UNIVERSIDAD DE BURGOS

Ph. D. Thesis

A methodology for the definition of profitable scenarios for electrical microgrid establishment

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A methodology for the definition of profitable scenarios for electrical microgrid establishment

Metodología para la definición de escenarios rentables en el desarrollo de microrredes eléctricas

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Robert E. Hebner

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UNIVERSIDAD DE BURGOS
DEPARTAMENTO DE INGENIERÍA ELECTROMECÁNICA

EDUARDO MONTERO GARCÍA, Catedrático de Universidad del Área de Máquinas y Motores Térmicos del Departamento de Ingeniería Electromecánica de la Universidad de Burgos,

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Que la presente memoria "Metodología para la definición de escenarios rentables en el desarrollo de micro-redes eléctricas / *A Methodology for the Definition of Profitable Scenarios for Electrical Microgrid Establishment*" ha sido realizada bajo mi dirección por D. CARLOS GAMARRA LÓPEZ en el programa de doctorado interuniversitario de Eficiencia Energética y Sostenibilidad en Ingeniería y Arquitectura de la Universidad de Burgos y constituye su Tesis para optar al grado de Doctor por la Universidad de Burgos. Esta memoria cuenta con mi informe favorable.

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That the above-mentioned student has worked on his Ph.D. Thesis under my supervision since September 2015 until its completion in February 2020. I have personally reviewed the Thesis document and it fulfills the quality criteria of a Ph.D. Thesis. Hereby, I authorize him to present the above-mentioned Ph.D. Thesis.

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Abstract

Microgrids have been frequently presented as the future of the power grids, taking part in the future Smart grids. However, there are still gaps between the research and development advances on one side, and the business models and the market conditions on the other side, which are preventing the stakeholders or the future owners from adopting microgrids. As in almost every kind of Project, profitability is the most common reason why a promoter would consider complex energy solutions, such as a microgrid.

In this thesis, the microgrid planning process has been modeled as a sequence of optimization algorithms. Optimization algorithms have been successfully applied to different stages of the microgrid planning process. However, no method or set of algorithms has been documented following a holistic approach to the multi-building microgrid planning process, combining in-depth technical and economic analysis and assessing how uncertainties in the framework conditions of the design process might affect the profitability of the project in the long term in competitive energy markets.

The main goal of this thesis is to advance the state of the art of the feasibility analysis methods for multi-building microgrids, helping the decision-makers to identify and compare the optimal designs based on long-term profitability indicators. This primary goal can be divided into different objectives, also addressed by this work, such as:

- To create an innovative feasibility analysis method for multi-building microgrids method, fast and oriented to the sales process.
- To reduce the modeling and simulation time and costs per solution analyzed in comparison with the software tools in the market.
- To compare the optimal solutions with the ones suggested by the user, complementing the deterministic approach with a probabilistic approach that identifies the probability of the economic goals of the project to be fulfilled in the long term.
- To reduce the engineering knowledge required by the user with the ultimate goal of giving independence, and even allowing promoters to complete a feasibility analysis of a microgrid by themselves, once this method is incorporated into a specialized software tool.
- To pre-design the microgrid by selecting, sizing, sitting, scheduling, and pricing the different subsystems.

The proposed method and algorithms have been implemented using MATLAB. The MATLAB tool has been successfully applied to a case study based on a campus of the University of Burgos.

Resumen

Las microrredes se han presentado con frecuencia como el futuro de los sistemas energéticos, formando parte de las futuras redes eléctricas inteligentes o *Smart Grids*. Sin embargo, aún existen lagunas entre los avances de I+D, por un lado, y los modelos de negocio y las condiciones de mercado, por el otro, las cuales ralentizan el nivel de adopción de microrredes por parte de los promotores o futuros propietarios. Al igual que la mayoría de los proyectos, la rentabilidad es la razón más común por la que un promotor consideraría soluciones energéticas complejas, como una microrred.

En esta tesis, el proceso de diseño de microrredes se ha modelado como una secuencia de algoritmos de optimización. Los algoritmos de optimización se han aplicado con éxito a diferentes etapas del proceso de planificación de microrredes. Sin embargo, ninguno de los métodos y algoritmos documentados considera un enfoque holístico del proceso de planificación: combinando análisis técnicos y económicos en profundidad y estudiando como las incertidumbres de las condiciones marco del proceso de diseño podrían afectar a la rentabilidad del proyecto a largo plazo en mercados de energía competitivos.

El objetivo principal de esta tesis es avanzar en el estado del arte de los métodos de análisis de viabilidad para microrredes multi-edificio, ayudando a los tomadores de decisiones a identificar y comparar los diseños óptimos basándose en indicadores de rentabilidad a largo plazo. El objetivo principal se puede dividir en diferentes objetivos también abordados por este trabajo, tales como

- Crear un método de análisis de viabilidad de microrredes multi-edificio rápido, innovador y orientado al proceso de venta del proyecto.
- Reducir el tiempo y los costes de modelado y simulación por solución analizada de las herramientas existentes en el mercado.
- Comparar las soluciones optimas con las sugeridas por el usuario, completando el enfoque determinístico con un enfoque probabilístico que identifique la probabilidad de que se cumplan los objetivos económicos deseados para el proyecto.
- Reducir el conocimiento de ingeniería requerido por el usuario con el fin último de dar independencia e incluso permitir a los promotores completar un análisis de viabilidad de una microrred por sí mismos, una vez este método este incorporado en una herramienta software especializada.
- Pre-diseñar la microrred seleccionando, dimensionando, ubicando y calculando los costes de los distintos subsistemas.

El método y los algoritmos propuestos se han implementado en una herramienta en basada en MATLAB y aplicado con éxito en un caso de estudio basado en un campus de la Universidad de Burgos.

LIST OF ACRONYMS

ACO	Ant Colony Optimization
ABC	Artificial bee colony
AMFA	Adaptive Modified Firefly Algorithm
AMPL	A Modelling Language for Mathematical Programming
ANN	Artificial Neural Networks
AIS	Artificial Immune System
BCR	Benefit to Cost Ratio
BFA	Bacterial Foraging Algorithm
CAGR	Compound Annual Growth Rate
CERTS	Consortium for Electric Reliability Technology Solutions
CES	Community Energy System
CF	Cash Flow
CHP	Combined Heat and Power
CSS	Charged System Search
DC	District cooling
DE	Differential evolution
DER	Distributed Energy Resources
DH	District Heating
DIEMS	Distributed Intelligent Energy Management System
DP	Dynamic Programming
DPP	Discounted Payback Period
EA	Evolutionary Algorithm
EIA	Energy Information Administration
EMS	Energy Management System
EP	Evolutionary programming
EPSO	Evolutionary Particle Swarm Optimization
ES	Evolutionary Strategy

ESCO	Energy Service Company
GA	Genetic Algorithm
GAMS	Generalized Algebraic Modelling System
GAS	Gravitational Search Algorithm
GIS	Geographical Information Systems
GRASP	Greedy Randomized Adaptive Search Procedures
ICTs	Information and Communications Technologies
IEEE	Institute of Electrical and Electronics Engineers
IEO2019	2019 *International Energy Outlook* report
IMP	Integer Minimization Problem
IoT	Internet of Things
ILS	Iterated Local Search
IRR	Internal Rate of Return
KEI	Key Economic Indicator
KKT	Karush-Kuhn-Tucker conditions
KRI	Key Risk Indicator
KTch	Key Technology Indicator
KTI	Key Technical Indicator
kWh	Kilowatt hour
LP	Linear Programming
MAS	Multi-Agent System
mCHP	Micro Combined Heat and Power
MILP	Mixed-Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
MIP	Mixed Integer Programming
MG	Microgrid
MGSA	Memetic Gravitational Search Algorithm
MPDP	Multi-pass Dynamic Programming
MV	Medium Voltage

MVA	Mega Voltamperes
MW	Megawatts
NLP	Non-Linear Programming
NN	Neural Networks
NPV	Net Present Value
NSGA-II	Non-dominated Sorting Genetic Algorithm II
NWI	Numerical Weather Information
OECD	Organization for Economic Cooperation and Development
OPF	Optimal power flow
O&M	Operation and Maintenance
PSO	Particle Swarm Optimization
PV	Photovoltaic
QP	Quadratic Programming
RAP	The Regulatory Assistance Project
RES	Renewable Energy Systems
RL	Resilience Level
R&D	Research and Development
SA	Simulated Annealing
SCSS	Self-adaptive Charged System Search
SG	Smart grid
SQP	Sequential Quadratic Programming
TS	Tabu Search
UBU	University of Burgos
USA	United States of America
VaR	Value at Risk
VERA	Versatile Energy Resource Allocation
VNS	Variable Neighborhood Search
WIPO	World Intellectual Property Organization
WOK	Web of Knowledge

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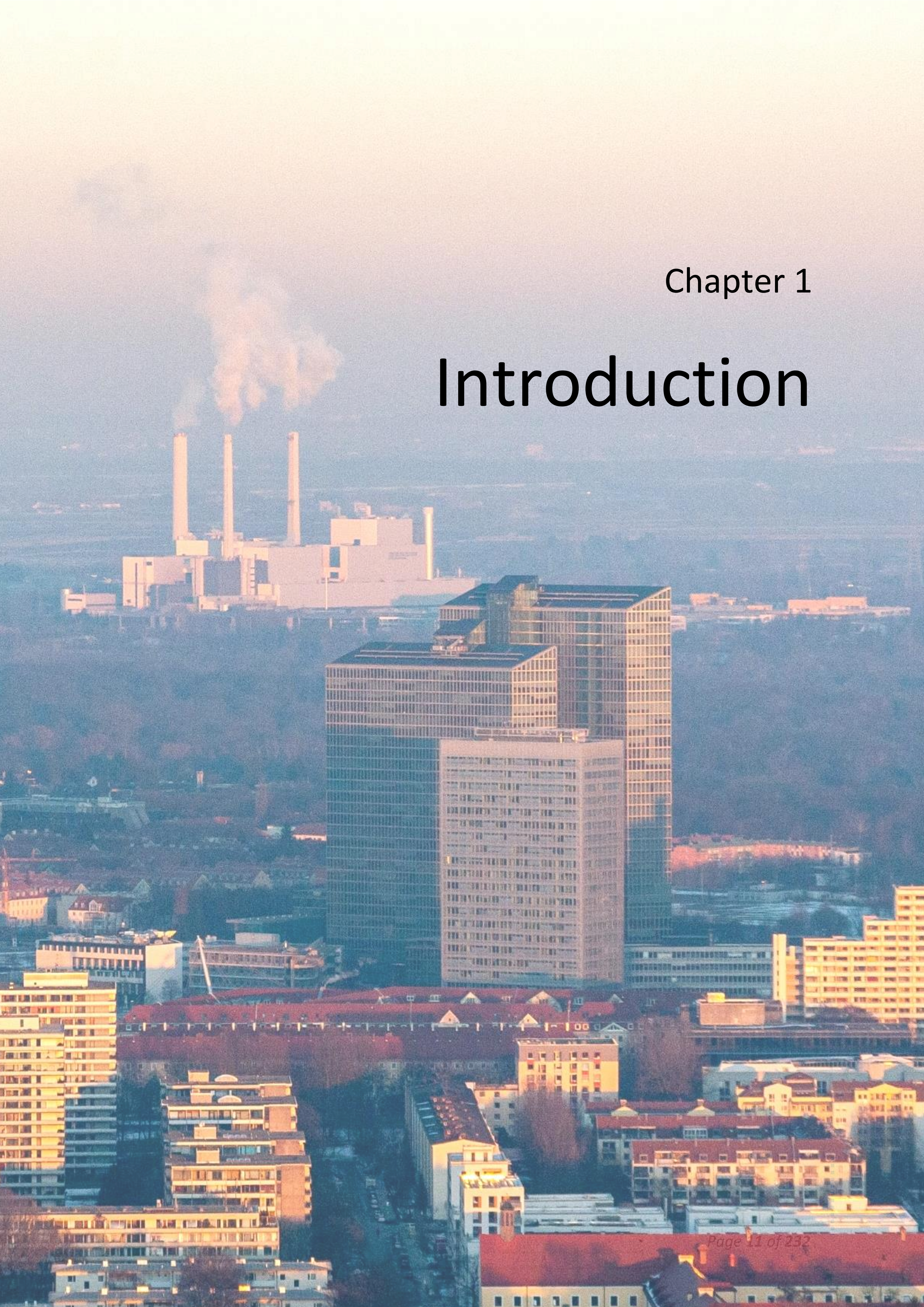

Chapter 1

Introduction

1. Motivation

1.1. World Energy Consumption and Trends

The world energy consumption is increasing, but so are its predictions. Back in 2017, the US Energy Information Administration (EIA) estimated a 28% increase between 2015 and 2040[1]. Most of this growth was expected to come from countries that are not in the Organization for Economic Cooperation and Development (OECD), and especially from countries where demand is driven by strong economic growth, particularly in Asia. Non-OECD Asia (which includes China and India) accounts for more than 60% of that estimated increase from 2015 through 2040.

