the solution is dominated if exists another one that is better in one attribute and not worse is another.

One of the most complex systems in the literature reviewed, was given by Gupta, A. in [Gupta et al. \(2007a\)](#). The complexity of the hybrid system was due to the large number of energy resources that composed the hybrid system: Small Hydro Power (SHP), Solar Photovoltaic (SPV), Wind Energy System (WES), Biomass Energy System (BES) and a Diesel Generator (DG). This study was made for particular interest of a cluster of villages in Jaunpur block district Tehri Garhwal of Uttaranchal state, India, which can not have access to electricity because of the consideration by Uttaranchal Renewable Energy Development Agency (URED A) to be remote and not economically viable for electrification by grid extension. By studying the assessment of energy potential and energy demand, the authors then applied a general model formulated in the basis of linear programming. Like in many other literature, the main objective was to reduce the total cost of providing energy to all the end users. We may look at this problem like the minimization of the amount of fuel consumed by the diesel generator, as this is the most expensive source for system dispatch.

In [Gupta et al. \(2008a\)](#) an action plan for the design of an hybrid renewable energy system was given. A step by step guide was presented so that a conscience and logical decision could be made. An explanation for the power supply of a certain village is given by figure 3.1.

The arguments used were quite simple, but very effective. First, certain criteria should be followed while selecting the villages for hybridization, i.e, the villages should be remote but reasonably accessible. Energy demand was another step to be studied to distinguish different types of needs assessment like household load, community demand, commercial demand and industrial demand. In order to estimate which villages would be suitable for which type of renewable energy source, a resource assessment was made based on the primary information collected from the field and on the secondary data available from different sources. The suggested thresholds for different resources for determining feasibility are given in the table 3.1. For last, a unit cost of resources was obtained by adding the capital recovery cost and operation & maintenance cost per unit of energy.

R.Ramakumar et al. presented in [Ramakumar et al. \(1992, 1995\)](#) a knowledge-based approach to the design of integrated renewable energy systems. With a year data, the authors divided into as many number of time-sections (seasons) as needed such that the resources and the loads had reasonably similar daily variations or were constant during each period of time. The knowledge-based technique was then used for each time-section to find the ratings of converters and the energy

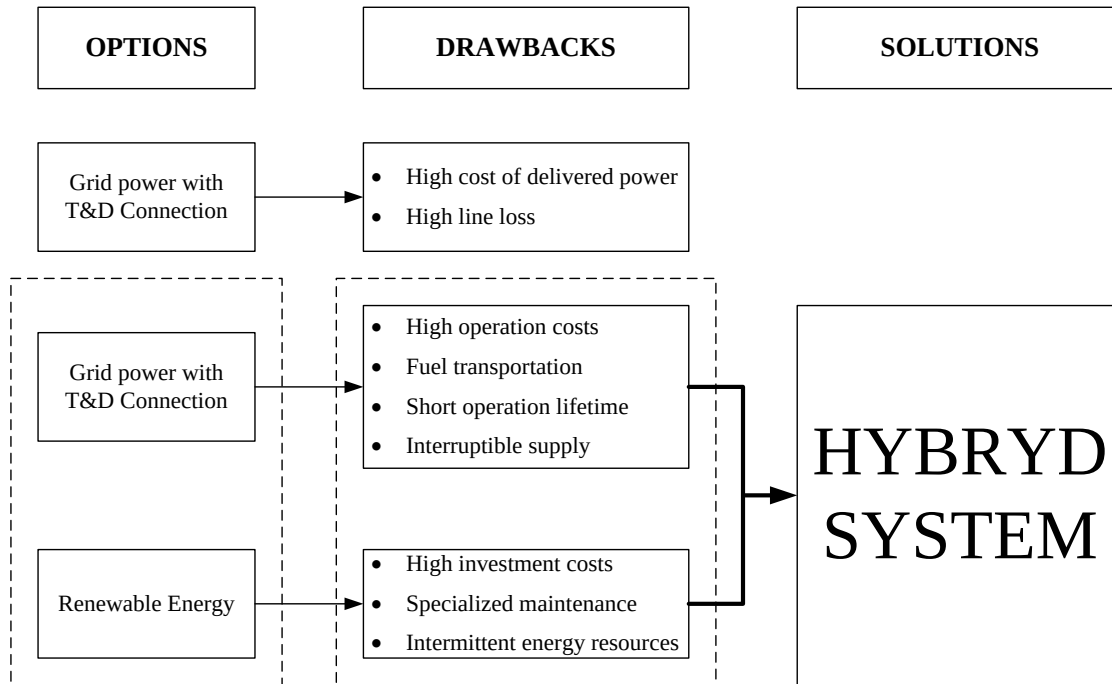


Figure 3.1: Power supply options for village electrification [Gupta et al. \(2008a\)](#)

needs at the desire reability level, subject to resource availability and at minimum capital cost. The final system design was base on the seasonal designs and the prioritization of the various seasons. If they were selected on the worst possible combination of resource availabilities and loads, an amount of energy excess would be available and the overall design failed to be cost effective.

Simulation approach [Beyer e Langer \(1996\)](#); [Celik \(2002\)](#) is another methodology used to design hybrid energy systems. The core of the procedure is formed by a time-step simulation for the evaluation of the system performance, using as input data, an hourly time series of meteorological data. To begin the simulation process, the user must first fix a level of desire reliability for the load supply (LLP) so that the performance of an initial system configuration could be simulated for a period of one or several years. The size of the components was then varied in an iteration until the desired performance was reached. Using a matrix search with a reasonable range of component sizes, a certain number of feasible configurations could be identified and, to decide one of those

Table 3.1: Amount of a site resource typically needed for feasibility [Gupta et al. \(2008a\)](#)

Site Resources	Typically needed
Full sunlight (<i>hrs/day</i>)	≥ 2
Wind speed (<i>m/s</i>)	≥ 4
Stream speed (<i>m/s</i>)	≥ 1
Biomass (<i>24kg – 1kWh</i>)	Depend upon cattle number
Fuel cost (<i>€/l</i>)	Depends upon application

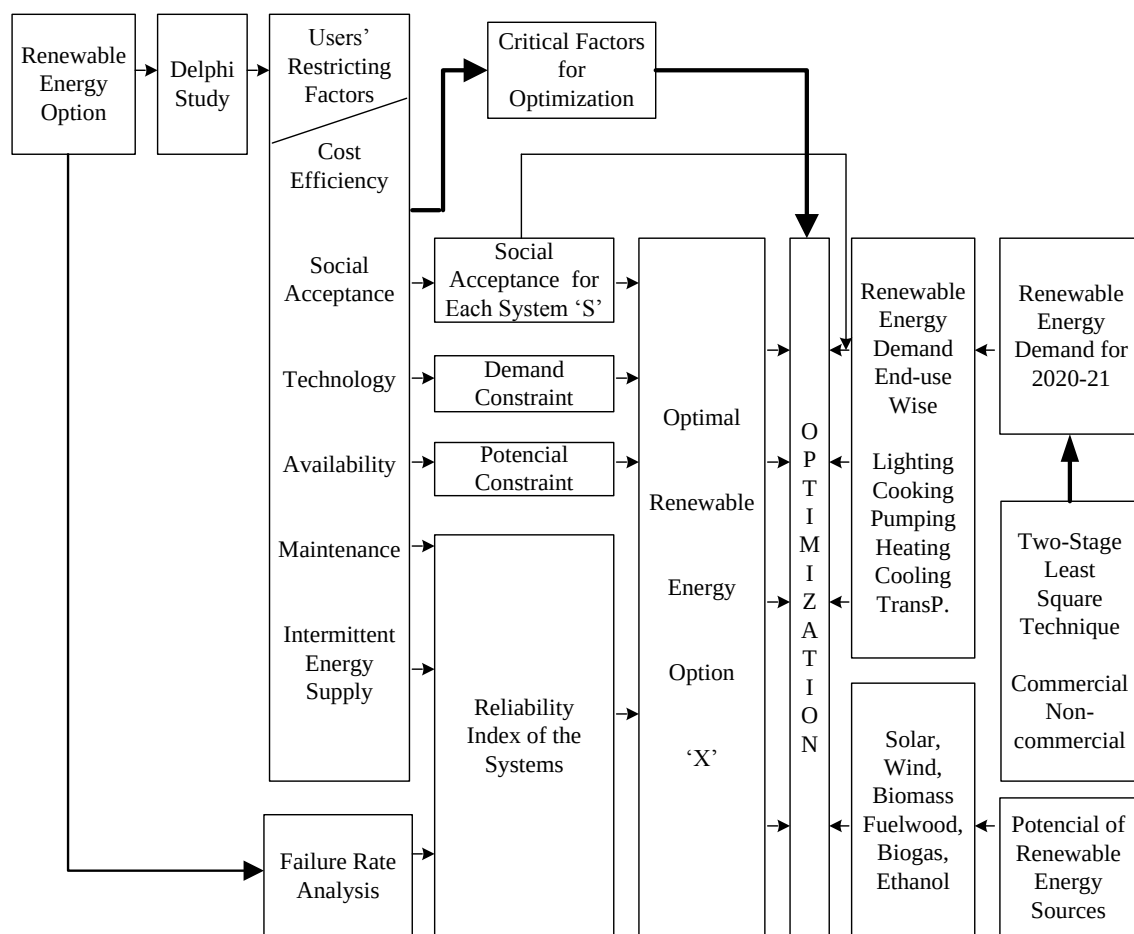


Figure 3.2: Flow-chart of a linear programming method including a Delphi study [Iniyan e Sumathy \(2003\)](#)

possible configurations, an optimization was applied according to a give figure of merit composed by the the number of components and the cost that the configuration implied. It is important to note that this approach was considered, by the authors, restricted to low LLP case systems. For intermediate LLP, the system was governed by seasonal meteorological conditions and so, the worst month approach should be abandoned.

Many authors studied the application of different models to developing countries with a huge potential in renewable energy resources. In [Iniyan e Sumathy \(2000, 2003\)](#), linear programming was applied to renewable energy models for different various-ends in India. Like almost all the literature reviewed, the main objective as to reduce the initial capital cost and the reliability of the system. Moreover, a Delphi study (see figure 3.2) was conducted to determine the social acceptance and the percentage use of renewable energy sources in different end-uses (lighting, cooking, pumping,...). When the social acceptance factor arrived from the Delphi study, it was used as a constraint in the model.

Kabouris et al. [Kabouris e Contaxis \(1992\)](#) used dynamic programming optimization techniques for determining the optimal expansion plan of an autonomous generation system including

diesel units, wind generators and photovoltaic generators. The total operation cost in a determinate year was considered under some planning and operational constraints like the maximum number of additions of each type of system component to be installed in that year, by an upper limit, so that this constraint represents limitations on capital investment. Diesel units reserve margin was also considered as a constraint. By limiting the interval operation of the diesel generator in percentage of peak load, it was possible to guarantee the system reliability. This procedure was done to limit a maximum wind and solar power penetration as well. The methodology processed the cost of the candidate additions period inflation during the expansion period, the estimate cost of fuels and the expected economic rates. In the end, a forward-backward dynamic programming algorithm was used to determine the optimal expansion policy and, if requested, it could also determine suboptimal solutions

A review of more than 90 published papers was made by S. D. Pohekar and M. Ramachandran [Pohekar e Ramachandran \(2004\)](#) where the applicability of various methods and models, concerning multi-criteria decision were analyzed.

An expert system was presented by Morea, F. et al. [Morea et al. \(2007\)](#). The algorithm was made on the basis of dynamic simulation, using a conventional simulation model, and all relevant information on cost, maintenance schemes and, for typically Italy and other countries in the Mediterranean area load profiles. The technology used included photovoltaic, wind generators, battery storage and a backup diesel. The expert system required generally information available at the initial stage of the project to determine the best hybrid mix unit sizing. Based on a neural network, the users wish to overcome the drawbacks of existing simulation software. The software initially used was HOMER and then, the neural network was trained using the generated database. The objective was to use a wide knowledge (technological specifications, costs, human experience in design) for redesigning the system after the simulation was done by HOMER. Figure 3.3 shows the basics of the expert system.

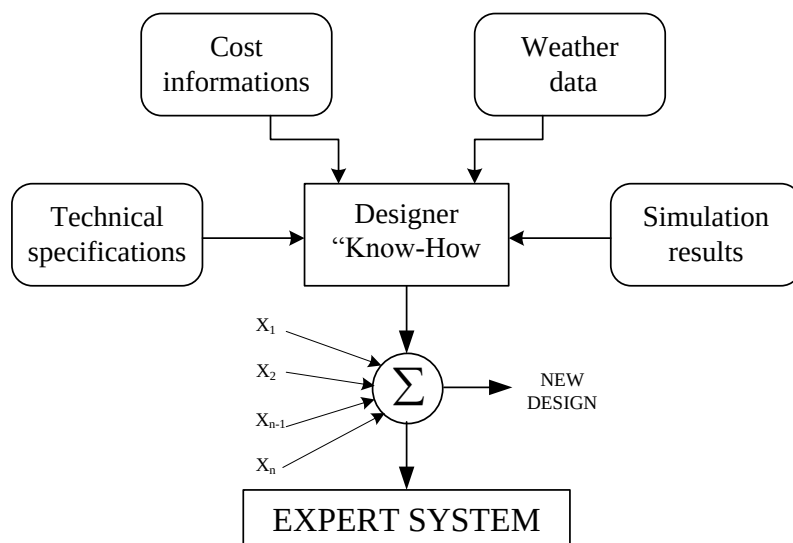


Figure 3.3: Data sources of the expert system [Morea et al. \(2007\)](#)

Koutroulis E. et al [Koutroulis et al. \(2006\)](#) proposed a methodology to calculate, among a list of commercially available system devices, the optimal number and type of units to ensure a 20 year operation with a minimized system cost, subject to the constraint that the load energy requirements were completely covered, resulting in zero load rejection. The main objective (total cost), was the minimization function, implemented using genetic algorithms. This technique was used due to the fact that the ability to attain the global optimum was relative computation simplistic, when compared to conventional optimization methods such as dynamic programming and gradient techniques. From a set of individuals which were composed by the system components, the algorithm chose the best combination in the evolution process so that after the maximum iterations defined by the user, the best set of components with the low cost were chosen. The methodology can be seen in figure 3.4.

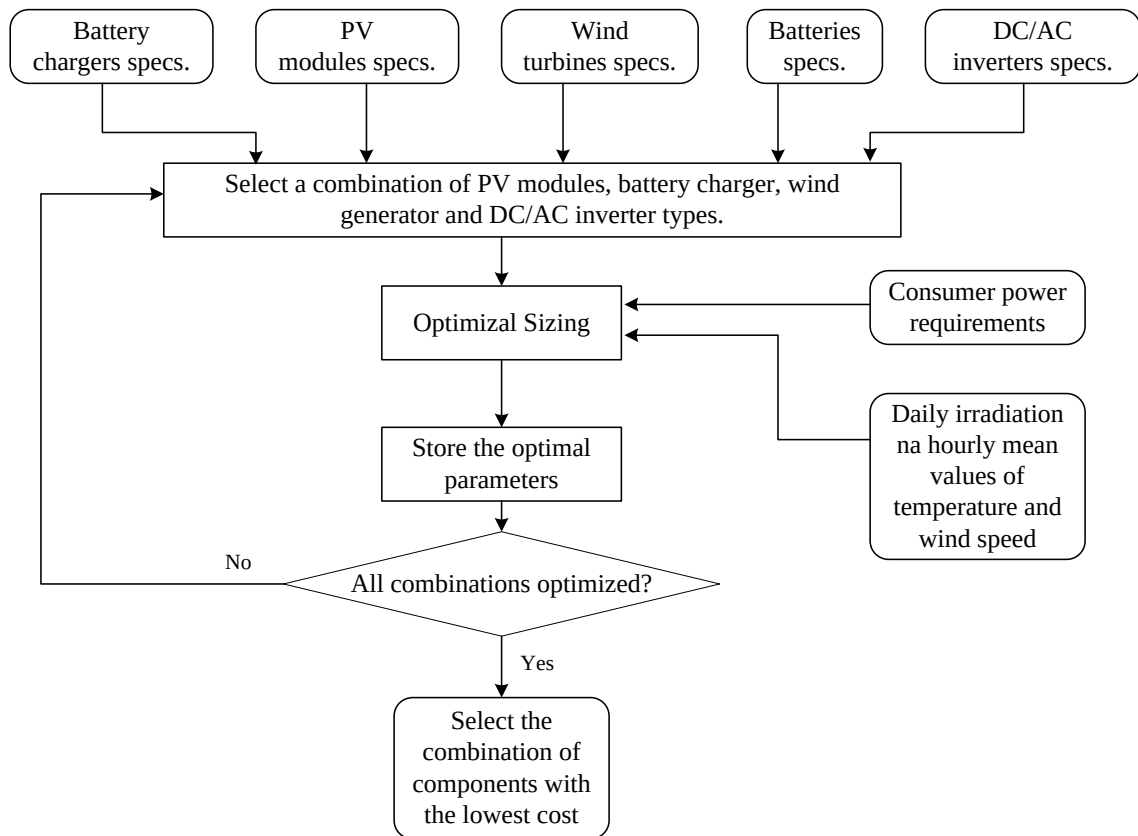


Figure 3.4: Flowchart of the genetic optimization methodology [Koutroulis et al. \(2006\)](#)

Yang [Yang et al. \(2009\)](#) also developed an optimization technique with genetic algorithms but a little more complexed. The author, instead of attaining to reach zero load rejection, he used the LPSP and the annualized cost of system concepts. The decision variables included in the optimization process were, as usual, the PV module number, wind turbine number, battery number and, for a more complex and complete algorithm processment, the PV slope angle as well as the wind turbine installation height. Like in [Koutroulis et al. \(2006\)](#), the author here justifies the genetic algorithm application like being generally robust in finding global optimal solutions,

particularly in multi-nodal and multi-objective optimization problems.

Still in the area of artificial intelligence applications in electric power systems, S.M. Hakimi and S.M. Moghaddas-Tafreshi [Hakimi e Moghaddas-Tafreshi \(2009\)](#) presented a novel intelligent method for optimal sizing of a stand-alone hybrid power system in Kahnouj area, south-east Iran. The system consisted of fuel cells, wind units, electrolyzers, an anaerobic reactor and some hydrogen tanks. The system used biomass as an available energy resource. The optimization process was carried out by a particle swarm algorithm who chose the best components, by simulating a flock of birds flying together to the optimal point. If the constraints of the problem were satisfied, the solution was a best optimal individual of the problem, and was carried to the next iterations like the best global solution, until the maximum iterations were achieved.

Some authors [Fung et al. \(1993\)](#) used simulated annealing techniques applied to hybrid energy systems. This approach consists in a random search method similar to the iterative improvement algorithm, but it may accept inferior solutions based on a probabilistic measure. The algorithm was therefore possible to escape from being trapped within local minimum points and to seek after the global or near global solution in the overall solution space. Therefore, starting from an initial system design, the total cost was calculated and in the next iteration, the new unit sizing components were perturbed, while satisfying all the constraints. The new solution was only accepted if the new cost was lower.

In [del Real et al. \(2009\)](#) the energy hub formulation was exploited, defined as an interface among energy producers, consumers and transportation infrastructure. The objective function was based on cost and efficiencies of the system elements, while taking into account the hub model, energy prices, input power flows availability and output energy demands. The optimization was stated as a multi-period nonlinear constrained problem. The system incorporated wind generators, batteries and an intermediate hydrogen storage to be optimized. Results of the hybrid system study reveal improvements in investment costs of almost 30% when compared with the equivalent hydrogen-only and battery-only storage systems.

Y.P. Cai et al [Cai et al. \(2009\)](#) implemented an interval parameter based two stage programming model for supporting community scale renewable energy management. The methodology was based on interval linear programming, two-stage programming and superiority-inferiority-based fuzzy-stochastic programming. This allowed the simulation process of unit sizing to incorporate complexities and multiple uncertainties, both probabilistic and possibilistic. The aim was to develop such method that could be applied to a case of long-term renewable energy planning for three communities. The final results prove the pre-objectives of the work, by generating decision alternatives and thus helping decision makers to identify their desired policies under various economic-reliability system constraints.

In [Gupta et al. \(2009\)](#), a mixed integer linear mathematical programming model has been developed to determine the optimal configuration, including the assessment of the economic penetration levels of photovoltaic array area. The novel methodology consisted in the incorporation of a constant cost (cost/unit) for each of the proposed resource (small hydro, biomass, PV modules, wind turbine, diesel generator) in the cost objective function so that the ones with lesser unit costs

share the greater percentage of the total energy demand.

3.3 Software

3.3.1 HOMER

Since 1993, the National Renewable Energy Laboratory (NREL) has been developing a powerful tool known as HOMER [kn: \(2008\)](#). This computer model was created to assist in the design of micropower hybrid systems, facilitating the comparison of different types of power generation technologies across a wide range of applications. Modeling a power system's physical behavior and its life-cycle cost, HOMER allows the comparison of many different design options based on their technical and economic merits. One of the great advantages with HOMER, relies on the ability to assist in understanding and quantifying the effects of uncertainty or changes in the inputs [Farret \(2006a\)](#).

HOMER is able to design grid and off-grid micropower systems comprising any combination of photovoltaic (PV) modules, wind turbines, small hydro, biomass power, reciprocating engine generators, microturbines, fuel cells, batteries, and hydrogen storage. To obtain the best possible solutions, HOMER is based on three main tasks: simulation, optimization and sensitivity analysis.

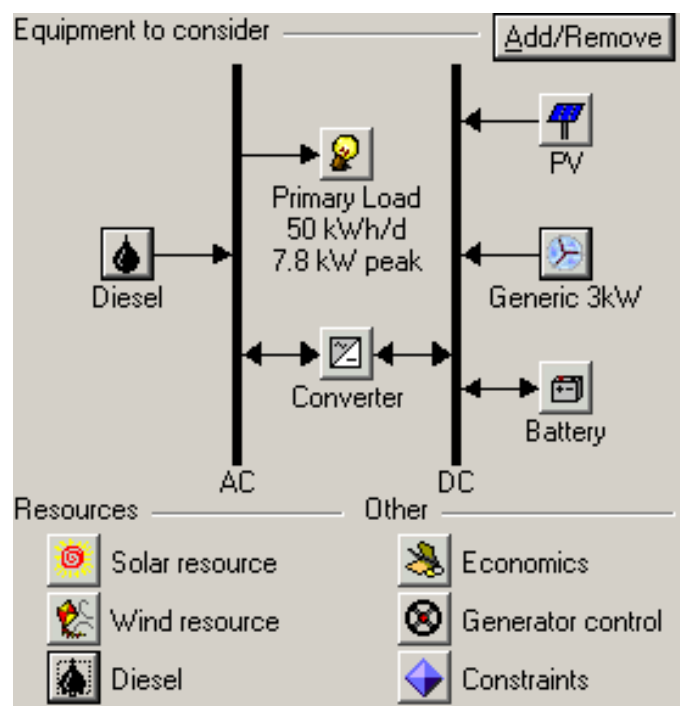


Figure 3.5: Schematic of a PV-wind-diesel system with HOMER [kn: \(2005\)](#)

In the simulation process, HOMER models a precise system configuration by carrying out an hourly time series simulation of its operation over one year, determining the system's technical feasibility and life-cycle cost.

The analysis of the surplus renewable power is made on a hourly basis, comparing the available renewable power previously calculated to the electric load. HOMER then decides what to do with this energy excess, changing the system configuration so that little or zero renewable surplus exists. After it has completed one year calculation, HOMER determines whether the system configuration fulfills the constraints imposed by the modeler. If the system is viable, the software estimates the life-cycle cost taking into account, i.e. annual fuel consumption, generator operating hours and expected battery life. HOMER uses the total net present cost (NPC) as the measurement to represent the life-cycle cost of a particular system. The NPC includes investment costs, operation, maintenance and replacement costs that take place within the project lifetime, always discounting future cash flows to the present date.

After the simulation process has been conducted to search for viable system configurations, the optimization process determined the best possible system configurations within the simulation solutions. The best possible, or optimal solutions, are those who satisfy user's specified constraints at the lowest possible NPC. To all feasible solutions, a rank is assigned according to the NPC and the one with the lowest NPC is considered as the optimal system configuration.

For a sensitive analysis, the software aim is to reveal how will the outputs of the problem change, when changes occur in the inputs. The HOMER user is able to enter a range of values for sensitivity variables like the fuel price, the lifetime of a PV array or wind turbine, the grid power price, among others. It is also allowed changing the magnitude of an hourly data set, such as load and renewable resource in study. All this sensitive analysis are optimized once again for a better long term knowing of systems behavior, permitting the user to deal with uncertainties and thus making better design decisions.

System components modeling with HOMER is quite simple and assumes many simplifications. This will not be specified at this point due to its extensiveness but can be better looked in [kn: \(2008\)](#).

The most complex part of HOMER's logic system is found in the control dispatch strategies - the so called energy flow management. In a simplistic way, the modeler has first to insert a margin of power supply (operation reserve) to ensure system reliability. In each hour of the simulation year, HOMER calculates the renewable source power output(s) and determines whether they are able to supply the electric load plus the pre-defined operation's reserve. If not, HOMER determines the best way (minimization cost) to dispatch the dispatchable system components, i.e. generators, battery bank, grid, so as to guarantee the power demand. The dispatchable energy sources are represented by a fixed cost in dollars and a marginal cost of energy in dollars per kilowatt-hour. Using this cost component dispatch, HOMER seeks for feasible ways to combine all system components in such mode that the required energy can be satisfied. Of all the paramount solutions found, the optimal solution is the one who can serve the load at the lowest cost.

For a system comprising both a battery bank and a generator, when the renewable power source is not able to supply the load, HOMER sets two strategies for battery-charging, called load-following and cycle-charging. In the first strategy, a generator produces the necessary power to serve the load, and does not charge the batteries. Under the cycle-charging strategy, a generator

operates at its maximum rated capacity to charge the battery bank with the excess power in the system.

3.3.2 HYBRID 2

Hybrid 2 [kn: \(2007\)](#) is a system computer model for hybrid systems design and operation simulation, developed at the University of Massachusetts and the National Renewable Energy Laboratory. A brief review on how does Hybrid 2 works will be made based on its theory manual [Manwell \(2006\)](#).

This software uses a combined time series/probabilistic method. The time series approach is useful for long term predictions but, for an accurate diesel dispatch, Hybrid 2 accounts for short term fluctuations in the wind and load power. This time steps can vary from 10min to several hours, and here appears the probabilistic, or statistical approach, applied in each interval. Both the approaches mentioned, assure that energy is conserved throughout the entire simulation, and that the Hybrid 2 model is internally consistent. The probabilistic approach can be explained due to the fact that the method is based on its use of probability density functions for addressing the statistics of generation and load short term fluctuations.

Using the time series/probabilistic method implies that the algorithm assumes mean values of the various inputs and internally calculated values. Hybrid2 assumes that this values are randomly distributed about the mean value used and, furthermore, that the distribution values can be described by a probability density function. The p.d.f. used are the normal Gaussian and in some cases, the Weibull distribution. This probability density functions are used in each time step to find expected maximum and minimum values, the fraction of time in which those values may be within a certain range, and the amount of energy that may be required or available in this range.

3.3.3 HOGA

HOGA stands for Hybrid Optimization by Genetic Algorithms and is a simulation and optimization program developed in C++ for Hybrid Renewable Systems. It allows both DC and/or AC generation and/or Hydrogen.

The optimization is accomplished by minimizing the total system costs, represented by the NPC. For this reason, the authors consider this a financial mono-objective optimization function. Nevertheless, HOGA allows multi-objective optimization by user's addition with variables like CO_2 emissions or unmet load. The program suggests different optimization solutions concerned to the minimization of costs, emissions or unmet load. Like HOMER, the software allows surplus energy, or surplus hydrogen produced in the electrolyzer, to be sold to the grid [Dufo-López e Bernal-Agustín \(2005\)](#).

HOGA uses Genetic Algorithms (GA) for optimization. This optimization is divided in two algorithms: the first one concerned with the optimization of system components (main genetic algorithm) and a secondary genetic algorithm for the control strategy. HOGA offers the choice

to perform an evaluation of all possible combinations, both for components and for control variable strategies. This is called the Enumerative Method, which does not use genetic algorithms. However, this approach is usually not feasible, since the number of components and strategies may be huge, thus resulting in calculation times of the order of months, or even years. Genetic algorithms allow for near-optimum solutions with relatively short calculation times [Dufo-López e Bernal-Agustín \(2008\)](#).

Chapter 4

System Modeling

4.1 Introduction

The aim in the present chapter is to demonstrate the tools and methodologies used for modeling the system components. Some basic concepts will be addressed regarding all the technologies composing the hybrid energy system in study, and an investigation of different dispatch strategies will be presented. These (dis)charging strategies will be applied to a previously designed hybrid system comprising wind, hydro, photovoltaic, a diesel generator and several hours of battery storage. Two strategies are presented and computer simulations are used to compare the system performance in terms of fuel costs, battery wear costs and diesel starts. Hourly samples of renewable source data are used, with the assumption that stability of system frequency and voltage are obtained by a dynamic control layer beyond the scope of this study.

4.2 Wind Turbine Model

There are numerous ways for simulating a wind system, i.e the output power of the machine. The simplest models are defined by four characteristic parameters, V_c (cut-in speed), V_r (rated wind speed), V_f (cut-off wind speed) and P_r (rated output power). Consequences of assuming different models have been thorough investigated but are not part of this thesis objective. Bearing in mind the objective of making a non-discrete design optimization for the multiple generator system, the Pallabazzer model [Pallabazzer \(1995\)](#) will be used which shows good accuracy with experimental data [G. Notton e Muselli \(2001\)](#). We can describe this as a piecewise function, as follows.

$$P_{wind}[0,1] = \begin{cases} 0 & , v < V_c \\ (v^2 - V_c^2)/(V_r^2 - V_c^2) & , V_c < v < V_r \\ 1 & , V_r < v < V_f \end{cases} \quad (4.1)$$

The wind turbine characteristic curve obtained by the Pallabazzer model in equation 4.1 shows that for wind speeds below V_c , the output power is 0. For wind speeds between V_c and V_r , the output power is obtained by the second expression (non linear equation), and for values above V_r to V_f , the output is 1. This standardization will be extremely useful for determining the wind turbine's rated power. The algorithm developed(explained later in this work) determines the optimized wind generator rated power, which is the maximum amplitude of a similar power curve as described above.

Another aspect to have in mind is the height h of the wind turbine hub. The wind speed v at a height of h meters from the measured wind speed v_0 at a height h_0 can be estimated according to the Justus equation 4.2. The exponent α depends on the topography and site climatic conditions G. Notton e Muselli (2001). For the purpose of this work, this will not be considered whereas the confidentiality of the data retrieve and therefore some lack of details about the resources.

$$\frac{v}{v_0} = \left(\frac{h}{h_0} \right)^\alpha \quad (4.2)$$

One of the sample wind data that was first used in this thesis is related to Holyoke Massachusetts (data retrieved from HOMER's sample website). In figure 4.1 the conversion between energy resource and output power machine is done. For demonstration purposes it was created an illustration (figure 4.2) as a representative graph of the output power of a 100kW rated wind generator, obtained by the simplified Pallabazzer model applied to the wind resource just referred.

4.2.1 Investment Costs

In figure 4.3 the investment curve per installed kW is graphed. All data related to renewable generators investments was provided by Professor Cláudio Monteiro, FEUP, and Professor Cristina Camus, ISEL. In table 4.1 the data points related to the investment costs per kilowatt installed are presented. The investment curve was achieve by a power fit curve approximation.

Hence, the equation that best assimilates the investment curve in relation with the wind generator rated power is:

$$C_{WG} = 4640,5 P_{Rwind}^{-0,173} \quad (4.3)$$

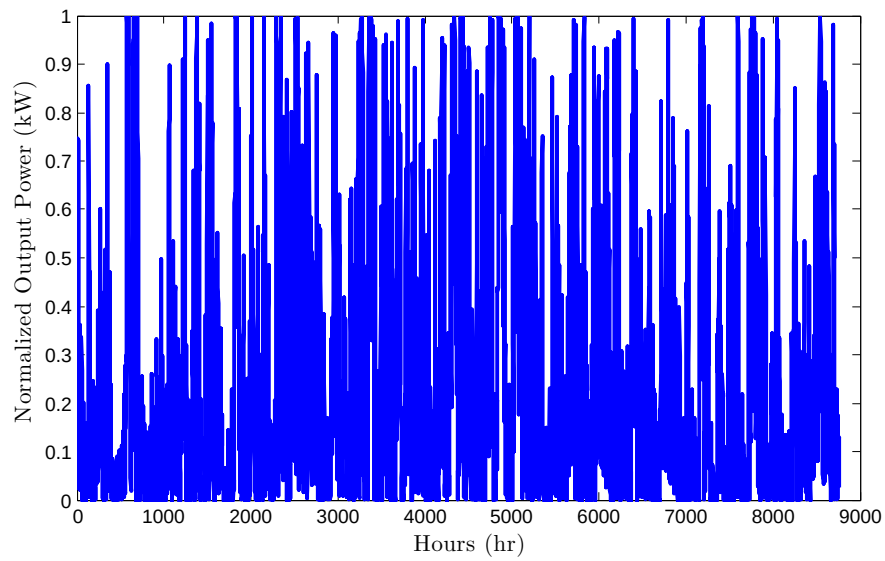


Figure 4.1: One year output power from a 1kW wind turbine

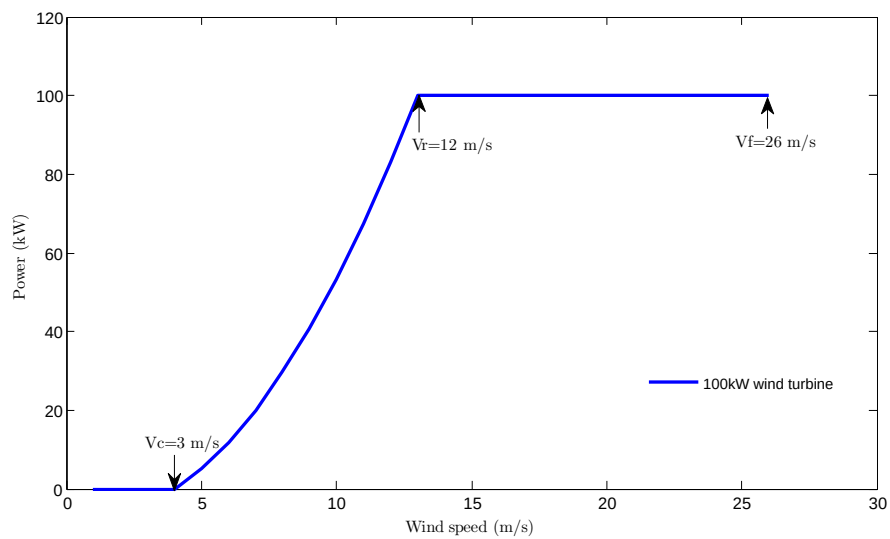


Figure 4.2: Modeling of a 100 kW wind generator

Table 4.1: Wind generator's investment costs (€/per installed kW) and respective fit curve with an average error $\varepsilon = 154$

Wind (kW)	Cost (€/kW installed)	Power Fit	Error
2,5	4500	3960	540
5	3500	3513	13
10	3000	3116	116
20	2500	2764	264
50	2300	2359	59
100	2000	2092	92
400	1700	1646	54
1000	1500	1405	95

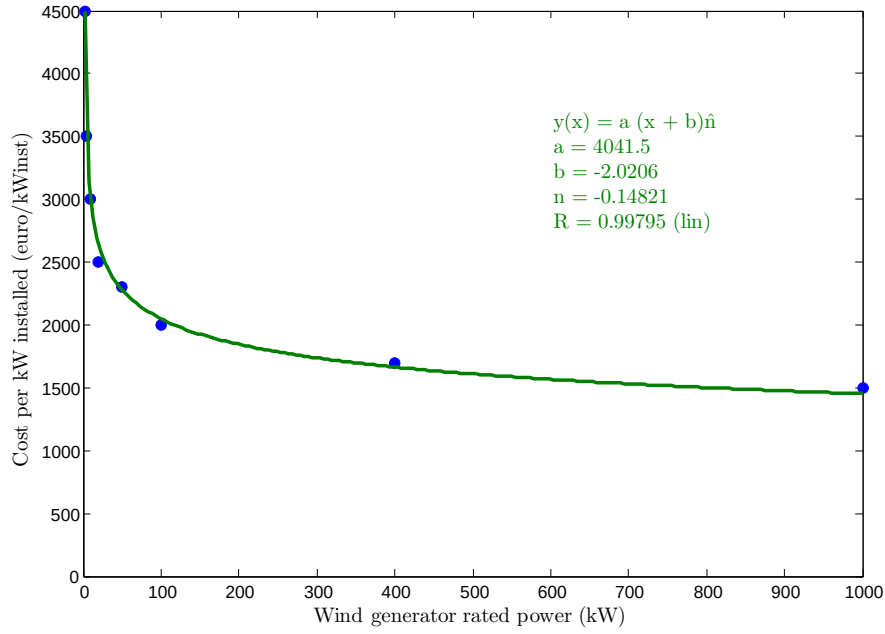


Figure 4.3: Cost per installed kilowatt of wind generating power

The annual operation and maintenance costs represent 5% of the total investment in the wind generator system. The annualized discount rate is estimated based in equation 4.4 with a value of 11,75%.

$$\tau_{WG} = \frac{i \times (1+i)^n}{(1+i)^n - 1} \quad (4.4)$$

where $i=0,1$ and represents the discount rate during the system's life years n assumed in this case to be 20 years.

4.3 Photovoltaic Performance Model

In order to simulate the output power of the generic photovoltaic generator, the model described in Monteiro (2008). To normalize the output power of the generator, the model was implemented and then, the hour generating energy was divided by the daily peak. In this way, we could have a normalized curve between 0 and 1, and later on the optimization process, the rated photovoltaic generator is the maximum of this curve.

$$P_P = \eta_{panel}(TC) \times \eta_{MPPT} \times A_{panel} \times h_t \quad (4.5)$$

where:

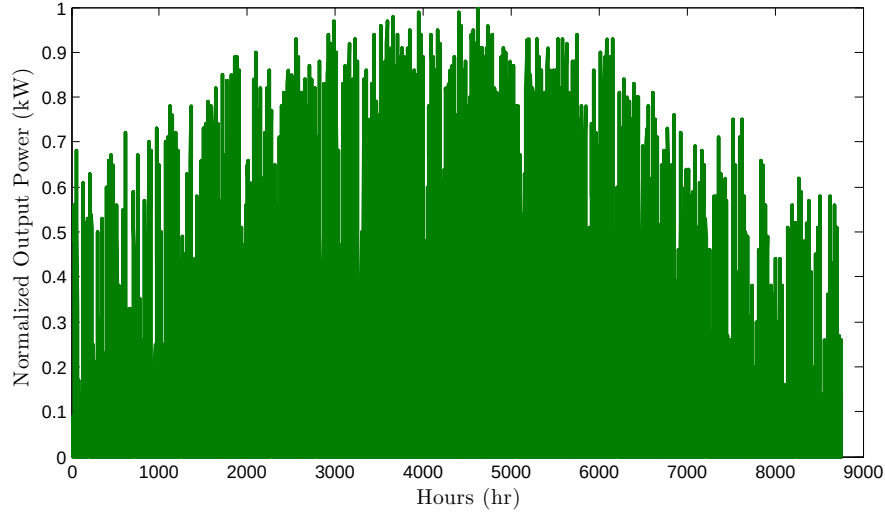


Figure 4.4: One year photovoltaic power output profile (kW)

P_p : represents the output power of the photovoltaic generator.

η_{panel} : panel's efficiency, adjusted to ambient temperature, according to equation 4.6.

TC : adjusted ambient temperature, according to equation 4.7.

η_{MPPT} : Maximum power point tracker efficiency.

A_{panel} : panel's area.

h_t : irradiance in a 30° tilt plan.

$$\eta_{panel}(TC) = \eta_{panel} \times [1 + \tau \times (TC - 25)] \quad (4.6)$$

where:

τ : coefficient of power variation with the panel's cell temperature.

$$TC = T_{amb} + h_t \times \left[\frac{NOCT - 20}{800} \right] \quad (4.7)$$

where:

$NOCT$: Nominal Operating Cell Temperature, measured at an ambient temperature of 20° and irradiance $800W/m_2$ with wind speed equal to 1m per second.

T_{amb} : Ambient temperature

4.3.1 Investment Costs

Hence, the equation that best assimilates the investment curve in relation with the wind generator rated power is:

Table 4.2: Photovoltaic generator's investment costs (€/per installed kW) and respective fit curve with an average error $\varepsilon=80$

PV	Cost (€/kW installed)	Logarithmic Fit	Error
2,5	5200	5341	141
5	5000	4904	96
10	4500	4466	34
20	4000	4029	29
50	3600	3450	150
100	3000	3013	13
400	2000	2138	138
1000	1600	1559	41

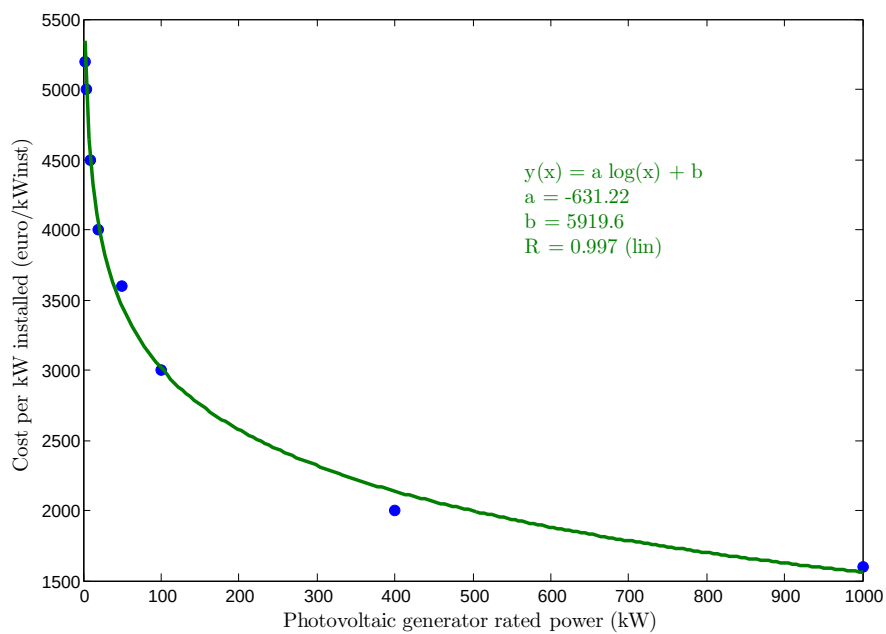


Figure 4.5: Cost per installed kilowatt of photovoltaic generating power

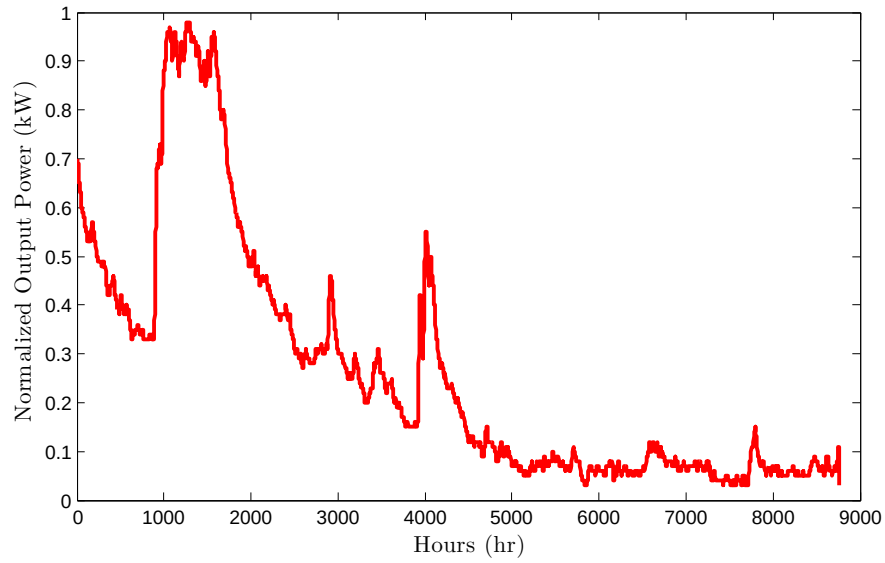


Figure 4.6: One year hydro power output profile (kW)

$$C_{PV} = -631,2 \ln(P_{Rpv}) + 5919,6 \quad (4.8)$$

The annual operation and maintenance costs represent 2% of the total investment in the wind generator system. The annualized discount rate is estimated based in equation 4.9 with a value of 11,01%.

$$\tau_{PV} = \frac{i \times (1+i)^n}{(1+i)^n - 1} \quad (4.9)$$

where:

$i=0,1$ and represents the discount rate during the system life years n assumed in this case to be 25 years.

4.4 Hydro Generator Model

In this point, it was not possible to use a reliable model capable of simulate the output power of a sample hydro resource. Allied not only to the inherent difficulty of the model itself, real synchronized resource data was not able to gather. The appropriate and suitable solution was to work with hourly sample of the real output power of the hydro generator, which was available and gently provided by the system owner. In figure 4.6 the year output power of the small hydro is graphed.

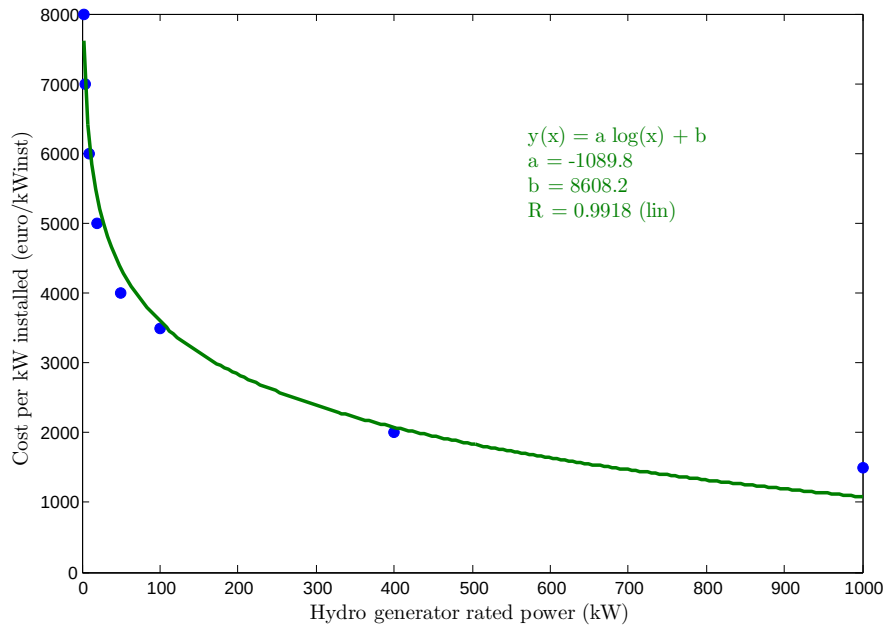


Figure 4.7: Cost per installed kilowatt of hydro generating power

4.4.1 Investment Costs

Table 4.3: Hydro generator's investment costs (€/per installed kW) and respective fit curve with an average error $\varepsilon = 133$

Hydro	Cost (€/kW installed)	Logarithmic Fit	Error
2,5	8000	7609	391
5	7000	6854	146
10	6000	6098	98
20	5000	5343	343
50	4000	4344	344
100	3500	3589	89
400	2000	2078	78
1000	1500	1079	421

Hence, the equation that best assimilates the investment curve in relation with the wind generator rated power is:

$$C_{HG} = -1090 \ln(P_{Rhydro}) + 8608,2 \quad (4.10)$$

The annual operation and maintenance costs represent 3% of the total investment in the wind generator system. The annualized discount rate is estimated based in equation 4.11 with a value of 11,75%.

$$\tau_{HG} = \frac{i \times (1+i)^n}{(1+i)^n - 1} \quad (4.11)$$

where:

$i=0,1$ and represents the discount rate during the system life years n assumed in this case to be 20 years.

4.5 Diesel Generator

A very important part of this work falls upon the diesel generator model. The operating cost of a DG is related to the fuel consumption, while the maintenance cost depends on the diesel run time and the load that is serving while in operation. Despite the fact that a fuel consumption characteristic curve of a typical diesel generator is somewhat quadratic in nature, the linear function is used as a simplified model, as in equation 4.12.

$$OC_{DGh} = C_{diesel} \cdot (B \cdot P_{rg} + A \cdot P_{gh}) \quad (4.12)$$

where:

OC_{DGh} is the diesel generator operation cost per hour h

C_{diesel} is the diesel cost.

B is the diesel generator fuel consumption at no load.

A is the incremental diesel fuel consumption rate.

P_{rg} is the rated power of diesel generator at full load.

P_{gh} is the diesel generator electrical power output per hour.

Skarstein and Uhlen [Skarstein e Uhlen \(1989\)](#) have suggested that the fuel consumption parameters can be approximated as:

- $A=0,246 \text{ liters/kWhr}$
- $B=0,08415 \text{ liters/kWhr}$

In accordance with the above sentences it is possible to see in figure 4.8, per example for an 150kW rated power DG, the fuel consumption linear behavior. Higher output powers fit to higher diesel consumptions, but as we will see, the same is not true when comparing the efficiency of a DG operating at levels near the rated power. When the generator is running at no load, it still requires approximately 20% of diesel consumption so it is particularly inefficient at low loads.

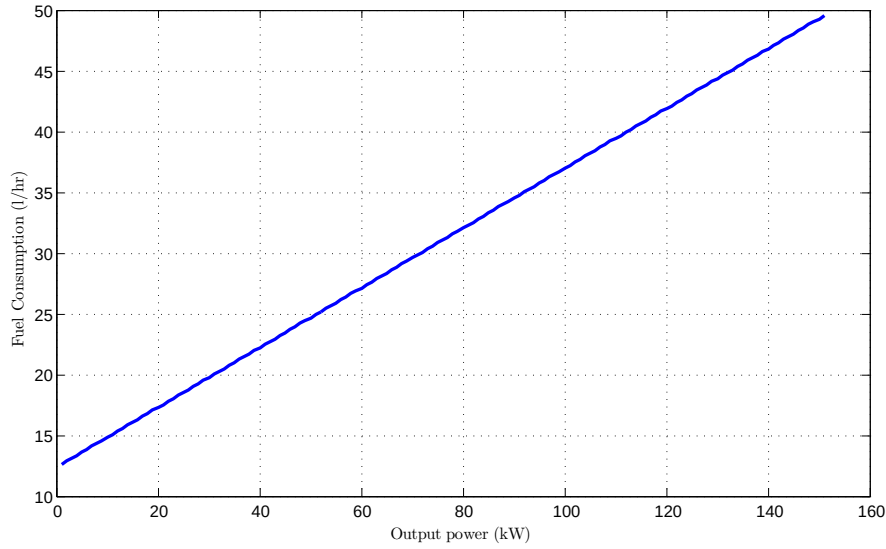


Figure 4.8: Fuel consumption of a 150 kW DG

The DG levelized energy cost of operation (LCO), i.e. the cost per kWhr of diesel generator power is found by the ratio between the fuel consumption costs and the generated power at hour h . In figure 4.9 we can see that for high loads, the diesel operates most efficiently, while the cost per kWhr of diesel generated energy becomes very high as the load is decreasing towards zero.

$$LCO_D = C_{diesel} \cdot \left(\frac{B \cdot P_r}{P_{gh}} + A \right) \quad (4.13)$$

This model has been used in several studies and assumes a reliable DG simulation cost [Ashari et al. \(2001\)](#), [Ashari e Nayar \(1999\)](#).

It is important to refer that the chosen cost of fuel was 1€/liter, a price which is practiced in Portugal. However, taking into account variations in oil prices from across the world, it will be at the program user's criteria to decide the best price to be assumed by the model. A sensibility analysis should be done in order to study possible variations of system sizing components.

4.5.1 Investment costs

To seek for investment costs in diesel generators was quite complicated. The only place where it was found with detail prices and rated powers, for a large variety of diesel generators, was in Hardy Diesel Generators¹. In figure 4.10 the investment costs are graphed and a linear fit curve is applied which suits better to the scatter plot.