These estimations were updated in September 2019 in the report titled *International Energy Outlook 2019*[2] (IEO2019), also published by EIA. In that report, EIA estimates that the world energy consumption might rise **by nearly 85% between 2018 and 2050**. As shown in Figure 1, in that time period energy consumption in non-OECD countries might increase nearly 70%, in contrast to a 15% increase in OECD countries. The growth in energy consumption is slower in OECD countries due to relatively slower population and economic growth, improvements in energy efficiency, and less growth in energy-intensive industries.

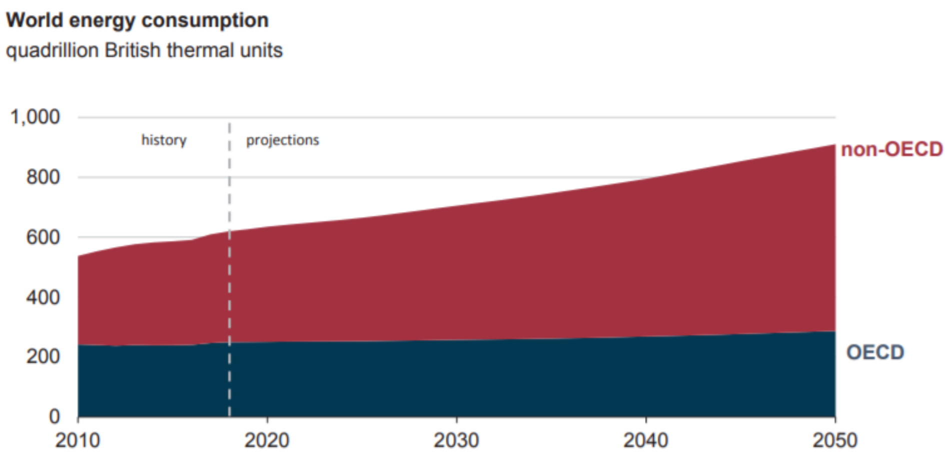

Figure 1. World Energy Consumption Projections. Source: EIA's IEO2019

As shown in Figure 2, IEO2019 agrees with the 2017 version on presenting the Non-OECD regions in Asia as primary contributors to substantial increases in energy consumption. Fast-paced population growth and access to ample domestic resources are important determinants of energy demand in Africa and the Middle East, where energy use increases by about 110% and 55%, respectively, between 2018 and 2050.

[1]. https://www.eia.gov/todayinenergy/detail.php?id=32912

[2] https://www.eia.gov/outlooks/ieo/

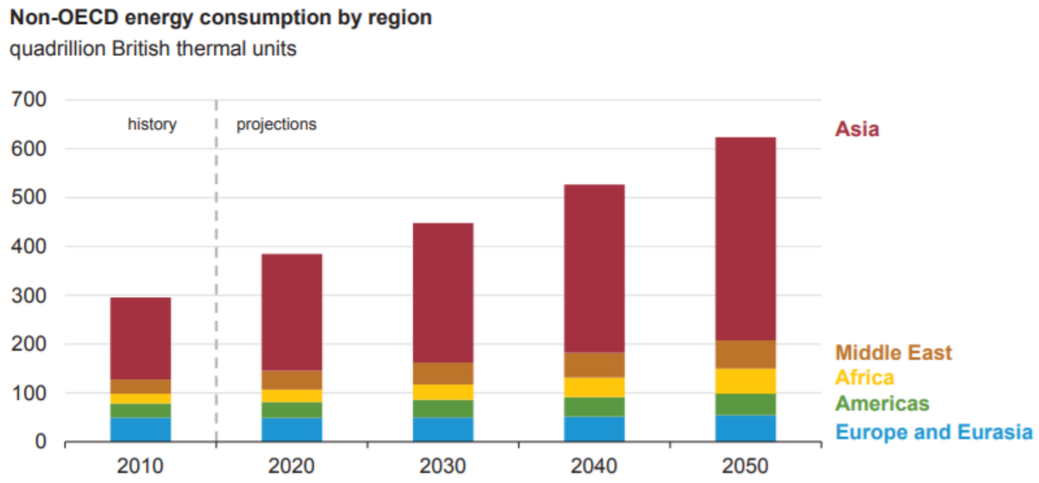

Figure 2. Non-OECD Energy Consumption by Region. SOURCE EIA IEO2019

Non-OECD Europe and Eurasia have the smallest projected increase in energy consumption (11%). This low growth is also a result of significant gains in energy efficiency achieved by replacing older physical assets with more efficient ones.

Many developed countries are aiming to achieve ambitious environmental goals by 2050 or earlier, but **it is still unclear how their strategies would contribute to a worldwide reduction in environmental emissions if developing countries do not adopt the most efficient technologies available for their future growth.** As shown in Figure 3, electricity consumption is expected to grow in every sector, with a projected growth rate in net electricity generation in non-OECD countries that doubles the one in OECD countries.

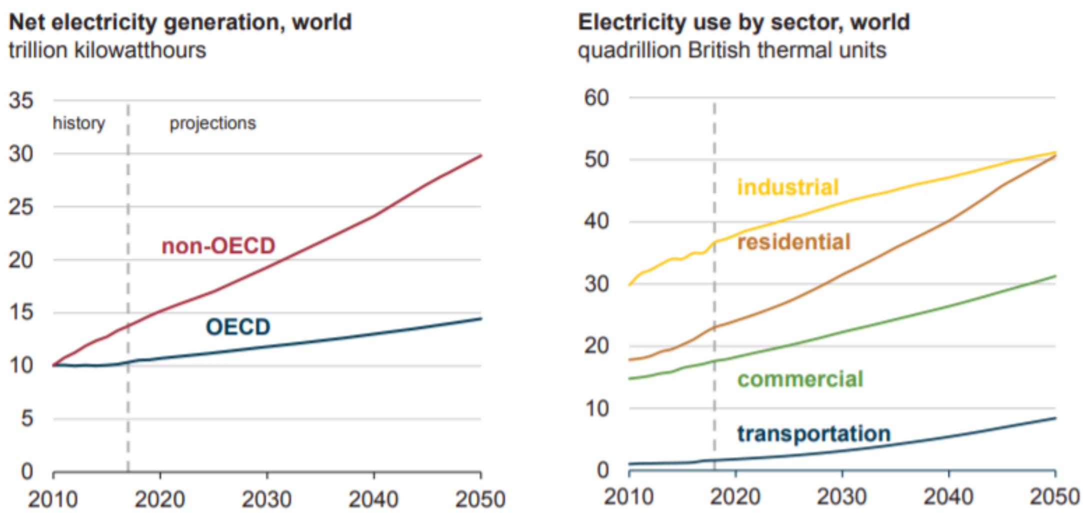

Figure 3. Electricity Used per Sector and Net Electricity Generation. Source: EIA IEO2019

An important fact when it comes to long-term sustainability is that both OECD and non-OECD countries increases in electricity demand are expected to be primarily met with renewables, as shown in Figure 4.

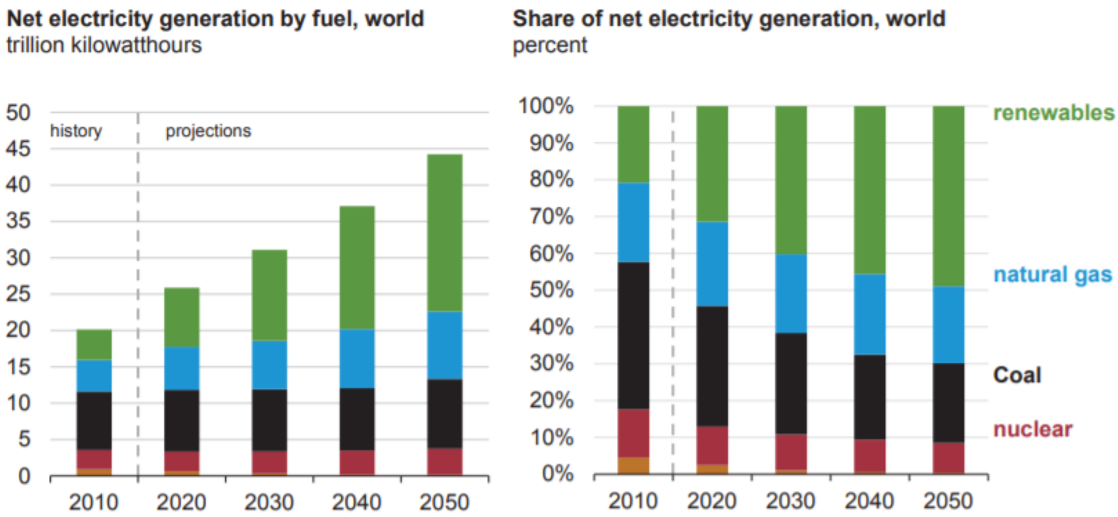

Figure 4. Net Electricity Generation 2010-2050. SOURCE: EIA, IEO2019

EIA points out in IEO2019 that although renewables are cost-competitive compared with new fossil-fired electric generating capacity additions, displacing existing non-renewable capacity usually requires of policy incentives. For instance, due to the European Commission's call for a climate-neutral Europe by 2050[3], OECD Europe is expected to add renewable generation faster than its electricity demand grows, progressively replacing existing power generation assets mainly fueled by coal and natural gas from 2020 to 2050. However, as shown in Figure 4, by 2050 renewables are estimated to produce worldwide just a 49% of net (to the grid) electricity generation, with a 9% of the electricity coming from nuclear plants, and 42% coming from coal and natural gas-fueled power plants (21% each approximately). If these forecasts are fulfilled, conventional fuels (coal and natural gas) will play an essential role in the world energy markets for at least 30 years more.

Some developed countries are following aggressive environmental policies to cut CO_2 emissions associated with their power grids. According to a report titled Decarbonization Pathways published by Eurelectric in 2018, Europe's power sector can be decarbonized by 2045[4]. Other entities are leading the way in other territories. With the approval of the Energy Transition Act in March of 2019, New Mexico is poised to join California and Hawaii in setting a mandate to decarbonize its electricity system by 2045[5].

Most of the strategies these countries plan to follow were presented in a report published in 2012 by The Regulatory Assistance Project (RAP), an independent organization dedicated to accelerating the

[3] https://ec.europa.eu/clima/policies/strategies/2050_en

[4] https://cdn.eurelectric.org/media/3457/decarbonisation-pathways-h-5A25D8D1.pdf

[5] https://pv-magazine-usa.com/2019/03/13/new-mexico-will-be-the-third-state-to-go-100/

transition to a clean, reliable, and efficient energy future[6]. Three technology strategies are mentioned in this report:

- Increasing the Energy Efficiency of Conversion
- Carbon Capture and Sequestration
- Non-Fossil Resources usage

Two sets of policies are also proposed by RAP in the same report:

- Policy Strategies Encouraging Low Carbon Sources.
- Policy Strategies Discouraging Fossil Fuel Use.

Combined Heat and Power (CHP) is mentioned in this report as part of the decarbonizing formula at different levels. In some countries like the USA, CHP is estimated to accumulate more than 240 GW of technical potential at over 291,000 sites[7].. CHP is probably the most efficient fuel-based energy generation systems in the market, but its future in the USA at a utility-scale is uncertain with some states not considering the installation of new power plants based on natural gas.

Traditional energy systems have evolved in different directions in the last decades: while heating and cooling systems have evolved from decentralization to centralization, power systems began in 1990 a decentralization process that continues in the present. One of the main drives of this decentralization has been the development of power generation and renewable energy technologies at a medium and small scales. The regulation has also evolved, allowing new actors to take part in the power grid at the transmission, distribution, and consumption levels.

To sum up, planning scenarios of power systems are rapidly changing throughout the world based on:

- Different policies are influencing the participation of different technologies on a regional basis.
- The promotion of distributed generation and energy storage both at a utility and at an end-user level, in order to increase the power generation from renewable energy.

1.2. The Role of Microgrids in the Future Power Grid

While the modernization of the power grids and markets started in the 1990s with its decentralization, a combination of advances at the business and technology levels is responsible for leading new power systems solutions into the market these days. The guidelines of future technologies in this field can be

[6] http://www.raponline.org/wp-content/uploads/2016/05/rap-gpbp-decarbonizingpowersupply-2012-nov-16.pdf
[7] https://www.energy.gov/sites/prod/files/2016/04/f30/CHP%20Technical%20Potential%20Study%203-31-2016%20Final.pdf

identified in the research literature. Two of the most popular concepts found in research literature in the last years are the microgrids and the smart grids.