Hence, the equation that best assimilates the investment curve in relation with the wind generator rated power is:

¹<http://www.hardydiesel.com>

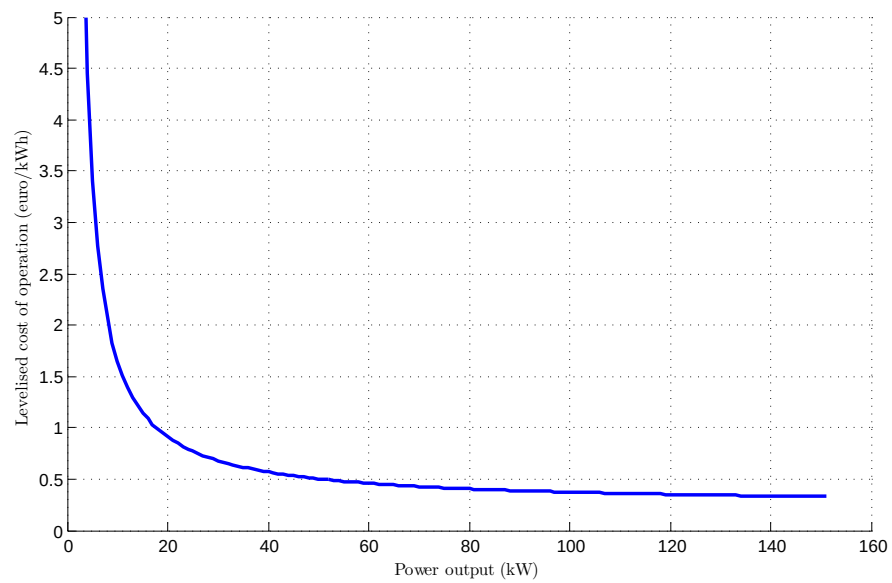


Figure 4.9: Levelised cost of operation of a 150kW DG

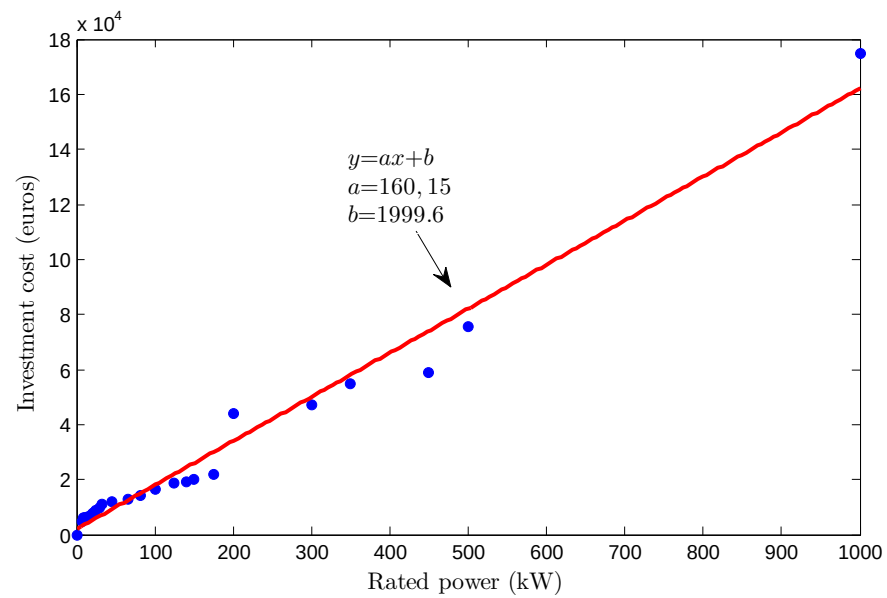


Figure 4.10: Diesel generator investment cost curve (€/per kilowatt)

$$C_D = 160P_{rg} + 2000 \quad (4.14)$$

The annual operation and maintenance costs represent 2% of the total investment in the diesel generator system plus the fuel consumption costs. The annualized discount rate is estimated based in equation 4.15 with a value of 11,75%.

$$\tau_D = \frac{i \times (1+i)^n}{(1+i)^n - 1} \quad (4.15)$$

where:

$i=0,1$ and represents the discount rate during the system life years n assumed in this case to be 25 years.

4.6 Storage

Battery storage is also a prominent aspect when designing a hybrid energy system. The two main factors which determine the life of lead-acid storage batteries are ambient temperature and depth of discharge [Glenn Macleod \(1999\)](#), but in this study only the last one is taken in account. Due to the fact that the dispatch strategies adopted in this study determines the frequency of charge and discharge cycles as well as the depth of battery discharge, the costs to them associated are severely influenced by the DOD parameter. As we can see in figure 4.11, at high discharge depths, the number of discharge cycles achievable is relatively low, while as the discharge depth is decreased, the number of cycles increases.

In order to make a reasonable choice on where to bound the maximum and minimum state of battery discharge (SOC), the number of equivalent full cycles of energy should be estimated. In other words, we have to consider that for a full DOD (100%) the number of battery life cycles would be less than that with a 10% DOD but the energy retrieved from the battery should be approximately the same. In figure 4.12, we are able to see the behaviour of the battery chose for this study, witch according to [Glenn Macleod \(1999\)](#), is a typical characteristic, similar to all lead-acid batteries.

Therefore, the minimum and maximum SOC for an average of 8502kWhr corresponding equivalent cycles are as follow:

$$\Rightarrow SOC_{\min} = 40\% \rightarrow 3580 \text{ equivalent life cycles} \rightarrow 7732\text{kWh life charge or discharge power}$$

$$\Rightarrow SOC_{\max} = 100\% \rightarrow 1500 \text{ equivalent life cycles} \rightarrow 8100\text{kWh life charge or discharge power}$$

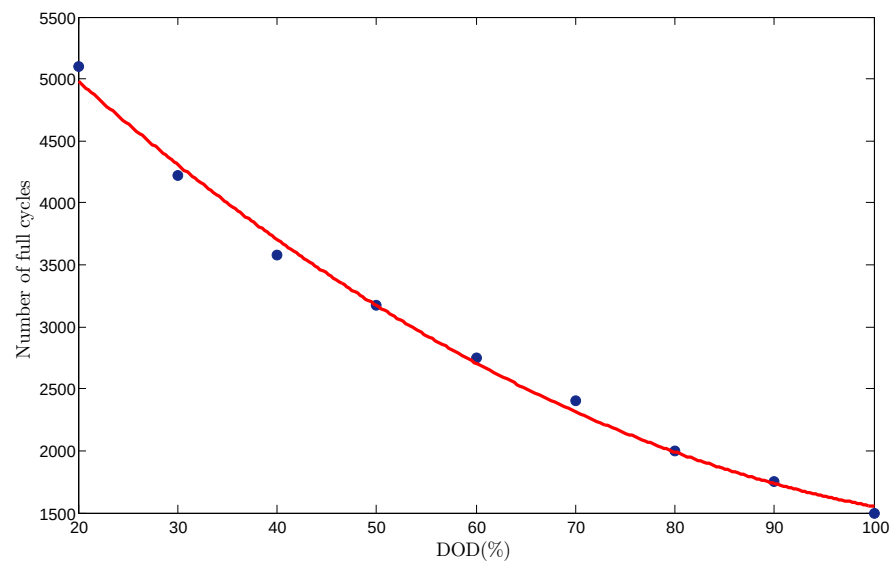


Figure 4.11: Battery discharge cycles and corresponding depth of discharge

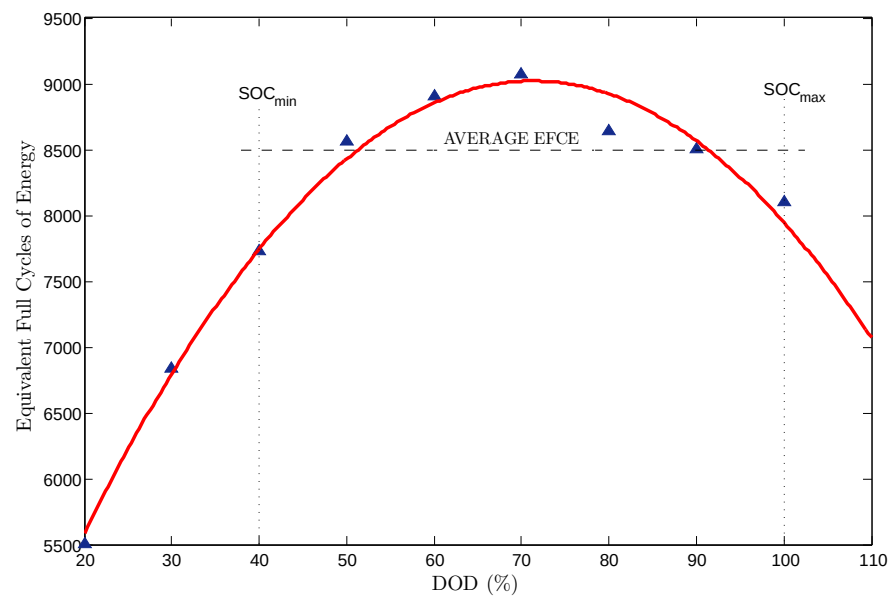


Figure 4.12: Total life energy and equivalent depth of discharge

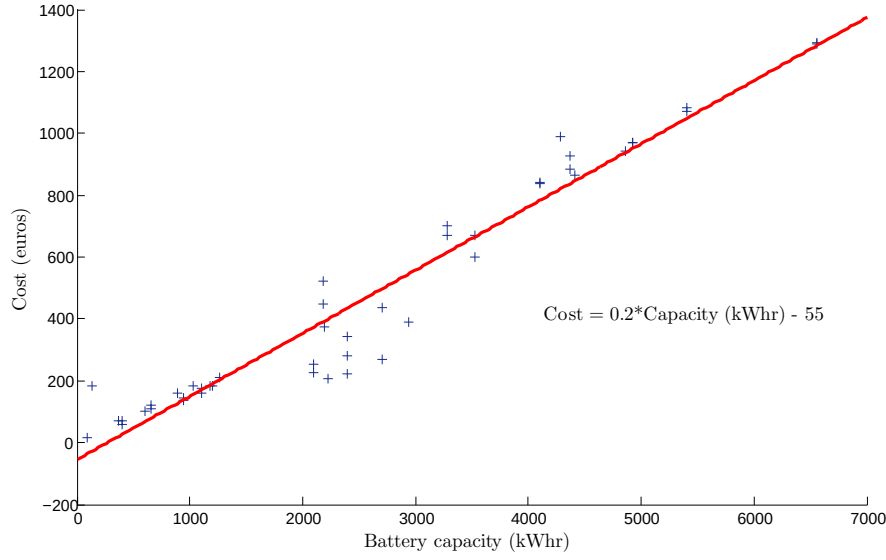


Figure 4.13: Battery cost versus capacity

Remembering that each equivalent full cycle of energy is calculated from the following equation:

$$EFCE = \frac{DOD(\%) \times Cycles\ to\ Failure \times U_n}{1000} \quad (4.16)$$

where:

U_n represents the battery nominal voltage.

4.6.1 Investment Costs

The battery used is the 4 KS 25PS Rolls Battery, and the specifications can be obtained in². This battery has a unit cost of 1033€.

Several data sheets and prices from Rolls Battery retailers were assembled. In figure 4.13 we show the linear behavior between the batteries capacity and the match prices. Considering the relatively linearity it was supposed that the battery investment cost was given by the number of batteries multiplied by the unit cost of the battery first mentioned.

Assuming the 4 KS 25PS Rolls Battery first mentioned. The specifications are, for a 20 hour rate of discharge: Capacity 1350Ah ; Nominal Voltage 4V ; which makes it 5400kWhr capacity battery at full charge. Using the trend line used in figure 4.13:

$$Cost = 0,2 \times 5400 - 55 = 1025e \quad (4.17)$$

²<http://www.rollsbattery.com/content/specifications-renewable-rolls>

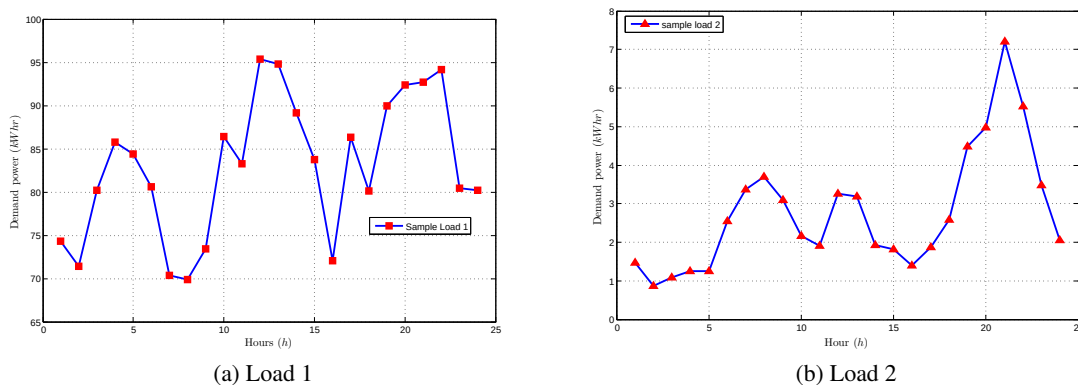


Figure 4.14: Sample load diagrams

The error is minimum (1033€-1025€), but the uncertainty of assuming different batteries for each hybrid system could lead to bad assumptions when estimating the best solutions. Once more, the user is advised to have some information about the kind of batteries he wants to use, even so if merely for the right sizing of the batteries chose in this work.

4.7 Load Diagram

For the purpose of this study, several load diagrams were used. From the NREL's home page³ we could retrieve particular load data comprising 8760 data points (1 year) of hourly average system load. Studying different daily profiles of load data, with different daily profiles and seasonal variations, allows us to take some conclusions about which hybrid system optimizes the energy flow between produced energy from the system and the respective load. As is expected, an PV/Diesel system will be better applied to a load profile with a daily peak at 12:00 pm and with the highest demand being during the summer months. In figure 4.14a and figure 4.14b two different sample daily profiles are shown.

4.8 Dispatch Strategies

4.8.1 Load Following

Under the load-following strategy, renewable power sources charge the batteries but the generators do not. The battery bank is only ever charged by surplus electricity, so the cost associated with charging the battery bank is always zero. When the difference between the renewable output power of the system and the load – net load – at hour h , is more than zero, the battery bank will be charged until it reaches the maximum state of charge (SOC_{max}) or the maximum allowable battery flow charge rate (B_{fmax}), always having in account the surplus power available. If we are facing a maximum SOC, all surplus energy will be dealt as excess load (EL). On the other hand, if the

³http://homerenergy.com/sample_files.asp

net load is less than zero, the battery bank will discharge until it reaches the minimum state of charge (SOC_{min}) or the maximum allowable battery flow discharge rate. In a deficit case where the battery bank capacity is not able to supply the net load, the diesel generator will be turned on. If even so with the battery capacity plus the maximum power output from the DG, the net load can not be supplied, there will be unmet load (UL) which incur in a penalization cost that can be defined by the user. In this work, the UL penalization cost was defined as 0.5€/kWhr not supplied. In figure 4.15 we can represent the main function of this dispatch strategy.

In figure 4.16 we can see the way that the load is followed by the battery flow and how the diesel generator is reserved for energy fault pikes.

4.8.2 Cycle Charging

Of particular interest and controversy is the possibility of using diesel power to charge batteries, as opposed to the load following strategy. According to the cycle charging strategy, the generator will produce extra electricity and hence consume additional fuel for the purpose of charging the battery bank, so the cost associated with charging the battery bank is not zero. Benefits of this strategy included the optimization of the diesel operation point, at levels near the rated power (see figure 4.9), minimizing the frequency of diesel starts but some disadvantages are included, such as the shortening of battery wear life, electrical losses in the battery and in power converters and last but not the least, the lost opportunities for storing renewable energy in the batteries. In figure 4.17, the battery energy flow behavior is presented. Notice the iterative process updating the battery bank SOC in each hour of the year (8760 hours). Due to the fact that the cycle charging algorithm is more complicated than the load following dispatch strategy, we had to divide it in 3 parts, being the first part referent to the battery flow process; the second part to the diesel generator scheduling, in figure 4.18; and the third part to the excess and unmet load, in figure 4.19

In figure 4.20 we can see the diesel generator always following the battery charge and the battery discharge only happening when the maximum battery flow is less than the net load value.

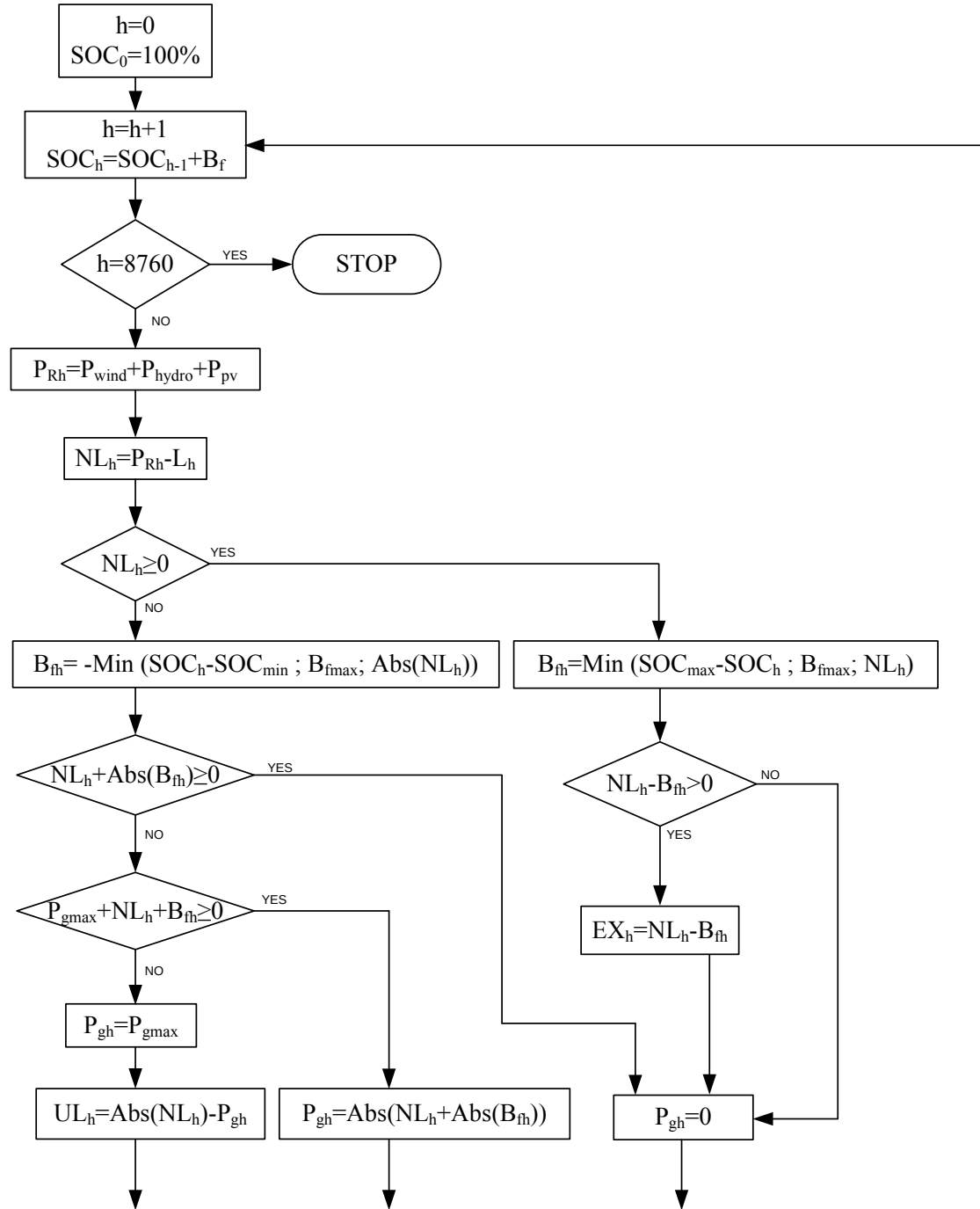


Figure 4.15: Load following Algorithm flow-chart

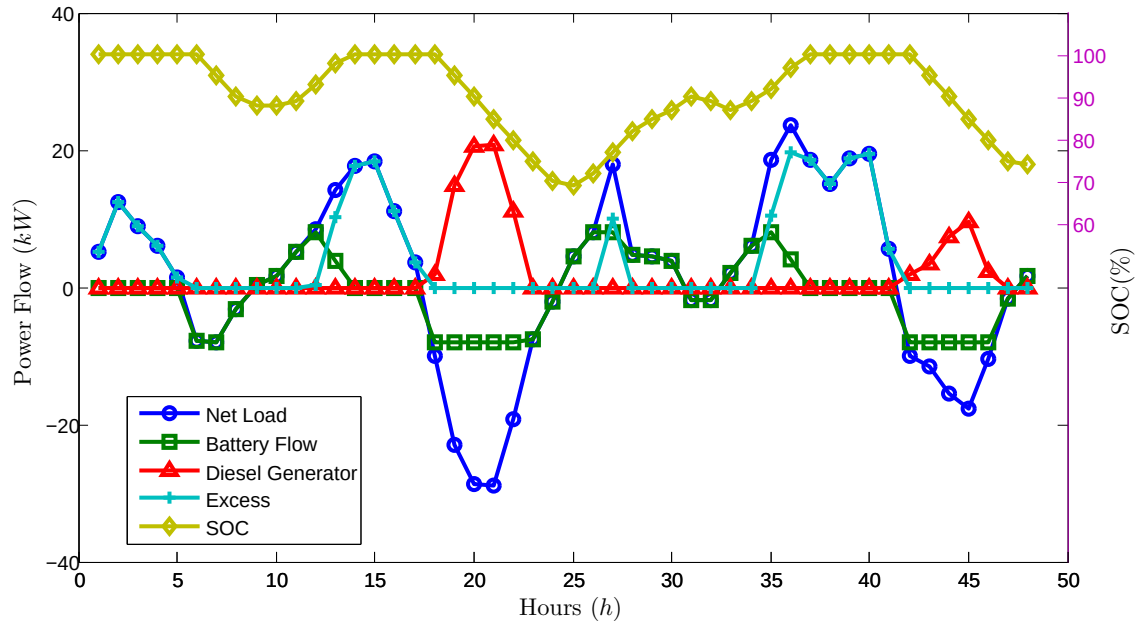


Figure 4.16: Load following dispatch for 48 hours

4.8.3 Other Strategies

Two dispatch strategies were used in this study - load following and cycle charging - but many other strategies can be applied and have been thorough investigated concerning the effects on diesel savings or battery replacement costs. C. Dennis Barley and C. Byron Winn [Barley e Winn \(1996\)](#) have conducted a serious study about the implementation of different types of dispatch strategies for small villages. A brief review will be made, having in mind that, as discussed by Barley, although many other strategies may be proposed, no further reduction in operating costs is deemed possible comparing to the dispatch strategies applied in this thesis.

A simple strategy that is often used in practice is the State-Of-Charge Setpoint Strategy. The battery bank is charged to a pre establish SOC every time the diesel must be started. If the diesel generator still has a margin to its rated power, they operate at full-power as long as the excess power can be accommodated by the batteries. Otherwise, the DG operating point is set to the highest value possible without dumping power. In a Setpoint-Optimal strategy, an optimal setpoint within the range 0%-100% may be determined for which the operating cost is a minimum.

Full Power/Minimum Run Time (FPMRT) is a dispatch strategy aimed to achieve the maximum diesel fuel efficiency by operating at full power. Reserving the majority of the battery storage capacity for renewable energy and avoiding excessively frequent starting and stopping of the diesel generator, this strategy calls for operation of the diesel at full power for a prescribed minimum run time (per example one hour), after which it is shut off. The effect of this strategy is similar to that of the Setpoint Strategy with a low setpoint.