- A Smart grid (SG) can be defined as *an electricity network based on digital technology that is used to supply electricity to consumers via two-way digital communication. This system allows for monitoring, analysis, control, and communication within the supply chain to help improve efficiency, reduce energy consumption and cost, and maximize the transparency and reliability of the energy supply chain*[8]*.* Thus, the SG can be considered the evolution of the traditional power systems, designed to serve power and other additional services to large areas.
- The microgrid (MG) concept appears as a candidate to take part in the future SGs as a novel power grid structure based on distributed energy resources (DERs), Renewable energy systems (RES), power electronics, and Information and Communications Technologies (ICTs). One of the most widely accepted definitions for a microgrid was presented by CERTS: *clusters of generators, including heat recovery, storage, and loads, which are operated as single controllable entities*. A comparison between microgrid definitions is presented by J.I. Ping et al. in [1].

The main difference between MG and SG concepts is their scope: since MGs are expected to supply energy to their surrounding or influence areas, SG is expected not to consider geographical limitations or necessarily employ local resources, just as the traditional power systems do in the present.

Different classifications have been presented for MGs since this concept appeared in 1998, according to Web of Science references. For instance, P. Lilienthal points out in [2] different criteria for MG classification, such as types of energy generation, the voltage of the distribution system, peak load, generation capacity, energy production, number of customers served, load management and metering. Due to the modular nature of MGs, they can operate either independently or in conjunction with the traditional electrical grid. They are expected to be able to **compete, coexist, or even support the traditional power grid at a distribution level, shaping the grid of grids concept outlined by IEEE in Figure 5.**

MGs usually have fewer financial commitments and require fewer technical skills to operate since they rely on automation [3,4]. **These advantages make MGs a suitable solution to gradually modernize existing power grids.**

[8] https://www.techopedia.com/definition/692/smart-grid

Microgrids have been a hot research topic for more than ten years now. Since *microgrid* is not a term exclusively used to describe a power system, the following numbers should be considered as a close estimation for the actual number of documents (papers or patents) published. For instance, 2002 is the year considered in this analysis because it is the year of publication of the first paper about *electrical microgrids* in the database Web of Knowledge (WOK). Figure 6 compares the number of papers published in Scopus, WOK, and IEEExplore since 2002, including journals, conferences, and review papers.

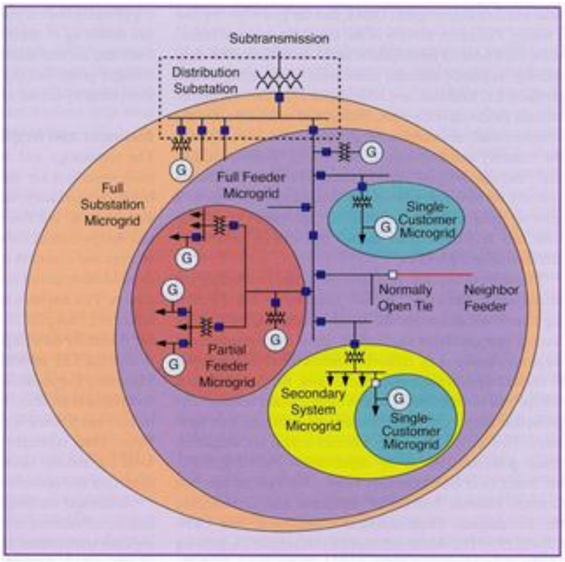

Figure 5. Future Power System Structure Source: IEEE Power & Energy. Vol.14, Number 5, September/October 2016

The number of papers listed by the three databases has continuously been growing from 2002 to 2016. However, in 2017 and for the first time WOK and IEEExplore registered fewer papers about microgrids than in previous years.

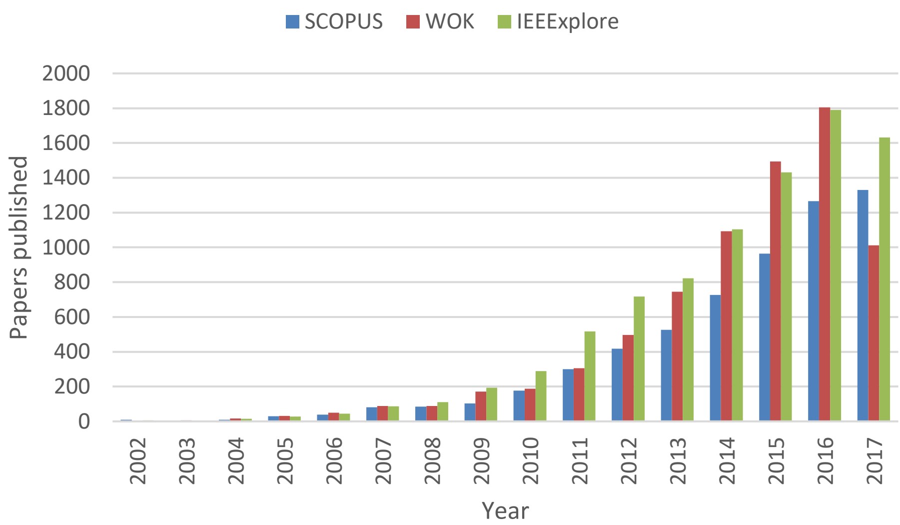

Figure 6. Paper Published on Microgrids per Database

Another indicator of technology advance related with microgrids is the number of patents published. In January 2018, a search of the term *microgrid* into the World Intellectual Property Organization (WIPO) database showed 1,247 results, being the first microgrid patent published in March of 2002, and the last one on December of 2017 [9], as shown in Figure 7.

[9] https://patentscope.wipo.int/search/en/detail.jsf?docId=US39667583&recNum=25&office=&queryString=FP%3A%28microgrid%29&prevFilter=&sortOption=Pub+Date+Asc&maxRec=1247

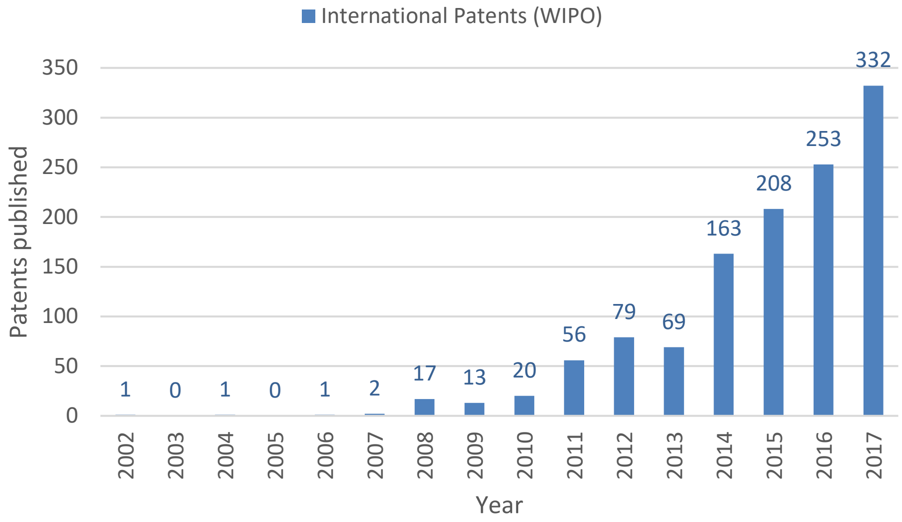

Figure 7. International Patents Published on Microgrids by WIPO from 2002 to 2017

The search engine *Google Patents* lists 2,630 granted and published patents, including both international and national patents, for the same period and search term. As shown in Figure 7, the transfer of knowledge from research to the market has been continuously increasing since 2014. **Microgrids might be reaching maturity as a research concept** since the number of published papers is starting to decrease, while the number of annual patents is increasing every year**.**

The microgrid market was valued at USD 16.58 Billion in 2015 and is expected to reach USD 38.99 Billion by 2022, at a CAGR of 12.45% during the forecast period, according to the market analysis company *Markets and Markets*[10]. However, different authors cite different barriers for the number of microgrid projects to keep on growing, such as control systems development, regulation and standardization, technological advances, and innovative planning techniques [5,6]. In the second quarter of 2017, a report from the company Navigant Research presented data on known grid-tied and remote microgrid projects across six geographies and seven microgrid segments[11]. A total of 1,842 Microgrid projects were identified worldwide, representing 19,279.4 MW of capacity for projects that are operating, under development, and proposed. In in the 10th edition of its *Microgrid Deployment Tracker*, a previous report published in June of 2016, the same company identified 1,568 projects representing more than 15 GW of capacity. That makes a 5 GW increase for 274 new microgrids worldwide from June 2016 till June 2017. As of 2Q 2019, Navigant Research has identified 4,475 projects representing 26,769 MW of planned and installed power capacity. The 2Q 2019 results

[10] https://www.marketsandmarkets.com/Market-Reports/micro-grid-electronics-market-917.html?gclid=EAIaIQobChMI4-qJh9-02AIVTLjACh1aBAfgEAAYASAAEgL8BfD_BwE

[11] https://www.navigantresearch.com/newsroom/navigant-research-identifies-1842-microgrid-projects-representing-nearly-20-gw-of-capacity

include 575 new entries, a total of 2,915.3 MW with the Asia Pacific emerging as the global leader in microgrid capacity, followed by North America, the Middle East and Africa.

1.3. Challenges Associated with Microgrid Planning

Multi-node microgrids are less popular than single building microgrids, same as district heating systems are less common than individual heating systems. One of the reasons for this might be the costs and complexity associated with developing the energy distribution system, especially if they are compared with distributed generation systems connected to individual buildings. Community or multi-building microgrids are projects with at least 25 years of lifespan which require high initial investments, and consolidated clients committed with the system in the long term to be successful. However, multi-building microgrids can take advantage of several economies of scale that individual microgrids cannot, such as lower the installation, maintenance and operating costs per kilowatt installed. That is the reason why military campuses, universities, hospitals, local administrations, or private companies and ESCOs are actively considering microgrids when expanding or upgrading their power facilities.

A multi-building microgrid planning process deals with complexities and uncertainties that lead different actors such as planners and future microgrid owners to not follow the best paths for the identification of the best alternatives. The facility owner's perspective of the microgrid planning process can be characterized by the following singularities:

- They **do not always have the expertise** required to lead the planning process from a technical point of view.
- **They have a clear picture of how the economics of the project should look like to be approved**. Stakeholders are usually open to different business models. They define their economic and financial goals, and constraints based on economic indicators such as, for example, a threshold for the payback period or the Internal Rate of Return (IRR).
- Some owners might have some **technology preferences** based on what they know about similar projects or just on their own goals. For instance, to install photovoltaic solar to minimize local CO_2 emissions.
- **They are not always aware of the environmental trends and potential regulatory changes that** should be considered in the process. For example, installing natural gas generators might be the cheapest, but not the best option if a new regulation on environmental emissions is about to be approved.

- They do not always know that the **emergency plan and resiliency requirements should be considered** during the design process.
- **They are open to paying for some hours of consultancy** to find the best solution.
- **They are not necessarily familiar with the risks** associated with microgrid projects but still exposed to them. Engineering firms will never discuss most of these risks beforehand.
- **Facility owners are open to transfer those risks through contracting, for instance, through an Energy Service COmpany (ESCO).** However, they are likely to add additional costs that might be justified or not, depending on how risky the project is.

Some of the characteristics of a microgrid planning process from the planning engineers´ standpoint are:

- **The number of potential solutions**: Each microgrid project is unique, with thousands of potential combinations of technologies, sizes, and manufacturers to consider. The need for a power distribution system just adds complexity to the multi-node microgrid design problem: a 10-node system with two potential wire sizes has 3.5×10^{13} potential configurations.
- **A time-consuming process**: Although there are thousands of potential alternatives to check, less than five alternatives are usually modeled in detail in a microgrid feasibility analysis. A microgrid feasibility analysis can take from 100 to 400 hours depending on the size of the microgrid, but it how much time is dedicated to identifying the optimal solutions usually depends on the budget, if there is any for feasibility analysis.
- **Subjectivity**: In this scenario, many early-stage decisions are made based on subjective engineering criteria. The number of alternatives to model is usually cut without the participation of the stakeholder team, based on the previous project experience of the team and their preferences.
- **Low-Cost analysis:** feasibility analyses are sometimes provided for free in order to engage the client. That leads to an even lower number of alternatives studied and a **poor exploration of the potential solutions**. For example, a project developer has good relationships with a CHP manufacturer, and they decide to provide a feasibility analysis based on CHP at no cost without considering other manufacturers or power technologies.

Ten years after microgrids started gaining traction in the research literature, planning tools have not evolved considerably: most of them are design/engineering tools, and just a few can provide a complete design of a multi-building microgrid (power distribution and generation systems included). As described in Chapter 2, scenario tools can only analyze one design at a time, and simulation tools require a high level of technical skills to be used, not covering the economic aspects of the project in-depth.

As mentioned before, microgrids are systems designed to last at least 25 years. When planning for such a long lifespan, there exist several uncertainties in a microgrid to be avoided, or at least to be controlled [7–9]. **Thus, it is crucial to research about innovative methodologies allowing microgrid planners not only to design efficient, clean and reliable microgrids, but also to allow estimating the potential impact of uncertainties on the economics of the project, and to explore and quantify the probability for a design to be profitable in future scenarios.** No method has been documented combining a technical and economical approach for multi-node microgrid planning (sizing, siting, scheduling, and prizing problems), which considers the impact of oscillations in the design framework conditions in the long-term. Since most of them have evolved from power systems design tools, risk analysis is barely considered among the existing multi-building microgrid planning tools. New analysis methods are needed to study feasibility scenarios under a more significant number of complex variables: not only enabling an optimal selection of technical alternatives but also assessing future scenarios related with long-term feasibility.