Another suggested strategy is the use of a Frugal Discharge. Using this strategy, the power level below which is more economical to use stored energy than diesel power is calculated. The dispatch controller is designed to ensure that the stored energy is used only to meet net loads below

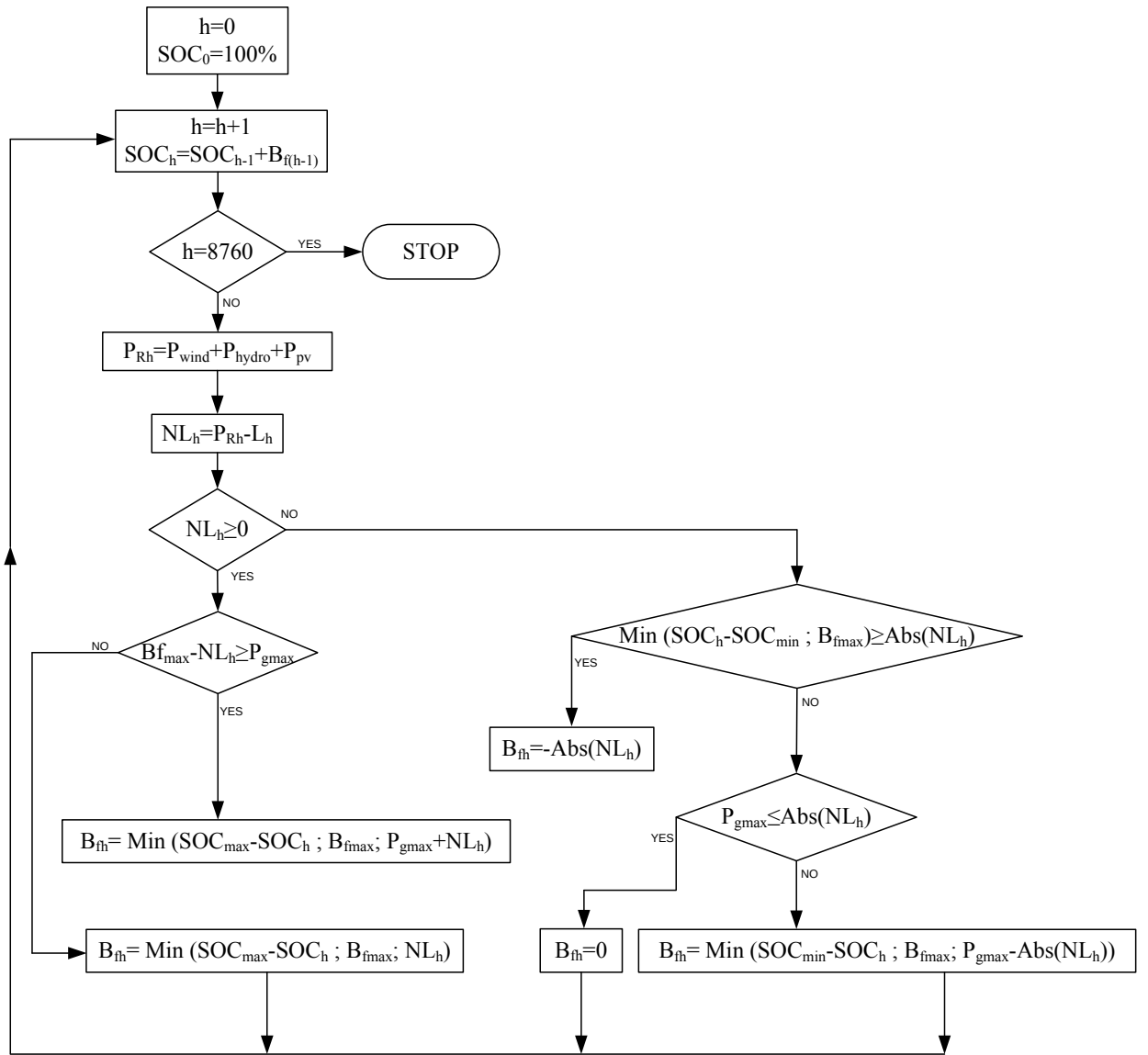


Figure 4.17: Cycle charging flowchart - part I - batteries

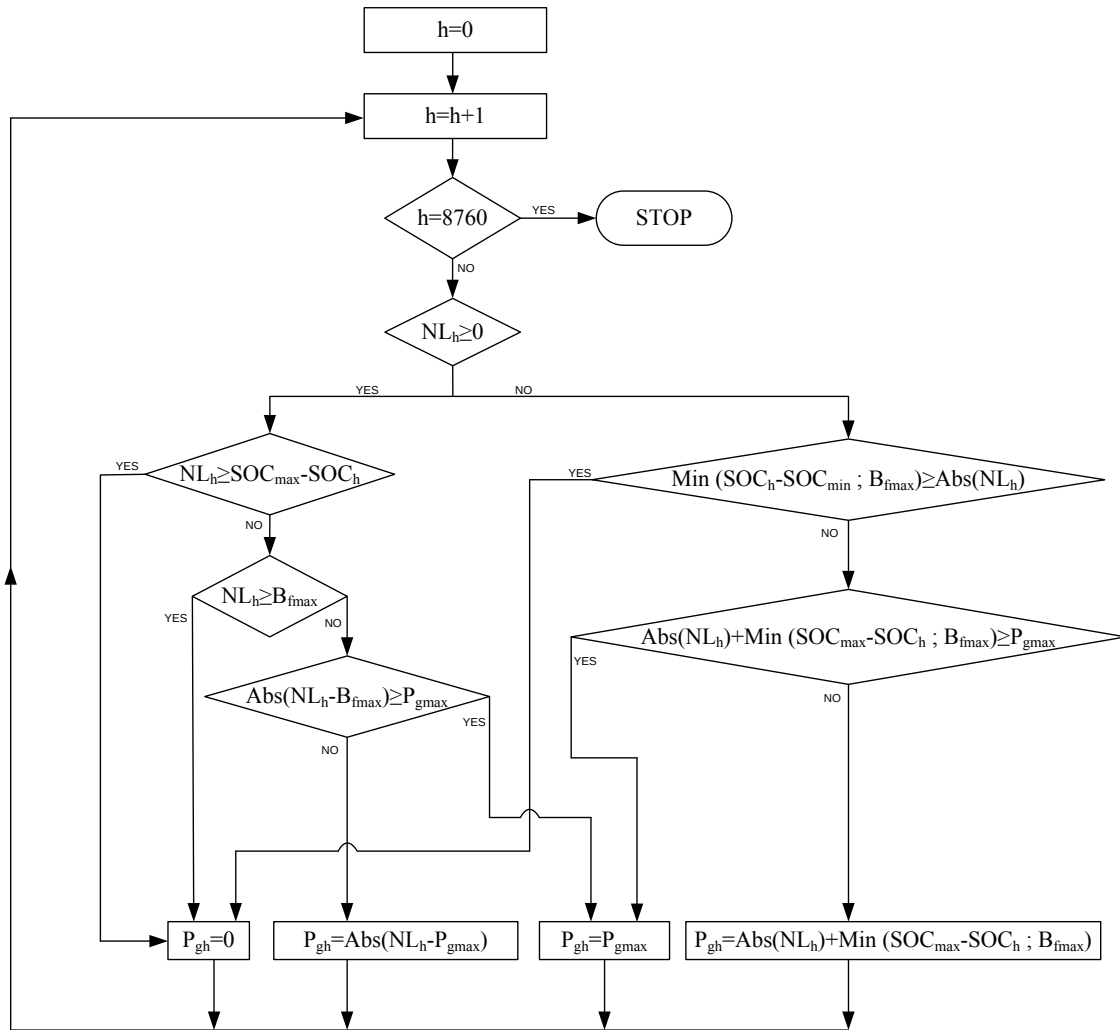


Figure 4.18: Cycle charging flowchart - part II - diesel generator

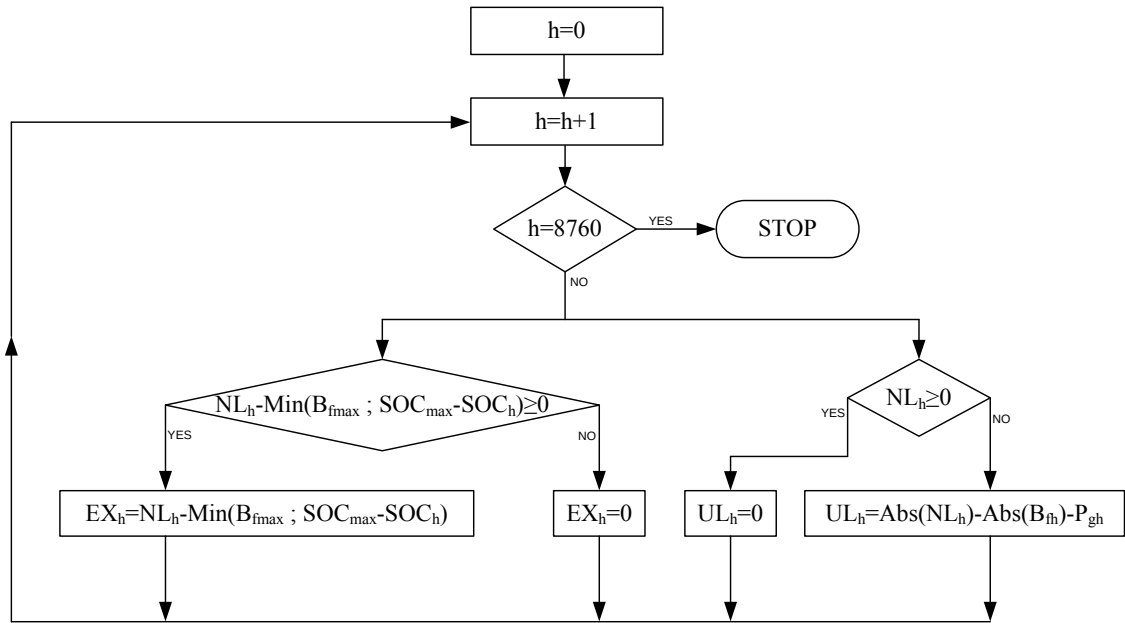


Figure 4.19: Cycle charging flowchart - part III - excess and unmet load

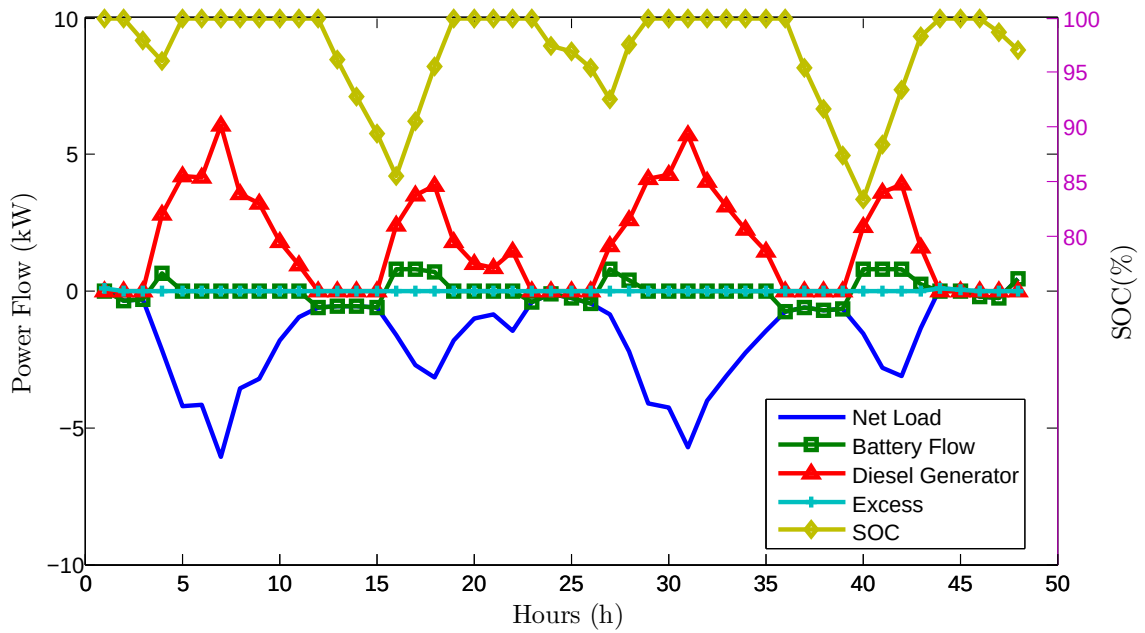


Figure 4.20: Cycle charging dispatch for 48 hours

this "critical load" L_c . This strategy ensures that batteries will never be used to meet loads when it would be cheaper to use diesel generator power instead. This seems to be a reliable strategy with good results, but in this work and considering a diesel cost of 1 /liter, the cost curves never intersected. From the literature reviewed the diesel costs were considered to be approximately 0,26 /liter, which we consider sincerely impossible for present and future investigations on this theme.

An ideal discharge strategy would be one that makes use of stored renewable resources by always using this energy to meet those net loads that will result in maximum cost savings over the entire period. Of course that this strategy is not achievable, at least with accuracy results, since perfect knowledge of future data and load conditions is impossible. However, the resulting savings can be used as a benchmark in evaluating more practical discharge strategies. Paulo Ribeiro in [Ribeiro \(2009\)](#) proved that using an ideal dispatch strategy (with some modifications) would incur in operation cost savings as well as a lower system levelized cost of energy (LCOE).

4.8.4 Final Model

The final model is a complete user friendly interface where the data described in the previous sections can be changed if the user wants. It just has to insert annual wind, hydro and solar profiles; the nominal voltage, and apparent capacity at 20 hour rate of the battery chose. Then, the only thing to do is press the test button and wait for the algorithm that was developed (explain in next chapter) to return the optimized levelized cost of energy and the rated power of which one of the technologies. It did not seem correct to insert images from the interface of the program because they are still extensive but if the reader of this thesis has any doubt concerned to the function of the software, please feel free to contact me at⁴ and i will send you a copy.

⁴francisco.mesquita@fe.up.pt

Chapter 5

GraSO - A Novel Optimization Technique

5.1 Introduction

Optimization or mathematical programming algorithms are search methods with the purpose to find the best solution to an optimization problem subject to a set of constraints. Although this definition is simple it hides a number of complex issues, per example the solution can be composed of a combination of different data types. Possibly nonlinear boundaries may restrict the search area, the search space can be involved with many possible solutions, the characteristics of the problem may change over time, or the quantity being optimized may have conflicting objectives [Englebrecht \(2007\)](#).

Applications of optimization algorithms involve science, engineering, economics, and industry. The wide and growing use of optimization makes it essential for worldwide science and technology. A transportation problem in which a product must be shipped in certain amounts from several service points to several destinations we always want to consider the minimum transportation costs; a power circuit state estimation problem; a profit problem respecting an investment spreading over a large set of areas; the increase of market players caused a growth in competition thus forcing today's society to search for more effective processes. In all of these situations we seek for an optimal solution, the most efficient and effective manner, the most economical process - the best way to do things [Pedregal \(2004\)](#).

5.2 Motivation

From the beginning the main objective of this thesis is clearly related to the optimization of stand-alone hybrid energy systems. The first thought was to use simple optimization techniques, most of them previously developed, like Microsoft Excel Solver. When first attempting to optimize a simple wind-diesel system, it became clear that the optimization capabilities of this software were not able to fulfill the problem requirements - it simply did not work properly. The method's

efficiency failed in three major criteria: the capability to converge to the global optimum - when endeavor to optimize the minimization function LCOE, the algorithm got trapped in local optimal solutions; the inability to search within the landscape of solutions - being stuck in the initial solution; the substantially long time consumption - even when converging to local optimum the computation requirements were strong and the process was slow.

Programs such as HOMER, carry out optimization by trying out all possible combinations. For a significant number of feasible solutions, however, calculation times may be enormous. Hybrid 2 and HOGA, even the last one applying Genetic Algorithms for optimization of the system components, act in discrete feasible solutions and not in a continuous way. The new algorithm developed –GraSO– is able to perform this in-depth optimization and discover the best possible solution within a large search space.

5.3 Concept

The algorithm developed in this work is classified as a sub class of, as known in statistics, as response surface methodologies (RSM). These methods explore the relationship between several explanatory variables and on or more response variables and was introduced by G.E.P.Bos and K.B. Wilson [Box e Wilson \(1951\)](#). The major idea of RSM is to employ a sequence of designed experiments to obtain an optimal response. The authors used a second-degree polynomial model but they acknowledge that this model was only an approximation, but easy to estimate and apply, even when little was known about the function to optimize.

Even deeper in the optimization algorithm's world, we can compare the developed algorithm with IOSO (Indirect Optimization on the basis of Self-Organization) [kn](#): which is a multiobjective, multidimensional nonlinear optimization technology. IOSO Technology is based on the response surface methodology approach.

The difference is that GraSO uses a swarm to construct a response surface model for the object that is being optimized within the search space. From a queen swarm which is the best fitness point of the swarm, a new "region" is created based in a Gaussian distribution variance. The movement of the new queen is the response of a weight mean between the second-degree polynomial fit curve and the best fitness point of the swarm. The weight is measured by the coefficient of determination of the fit curve. An adaptive adjustment of the current search space is performed by two inverted sigmoid functions controlled by the coefficient of determination for each particle evaluation. The first evaluation is perform in relation with the swarm second degree gradient, and the second one is relates to the normalized variation of the distance between the swarm queen and each one of the particles.

5.4 Algorithm Description

In figure [5.1](#) the flowchart for the GraSO algorithm is described. Beyond, a step-to-step instruction description is made.

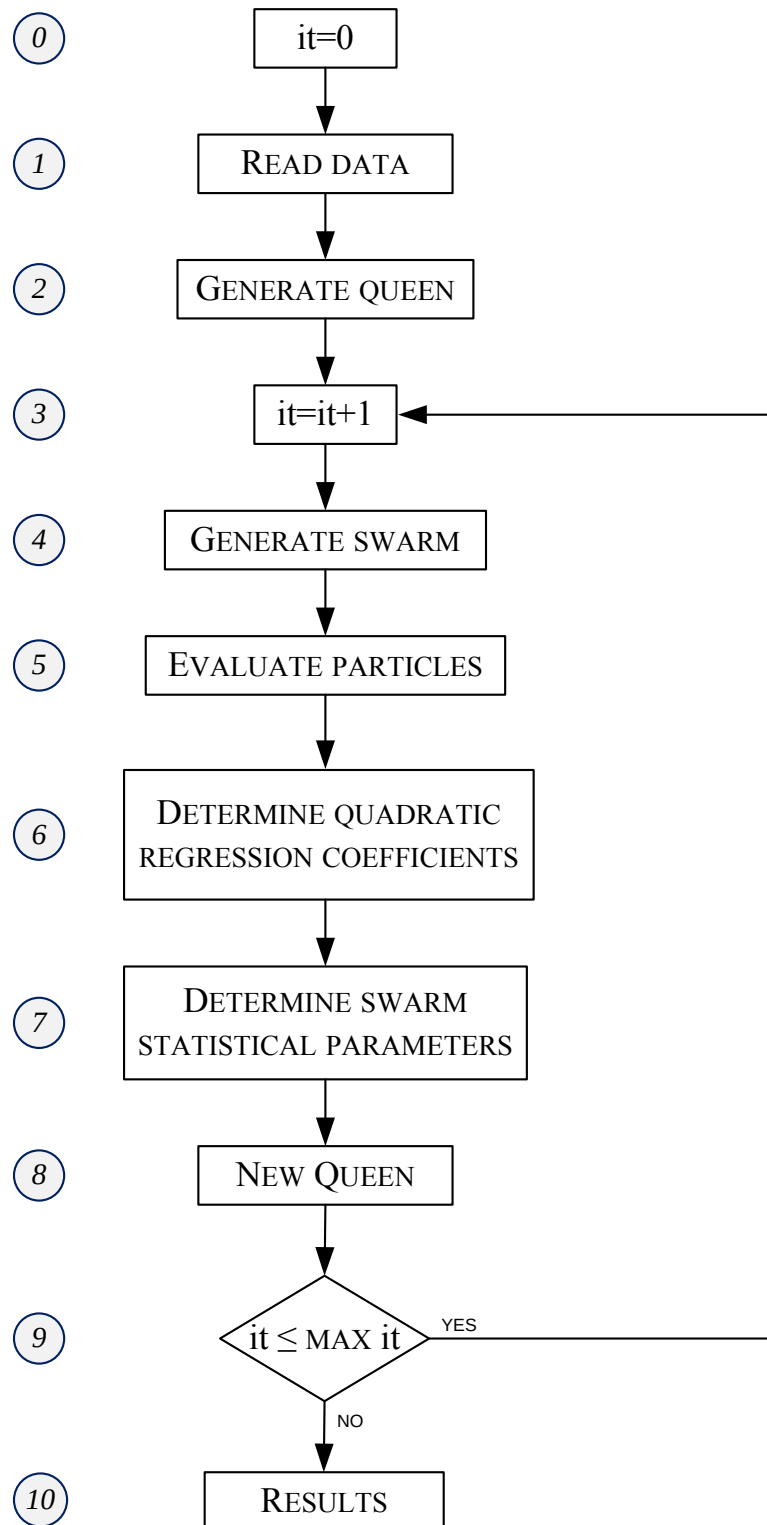


Figure 5.1: GraSO Flowchart

① This point represents the beginning of the iterative process.

② In the read data sub-routine, all initial parameters inserted by the user are converted to the algorithm memory. The parameters included the swarm size, i.e the number of particles (n_{swarm}); number of maximum iterations (max_{it}); minimum and maximum function $F(x_i)$ variables delimiting the search space (x_{min} and x_{max}); the initial variance σ^2 of the Gaussian distribution $\mathcal{N}(\mu, \sigma^2)$ for each x_i .

③ The first queen swarm (X_{queen} for $it = 0$) is randomly generated by a min-max method in agreement with equation 5.1.

$$X_{queen} = Rnd(0, 1) \times (x_{i.max} - x_{i.min}) + x_{i.min} \quad (5.1)$$

④ Resemble with step 0, this is a very intuitive one. The variable it is incremented for the beginning of a new swarm queen search, with all underlying processes.

⑤ Each random swarm particle (X_{swarm}) is normally distributed with mean μ and variance σ^2 . We want every particle to be established as the inverse Gaussian distribution with a mean represented by the queen swarm and variance (for $it=1$) defined by the user in step 1. For $it \neq 1$, σ^2 will be an internal program self adaptive parameter estimated according to the swarm statistical parameters and the activation functions F_{s1} (equation 5.10) and F_{s2} (equation 5.11), both calculated in step 8. The ϕ internal parameter is determined by the distance between the queen swarm and each one of the particle, as follows:

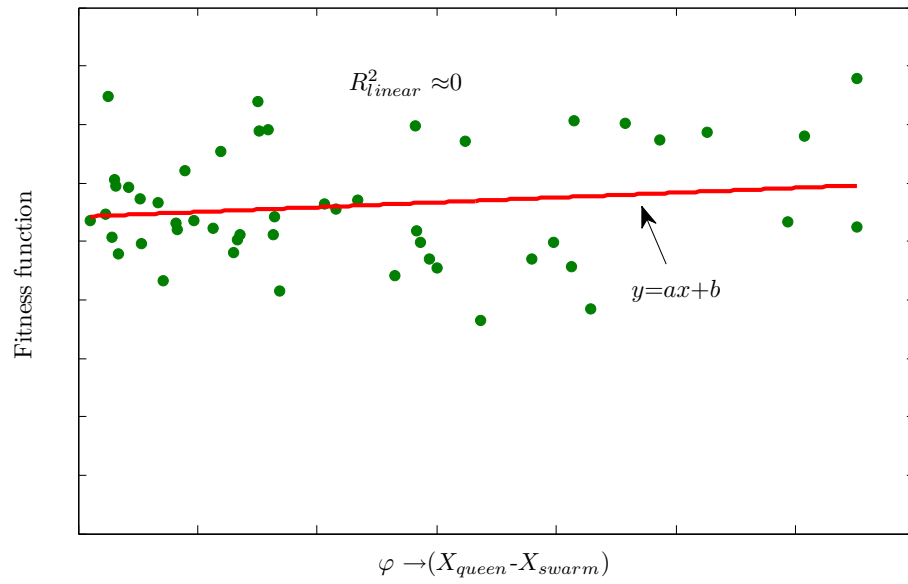
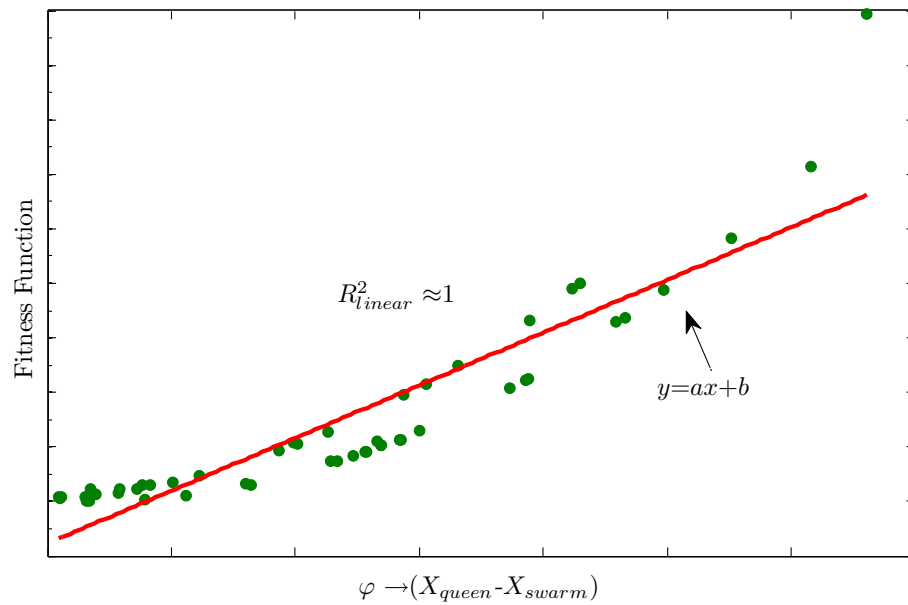
$$\phi = \frac{|X_{queen} - X_{swarm}|}{\alpha} \quad (5.2)$$

where $\alpha=0,675$ and was computed by experiment.

The ϕ parameter is computed so as to understand if the best fitness particles are far or close to the queen swarm. In figure 5.2 we can observe the behavior of a swarm where the created particles do not have sufficient decision capacities to determine if far away or close particles represent best fitness values.

In figure 5.3 the behavior of a near optimum ϕ is demonstrated. We can see by the positive gradient that randomly generated particles far from the swarm queen represent worst fitness values.

⑥ This part of the algorithm has the objective of determining the best fitness particle F_{best} from each iteration as well as its position in the swarm space X_{best} .

Figure 5.2: Evaluation of the φ parameter in distant optimal solutions situationsFigure 5.3: Evaluation of the φ parameter in near optimal solutions situations

⑥ In this step we attempt to program the least square method for estimating the parabola quadratic regression coefficients which best fit the particle swarm. If the second term is positive, the fit curve is concave and there is a local or global minimum. If the second term is negative there is a local or global maximum and the fit curve is convex.

⑦ The purpose of this sub-routine is to compute several swarm statistical parameters. This are:

R_{swarm}^2 - represents the particle swarm coefficient of determination, i.e the goodness of the quadratic fit model, presented in figures 5.5 and 5.4:

$$R_{swarm}^2 = \frac{\sum_{i=1}^{n_{swarm}} (F(X_{swarm}) - F(\bar{X}_{swarm}))^2}{\sum_{i=1}^{n_{swarm}} (F(X_{quadratic}) - F(\bar{X}_{swarm}))^2} \quad (5.3)$$

R_{φ}^2 - represents the φ coefficient of determination, i.e the goodness of the linear fit model, presented in figures 5.2 and 5.3.

$$R_{\varphi}^2 = \frac{\sum_{i=1}^{n_{swarm}} (F(\varphi_{swarm}) - F(\bar{\varphi}_{swarm}))^2}{\sum_{i=1}^{n_{swarm}} (F(\varphi_{linear}) - F(\bar{\varphi}_{swarm}))^2} \quad (5.4)$$

σ_{φ} - represents the distance's standard deviation between X_{queen} and X_{swarm} .

$$\sigma_{\varphi} = \sqrt{\frac{1}{n_{swarm}} \sum_{i=1}^{n_{swarm}} (X_{queen} - X_{swarm})^2} \quad (5.5)$$

$\sigma_{Fitness}$ - represents the fitness standard deviation from all composing swarm particles.

$$\sigma_{Fitness} = \sqrt{\frac{1}{n_{swarm}} \sum_{i=1}^{n_{swarm}} (F(X_{queen}) - F(X_{swarm}))^2} \quad (5.6)$$

∇_{φ} - represents the φ slope:

$$\nabla_{\varphi} = \frac{\partial F(\varphi_i)}{\partial \varphi_i} \quad (5.7)$$

Δ_{φ} - represents the normalized variation of φ :

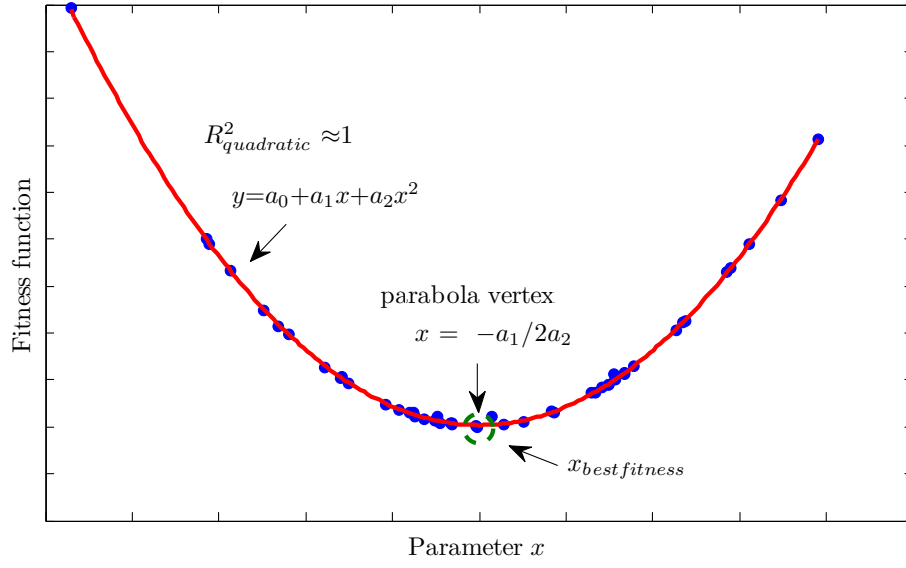


Figure 5.4: Particle swarm behavior near the optimal solution

$$\Delta\varphi = \frac{1}{1 + h\nabla\varphi\left(\frac{\sigma_\varphi}{\sigma_{Fitness}}\right)} \quad (5.8)$$

⑧ The new swarm queen is determined based on R^2_{swarm} , the parabola vertex and the best fitness particle. We know that the particles generated from the Gaussian distribution have a similar behavior as the quadratic fit curve if R^2_{swarm} is approximately 1, therefore the new queen should go in the direction or to the vertex of the parabola. This is demonstrated in figure 5.4.

On the other hand, if R^2_{swarm} is approximately 0, the confidence of the quadratic fit curve is null and the new queen should follow the particle with the best fitness value of that iteration, behavior shown in figure 5.5. So, as to create a weight mean between the best fitness value and the parabola minimum the new queen is determined as follows:

$$X_{queen} = R^2_{swarm} \times \left(\frac{-a_1}{2a_2}\right) + (1 - R^2_{swarm}) \times X_{best} \quad (5.9)$$

The variance should be mutated for the next swarm generation. This is established upon the F_{s1} and F_{s2} functions:

$$F_{s1}(R^2_{\varphi_i}) = 1 - \frac{(1 - \Delta\varphi)}{1 + e^{(-10R^2_{\varphi_i} + 5)}} \quad (5.10)$$

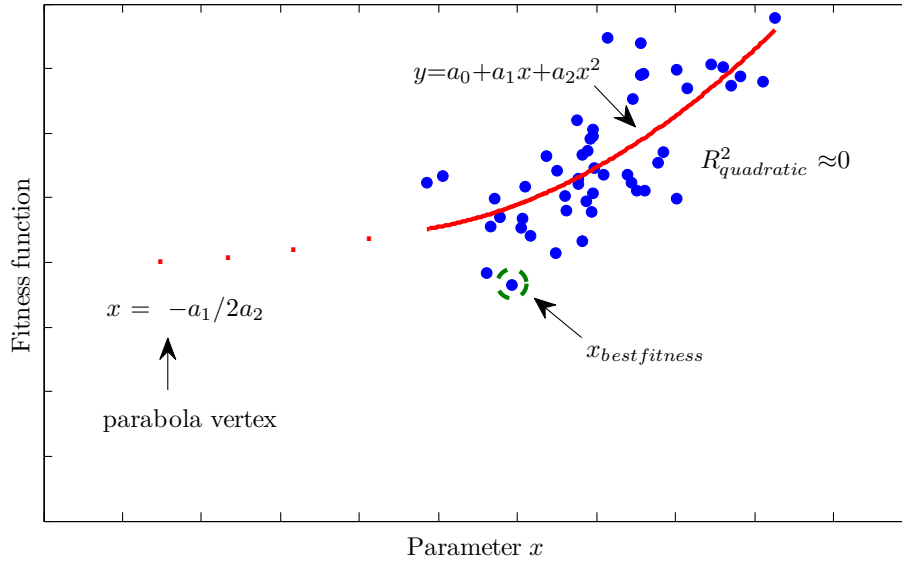


Figure 5.5: Particle swarm behavior distant from the optimal solution

$$F_{s2}(R_{x_i}^2) = 1 - \frac{(1, 5 - 1)}{1 + e^{(-50R_{x_i}^2 + 5)}} \quad (5.11)$$

The inverted sigmoid functions previously described are pictured in figures 5.6a and 5.6b. To explain the logic of this activation operators is quite simple. With the F_{s1} function we want to expand the search space for the next iteration if R_{swarm}^2 is very poor. Hence, if R_{swarm}^2 is approximately 1, low or no variations are made to the search space. With the F_{s2} function the behavior is similar, taking in account that for values of R_{ϕ}^2 near 1, we are near an optimal solution and the algorithm should narrow the search space for the next iteration. If low values of R_{ϕ}^2 are present, nothing should occur because no confidence is available and for sure, R_{swarm}^2 has low values as well and the domain of the problem is enlarging. The new variance is then calculated by multiplying the two activation functions and the previous variance from $it-1$:

$$\sigma_{it+1}^2 = \sigma_{it}^2 \times F_{s1}(R_{\phi}^2) \times F_{s2}(R_{swarm}^2) \quad (5.12)$$

⑨ The termination process takes place when $it = \max_{it}$. If $it \leq \max_{it}$ the algorithm returns to step 3.

⑩ When $it = \max_{it}$, the results of the algorithm are presented. These results include the objective function, the independent variables of the problem and the variance.

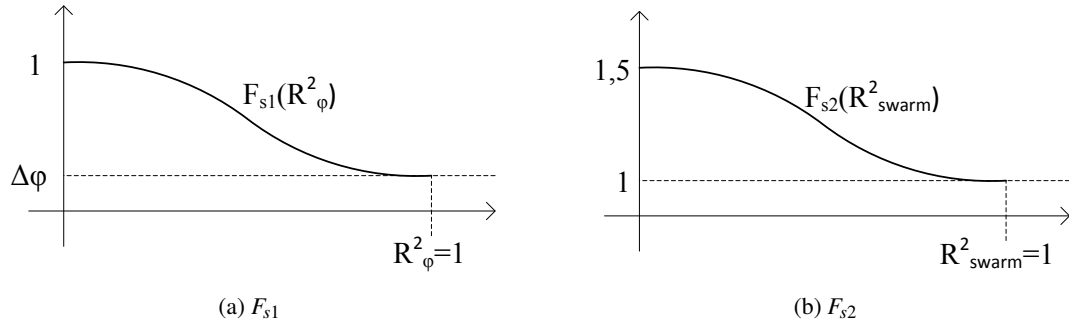


Figure 5.6: Inverted sigmoid activation functions behavior

5.5 Test Functions

5.5.1 Sphere Function

The sphere function 5.13 is a continuous, convex, unimodal function [Marek Pilski e Seredyski \(2004\)](#) with no local minimum except the global one $F(x_i)=0$ for $x_i=0$. It has been used in the development of the theory of evolutionary strategies, and in the evaluation of genetic algorithms as part of the test set proposed by De Jong [De Jong \(1975\)](#). The sphere graph is presented in figure 5.7. To understand the iteration process that was developed, it is graph in appendix A the evolution of the three variables of the system (X_{swarm} , Y_{swarm} and Z_{swarm}) and the respective φ parameters.

$$f(x) = \sum_{i=1}^n x_i^2 \quad (5.13)$$

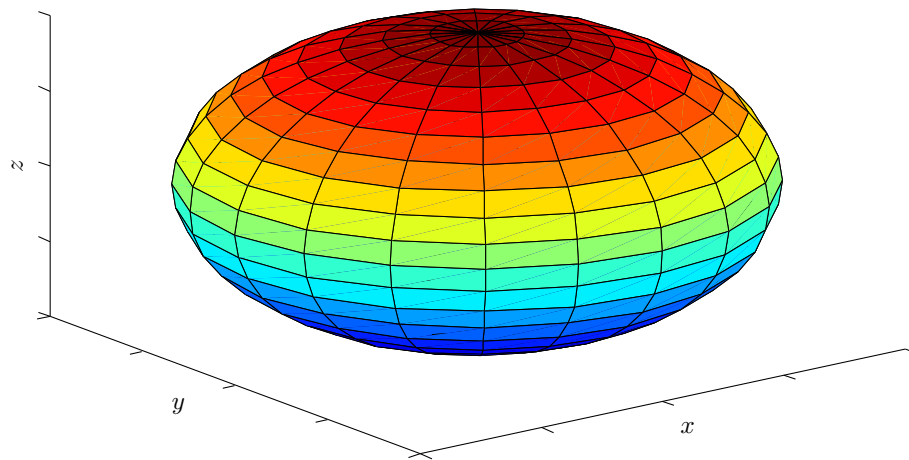


Figure 5.7: De Jong's function 1 - sphere

The next purposed test was to apply the GraSO to a sphere within a R^{30} space dimension. This would complicate the convergence but as we can see in figure 5.8 the algorithm shows real good results. The convergence with a 30 particle swarm happened in 13 iterations for 0,01 and in about 60 iterations for 1E-10. As realized during the construction and testing of this new optimization algorithm, we were able to conclude that when reaching a global optimum, the fitness value tends to oscillate but in a sparse way.

Table 5.1: Performance evaluation parameters - Sphere function

Standard deviation	Mean value	Best fitness
2,96202E-06	1,12674E-06	8,41708E-09

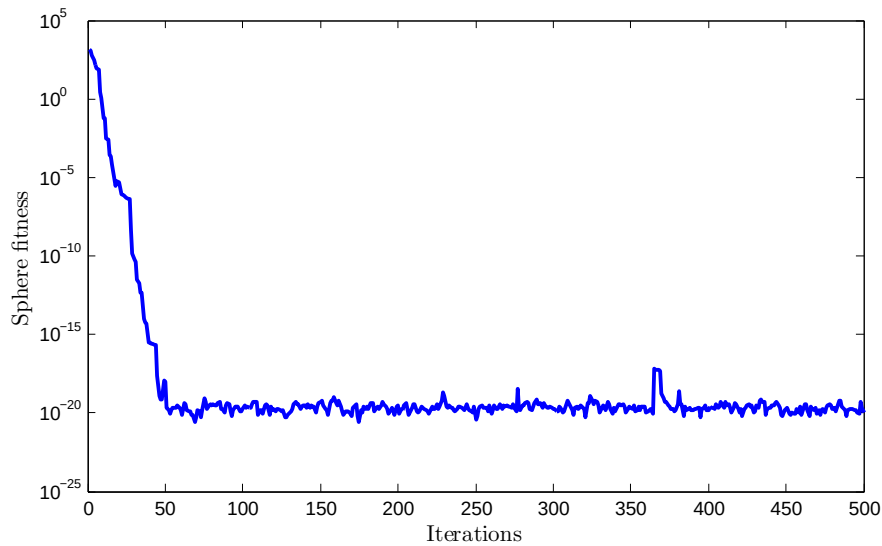


Figure 5.8: Sphere's fitness function convergence in R^{30}

5.5.2 Schaffer's Function

The Schaffer function 5.14 has many local optimums in which an optimization algorithm can be trapped. In figure 5.10 the graph is pictured, illustrating many local optimal solutions in the fitness landscape. To find the valley is a minor problem, however, to converge to the global minimum can cause some difficulty. It has a global minimum at $(x,y) = (0,0)$ where $f(x,y) = 0$ [Chevalier \(2004\)](#).

$$f(x,y) = 0,5 + \frac{\left(\sin\left(\sqrt{x^2 + y^2}\right)\right)^2 - 0,5}{(1,0 + 0,001 \cdot (x^2 + y^2))^2} \quad (5.14)$$

In [Miranda e Fonseca \(2002\)](#) the authors have applied an Evolutionary Self-Adaptive Particle Swarm Optimization (EPSO) to the minimization of the Schaffer's function. They used 2 particles

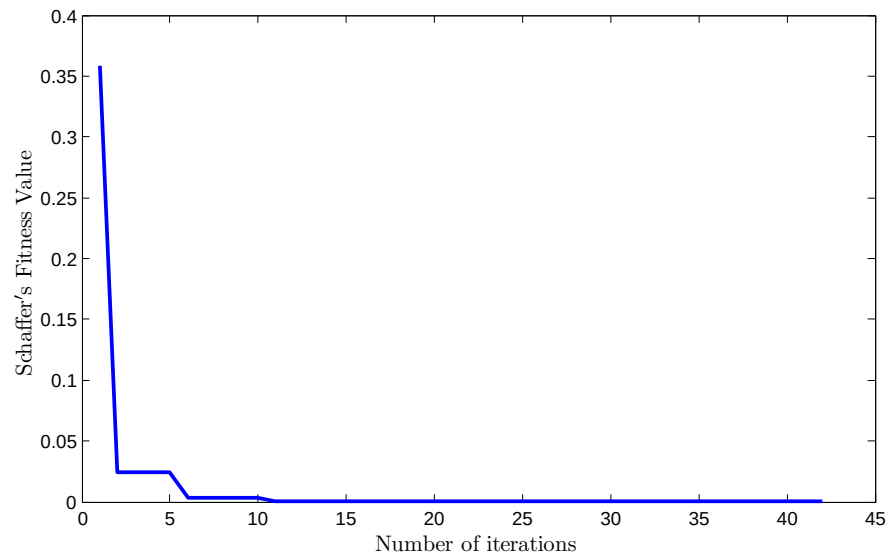


Figure 5.9: Schaffer's convergence with GraSO

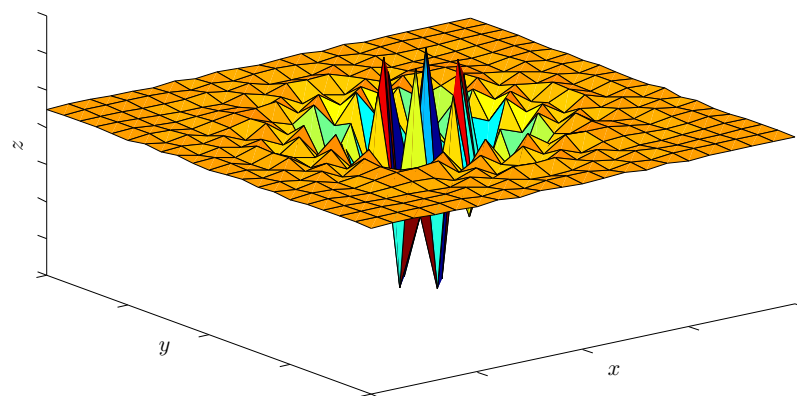


Figure 5.10: Schaffer's function

and the number of evaluations needed for convergence was approximately 25000 for 1E-11. In table 5.2 the results obtained with GraSO are described for 10 experiments. It was used in the GraSO algorithm, 50 particles and the convergence to 1E-11 was achieved at 20 iterations, performing 1000 evaluations, which were much more efficient than the EPSO approach.

Table 5.2: Performance evaluation parameters - Schaffer's function

Standard deviation	Mean value	Best fitness
5,33329E-08	2,80736E-08	2,40194E-11

5.5.3 An ELD problem

Energy electric system analysis contemplates non-linear problems of high computational complexity [V \(2005\)](#). Energy delivery to consumers without compromising voltage control and wave quality has been a major goal in which optimal levels of dispatch are required. Evolutionary algorithms are an important tool for economic load dispatch (ELD) calculation so that the constraints imposed are efficiently satisfied and the energy requirements are minimized [Sinha et al. \(2003\)](#).

From a previous work [Miranda \(2009\)](#) three different evolutionary algorithms were presented: Evolutionary Strategy (ES), Self Adaptive Evolution Strategy (SAES) and Particle Swarm Optimization (PSO). The point here is to compare these methodologies, when confronted with GraSO, in order to search for the most efficient and effective one within the ELD results obtained. The algorithms were developed in Visual Basic running behind a Excel spreadsheet. It was considered a single bus system like the one in figure 5.11 with six generators characterized by the coefficients of table 5.3.

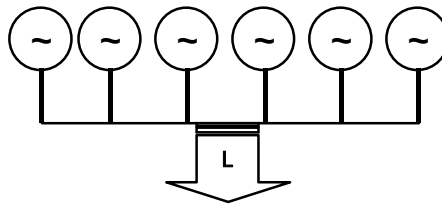


Figure 5.11: Studied single-bus system [Miranda \(2009\)](#)

Table 5.3: Generator's cost curve parameters and output power limits

Generator	a_0	a_1	a_2	a_3	P_{min}	P_{max}
g_1	1	0,5	0,1	0,03	1,00	10
g_2	2	0,4	0,2	0	7	10
g_3	4	0,3	0,3	0	2	10
g_4	6	1,5	0,1	0	2	10
g_5	0	4	0	0	1	10
g_6	0	4	0	0	1	10

In figure 5.12 we can see the better convergence of GraSO compared to the other strategies implemented. With only seven iterations the algorithm converges to the optimal solution for the ELD problem.

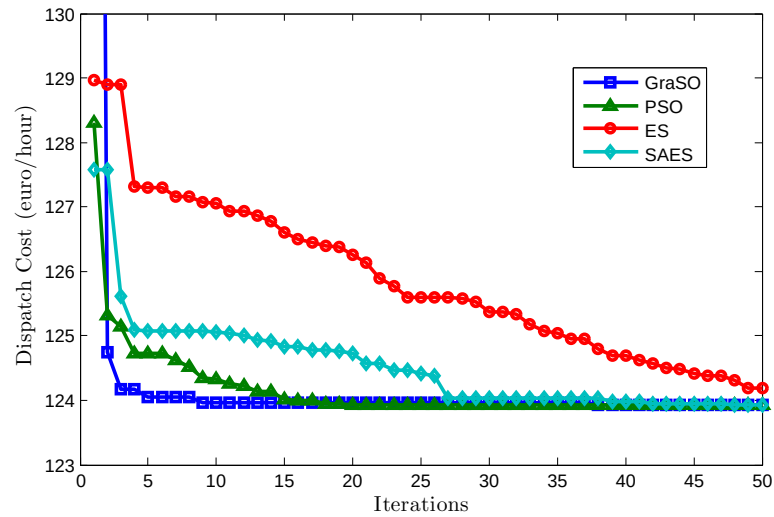


Figure 5.12: Comparative analysis of using GraSO in an economic load dispatch problem

Chapter 6

The GraSO approach to the Design Optimization of Hybrid Energy Systems

6.1 Introduction

In this chapter we will apply the novel algorithm to the optimization of a generic hybrid energy system. This system model is clearly explained in chapter 4. The objective of the present investigation is to study the behavior of GraSO applied to the levelized cost of energy minimization for each hybrid combination. Several load diagrams and data resource are used and a sensibility analysis is made regarding the cost curves per installed kilowatt for each renewable generator.

6.2 Objective Function

The levelized cost of energy equation is an evaluation of the life-cycle energy cost and life-cycle energy consumption. It allows alternative technologies to be compared when different scales of operation, investment or operating time periods exist. It captures capital costs, ongoing system-related costs and fuel costs – along with the amount of electricity produced – and converts them into a common metric in €/kWh [CorporaTion \(2008\)](#).

The objective function is the minimization of the LCOE of the system, as follows:

$$LCOE = \frac{\tau_W C_W + OM_W + \tau_H C_H + OM_H + \tau_P C_P + OM_P + \tau_D C_D + OM_D + \tau_B I_B + OM_B}{ADP} \quad (6.1)$$

•

where:

- τ : annualized discount rate for each technology
- OM : operation and maintenance costs for each technology
- C : investment cost for each technology

- *ADP*: annual demand power

6.3 Constraints

The restrictions to the problem are the ones explained in chapter 4, for the load following and cycle charging strategies. These strategies limit the energy flow within the system, always respecting the real characteristics of the system and the simulated energy balances for each hour. The user of the software can establish penalization costs for unmet load (*UL*) and for excess load (*EL*). In this work, it was assumed:

- $UL=3\text{€}/\text{kWhr}$
- $EL=0\text{€}/\text{kWhr}$

These penalty costs are a contribution to the LCOE equation 6.1. These costs represent a tremendous assistance for GraSO to reach the global minimum LCOE. It was not attributed any kind of penalty for excess load because it is the purpose of this work to find the best possible scenario within generators from 0 to 1MW. This boundary was this way determined so that the algorithm could be tested to find the possible best solution within a big search space, and not to find the best solution to one case in particular. If so, the user can restrict the search space by simply limiting it in the appropriate cells of the Excel interface.

It is then assumed that the rated power for each one of the technologies can not pass the limits imposed by the user in the interface:

$$P_{Gmin} \leq P_G \leq P_{Gmax} \quad (6.2)$$

$$N_{BATmin} \leq N_{BAT} \leq N_{BATmax} \quad (6.3)$$

6.4 Developed Software

In this sub-chapter the joined operation of the algorithm programmed in VBA and the hybrid system designed in an Excel spreadsheet will be explained. In figure 6.1, the combined performance of both of them is described. The trace square box represents the internal code, the core of the optimization algorithm — **GraSO**. The bold square boxes stand for graphic interface modules, in which the user can see how the algorithm evolves iteration by iteration. It is also in this module that the initial restrictions of the problem are inserted.

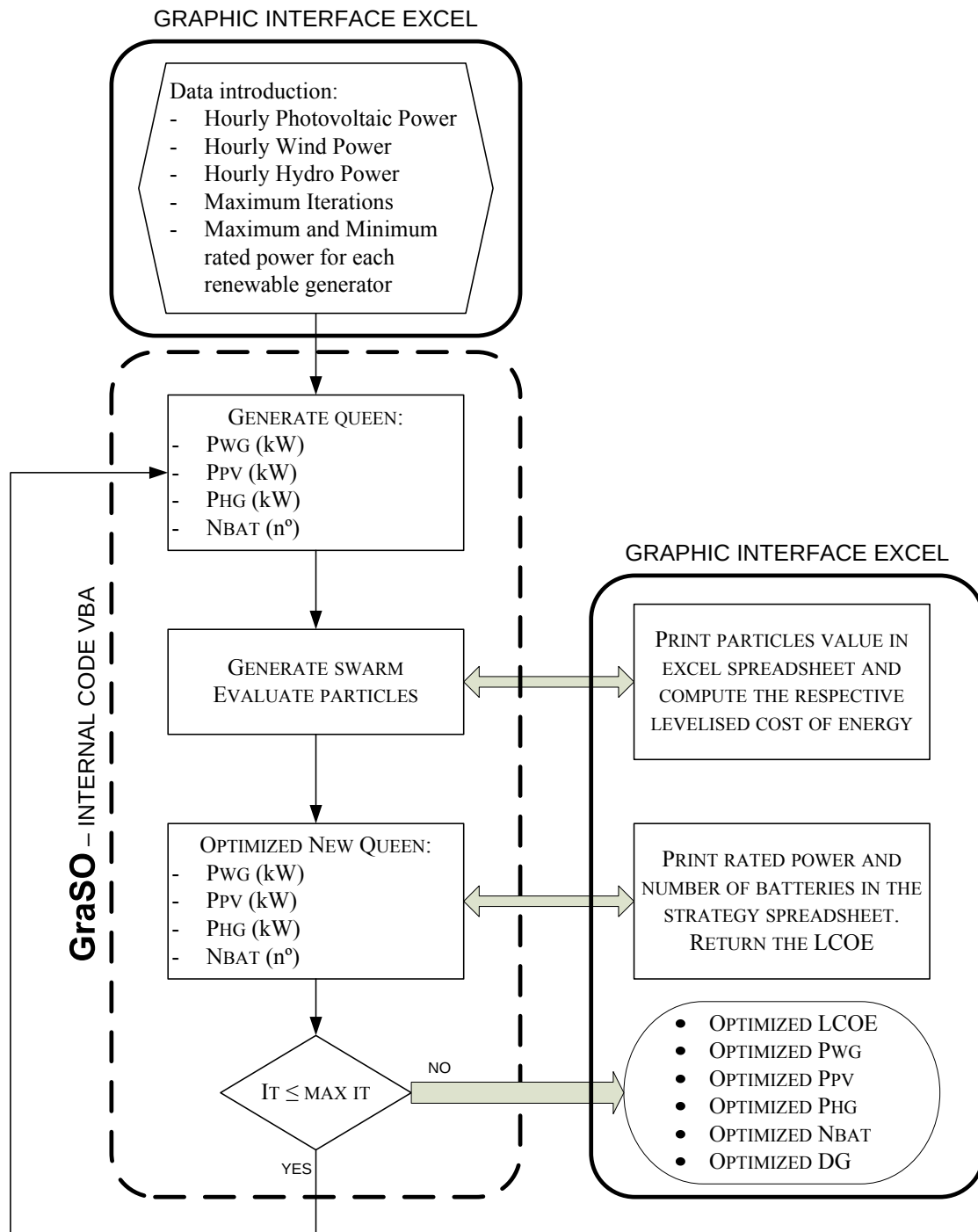


Figure 6.1: Levelized cost of energy minimization block diagram

6.5 Case Studies

6.5.1 Assuming Different Investment Costs

The algorithm's behavior was tested for different technology investment values. The excess penalization in this case is 0€/kW and the renewable generators are limited between 0 and 1MW. Hence, as expected, the algorithm results mostly consisted in wind power and ignored the use of hydro and photovoltaic generators. A sample result is shown in figure 6.2.

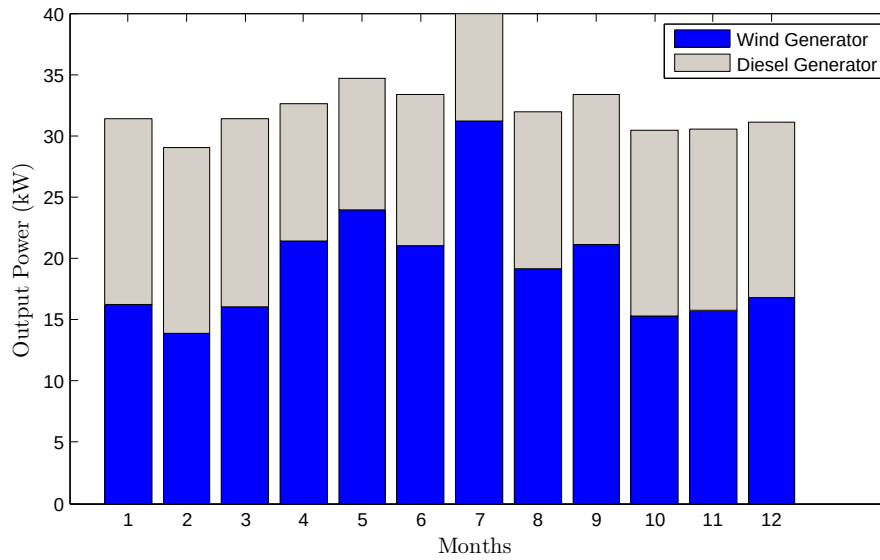


Figure 6.2: Monthly output power assuming different technology investment costs

6.5.2 Assuming Equal Investment Costs

To test the GraSO operation with the hybrid system previously designed in chapter 4 some sceneries were assumed, which included four distinct load diagrams. In this case, to see the influence of equal investment costs in all technologies, all investments were defined as the cost curve of a wind generator, defined in figure 4.3.