Modern computational optimization techniques have been developed during the last decades and successfully applied to different stages of the microgrid planning process [10]. Many authors such as Sims et al. have studied in [11]the process of project evaluation for different applications. Mahmoud and Ibrik have applied in [12]some of these criteria to power systems and Dilworth describes in [13] some common indicators which are usually used to evaluate projects from an economic point of view. There are multiple algorithms proposed to solve sizing, siting, scheduling, and pricing problems in research journals, but commercial software mostly rely on consolidated algorithms looking for the optimal solution analyzing one alternative at a time: **One set of inputs→ Run algorithm→ One Set of Outputs**.

There is a need for more advanced and intuitive feasibility analysis for multi-building and community microgrids:

- Able to explore thousands of potential designs in a limited amount of time.
- Able to analyze the long-term profitability of the system under future scenarios
- More accessible to users with limited or no technical skills in order to provide independence and let the stakeholder develop their own feasibility analysis before reaching out to external companies.

2. Objectives and Scope

The objective of this thesis is to advance the state of the art of feasibility analysis methods for multi-building microgrids through an innovative combination of algorithms able to provide detailed information on the economic and technical aspects of the solutions but also including outputs that give a more relevant role to stakeholder during the feasibility analysis stage.

The main goals pursued by this work are:

1. To create a fast and innovative multi-user microgrid feasibility analysis method oriented to the sales process.
2. To reduce the modeling time and costs for the same number of potential designs analyzed by other software tools in the market.
3. To enable the comparison between the values of the economic indicators calculated for the solutions through deterministic and probabilistic approaches, identifying the probability of optimal and user-defined solutions to fulfill the economic goals of the project.
4. To present the feasibility of the project from a strictly economic standpoint, while providing the stakeholder with enough technical details to define the solution. To reduce the power engineering skills required by the user, and to ultimately allow decision-makers with limited or no technical skills to complete a microgrid feasibility analysis by themselves, once this method is incorporated into a commercial software tool.

This work aims to help decision-makers identifying and benchmarking optimized multi-node microgrid designs based on specific economic goals and their probability to fulfill those goals in the long term. The proposed method has been modeled and implemented in MATLAB, and can perform the following tasks:

1. To benchmark the optimized designs calculated based on quantitative project profitability indicators, and the profitability thresholds defined by the stakeholders at the beginning of the project.
2. To provide detailed information on the technical solutions behind the financial results based on the optimized one-hour interval scheduling of the whole microgrid design.
3. To solve sizing, siting, scheduling, and pricing problems and to identify the best solutions under different design constraints such as technologies and fuels involved, or hours of resilience required by the facilities.

4. To model long-term profitability scenarios through optimization and risk analysis techniques, based on current and future market conditions, allowing the user to consider potential regulation and policy changes.

This method is expected to contribute to the deployment of multi-node microgrid systems at two levels:

1. **Sales, Individual project promotion level**: helping stakeholders to answer questions related with the economics of developing a microgrid, and more importantly, with its long-term profitability such as:
    - Can a microgrid be a solution for the facilities considering the economic constraints and goals?
    - What is the probability of a microgrid to achieve the economic goals in the long-term?
    - How far is a microgrid from fulfilling the economic goals? Can incentives help? How much should the energy costs change to fulfill the profitability goals?

2. **Market level:** allowing researchers and microgrid market analysts to study the impact of uncertainties on the profitability of different types of microgrids:
    - Potential oscillations of design conditions such as the price of fuels.
    - Potential impact of different types of economic incentives and policies.
    - Long-term profitability of designs following strategies that consider future regulation changes.

3. Thesis Document Structure

This thesis document describes the state of the art of microgrid planning and the development of a method based on an innovative combination of consolidated optimization and risk analysis algorithms such as Genetic Algorithm (GA) and Linear Programming and Monte Carlo simulation.

Chapter 2 presents the state of the art of microgrid planning, including a detailed analysis of the algorithms proposed in research literature during the last decades for solving the problems that shape the MG planning process, and also of the commercial software tools available in the market. This chapter compiles the findings of two different research articles published by the author of this thesis about the past, present, and future of microgrid planning [10,14].

Chapter 3 describes the whole method and the main algorithms involved in it, including the data collection and planning scenario modeling stage, the power distribution optimization problem, the power generation optimization problem, and the risk analysis stage.

Chapter 4 presents the results of testing the method developed in Chapter 3 on one of the campuses of the University of Burgos (UBU). The UBU has almost 10,000 students divided among different campuses around the city, being the highest concentration of buildings located West from the historic city center. The sets of buildings considered in this study are owned and operated by UBU and have different uses such as academic buildings, sports centers, student housing, libraries, and research facilities.

Image 1. Administrative Services Building. University of Burgos

Chapter 5 presents the conclusions of this work, discussing the fulfillment of the goals of the thesis, the pros and cons of the method, and future work to be developed in this research line.

Chapter 6 presents a summary of the related activities developed during the time the author has been involved in the Doctorate Program, including peer-reviewed publications, publications and presentations in conferences, and collaborations with international microgrid research groups.

A complete set of results of the analysis has been incorporated into the Appendix, while the most relevant tables and charts are presented in Chapter 4 for its discussion.

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Capítulo 1

Introducción

5. Motivación

5.1. Consumo energético mundial y sus tendencias

El consumo energético mundial está aumentando, pero también sus previsiones. En 2017 la US Energy Information Administration (EIA) estimó un aumento del 28% entre 2015 y 2040[12]. La mayoría de ese crecimiento vendría de los países que no pertenecen a la Organización para la Cooperación y el Desarrollo Económicos (OCDE): especialmente de países donde la demanda energética está motivada por el crecimiento económico, y particularmente de Asia. Los países asiáticos no miembros de la OCDE (incluyendo China e India) serán responsables del 60% del crecimiento de la demanda energética estimado entre 2015 y 2040.

Estas previsiones fueron actualizadas por el informe titulado International Energy Outlook 2019[13] (IEO2019), en septiembre de 2019. En ese informe, la EIA estima que el consumo energético mundial podría crecer entre 2018 y 2050 cerca de un 85%. Como muestra la figura 1, el consumo energético en los países no miembros de la OCDE podría aumentar cerca del 70%, contrastando con el 15% de aumento en los países miembros. El menor aumento en los países miembros seria debido a que se espera un menor crecimiento económico y de población, mejoras en la eficiencia energética y un menor crecimiento de las actividades industriales de alto consumo energético que en los países no miembros.

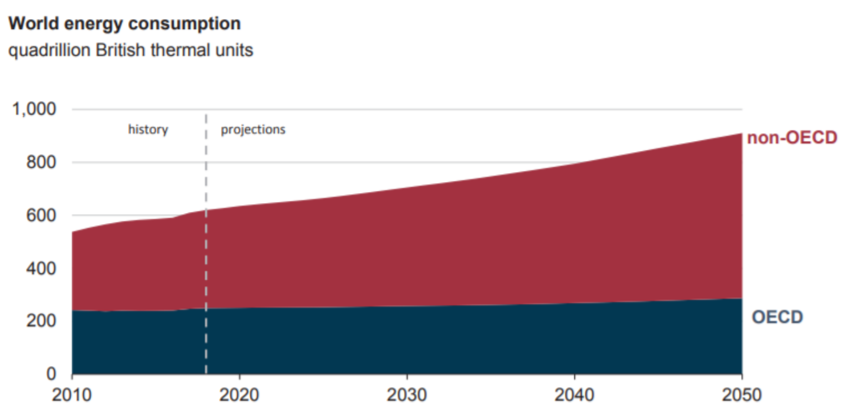

Figura 2. Estimación del consumo energético mundial. Fuente: EIA’s IEO2019

Como se muestra en la figura 2, IEO2019 coincide con la versión de 2017 en que los mayores contribuyentes al aumento del consumo energético mundial serán los países no miembros de la OCDE de Asia. El rápido crecimiento de la población y el acceso a recursos energéticos en el ámbito doméstico son factores determinantes de la demanda energética en África y Oriente Medio, donde el consumo se prevé que aumentara en torno a un 110% y un 55% respectivamente entre 2018 y 2050.

[12]. https://www.eia.gov/todayinenergy/detail.php?id=32912
[13] https://www.eia.gov/outlooks/ieo/

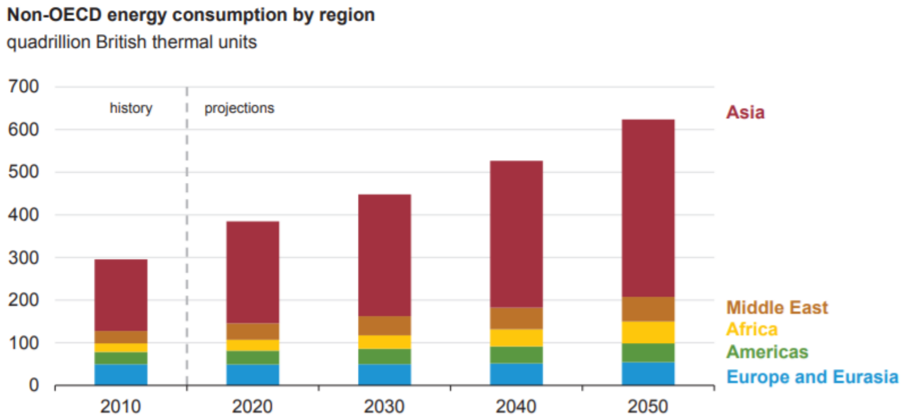

Figura2. Consumo energético en los países no miembros de la OCDE por región. Fuente: EIA IEO2019

El menor aumento en la previsión de consumo energético para los países europeos no miembros de la OCDE y Eurasia se estima en un 11%. Este bajo incremento se debe principalmente a las mejoras esperadas en eficiencia energética.

Muchos países desarrollados están fijando metas ambientales ambiciosas para el año 2050 o incluso antes. Pero aún no está claro si sus distintas estrategias acabaran logrando una reducción de emisiones ambientales a nivel mundial, si los países en vías de desarrollo no basan su crecimiento en las tecnologías energéticas más eficientes disponibles en el mercado. Como muestra la figura 3, el consumo de electricidad está previsto que crezca en todos los sectores, duplicando los países no miembros de la OCDE a los países miembros en tasa de crecimiento.

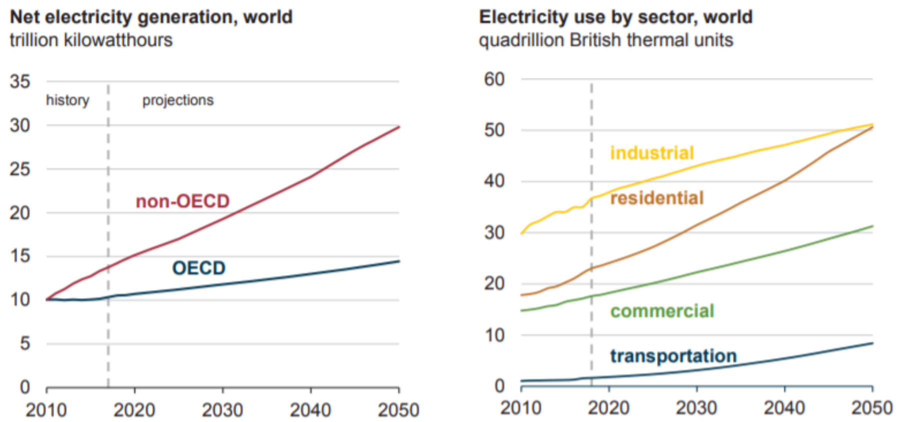

Figura 3. Demanda de electricidad por sector y generación eléctrica neta mundial. Fuente: EIA IEO2019

Como muestra la figura 4, se espera que la mayoría del aumento de la demanda energética sea cubierto por energía solar tanto en los países miembros como en los no miembros de la OCDE, un factor importante cuando se trata de sostenibilidad a largo plazo.