The first step consisted in verifying how many iterations together with how many particles were necessary so that the hybrid system LCOE was minimized. A test was done in which the convergence is shown in figure 6.3, and approximately occurs in 40 iterations.

In figure 6.4 we are able to see the external system parameters variation, i.e. the generators rated power and the number of batteries. From this figure we are capable of assuming a different number of iterations to the LCOE convergence, which is 60. From figure 6.5 we can confirm the previous sentence because is visible that the oscillation of the Gaussian variation only stops near 60 iterations.

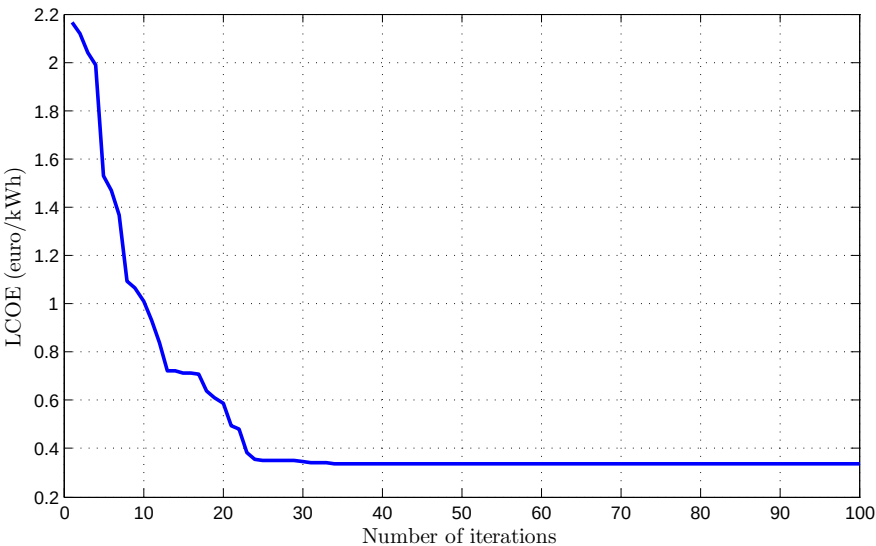


Figure 6.3: LCOE convergence

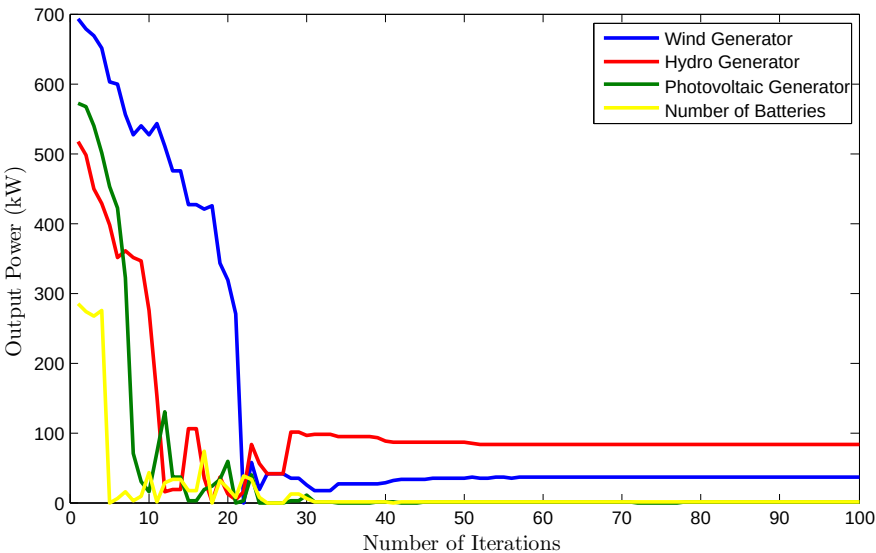


Figure 6.4: External parameters convergence

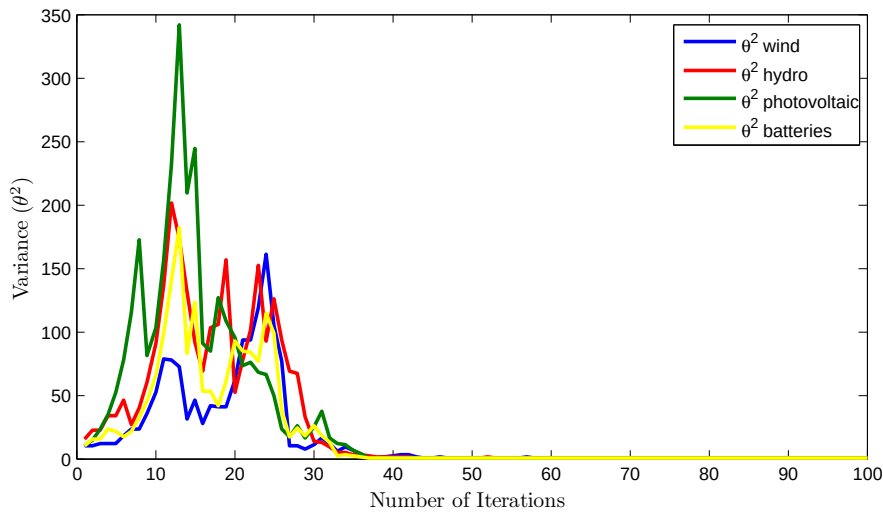


Figure 6.5: Variance oscillation until convergence

6.5.2.1 Load Diagram 1

In this first case, the load diagram in figure 6.6 is used to study the system behavior. It is important to refer that this was a daily sample of an annual load diagram. The average daily load is 29,59kW and the annual average is 25,96kW. An high peak occurs at approximately 20 p.m. and some minor peaks occur at 6 a.m. and 13 p.m..

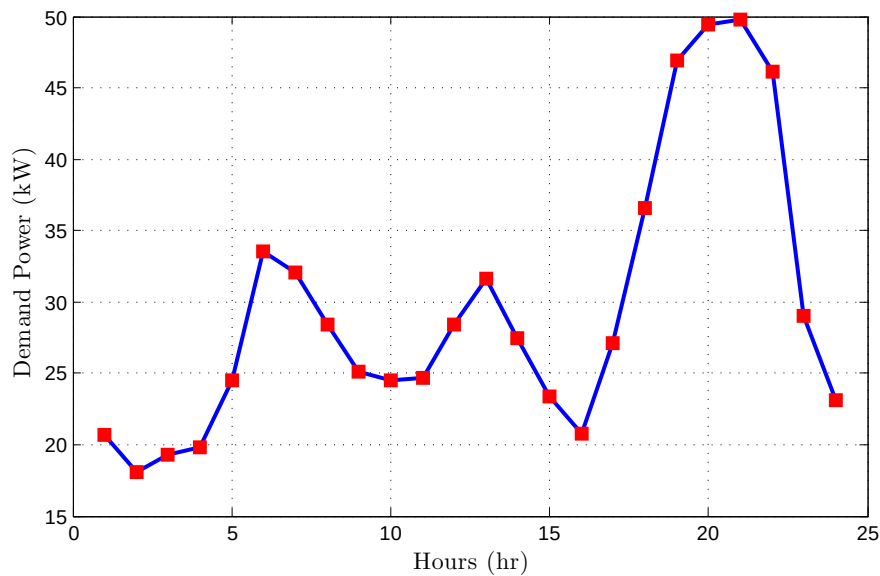


Figure 6.6: Load sample 1

With this load as the annual demand power of a particular hybrid system, the algorithm was tested, first concerning the load following strategy and later on, the cycle charging strategy.

In table 6.1 the results of the algorithm for a load charging strategy are described. It was neglected the use of any kind of photovoltaic power and batteries. On the other hand, the rated

power of both hydro and wind generators are fairly high. One possible solution to this problem is that the peak load only occurs later at 8 p.m, where there is no sun at almost any time of the year.

Table 6.1: Unit sizing for load diagram 1 with a load following dispatch strategy

Wind Turbine Rated Power (kW)	37
Hydro Generator Rated Power (kW)	84
PV Generator Rated Power (kW)	0
Batteries (n°)	0
Diesel Generator Rated Power (kW)	51

In figure 6.7 it is possible to see the monthly output power variation of all types of power sources that constitute the system. As the system was able to retrieve almost all the power from hydroelectricity at the beginning of the year, the same can not be told of the end of the year where the hydro resource is sincerely low (see figure 4.6). The investment is well made in the hydro capacity and later on, the diesel generator fills the needs when required. The wind generator occupies the off-peak of the load diagram.

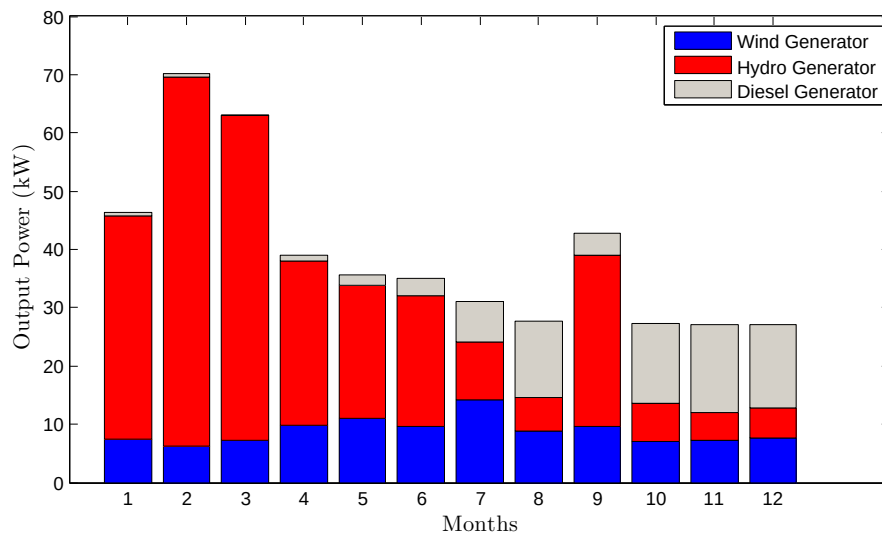


Figure 6.7: Monthly energy production with a load following strategy for load diagram 1

In table 6.2, the results of the cycle charging strategy are presented. It is noticeable that no photovoltaic or batteries were chosen once again, but the wind generator rated power is higher than in the previous case with the LF strategy, hence the hydro rated power is lower than the previous one.

In figure 6.8 we can see the monthly average production for the three generators — wind, hydro and diesel. Despite the fact that the graphics in figures 6.7 and 6.8 seem equal, it is easy to see the difference between the amplitude in the first months of production. At the end, the diesel generator behavior is the same in both cases because no excess is encountered.

Table 6.2: Unit sizing for load diagram 1 with a cycle charging dispatch strategy

Wind Turbine Rated Power (kW)	41
Hydro Generator Rated Power (kW)	74
PV Generator Rated Power (kW)	0
Batteries (n°)	0
Diesel Generator Rated Power (kW)	51

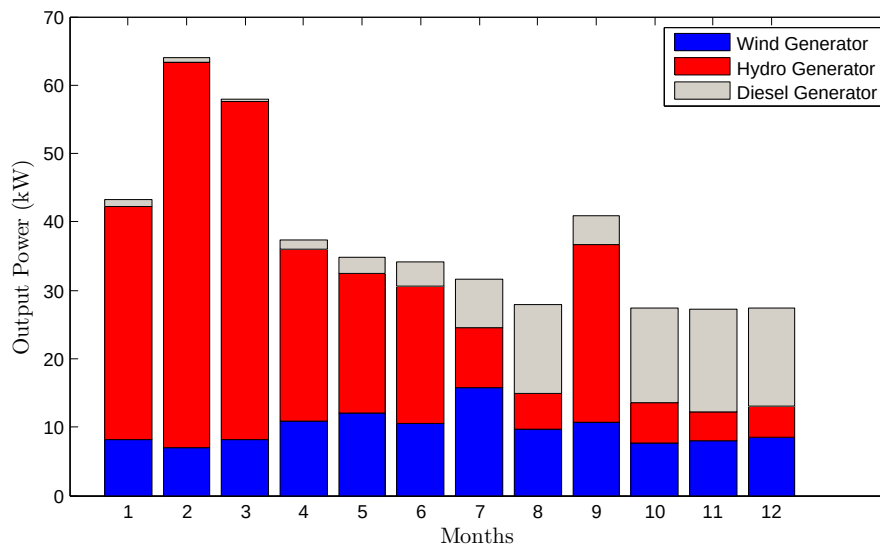


Figure 6.8: Monthly energy production with a cycle charging strategy for load diagram 1

6.5.2.2 Load Diagram 2

The load diagram 2, picture in figure 6.9 has some similarities with the sample load 1 in figure 6.6. With a high peak at 21 p.m. and two minor peaks at 7 a.m. and 13 p.m.. The big difference between this two diagrams is the load amplitude that in the load sample 1 reaches 50kW and in sample 2 only reaches approximately 7kW. The load daily average in this sample is 2,77kW and the year average is 2,5kW.

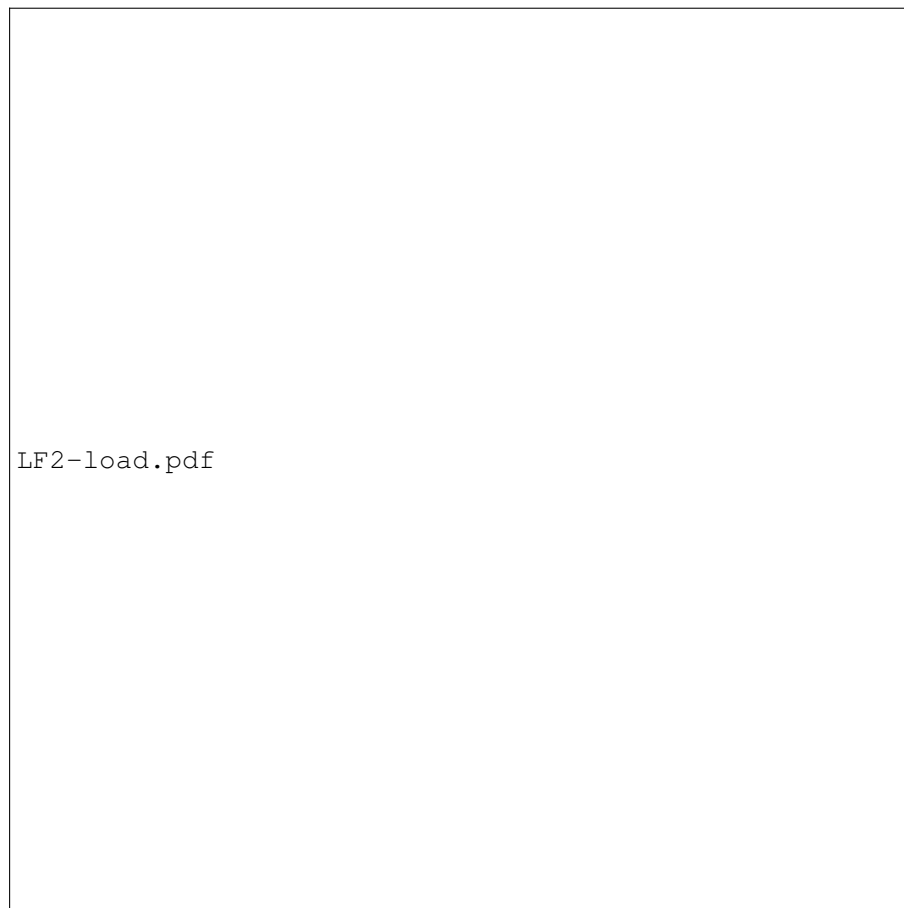


Figure 6.9: Load sample 2

The results obtained from the load following strategy are presented in table 6.3. Obviously, the generators rated power decreases when compared to the case study of load sample 1. The emphasis here is that only the wind generator is laid aside. The hydro and photovoltaic generators assume the same 5kW rated power, the diesel generator 8kW and for the first time, the algorithm selected 2 batteries for system composition. This is explained due to the fact that the photovoltaic generator only generates power during the day, where the peak is not as high as during the night, and the batteries can then storage the excess energy to feed the load during the night.

In figure 6.10 we are able to see the behavior of the one year monthly energy production from the LF strategy, applied to the load diagram 2 (see figure 6.9). We can see the high peaks of hydroelectricity at the beginning of the year, as expected, and the photovoltaic off-peak curve

Table 6.3: Unit sizing for load diagram 2 with a load following dispatch strategy

Wind Turbine Rated Power (kW)	0
Hydro Generator Rated Power (kW)	5
PV Generator Rated Power (kW)	5
Batteries (n°)	2
Diesel Generator Rated Power (kW)	8

perfectly drawn from January to December. The diesel generator serves the purpose of filling suppositional unmet load in the first months, where still exists plenty of hydro electricity available, combined with the joined operation of the photovoltaic generator and the batteries. In the last months of the year, with lack of hydro resource, and because it did not compensate to invest more in the photovoltaic generator, the diesel generator is called to fill almost the load. There is still a little hydro and photovoltaic power, but in a lower percentage of the DG.

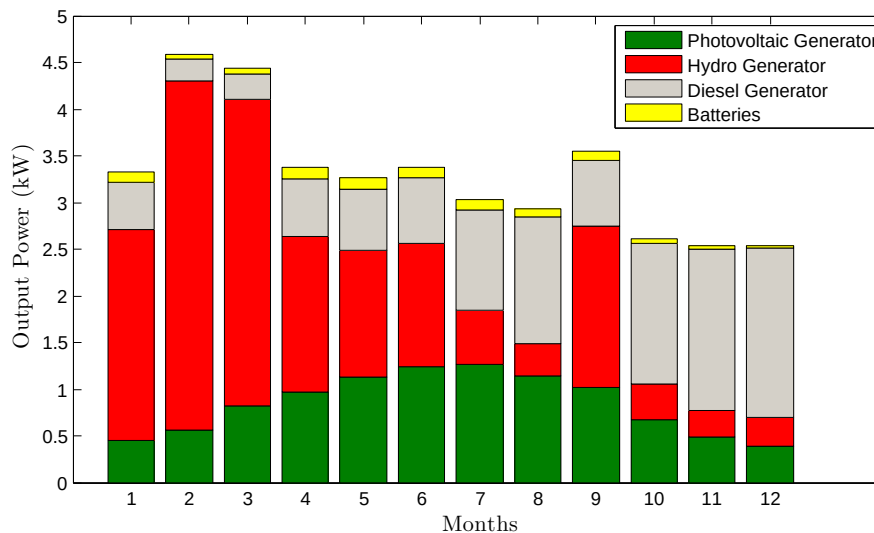


Figure 6.10: Monthly energy production with a load following strategy for load diagram 2

For the same sample load 2, the testes were done regarding the cycle charging strategy. The final results obtained are shown in table 6.4. The Diesel Generator is the same as the one acquire from the LF strategy. The real differences consist in one more battery then the previous test, being the number of batteries equal to 3; The Hydro generator rated power is 6kW and the photovoltaic generator rated power is 3kW.

Table 6.4: Unit sizing for load diagram 2 with a cycle charging dispatch strategy

Wind Turbine Rated Power (kW)	0
Hydro Generator Rated Power (kW)	6
PV Generator Rated Power (kW)	3
Batteries (n°)	3
Diesel Generator Rated Power (kW)	8

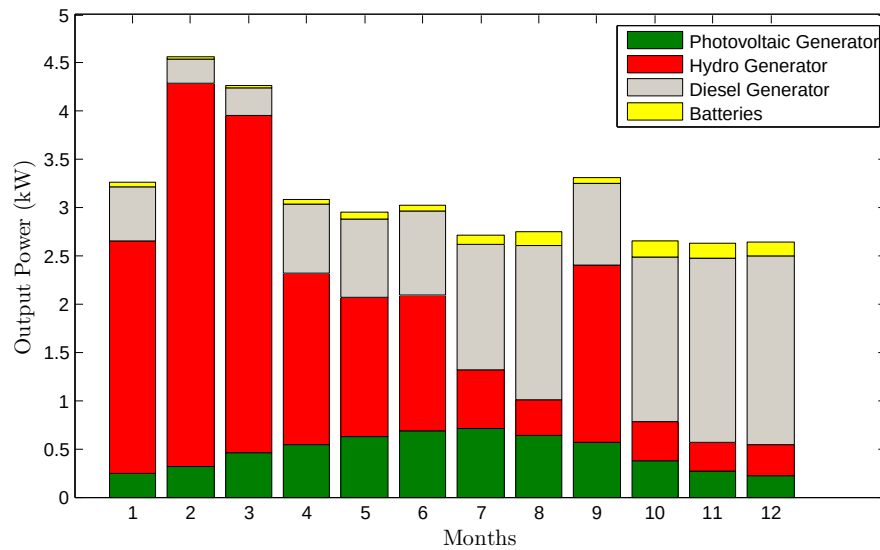


Figure 6.11: Monthly energy production with a cycle charging strategy for load diagram 2

The behavior, graph is figure 6.11 is yet similar to the one with the LF strategy, but is possible to see the difference between the energy retrieved from the batteries in the last months of the year. The cycle charging strategy is in that way called because the diesel generator runs to fill the batteries SOC whenever it is possible. In the beginning of the year, the batteries in the load following strategy were always able to supply the load but in the cycle charging strategy, they could work only if the net load was less than the maximum battery flow in the hour of deficit. So, the batteries were charged in the first months (still working with some cycles), but at the end of the year the renewable output power is minimal and therefore, the diesel and the batteries start to work.

6.5.2.3 Load Diagram 3

The load sample 3, pictured in figure 6.12 is a particular case where the load peak occurs at approximately 15 p.m. It has an average daily load of 8,29kW and a year average load of 8,33kW. This is an interesting case due to the hours where the peaks occur, seeming possibly the increase of the photovoltaic power.

The first strategy applied was the load following one. Final results from this strategy are shown in table 6.5. Here we can see the superiority of the hydro generator, as being usual in all the case studies. This is again explain because there are no problems in having excess energy in the system, and the hydro profile is higher than the other ones in the first months.

In figure 6.13 the monthly energy productions are described. It is important to refer the increase in the photovoltaic generator rated power, which is more or less the daily peak of load sample 3. Because it was not needed to store energy to night loads, the photovoltaic generator only supplies daily loads, leaving for the diesel generator and the hydro generator to fulfill night

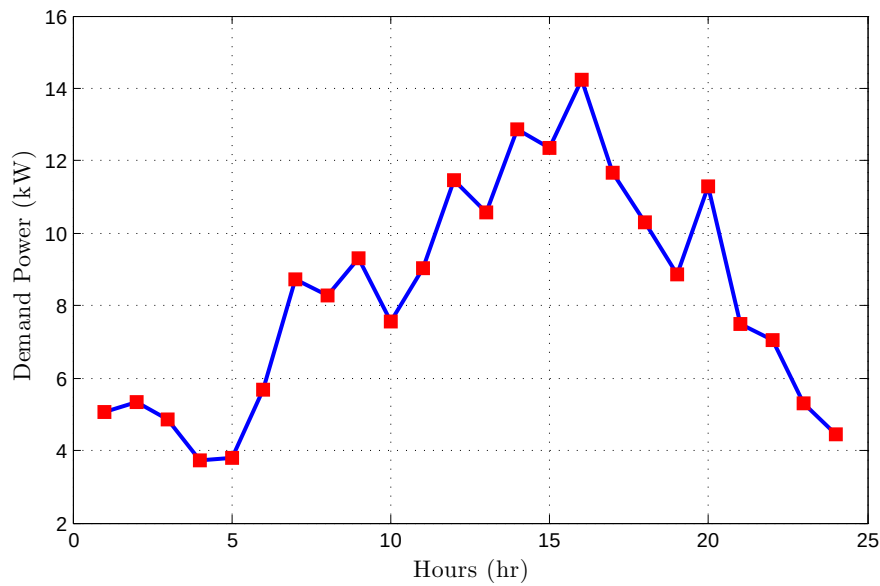


Figure 6.12: Load sample 3

load requirements. In other words, the photovoltaic profile follows the daily load diagram profile and the system does not have the needs to store energy from this particular generator.

In table 6.6 the final results of applying the cycle charging strategy to the load sample 3 are depict. In figure 6.14 the monthly average productions are graphed. Both results are equal to the one described above, because there are no batteries serving storage principles.

6.5.2.4 Load Diagram 4

This case is yet another distinct one, where the load has a distinctive discontinuous behavior. The load sample is graphed in figure 6.15. There are several peaks during the day, at 4 and 10 a.m. and 13, 17 and 22 p.m.. The average daily load is 82,96kW but the year average is only 66,67kW, representing the biggest difference between both mean values in all case studies.

The rated power for each technology has grossly exceed the expected. The diesel generator has reached the limit imposed by the user (60kW) and all other discontinuous power sources, mainly renewable, had to rudely surpass the load values so that the systems year load could be supplied.

Due to the complexity of this problem, it can not be explained the algorithm behavior to determine such values. The only thing that can be accomplished is the comparison between both LF and CC cases. In the load following strategy all the generators rated power exceed the ones from the cycle charging strategy (see table 6.7 for LF strategy and table 6.8 for CC strategy).

In figure 6.16 we can see the monthly average production from each technology. From the joined visualization of table 6.7 and figure 6.16 we are able to deduce that the photovoltaic generator has the higher rated power, followed by the hydro and wind generator respectively. As was expected, the diesel generator works at full power in months where there are no hydro or photovoltaic power available. It is then a possible solution to this problem that the algorithm choose not to increase the wind generator rated power because it knew that the 60kW diesel generator and the

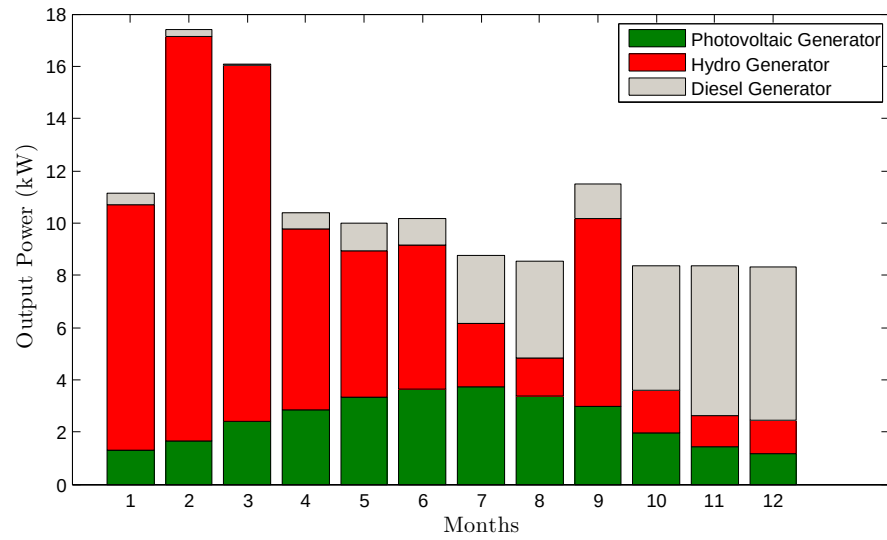


Figure 6.13: Monthly energy production with a load following strategy for load diagram 3

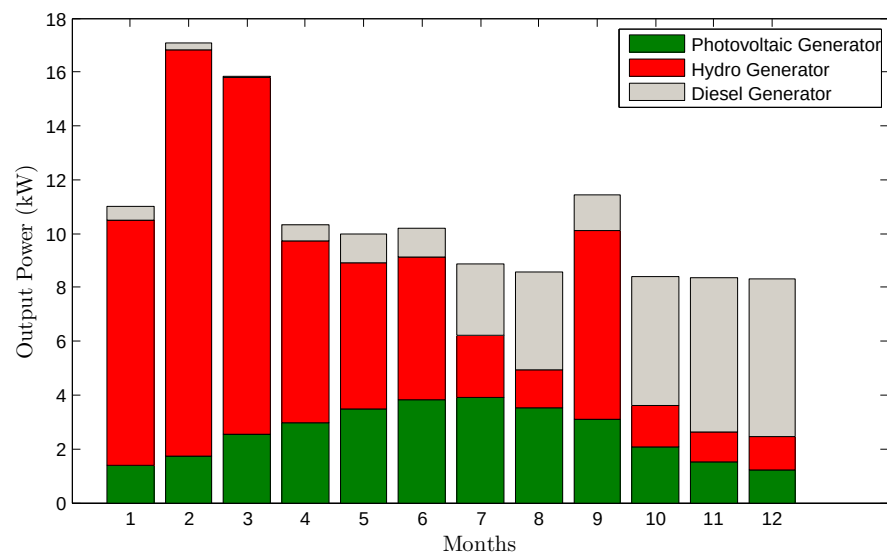


Figure 6.14: Monthly energy production with a cycle charging strategy for load diagram 3

Table 6.5: Unit sizing for load diagram 3 with a load following dispatch strategy

Wind Turbine Rated Power (kW)	0
Hydro Generator Rated Power (kW)	21
PV Generator Rated Power (kW)	13
Batteries (n°)	0
Diesel Generator Rated Power (kW)	14

272 batteries could supply the load in such hydro and photovoltaic deficit months like November and December.

In table 6.8 the results from the cycle charging dispatch strategy are shown. When compared to the load following strategy results, it is clear the decrease of all generators rated power (less the DG which still is at its maximum nominal output power 60kW). We can observe, as well, that the number of batteries increased from 272 to 387. This is due to the fact that in the cycle charging strategy, the diesel runs at full load to charge the batteries whenever it can, reducing the amount of energy needed from the renewable generators and increasing the number of batteries to supply the load.

in figure 6.17 the profile of the monthly average productions is described. The similarities between the profile results obtained by the load following strategy and the cycle charging strategy were sincerely good but the amplitude of each generator output power was fairly different, being less in the CC strategy, for reasons already explained above.

6.6 Critical Analysis

In this section a critical analysis of the results will be discussed. For simple understanding of the different results obtained in the different case studies presented, the levelized cost of energy for each sample load diagram and respective dispatch strategy are presented in table 6.9.

For all the cases except the one with sample load 3, the LCOE was lower with a cycle charging strategy. This happens because we decide not to consider any excess load penalization. For all hybrid combinations that do not include batteries (sample 1 and sample 3), the respective LCOE's are almost equal between the two strategies. In those cases where the hybrid system comprise batteries (sample 2 and sample 4), the difference between the two LCOE's for different dispatch strategies are sincerely different. For case study 2 with the CC strategy, with 3 batteries, the system's LCOE was 0,008 cents lower then the one for LF dispatch strategy. In case study 4, a more accentuated difference was obtained – the cycle charging strategy LCOE was 0,028 cents lower then the load following.

By being critical, it should be noticed that this results are aimed at only one renewable resource profile for each technology, and only the load diagram has changed. The scope of this thesis pointed to see the behavior of the optimization algorithm for designing an hybrid energy system and not to make a profile of which hybrid system best suited a determined load. For that, the

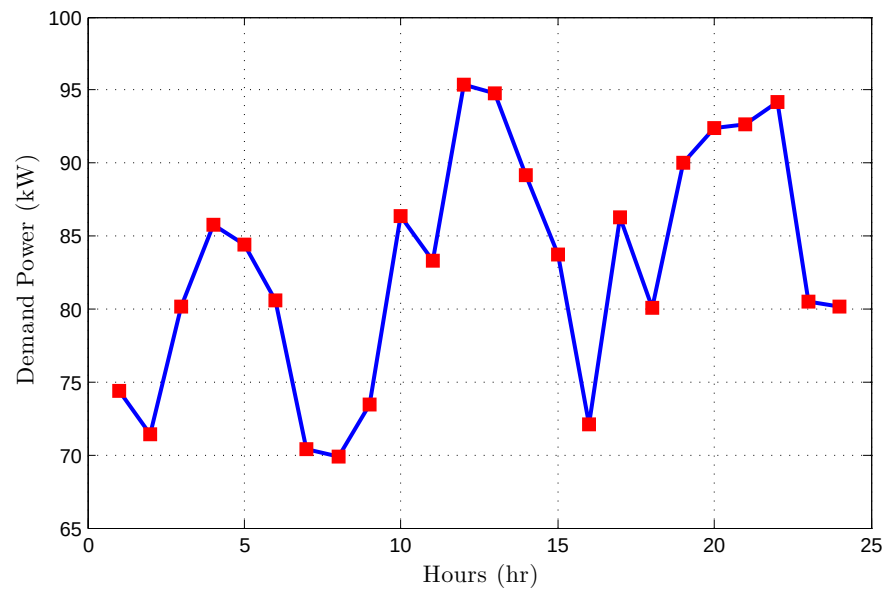


Figure 6.15: Load sample 4

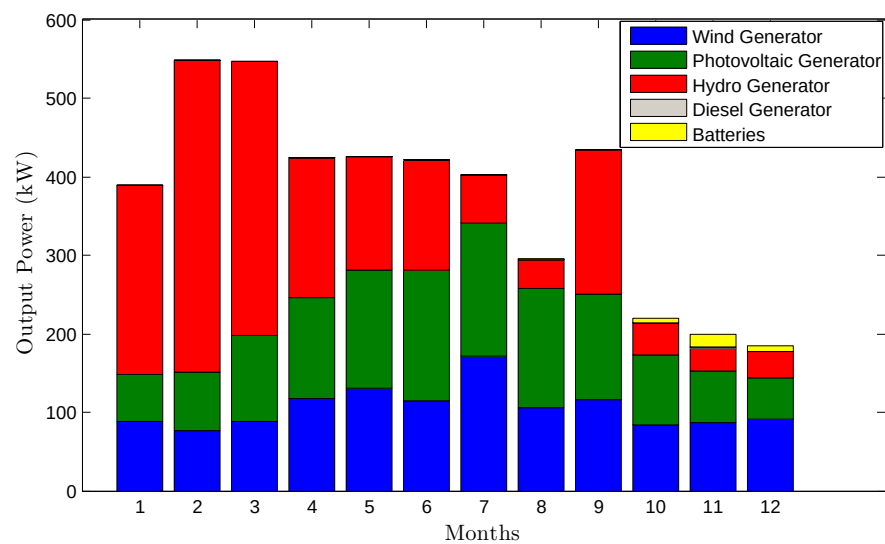


Figure 6.16: Monthly energy production with a load following strategy for load diagram 4

Table 6.6: Unit sizing for load diagram 3 with a cycle charging dispatch strategy

Wind Turbine Rated Power (kW)	0
Hydro Generator Rated Power (kW)	20
PV Generator Rated Power (kW)	13
Batteries (n°)	0
Diesel Generator Rated Power (kW)	14

algorithm is well capable of making that study, but several distinct data information on renewable resources should be applied to all kinds of loads, so that conclusions could be done.

Table 6.7: Unit sizing for load diagram 4 with a load following dispatch strategy

Wind Turbine Rated Power (kW)	435
Hydro Generator Rated Power (kW)	522
PV Generator Rated Power (kW)	563
Batteries (n°)	272
Diesel Generator Rated Power (kW)	60

Table 6.8: Unit sizing for load diagram 4 with a cycle charging dispatch strategy

Wind Turbine Rated Power (kW)	325
Hydro Generator Rated Power (kW)	495
PV Generator Rated Power (kW)	423
Batteries (n°)	387
Diesel Generator Rated Power (kW)	60

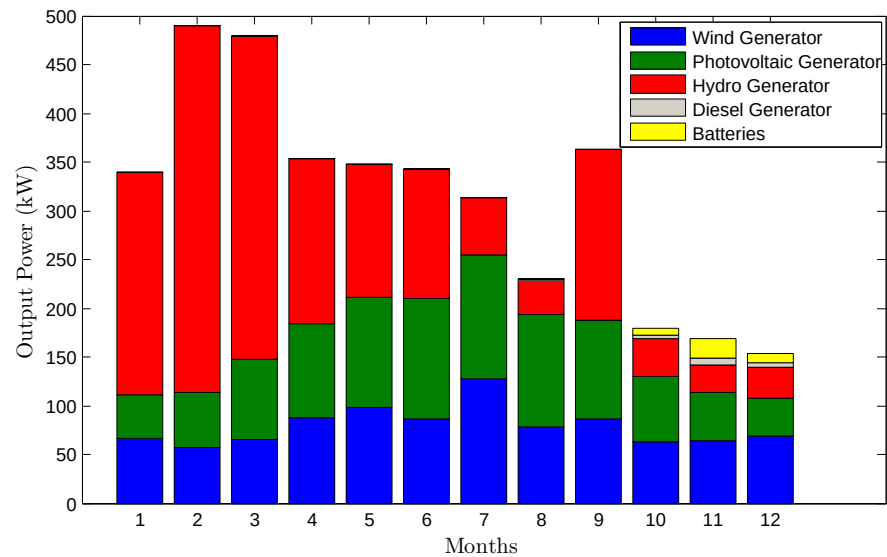


Figure 6.17: Monthly energy production with a cycle charging strategy for load diagram 4

Table 6.9: Case studies LCOE results (€/kWhr)

Strategy	Load 1	Load 2	Load 3	Load 4
Load Following	0,3359	0,4832	0,3473	0,7436
Cycle Charging	0,3353	0,4752	0,3472	0,7156

Chapter 7

Conclusions

7.1 Final Conclusions

The first conclusion that can be withdrawn from this work is the possibility to create a typical design portfolio for hybrid energy systems. Starting from the operation system model and with the optimization algorithm developed, this portfolio is an easy made requirement. So as to create this case folder containing pilot rules for the design of hybrid systems, several distinctive resource data and information is essential, as well as large number of load diagrams. By successively running the program, it will be manageable to generate an optimal portfolio for each suitable situation.

The design optimization of hybrid energy systems depends on countless variables. For sure, the more important parameters that influence the capital costs of the system are concerned to the technologies and components investment costs. However, a very significant portion of this problem is extremely correlated with the unpredictability of renewable resources.

An important conclusion relies on the fact that it is possible to in a cooperation way, optimize dispatch strategies and the design of the system and, once again, both this components are strongly correlated with renewable resources site data information.

The cycle charging strategy presents the best results, relative to levelized costs of operation and energy consumption, when we want the diesel generator to run at output powers near the rated one so that its efficiency reaches high levels. By doing this, it allows the system to minimize the investments on other types of technologies, reducing the system's redundancies up the year. The load following strategy penalizes more the batteries because it constantly have to meet the load deficit and therefore, the diesel generator cannot get the same efficiency than the cycle charging strategy due to its low operation power outputs.

Despite the fact that costs for excess or surplus energy were not established, these are extremely important variables, working as restriction parameters to the system optimization design. The problem in this case is to quantify the value of an excess energy cost penalization, which should be an intersection, for each hour, of the investment curve costs and the unmet load. This intersection will diversify for different solutions creating a even more complex problem.

One of the main conclusions retreat from this work is related to the fact that a continuous optimization process of the hybrid system unit sizing (within a continuous search space - wind, solar, hydro, diesel, batteries) is possible. All reviewed and tested software like HOMER, HOGA and Hybrid2, "optimize" pre-selected solutions by choosing the best one of them all. This cannot be considered as an in-depth optimization. To enhance the possibility of algorithms, like the described above, to optimize an almost continuous function, a near infinite group of pre-based-solutions is needed. However, this has no logic point at the eyes of the user because it would become of an extremely cost/time computational involution.

With the algorithm developed in this thesis, the user do not have to know what kind and/or mix of technologies and the respective unit sizing for the beginning of the optimization process. In this software, the user just has to insert the renewable data information and wait for GraSO to return the optimum solution to the problem. As it is a continuous optimization problem, the solutions obtained belong to a continuous space and so, it is advised to the software's user to round up the rated power for each technology to an available market level.

A new optimization algorithm was developed – GraSO – capable to answer in a efficient and effective way to several complex problems, including the one studied in this thesis, the design optimization of hybrid energy systems. This algorithm has inhabited capacities to evaluate tendencies from a group of points to the optimal solution that confers it the ability to make judgments both in a discrete or continuous dimension. With GraSO we can control the search space density in a self-adaptive way, i.e. the search space can be diminished as the algorithm is near an optimal solution or, if in a far way optimal solution, extended so that new search points can be encountered.

7.2 Future Works

As future works, it is proposed a deepened investigation of the developed algorithm. Despite the good results obtained, it still exists a vast research field that can be explored.

It is also advised the algorithm programming in other language than VBA. Hence, the system modeling should be implemented in a more user friendly interface like Delphi.

The idea that overhangs more is that the new algorithm GraSO can be enlarged to other problem types due to its reliability proved in high complexity problems. One of this problems can be the use of GraSO to solve the economic dispatch of hybrid energy systems, considering at a new instance, the prediction of the renewable resources and the errors associated with them.

Anexo A

Sphere's Iteration Process

In the ambit of chapter 5, it is demonstrated in this appendix the evolutionary process of the spherical convergence function. In each illustration two iterations are described, and inside of every iteration the behavior of each one of the R^3 parameters as well as the respective φ are pictured. It is also demonstrated the tendency (quadratic and linear) fit curves for each one of these cases and the coefficient of determination R^2 .