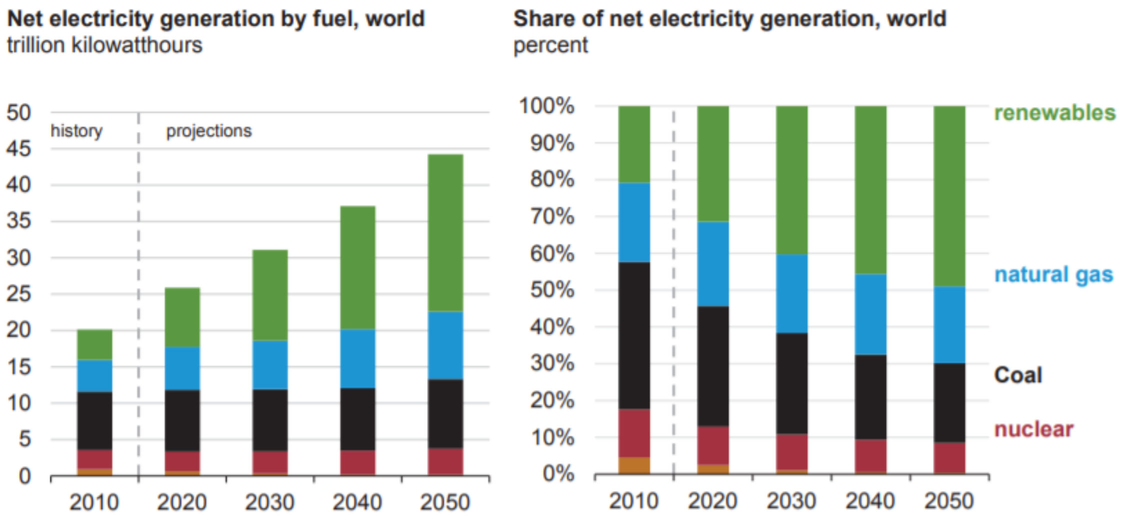

Figura 4. Generación eléctrica neta 2010-2050. Fuente: EIA, IEO2019

Pero la EIA también señala en su informe IEO2019 que, a pesar de que las energías renovables son competitivas en coste con las nuevas alternativas no-renovables, desplazar la capacidad de generación de electricidad ya instalada en combustible tradicionales (no renovables) requerirá de políticas de incentivos. Por ejemplo, los países europeos miembros de la OCDE esperan añadir capacidad de generación basada en energías renovables a un ritmo mayor del crecimiento de la demanda de acuerdo a las directrices de la Comisión Europea para evolucionar hacia una Europa de impacto climático neutro en 2050[14]. Esta estrategia contribuirá al progresivo reemplazamiento de los activos de generación eléctrica existente entre 2020 y 2050, la mayoría de ellos basados en carbón y gas natural. Sin embargo, y como se ha descrito en la figura 4, se estima que en 2050 las energías renovables producirán a nivel mundial solamente el 49% de generación eléctrica vertida a red, combinado con un 9% basado en energía nuclear y un 42% generado en plantas que usan carbón y gas natural como combustible (21% cada una aproximadamente). Si estas predicciones se cumplen, los combustibles tradicionales van a seguir teniendo un rol importante en los mercados energéticos mundiales en los próximos 30 años.

Algunos países desarrollados están siguiendo políticas agresivas para recortar las emisiones de CO_2 asociadas con su sistema eléctrico. En el estudio titulado *Decarbonisation Pathways, publicado por* Eurelectric in 2018, se afirma que el sector energético en Europa puede ser descarbonizado para 2045[15]. Otras entidades están marcando el camino en los Estados Unidos. Con la aprobación *del Energy Transition Act* en Marzo de 2019, el estado de Nuevo Méjico se unió a California y Hawai aprobando una orden legislativa para descarbonizar su sistema eléctrico para 2045[16].

[14] https://ec.europa.eu/clima/policies/strategies/2050_en

[15] https://cdn.eurelectric.org/media/3457/decarbonisation-pathways-h-5A25D8D1.pdf

[16] https://pv-magazine-usa.com/2019/03/13/new-mexico-will-be-the-third-state-to-go-100/

La mayoría de las estrategias que estos territorios contemplan fueron presentadas en un estudio publicado en 2012 por el Regulatory Assistance Project (RAP), una organización independiente dedicada a acelerar la transición hacia un futuro energético limpio, eficiente y seguro[17]. Este informe menciona tres estrategias tecnológicas principales:

- Aumentar la eficiencia energética de la conversión de energía en CO_2.
- Captura y almacenamiento de CO_2.
- Uso de recursos energéticos no basados en combustible fósiles.

RAP propone en el mismo informe dos conjuntos de políticas:

- Políticas de promoción de alternativas energéticas libres o bajas en CO_2.
- Políticas que hagan menos atractivo el uso de combustibles fósiles.

La cogeneración (CHP) se menciona en este informe como parte de la fórmula de descarbonización a diferentes niveles. En algunos países como los Estados Unidos de América, la cogeneración se estima que tiene un potencial de 240GW en más de 291,000 localizaciones potenciales[18].. La cogeneración es probablemente la tecnología de generación eléctrica más eficiente que existe en el mercado de las basadas en combustibles fósiles. Pero su futuro a largo plazo es incierto ya que, como se ha mencionado anteriormente, algunos estados no contemplan entre sus opciones instalar nuevas plantas de generación eléctrica que usen gas natural.

Los sistemas energéticos tradicionales han evolucionado en direcciones opuestas en las últimas décadas: mientras que los sistemas térmicos han evolucionado de la descentralización a la centralización, los sistemas eléctricos empezaron en 1990 un proceso de descentralización que aun continua. Uno de los factores mas relevantes en esta descentralización ha sido el desarrollo de tecnologías de generación eléctrica a pequeña y mediana escala (decenas y centenas de kW respectivamente). La normativa también ha evolucionado, permitiendo a nuevos actores participar de la red eléctrica a nivel de generación, transmisión y consumo.

Como conclusión, cabe destacar que los escenarios de planificación de sistemas eléctricos están evolucionando rápidamente en todo el mundo en base a:

- Políticas que influencian la participación de diferentes tecnologías en diferentes regiones.

[17] http://www.raponline.org/wp-content/uploads/2016/05/rap-gpbp-decarbonizingpowersupply-2012-nov-16.pdf
[18] https://www.energy.gov/sites/prod/files/2016/04/f30/CHP%20Technical%20Potential%20Study%203-31-2016%20Final.pdf

- Distintos grados de promoción de generación distribuida y almacenamiento energético a nivel tanto de compañía eléctrica como de usuario, con el objetivo de aumentar la producción de electricidad con origen en fuentes renovables.

5.2. El rol de las microrredes en la red eléctrica del futuro

Si bien la modernización de las redes y los mercados de energía comenzó en la década de 1990 con su descentralización, actualmente es la combinación de avances a nivel comercial y tecnológico la responsable de impulsar nuevas soluciones al mercado. Las huellas de las tecnologías presentes y futuras en este campo se pueden identificar en la literatura de investigación. Dos de los conceptos más populares encontrados en artículos cientificos en los últimos años son las microrredes y las redes inteligentes.

- Una red inteligente (SG) se puede definir como *una red eléctrica basada en tecnología digital que se utiliza para suministrar electricidad a los consumidores a través de la comunicación digital bidireccional. Este sistema permite la monitorizacion, el análisis, control y la comunicación dentro de la cadena de suministro para ayudar a mejorar la eficiencia, reducir el consumo de energía y los costos, y maximizar la transparencia y confiabilidad de la cadena de suministro de energía*[19]. Por lo tanto, el SG puede considerarse la evolución de los sistemas de energía tradicionales, diseñados para suministrar energía y otros servicios adicionales a grandes áreas.
- El concepto de microrred (MG) aparece como un candidato para participar en las futuras SG como una nueva estructura de red eléctrica basada en recursos de energía distribuida (DER), sistemas de energía renovable (RES), electrónica de potencia y las Tecnologías de Información y Comunicación (TIC)) CERTS presentó una de las definiciones más ampliamente aceptadas para una microrred: *grupos de generadores, que incluyen recuperación de calor, almacenamiento y cargas, que funcionan como entidades controlables únicas*. Ping presenta en [1] una comparación entre las definiciones de microrredes eléctricas.

La principal diferencia entre los conceptos de MG y SG es su alcance: al igual que se espera que las MG suministren energía en sus alrededores o áreas de influencia, se espera que las SG no tenga en cuenta las limitaciones geográficas o emplee necesariamente recursos locales, tal como lo hacen las redes eléctricas en el presente.

Se han presentado diferentes clasificaciones de MG desde que apareció este concepto en 1998, según referencias de *Web of Science*. Por ejemplo, P. Lilienthal señala en [2] diferentes criterios para la

[19] https://www.techopedia.com/definition/692/smart-grid

clasificación de MG, como los tipos de generación de energía, el voltaje del sistema de distribución, la carga máxima, la capacidad de generación, la producción de energía, el número de clientes atendidos, la gestión de carga y la medición. Debido su naturaleza modular, las MG pueden operar independientemente o conectadas a la red eléctrica tradicional. De una microrred se espera que pueda **competir y coexistir con, o incluso apoyar a la red eléctrica tradicional a nivel de distribución, dando forma al concepto de red de redes descrito por IEEE en la Figura 5.**

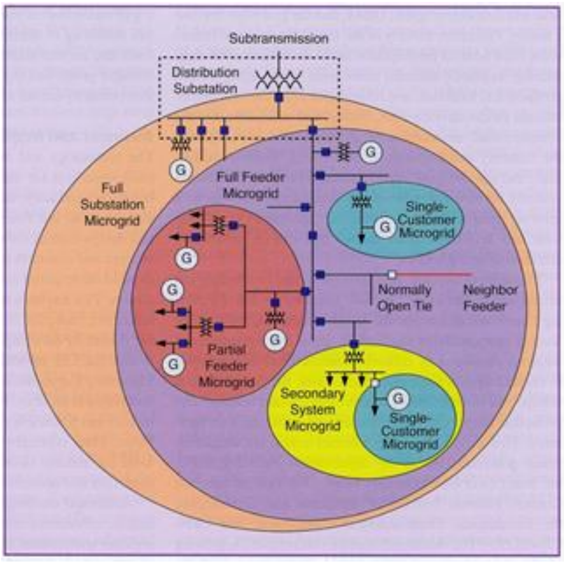

Figura 5. Estructura del Sistema Eléctrico del Futuro. Fuente: IEEE Power & Energy. Vol.14, Number 5, September/October 2016

Las MG tienden a requerir cada vez menor compromiso financiero y menos habilidades técnicas para operar ya que cada vez delegan más en la automatización [3,4]. Estas ventajas hacen de las MG una solución adecuada para modernizar gradualmente las redes e instalaciones eléctricas existentes.

Las microrredes han sido un tema de investigación de actualidad durante más de diez años. Dado que *microgrid* no es un término utilizado exclusivamente para describir un sistema energético, las siguientes cifras deben considerarse como una estimación cercana del número real de documentos publicados. Por ejemplo, 2002 es el primer año considerado en este análisis porque ser el año de publicación del primer artículo sobre microrredes eléctricas según datos de Web Of Knowledge (WOK).

La Figura 6 compara el número de artículos publicados en Scopus, WOK e IEEExplore desde 2002, incluyendo artículos de investigación, conferencias y artículos de revisión.

El número de documentos enumerados por las tres bases de datos ha crecido año tras año de 2002 a 2016. Sin embargo, por primera vez en 2017 WOK e IEEExplore registraron menos documentos sobre microrredes que en años anteriores.

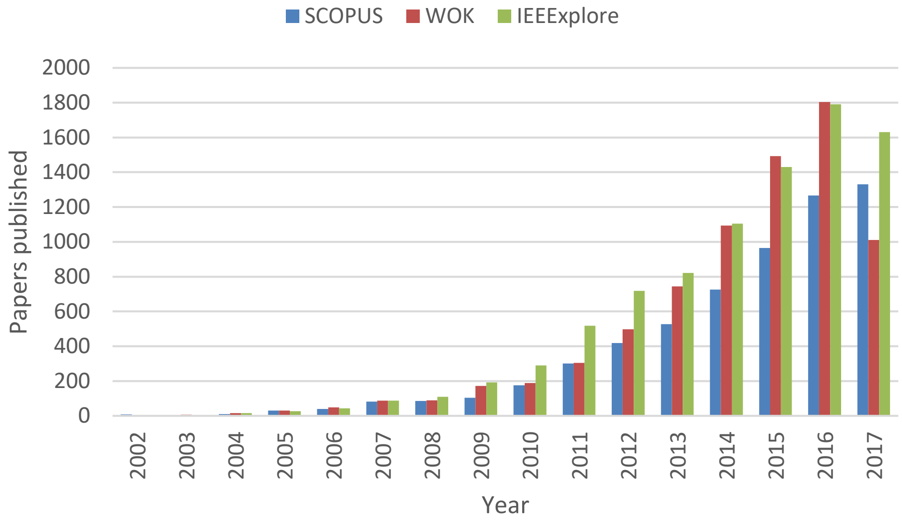

Figura 6. Artículos publicados sobre microrredes por base de datos

Otro indicador de los avances tecnológicos relacionados en el campo de las microrredes es el número de patentes publicadas. En enero de 2018, una búsqueda del término *microrred* en la base de datos de la Organización Mundial de la Propiedad Intelectual (OMPI) obtuvo 1.247 resultados, siendo la primera patente de microrred publicada en marzo de 2002 y la última en diciembre de 2017, como se muestra en la Figura 7[20].

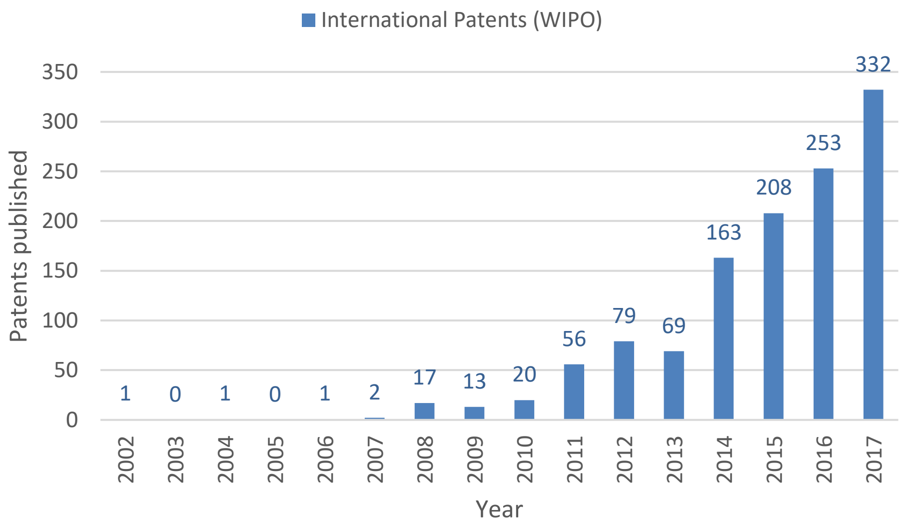

Figura 7. Patentes internacionales publicadas sobre microrredes por WIPO desde 2002 hasta 2017

El motor de búsqueda Google Patents encontró 2.630 patentes otorgadas y publicadas para el mismo período y término de búsqueda, incluidas patentes internacionales y nacionales. Como se muestra en

[20]https://patentscope.wipo.int/search/en/detail.jsf?docId=US39667583&recNum=25&office=&queryString=FP%3A%28microgrid%29&prevFilter=&sortOption=Pub+Date+Asc&maxRec=1247

la Figura 7, la transferencia de conocimiento al mercado de las microrredes se ha incrementado de manera continuada desde 2014. **Las microrredes podrían estar llegando a su madurez como concepto de investigación ya que el número de artículos publicados está comenzando a disminuir y el número de patentes anuales aumenta año tras año.**

Según la empresa de análisis de mercado Markets and Markets[21], en 2015 el mercado de microrredes estaba valorado en 16,58 mil millones de dólares americanos y se espera que alcance USD 38,99 mil millones en 2022, a una tasa de crecimiento anual del 12,45% durante el período de pronóstico. Sin embargo, diferentes autores identifican diferentes barreras para que el número microrredes siga creciendo, como el desarrollo de sistemas de control mas avanzados, la normativa y la estandarización, los avances tecnológicos, y las técnicas de planificación innovadoras [5,6]. En el segundo trimestre de 2017, un informe de la compañía Navigant Research presentó datos sobre proyectos conocidos de microrredes conectadas e independientes en seis geografías y siete segmentos de microrredes[22]. Este informe identifica un total de 1.842 proyectos en todo el mundo, lo que representa 19.279 MW de capacidad para proyectos que están en operación, en desarrollo y propuestos. En un informe anterior publicado en junio de 2016 llamado *Microgrid Deployment Tracker*, , la misma compañía identificó 1,568 proyectos que representan más de 15 GW de capacidad. Esto representa un aumento de 5 GW de capacidad en 274 nuevas microrredes en todo el mundo desde junio de 2016 hasta junio de 2017. En el segundo trimestre de 2019, Navigant Research ha identificado 4.475 proyectos que representan 26.769 MW de capacidad de energía planificada e instalada. Los resultados del segundo trimestre incluyen 575 nuevas entradas y un total de 2.915 MW con la región Asia-Pacífico emergiendo como el líder mundial por capacidad de microrredes, seguido por América del Norte, Medio Oriente y África.

5.3. Desafíos asociados a la planificación de microrredes eléctricas

Las microrredes eléctricas multi-edificio son menos populares que las de un solo edificio, al igual que los sistemas de calefacción de distrito son menos comunes que los sistemas de calefacción individuales. Las principales razones son la complejidad y los costes asociados con el desarrollo de sistemas de distribución energética, especialmente si se compara con sistemas distribuidos conectados a un solo edificio. Las microrredes de múltiples edificios son proyectos con al menos 25 años de vida útil que requieren de altas inversiones iniciales y clientes consolidados comprometidos con el sistema a largo plazo para tener éxito. Sin embargo, las microrredes de edificios múltiples

[21] https://www.marketsandmarkets.com/Market-Reports/micro-grid-electronics-market-917.html?gclid=EAIaIQobChMI4-qJh9-02AIVTLjACh1aBAfgEAAYASAAEgL8BfD_BwE

[22] https://www.navigantresearch.com/newsroom/navigant-research-identifies-1842-microgrid-projects-representing-nearly-20-gw-of-capacity

pueden aprovechar varias economías de escala que las microrredes individuales no, como menores costes de instalación, operación y mantenimiento por kilovatio de capacidad. Esa es la razón por la cual los campus militares, las universidades, los hospitales, las administraciones locales o las empresas privadas y las ESCO están considerando microrredes en sus proyectos de ampliación o mejora.

Un proceso de planificación de microrredes se enfrenta a las complejidades e incertidumbres que llevan a diferentes actores, como los ingenieros de diseño y promotores a no seguir los mejores caminos para la identificación de las mejores alternativas. **La perspectiva que el promotor o futuro propietario** tienen del proceso de planificación de una microrred se caracterizan por las siguientes singularidades:

- **No siempre tienen la experiencia requerida para liderar el proceso** de planificación desde un punto de vista técnico.
- Tienen una **idea clara de cómo deberían ser los resultados económicos** para que el proyecto sea aprobado. Si bien generalmente están abiertos a diferentes modelos de negocio, definen los objetivos económicos, financieros y sus límites basándose en indicadores económicos como, por ejemplo, un límite de años para el período de amortización de la inversión o un valor umbral para la Tasa Interna de Retorno (IRR).
- Pueden tener algunas preferencias tecnológicas basadas en lo que saben sobre proyectos similares, o simplemente en sus propios objetivos. Por ejemplo, instalar energía solar fotovoltaica para minimizar las emisiones locales de CO_2.
- **No siempre conoce los posibles cambios en los límites de emisiones ambientales y otras normativas.** Por ejemplo, la instalación de generadores de gas natural podría ser la opción más barata pero no la mejor si se aprueba una regulación más estricta sobre emisiones ambientales.
- **Conocen el plan de emergencia de las instalaciones** y los requisitos de resistencia a falta de suministro de la red, pero no siempre que estos pueden y deben ser considerados durante la fase de diseño de la microrred.
- **Se encuentran dispuestos a pagar algunas horas de consultoría** para encontrar la mejor solución.
- **No están necesariamente familiarizado con los riesgos asociados** con los proyectos de microrredes, pero están expuesto a ellos. Las empresas de ingeniería nunca discutirán la mayoría de estos riesgos de antemano.
- **Los promotores están abiertos a transferir esos riesgos mediante la contratación, por ejemplo, a través de una Compañía de Servicios de Energía (ESCO)**. Sin embargo, es probable

que traigan costos adicionales que podrían estar justificados o no, dependiendo de los riesgos que tenga el proyecto.

Algunas de las características del proceso de planificación de microrred desde el punto de vista de los ingenieros de diseño son:

- **Número de soluciones potenciales**: cada proyecto de microrred es único, con miles de combinaciones potenciales de tecnologías, tamaños y fabricantes a considerar. La necesidad de un sistema de distribución de energía solo agrega complejidad al problema de diseño de microrred multi-edificio: un sistema de 10 nodos con dos tamaños de cable potenciales tiene configuraciones potenciales de 3.5×10^{13}.
- **Consume mucho tiempo**: a pesar de existir miles de posibles alternativas, menos de diez soluciones son generalmente modeladas por estudio de viabilidad. Un análisis de viabilidad de una microrred multi-edificio puede llevar de 100 a 400 horas dependiendo del tamaño de la microrred, pero la cantidad de tiempo dedicado a identificar las soluciones óptimas generalmente depende del presupuesto, si es que hay alguno para el análisis de viabilidad.
- **Subjetividad**: en este escenario, muchas decisiones iniciales se toman en base a criterios de ingeniería subjetivos. El número de alternativas para estudiar se reduce en función de la experiencia previa y las preferencias del equipo de diseño sin la participación del promotor y el usuario final.
- **Análisis de bajo coste**: los análisis de viabilidad a veces se proporcionan de forma gratuita para atraer al cliente. Eso lleva a un número aún menor de alternativas estudiadas y una exploración deficiente de las posibles soluciones. Por ejemplo, una empresa de ingeniería tiene buenas relaciones con un fabricante de cogeneración, y deciden proporcionar un análisis de viabilidad basado en cogeneración sin coste, pero también sin tener en cuenta otros fabricantes o tecnologías energéticas.

Diez años después de que las microrredes comenzaran a ganar fuerza en la literatura de investigación, las herramientas de planificación no han evolucionado considerablemente: la mayoría de ellas son herramientas de diseño o ingeniería, y solo unas pocas pueden proporcionar un diseño completo de una microrred de múltiples edificios (sistemas de generación y distribución de energía incluidos). Como se describe en el Capítulo 2, las herramientas de escenarios solo pueden analizar un diseño a la vez, y las herramientas de simulación requieren amplios conocimientos técnicas para ser utilizadas, sin cubrir los aspectos económicos del proyecto en profundidad.

Como se mencionó anteriormente, las microrredes son sistemas diseñados para funcionar al menos 25 años. Cuando se planifica una vida útil tan larga, existen varias incertidumbres en una microrred que deben evitarse, o al menos controlarse [7-9]. **Por lo tanto, es crucial investigar sobre metodologías innovadoras que permitan a los planificadores de microrredes no solo diseñar microrredes eficientes, limpias y robustas, sino también permitir estimar el impacto potencial de las incertidumbres en la economía del proyecto y explorar y cuantificar la probabilidad de que un diseño sea rentable en escenarios futuros.** No se ha encontrado ningún método documentado que combine un enfoque técnico y económico para la planificación de microrredes multi-edificio (problemas de dimensionamiento, ubicación, programación y balance coste-beneficio), y que considere el impacto de las oscilaciones en las condiciones del marco de diseño a largo plazo. El análisis de riesgos apenas se considera entre las herramientas software de planificación de microrredes de múltiples edificios, dado que la mayoría de ellos han evolucionado a partir de las herramientas de diseño de sistemas energéticos. Se necesitan nuevos métodos de análisis para estudiar escenarios de viabilidad bajo un número más significativo de variables complejas: no solo permitiendo una selección óptima de alternativas técnicas sino también evaluando escenarios futuros y viabilidad a largo plazo.

Ha habido un fuerte desarrollo en las últimas décadas de las técnicas de optimización matemática, habiendo sido aplicadas con éxito a diferentes etapas del proceso de planificación de microrredes [10]. Muchos autores como Sims et al. han estudiado en [11] el proceso de evaluación de proyectos para diferentes aplicaciones. Mahmoud e Ibrik han aplicado en [12] algunos de estos criterios a los sistemas de energía y Dilworth describe en [13] algunos indicadores comunes que generalmente se utilizan para evaluar proyectos desde un punto de vista económico. Múltiples algoritmos han sido propuestos en revistas de investigación para resolver problemas de dimensionamiento, localización, programación y análisis de costes en, pero el software comercial se basa principalmente en algoritmos consolidados que buscan la solución óptima para analizar una alternativa cada vez: **un conjunto de entradas→ un algoritmo de ejecución →un conjunto de resultados**.

Como resumen, solo destacar que existe la necesidad de desarrollar análisis de viabilidad más avanzados e intuitivo para las microrredes de edificios múltiples (con uno o múltiples usuarios):

- Capaz de explorar miles de diseños potenciales en un tiempo limitado.
- Capaz de analizar la rentabilidad a largo plazo del sistema en futuros escenarios.
- Más accesible para los usuarios con habilidades técnicas limitadas o nulas con el fin de proporcionarles independencia y permitirles que desarrollen su propio el análisis de viabilidad antes de ponerse en contacto con otras compañías.

6. Objetivos y alcance

El objetivo de esta tesis es avanzar el estado del arte de los análisis de viabilidad de las microrredes eléctricas multi-edificio a través de una innovadora combinación de algoritmos capaz de suministrar información detallada sobre los aspectos técnicos y económicos de las soluciones, dando un papel más relevante al grupo promotor durante esta etapa del proyecto.