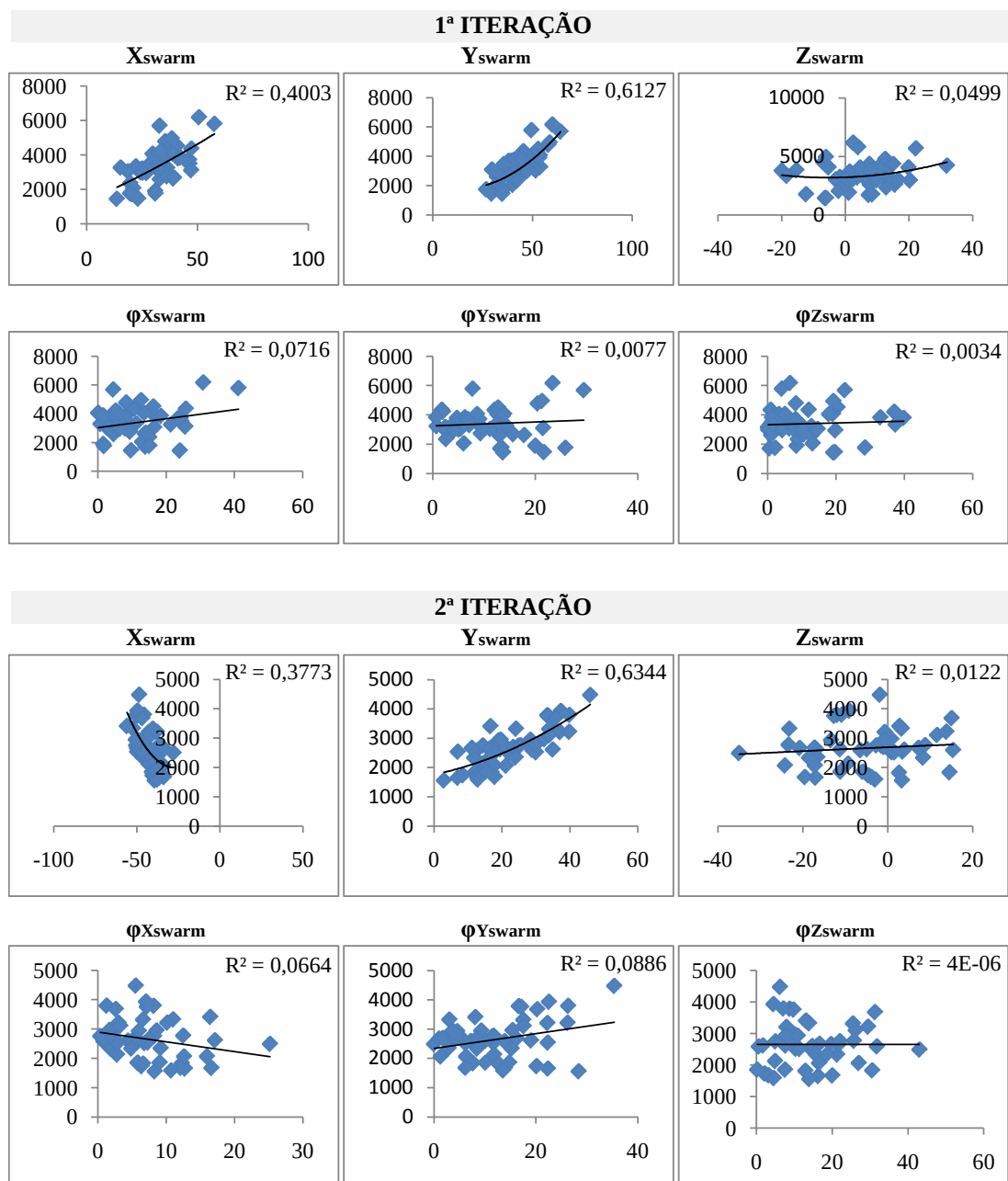


Figure A.1: Graso's Sphere optimization - Iterations 1 and 2

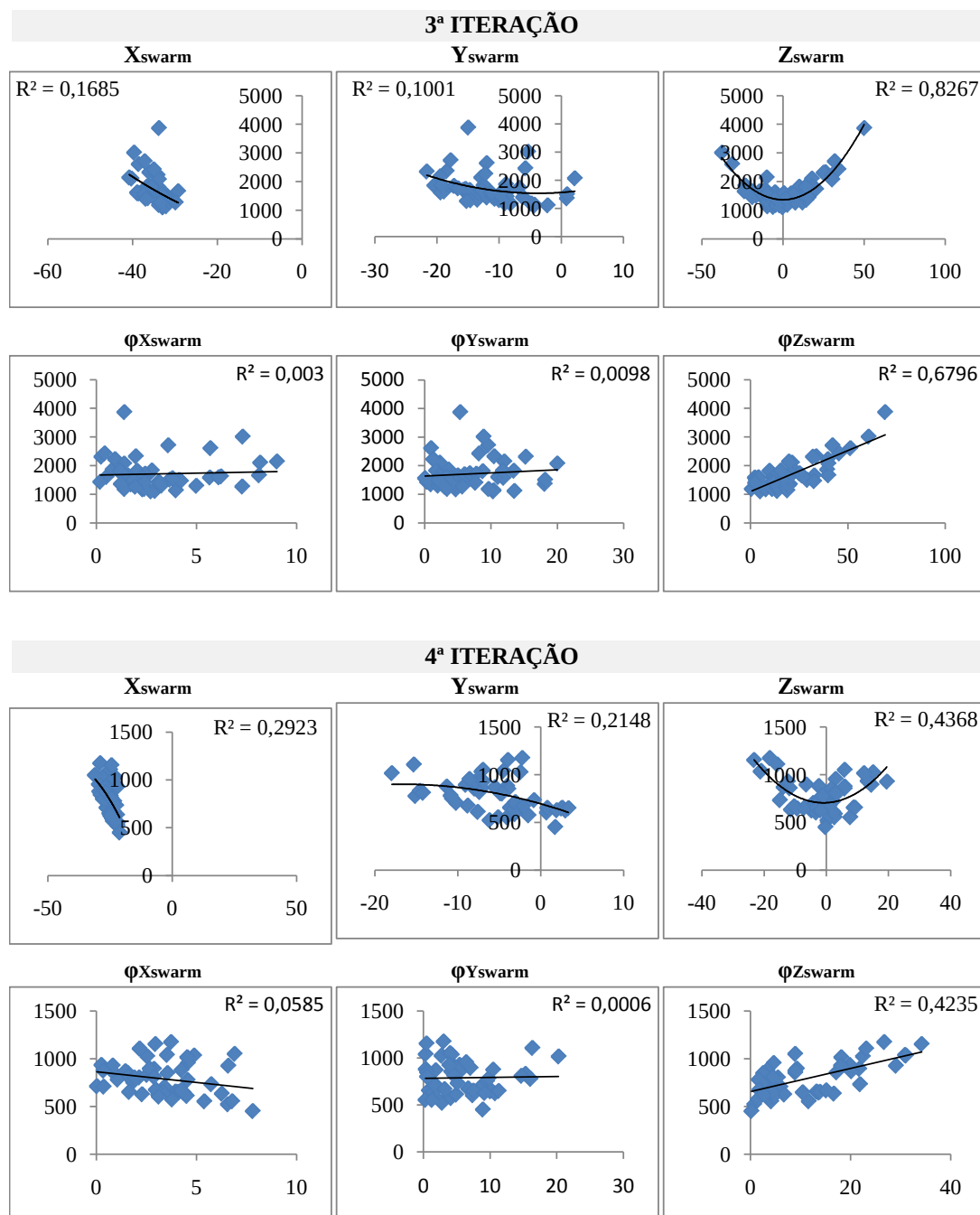


Figure A.2: GraSO's Sphere optimization - Iterations 3 and 4

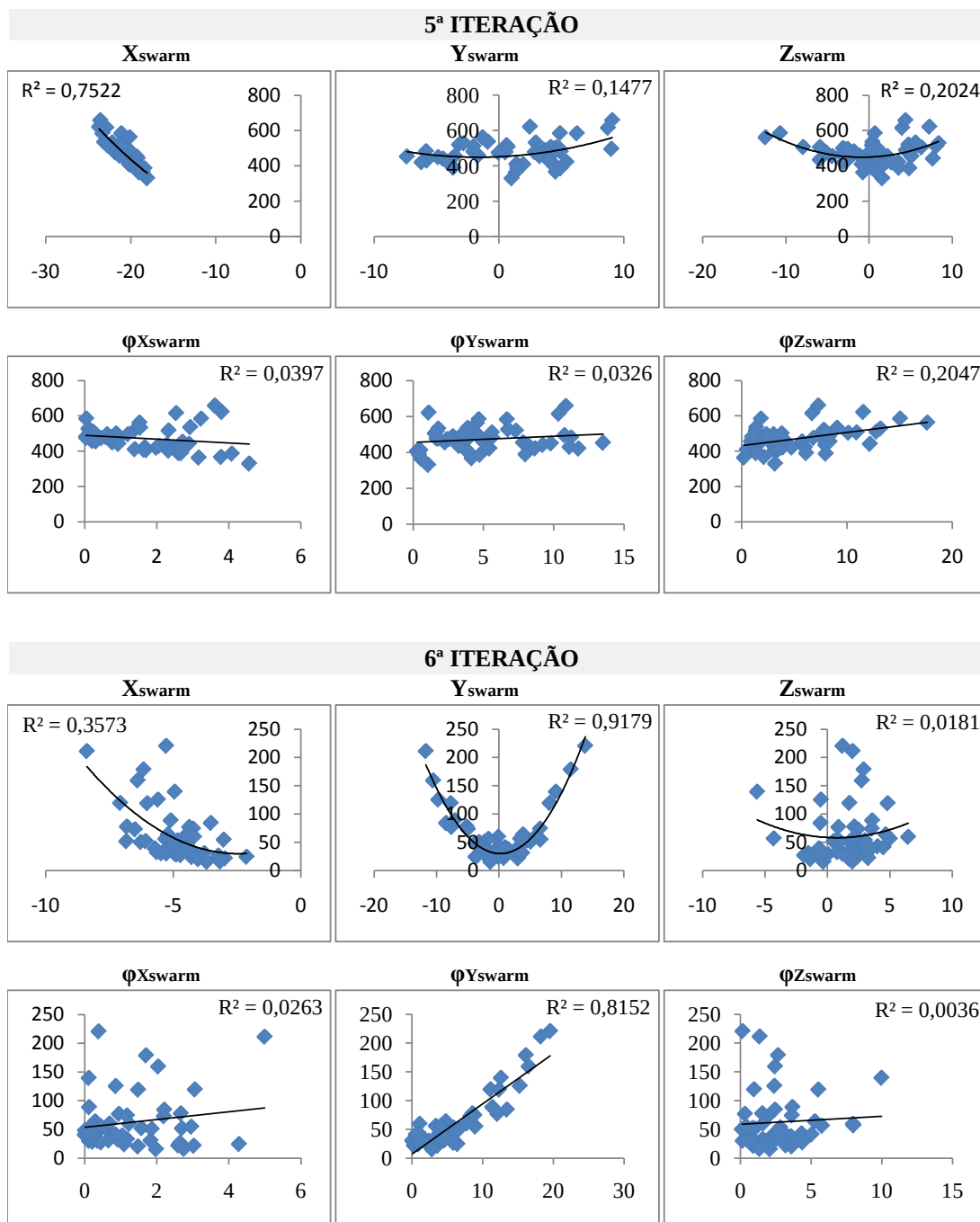


Figure A.3: GraSO's Sphere optimization - Iterations 5 and 6

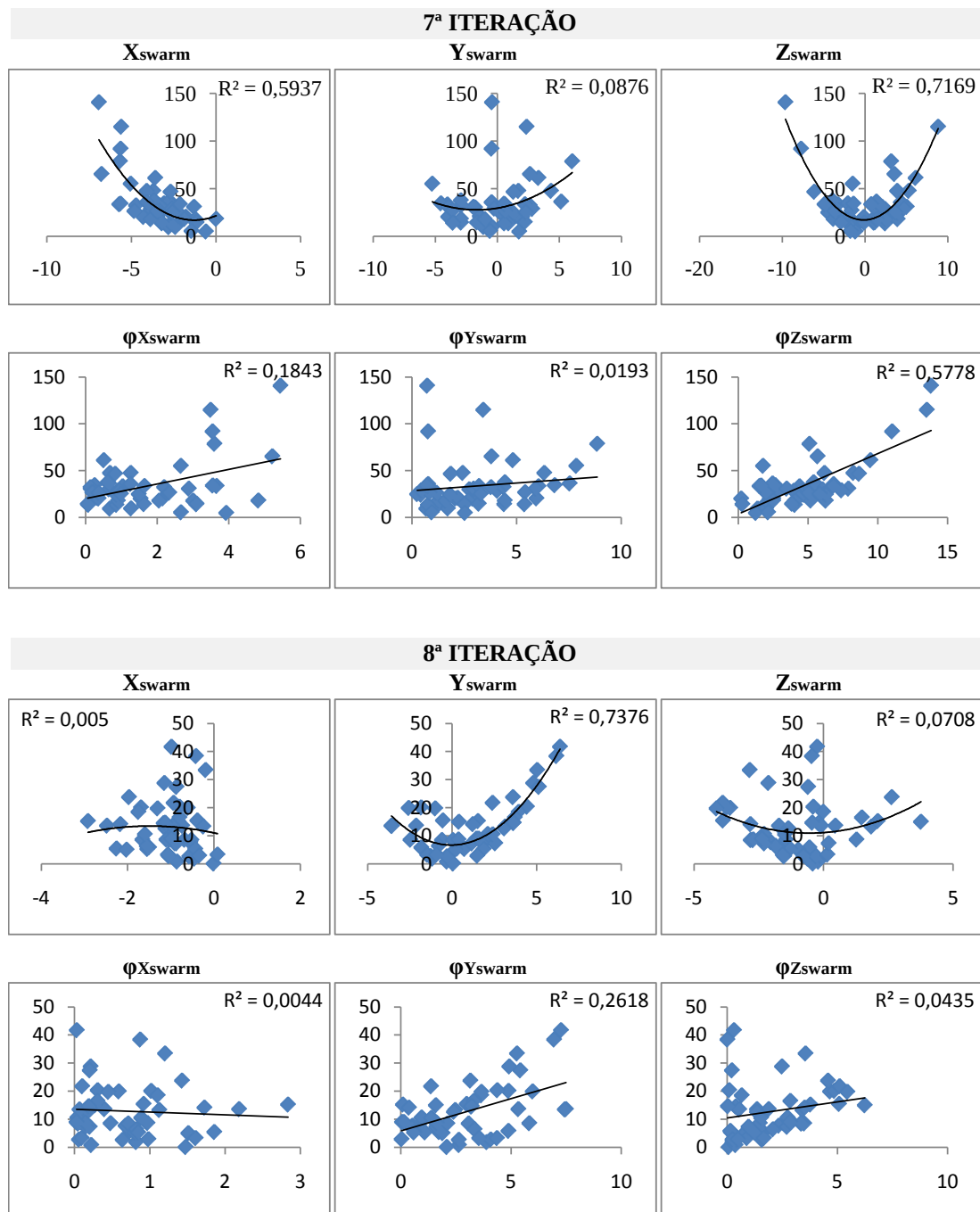


Figure A.4: GraSO's Sphere optimization - Iterations 7 and 8

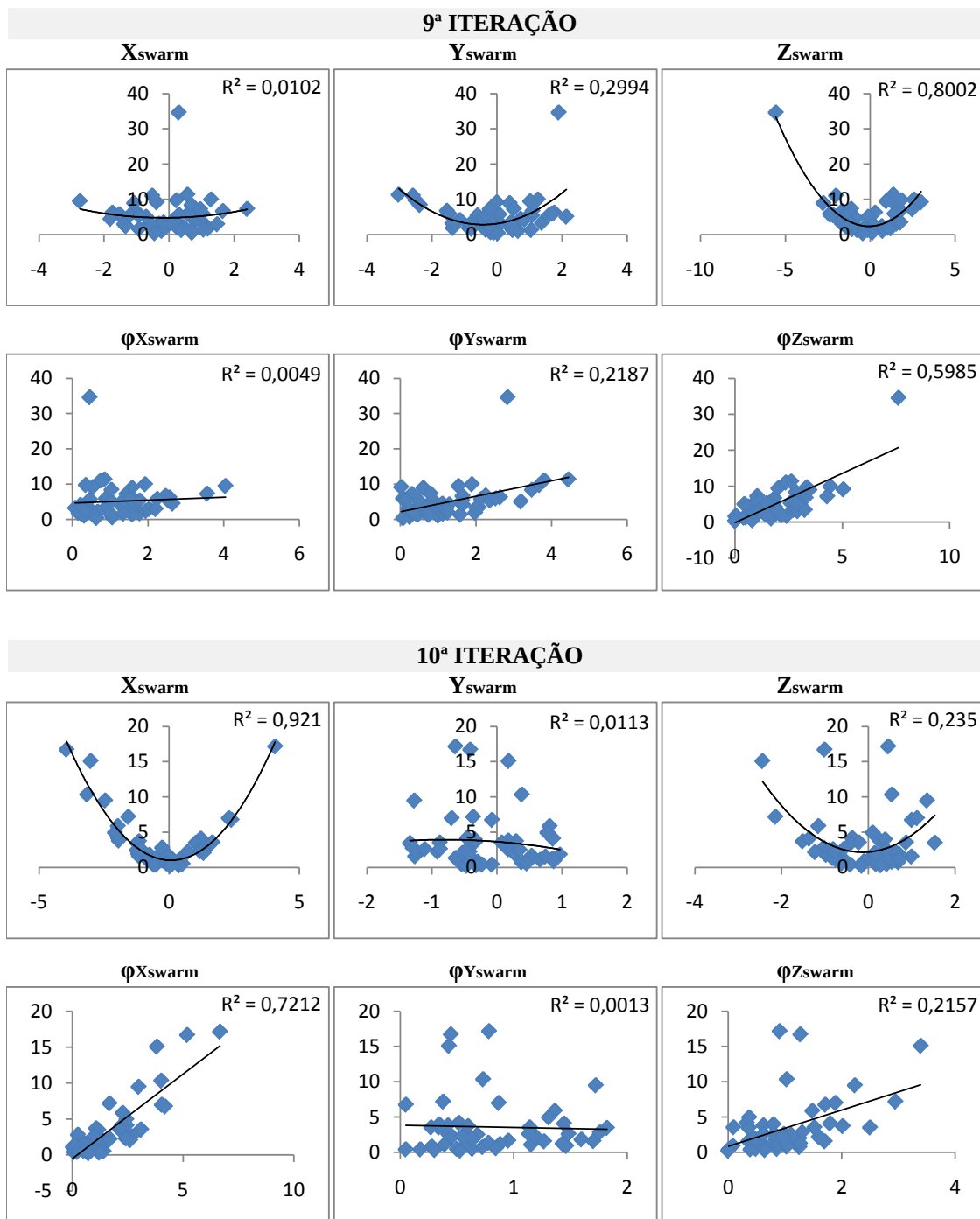


Figure A.5: GraSO's Sphere optimization - Iterations 9 and 10

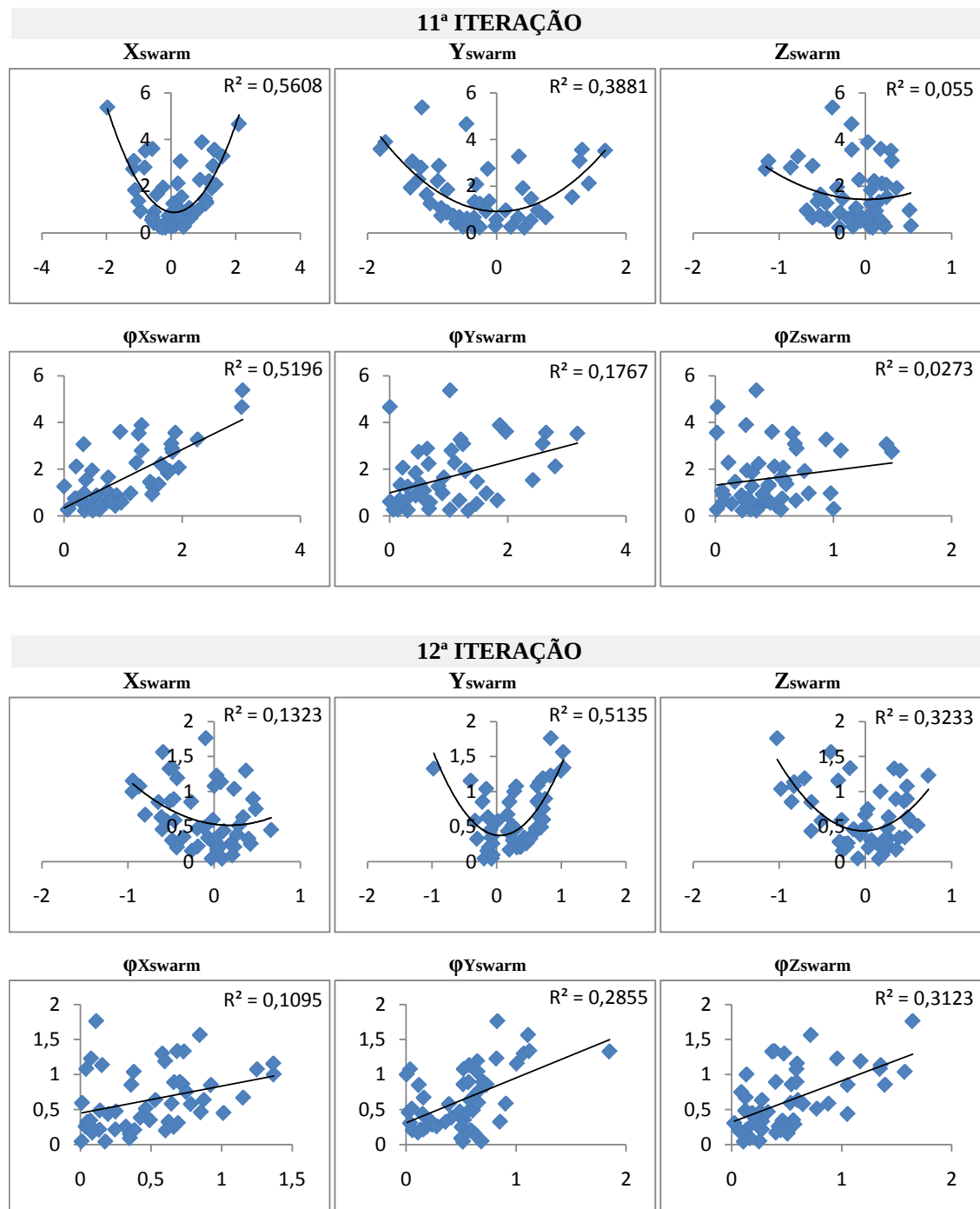


Figure A.6: GraSO's Sphere optimization - Iterations 11 and 12

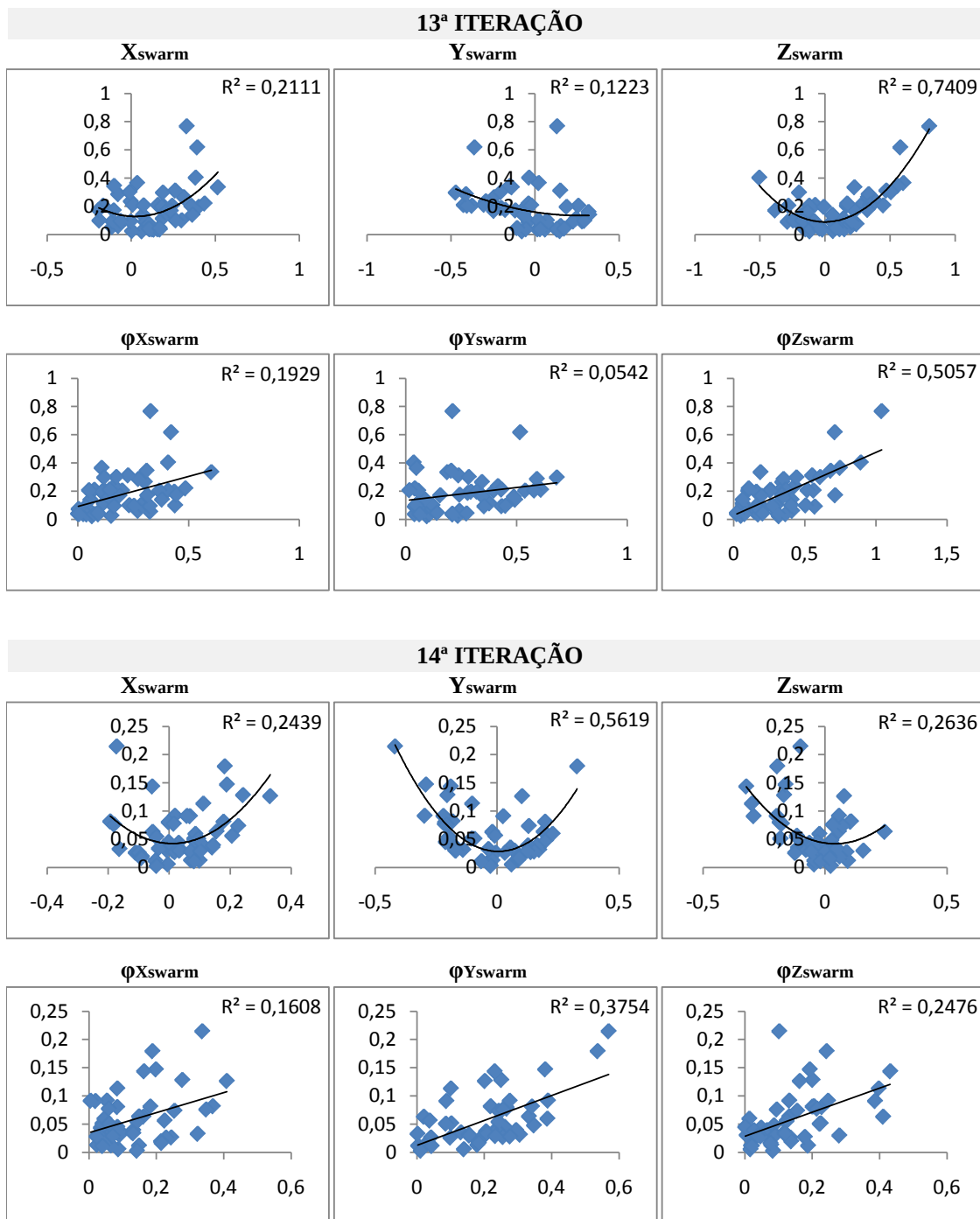


Figure A.7: GraSO's Sphere optimization - Iterations 13 and 14

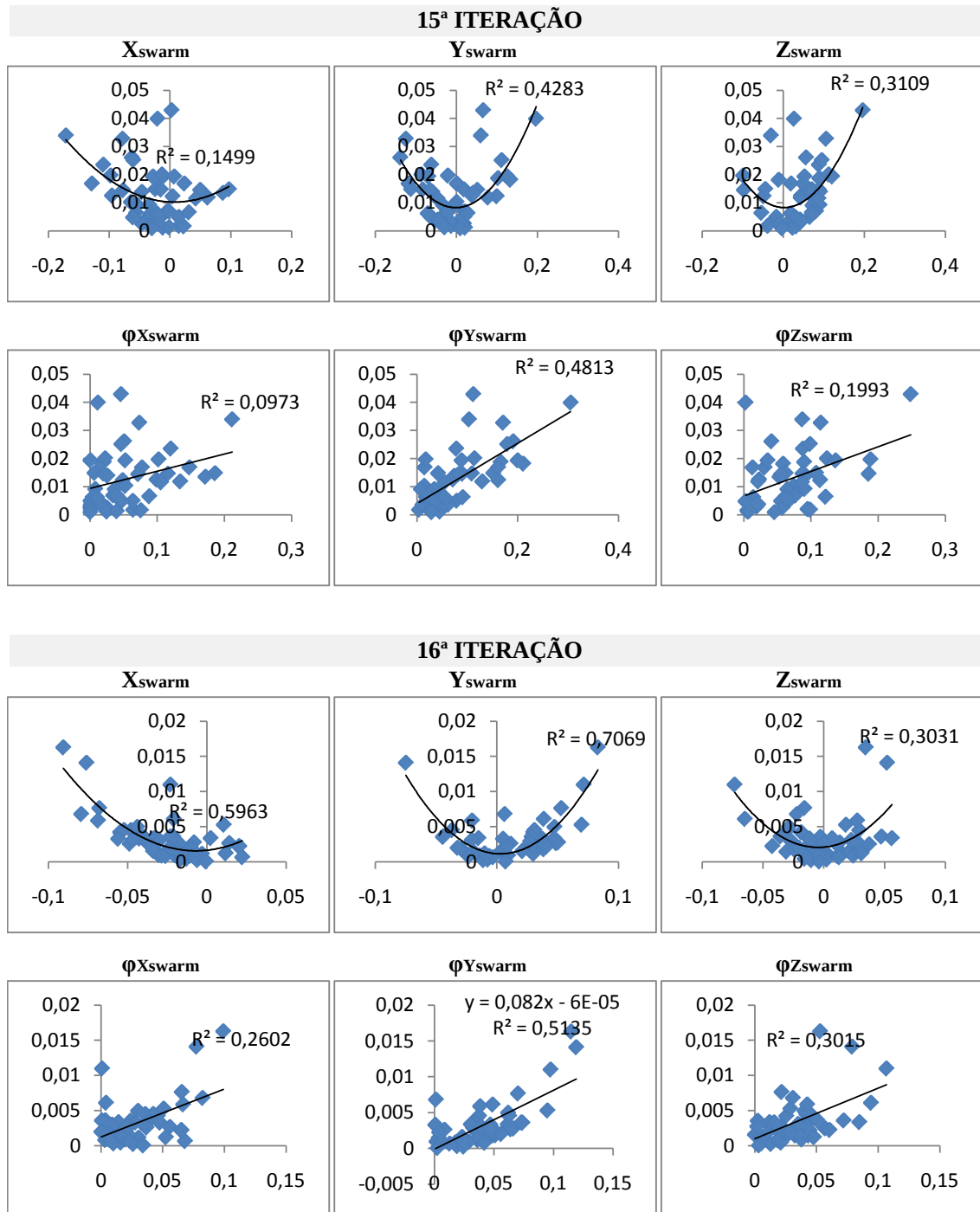


Figure A.8: GraSO's Sphere optimization - Iterations 15 and 16

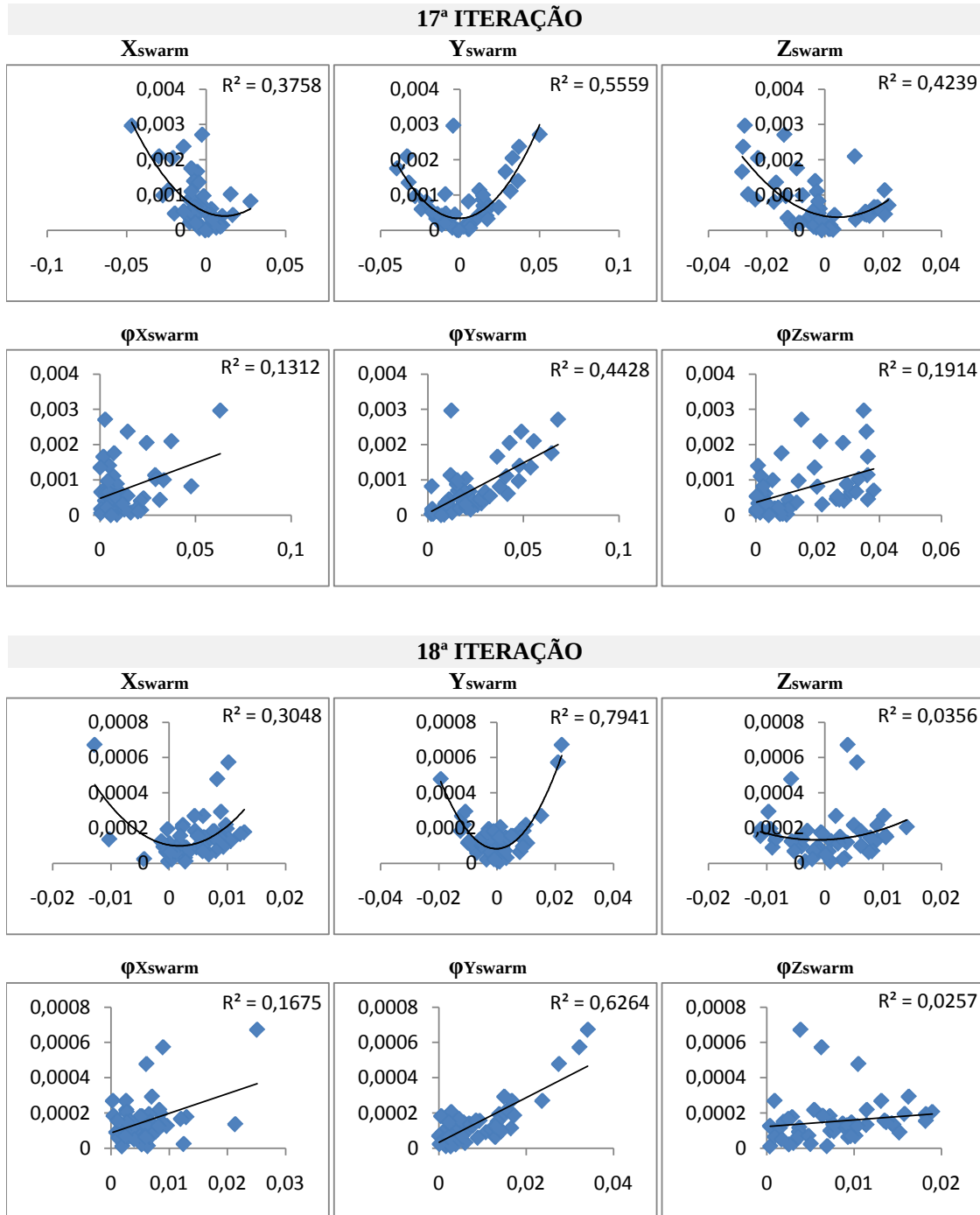


Figure A.9: GraSO's Sphere optimization - Iterations 17 and 18

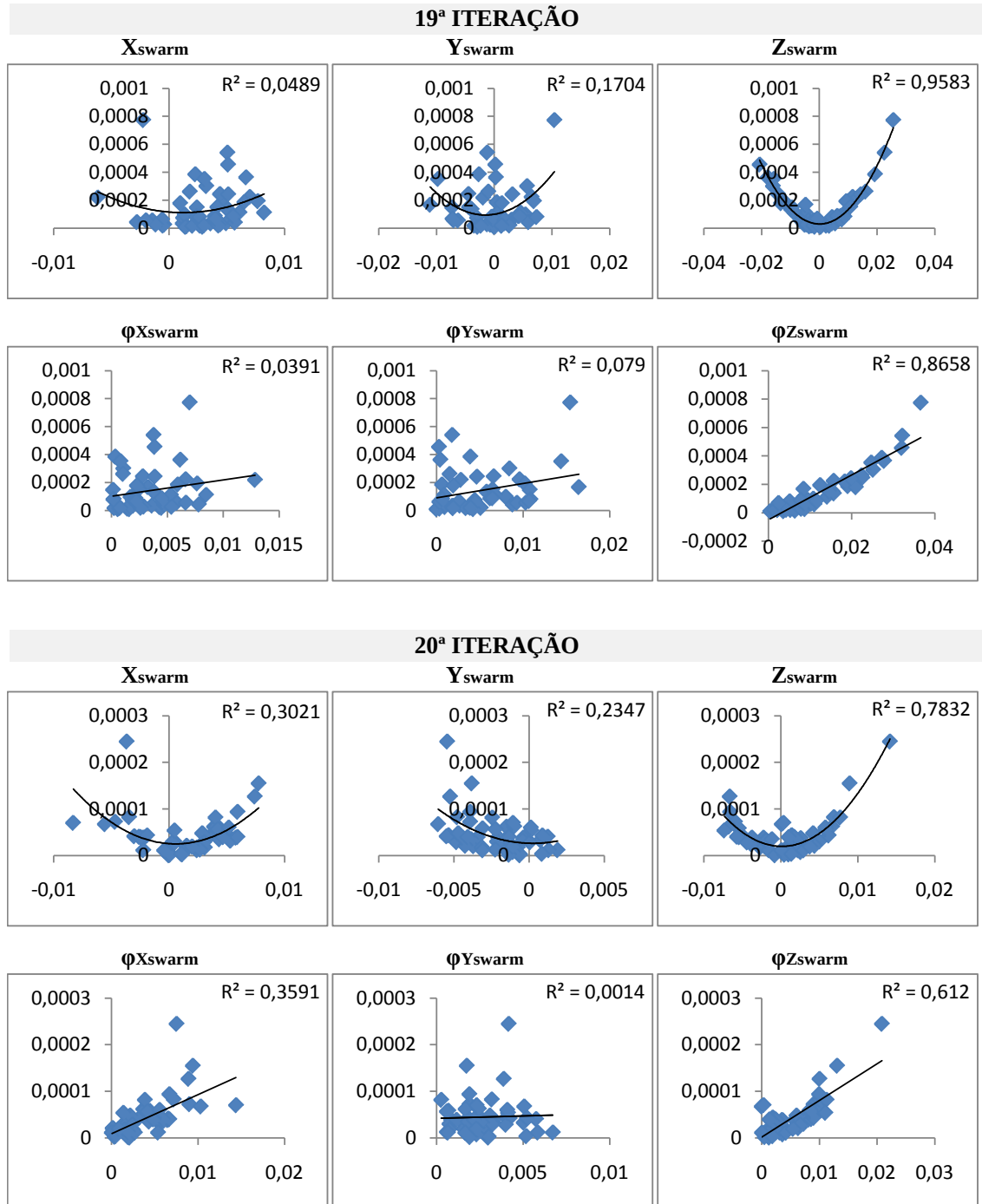


Figure A.10: GraSO's Sphere optimization - Iterations 19 and 20

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