Las principales metas que persigue esta tesis son:

1. Crear un método de análisis de viabilidad de microrredes multi-edificio rápido, innovador y orientado al proceso de venta del proyecto.
2. Reducir el tiempo y los costes de modelado y simulación por solución analizada de las herramientas existentes en el mercado.
3. Comparación de las soluciones optimas y de las sugeridas por el usuario en base a los valores cuantitativos de indicadores de rentabilidad económica siguiendo un enfoque determinístico y un enfoque probabilístico, e identificando la probabilidad de que se cumplan los objetivos económicos del proyecto.
4. Presentar la viabilidad del proyecto desde un punto de vista estrictamente económico mientras se provee al promotor con suficientes detalles técnicos para definir las distintas soluciones. Reducir el conocimiento de ingeniería requerido por el usuario con el fin último de permitir a los promotores completar un análisis de viabilidad de una microrred por si mismos, una vez este método este incorporado en una herramienta software especializada.

El objetivo de este trabajo es ayudar a las personas que tomaran la decisión final a identificar y comparar diseños de microrredes optimizados en base a objetivos económicos, así como la probabilidad de que estos sean cumplidos a largo plazo. El método propuesto se ha implementado en una herramienta en basada en MATLAB y puede desarrollar las siguientes tareas:

1. Comparar los diseños óptimos calculados en base a indicadores cuantitativos de rentabilidad económica y la probabilidad de que estos se alcancen los valores definidos por el promotor al inicio del proyecto.
2. Proveer información detallada sobre las soluciones técnicas que se encuentran detrás de los resultados económicos, calculando los parámetros de operación horaria específicos para de cada activo del sistema.
3. Resolver lo problemas de dimensionado, localización, programación y cálculos de costes calculando las soluciones optimas bajo diferentes restricciones como tecnologías o

combustibles involucrados, o horas de resistencia a caídas de la red eléctrica requerida por las instalaciones.

4. Modelar los escenarios de rentabilidad a largo plazo mediante el empleo de técnicas de optimización y análisis de riesgos basadas en condiciones de mercado futuras, permitiendo al usuario considerar posibles cambios de normativa o nuevas políticas.

Este método contribuirá al desarrollo de microrredes eléctricas multi-edificio a dos niveles:

1. **Ventas y promoción de proyectos individuales**: ayudando a los promotores a contestar preguntas relacionadas con la viabilidad económica de una microrred y especialmente con su rentabilidad a largo plazo como:
    - ¿Puede una microrred ser una solución viable para mis instalaciones en base a mis objetivos y restricciones económicas?
    - ¿Cuál es la probabilidad de que una microrred alcance los objetivos económicos a largo plazo?
    - ¿Por cuánto no cumpliría la microrred con los objetivos? ¿Podrían ser de ayuda ciertos incentivos? ¿Cuánto deberían cambiar mis costes energéticos actuales para que Microred cumpla con los objetivos?

2. **Análisis de mercado:** permitiendo a los investigadores y analistas de mercado estudiar el impacto de las incertidumbres en la rentabilidad de diferentes tipos de microrredes:
    - Cambios potenciales en las condiciones de diseño como el precio de los combustibles.
    - Impacto potencial de diferentes incentivos y políticas.
    - Rentabilidad a largo plazo de diseños adaptados a futuro cambios de normativa.

7. Estructura del documento de tesis

Este documento de tesis presenta el estado del arte de la planificación de microrredes y el desarrollo de un método basado en una novedosa combinación de algoritmos de optimización y análisis de riesgos como son los algoritmos genéticos (GA), la programación lineal, y la simulación de Monte Carlo.

En el capítulo 2 se presenta el estado del arte de la planificación de microrredes eléctricas, incluyendo un análisis en detalle de los algoritmos propuestos durante las últimas décadas como parte del proceso de planificación de microrredes, así como de las herramientas software disponible sen el mercado. Este articulo recopila el trabajo de dos artículos publicados por el autor de esta tesis sobre el pasado, presente y futuro de la planificación de microrredes eléctricas. [10,14].

El capitulo 3 describe el método y los algoritmos involucrados en el, incluyendo las etapas de recogida de datos, modelado de los escenarios de planificación, optimización del sistema de distribución, optimización de los sistemas de generación y almacenamiento y análisis de riesgos.

El capitulo 4 presenta los resultados de la aplicación del método desarrollado en el capítulo 3 en uno de los campuses de la Universidad de Burgos (UBU). La UBU cuenta con casi 10.000 estudiantes divididos en diferentes campuses alrededor de la ciudad, encontrándose la mayor concentración de edificios al oeste del casco histórico. Los conjuntos de edificios considerados en este estudio son propiedad de y operados por la UBU y presentan usos diferentes como edificios académicos, polideportivos, alojamiento para estudiantes, bibliotecas e instalaciones de investigación.

Imagen 1. Edificio de servicios administrativos de la Universidad de Burgos

El capitulo 5 presenta las conclusiones de este trabajo en base al cumplimiento de los objetivos planteados al inicio de la tesis, las ventajas y desventajas del método propuesto, y el trabajo a desarrollar en un futuro en esta línea de investigación.

El capitulo 6 presenta un resumen de actividades desarrolladas durante el tiempo que el autor ha permanecido vinculado con el programa de doctorado, incluyendo publicaciones revisadas por pares, publicaciones y presentaciones en conferencias, y colaboraciones con grupos de investigación en microrredes.

La totalidad de los resultados del análisis ha sido incorporada en el Apéndice a esta tesis, siendo las tablas y gráficos más representativos presentados y comentados en el capítulo 4.

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Chapter 2

State of the Art of Microgrid Planning

9. About Microgrids

Energy systems have been evolving in opposite directions in the last decades. While heating and cooling systems are evolving from decentralization to centralization, power systems are moving from centralized to decentralized deployment strategies. One of the main challenges our societies face these days is how to figure out what is the best energy mix to achieve the future decarbonization goals, meaning not only which technologies but also which is the most efficient strategy to deploy them. A centralized energy system can provide several benefits at different levels (city, district, or even building) but it also involves more complex planning conditions that individual systems.

Different terms have been widely used to define systems that supply energy to groups of buildings, such as *district energy systems*. Community Energy System (CES) is a term that appeared for the first time in 1977 in three different papers written by R.E. Holtx in collaboration with other co-authors [1–3]. However, it is the definition by G. Walker and N. Simcock in [4] the one that, for the first time, considers under this term *the electricity and/or heat production on a small, local scale that may be governed by or for local people or otherwise capable of providing them with direct beneficial outcomes. In practice, it encompasses a wide variety of technologies, organizational arrangements, and potential outcomes, with these outcomes including collective economic returns, reduced fuel poverty, carbon mitigation, greater community cohesion, and increased knowledge of sustainable energy technologies*.

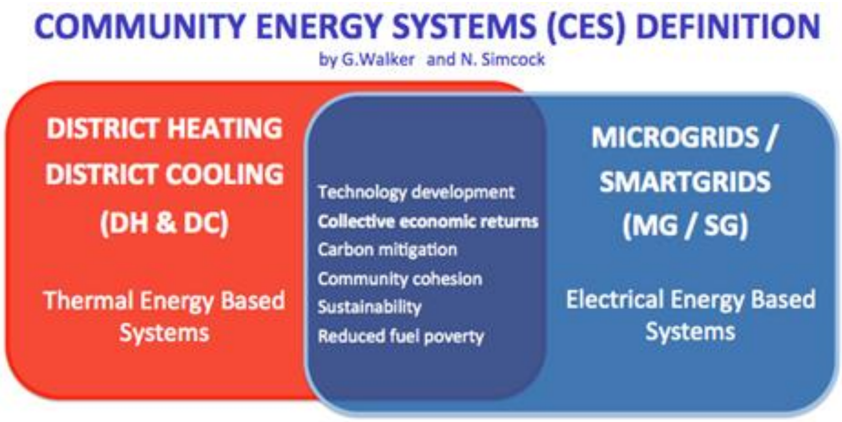

Figure 8. Interpretation of CES definition by G.Walker and N. Simcock

As mention in Chapter 1, new concepts of electrical CES, such as microgrids and smart grids, are getting the attention of an increasing number of public and private entities, interested in a cleaner and more cost-effective and resilient power supply. However, sometimes the similarities and differences between MGs and SG are not apparent for the decision-makers:

- Smart grids are leading the way to develop more advanced power grids. A smart grid can be defined as *an electricity network based on digital technology that is used to supply electricity to consumers via two-way digital communication. This system allows for monitoring, analysis,* *control, and communication within the supply chain to help improve efficiency, reduce energy consumption and cost, and maximize the transparency and reliability of the energy supply chain*[23].

- Microgrids appear as candidates to take part in the future smart grid as a novel power grid structure based on Distributed Energy Resources (DERs), Renewable Energy Systems (RES), power electronics, and Information and Communications Technologies (ICTs). CERTS has published one of the most widely accepted definitions of a microgrid[24]: *clusters of generators, including heat recovery, storage, and loads, which are operated as single controllable entities*.

Their main difference is their scope: since microgrids are expected to supply energy to their surrounding and influence areas, smart grids are expected not to consider geographical limitations or necessarily employ local resources, as the traditional power systems do in the present. A comparison between microgrid concepts is presented by J.I. Ping et al. [5].

Different classifications have been presented for microgrids since this concept appeared. Lilienthal points out in [6] different criteria for microgrid classification, such as connection with other grids, types of energy generation, the voltage of the distribution system, peak load, generation capacity, energy production, number of customers served, load management and metering. Due to the modular nature of microgrids, they can operate both independently or in conjunction with the traditional power grid.

Microgrids not only have less financial commitments and require fewer technical skills to operate than traditional power grids but also rely more on automation [7,8]. These advantages make microgrids a suitable solution to gradually modernize the existing power grids. Other advantages for microgrid establishment are the integration of renewable resources from local areas.

10.Impact of Research on Microgrids and Community Energy Systems Planning

During the last decades, new technologies for energy systems such as Information and Communication Technologies (ICTs,) smart meters, micro Combined Heat and Power (mCHP), energy storage, and renewable energy sources have enabled the apparition of new research topics within the scope of the CES definition presented in Figure 8. The impact of these technological advances can be analyzed by simple indicators found in the research literature.

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[23] https://www.techopedia.com/definition/692/smart-grid
[24] https://certs.lbl.gov/initiatives/certs-microgrid-concept

For example, 58,971 papers, including journal and conference papers, have been published from January of 1970 to May of 2015 under the four CES described by G.Walker and N. Simcock: District Heating, District cooling, Microgrids, and Smart grids. As Figure 9 shows, around a 72,48% of the research papers were on Smart grids, a 3,91% on District Heating, a 10,72% on Microgrids and a 3,19% on District Cooling. In 2015 the number of research papers about MG, SG, and DH decreased for the first time in 10 years. This could be a symptom of maturity for some research topics**.**

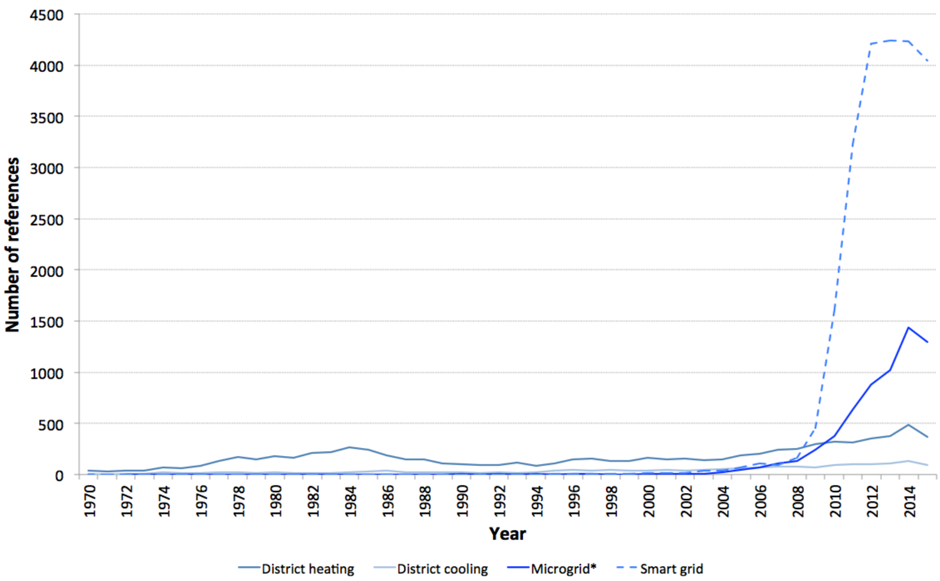

Figure 9. Number of Papers Published by CES and Year

The number of approved patents on a research topic is an interesting indicator of how mature and successful that specific topic has been. As shown in Figure 10, the evolution of IoT-based technologies and Machine Learning are driving an increase in the number of patents focused on management, control, communications, and (cyber) security.

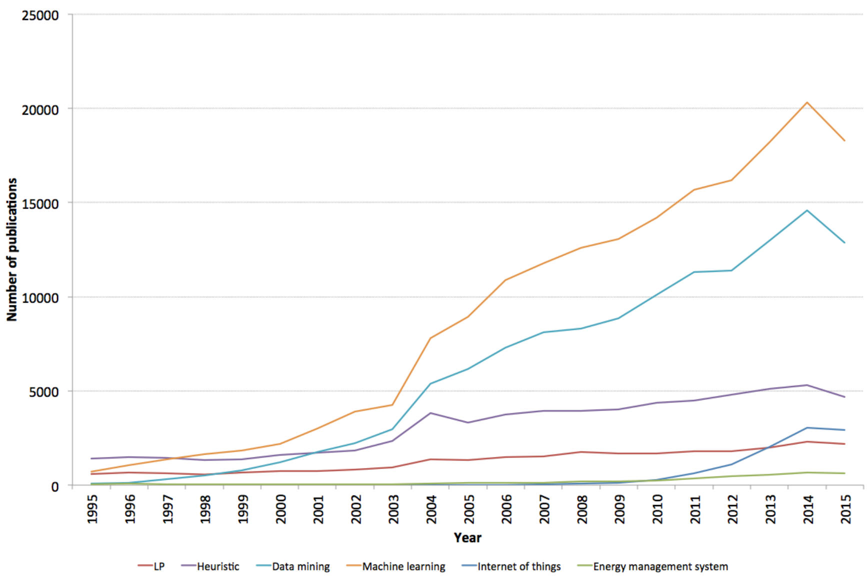

Figure 10. Papers per Search Term. Source: SCOPUS.

An intensive search of patents related with district heating, district cooling, microgrids, and smart grids has been developed, showing an increase of a 295.5% in the last five years, following different patterns presented in Figure 11 and Table 1:

- ✓ DH and DC systems have more patents at the generation and distribution levels (>62%).
- ✓ More than 50% of the patents on MG are on management and control systems.
- ✓ Almost 33% of the patents on SG are on security, communications, and other issues.

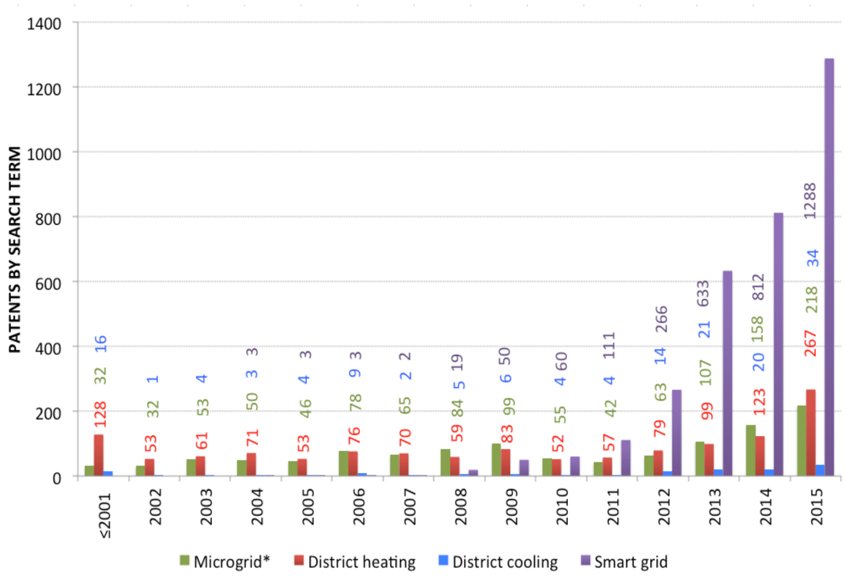

Figure 11. Number of Patents per Search Term

		QUANTITY	Planning level: ENERGY GENERATION & STORAGE	ENERGY DISTRIBUTION	CONSUMPTION, METERING & SUPERVISION	MANAGEMENT & CONTROL	OTHERS: COMMUNICATIONS, SECURITY, CONCEPTUAL DESIGNS AND METHODS
Term	DISTRICT HEATING	1442	37,68%	26,81%	12,32%	15,22%	7,97%
	DISTRICT COOLING	162	36,57%	26,12%	16,42%	9,70%	11,19%
	MICROGRIDS	1279	15,15%	16,16%	9,60%	51,01%	8,08%
	SMART GRIDS	3787	13,04%	18,01%	16,77%	19,88%	32,30%

Table 1. Number of Patents per CES and Planning Level

According to this data, microgrids are a very active topic when it comes to research and development. The question is if these technological advances are helping advanced the microgrid market.

In 2015 the market analysis company Markets and Markets published a report estimating that the microgrid market *was valued at USD 16.58 Billion and expected to reach USD 38.99 Billion by 2022, at a CAGR of 12.45%*[25]. In 2018 similar trends were published by the IMARC group: *the global microgrid market was worth US$ 19.3 Billion in 2018. The market is further projected to reach a value of US$ 36.3 Billion by 2024, growing at a CAGR of 10.9% during 2019-2024*[26]. In December of 2019, the energy

[25] https://www.marketsandmarkets.com/Market-Reports/micro-grid-electronics-market-917.html?gclid=EAIaIQobChMI4-qJh9-02AIVTLjACh1aBAfgEAAYASAAEgL8BfD_BwE
[26] https://www.imarcgroup.com/microgrid-market

research firm Wood MacKenzie reported a new record in the U.S. microgrid market *with 666 megawatts of capacity additions in 2018*. According to Wood MacKenzie, *project delays and cancellations have dropped the expected 2019 total to 553 megawatts*, identifying the reconversion plans of the energy bankrupt California utility PG&E *as a potential inflection point for the market*[27].

Research and technological advances are driving the development of the microgrid market. There is plenty of research literature about microgrid planning available, but not very detailed information on how the real-world microgrids are planned is publicly available.

11. About Microgrid Planning Resources

Planning a multi-building microgrid is considered a complex process due to all the alternatives to consider, especially at the feasibility analysis level**.** Every decision taken at the early stages of the planning process will influence the capacities of the system in a competitive energy market. Every planning process is built around specific goals and constraints. However, not only goals and constraints (such as technical, environmental, geographical, social, and regulatory constraints) define by themselves the whole framework of the planning process: uncertainties are a source of risks that system planners need to avoid, or at least to control.

S. French in [9] identifies several sources of uncertainties in all the main steps of a decision-making process: uncertainties in modeling, uncertainty expressed during the exploration of the model, and uncertainties in the interpretation of results. But other authors in [10], motivated by practical needs for modeling the decision-making problem, have classified every uncertainty under two main categories:

- ✓ External uncertainty: related to the lack of knowledge (about the consequences of an action, outside of the control of the decision-maker), and the nature of the environment.
- ✓ Internal uncertainties: presented in the process of identification, structuring and analysis of the decision-maker (depending on the decision-maker).

Microgrid planning can pursue multiple goals not necessarily compatible. For instance, while it is necessary to invest in renewable power sources to minimize the environmental impact of a microgrid, renewable technologies are more expensive than conventional power generation, and will increase the initial investment of the system. The microgrid planning process is, in fact, a process to find trade-off solutions to the goals of the system among a high number of alternatives. T**he core of the whole planning process can be described as a sequence of optimization problems** [11]**.**

[27] https://www.greentechmedia.com/articles/read/microgrid-development-slowed-in-2019

A microgrid planning process is composed of goals, strategies, and workflow required to achieve the results. Unlike than for district heating and district cooling systems, **it is not common to find documents describing holistic approaches to the microgrid planning process, being the scope and the level of detail the main differences between the existing publications.** There exist some different levels of detail in the MG planning literature, usually hidden behind similar names such as method or methodology. There exist slight differences among these and other related terms worth to be highlighted:

- A **methodology** is defined as a system of broad principles or rules from which specific methods or procedures may be derived to interpret or solve different problems within the scope of a particular discipline. Unlike an algorithm, a methodology is not a formula but a set of practices. *A methodology does not set out to provide solutions (…). Instead, a methodology offers the theoretical underpinning for understanding which method, set of methods, or so-called "best practices" can be applied to a specific case*[28].
- A ***method*** can be described as *an established, habitual, logical, or prescribed practice or systematic process of achieving certain ends with accuracy and efficiency, usually in an ordered sequence of fixed* steps. [29]
- An ***algorithm*** is defined as a *step by step procedure designed to perform an operation, and which (like a map or flowchart) will lead to the sought result if followed correctly. Algorithms have a definite beginning and a definite end, and a finite number of steps. An algorithm produces the same output information given the same input information, and several short algorithms can be combined to perform complex tasks* [2].

Based on these definitions, microgrid planning resources have been categorized in Figure 12 according to their level of detail, being in the lowest levels of the pyramid the resources providing more general contributions (levels 0 in Table 2)and at the highest levels the ones presenting the most specific procedures and outputs (level 5 in Table 2). Each type of document has a role to play in the microgrid planning process. A software tool executes a set of algorithms that have been previously defined in a method. At the same time, methods are based on methodologies, which typically describe the best practices in microgrid planning.

[28] https://en.wikipedia.org/wiki/Methodology

[29] https://en.wikipedia.org/wiki/Methodology

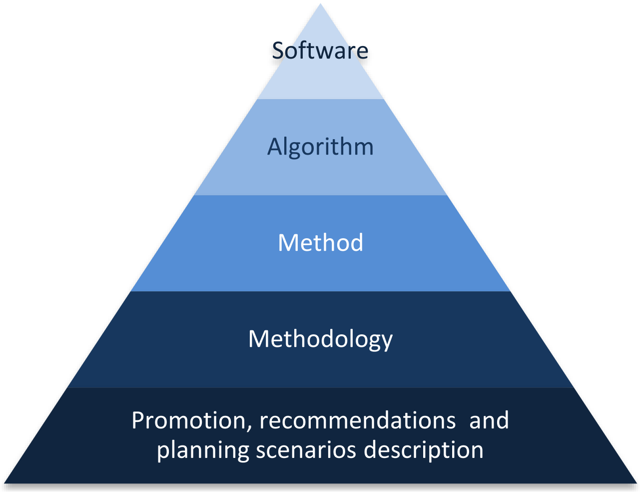

Figure 12. Relations Among Terms Methodology, Method and Algorithm and Scope of This Work

Table 2 presents a list of microgrids and CES planning resources, including their major contributions. Papers basing their approach in the use of a defined software tool have been considered but not exhaustively cited, due to their high number. Research papers developing partial approaches have been reviewed by this author in [11] and will be presented later in this chapter.

In addition to publications related with MG planning, those focused on DH and DC planning have been included too because of their synergies. Different planning and design guides for DH & DC systems have been published by international associations [12-17] since 1921 [14]. In the present, authors are more focused on incorporating the singularities of the planning framework into their models such as market conditions, regulations [18] and business model [19,21].

The absence of detailed literature describing holistic approaches to microgrid planning does not mean they have never been developed. **They are not published mainly because the methodologies and algorithms they are based on are critical competitive advantages of the software development companies.** Software tools oriented to MG, DH and DC planning will be analyzed in further sections.

Likely in DH systems, some entities such as local governments, universities and private companies are publishing their own guides and methodologies (levels 0 and 1 of the pyramid in Figure 12) about MG and SG planning [11,23,24,27,30]. Regarding microgrids, there are also some methods based on widely used software tools such as HOMER [22]. Similar approaches based in different software tools have been briefly described in [26,29,31].

Ref.	Level	System	Organization	Year	Major contribution
[13]	1	DH	CHPA	2012	Project stages definition, including financial and business approaches to the UK market.
[14]	1	DH	CHPA	2010	Project stages definition, including financial and business approaches to the USA market.
[15]	1-2	DH	IDEA	1983	Design guide including strong approaches to technical, economic and financial issues.
[16]	1-2	DC	IDEA	2008	Design guide including detailed approaches to technical, economic and financial issues.
[17]	1-2	DH	ASHRAE	2013	District heating design guide including planning advices and case studies.
[18]	1-2	DC	ASHRAE	2013	District cooling design guide, including planning advices and case studies.
[19]	0	DH, DC	University of waterloo	2012	Promotion, recommendations, insights and case studies at a local level.
[20]	0-1	DH	District Energy St Paul	2013	Project stages definition, including financial and business approaches to the UK market.
[21]	4	DH	IAT	2012	Example of the use of TRNSYS software in the feasibility analysis of DH facilities
[22]	2-3	DH, DC	Dalian University of Tech.	2010	Algorithm description and expanded design method for DH facilities including economic feasibility aspects.
[23]	4	MG	Georgia Southern Univ.	2014	Project stages definition, and example of the use of HOMER software in the feasibility analysis
[24]	1	MG	VirginiaTech	2012	Guidelines for the design of microgrids in campus facilities and presentation of project results-based insights
[25]	0	MG	California Energy Commission	2015	Summary of existing barriers and investment needs along the microgrid establishment process.
[26]	2-3	MG	Huysong corporation	2009	Algorithm and design method description for MGs, including some economic feasibility aspects.
[27]	2 & 4	MG	GT	2014	Description of design and operation conditions of a military campus. Simulation of operational conditions using software PSCAD.
[11]	1	MG	UBU & AAU	2015	Planning problems definition. Study of optimization techniques applied to solve MG planning problems.
[28]	0	MG	UBU & AAU	2016	Guidelines of IoT-based approaches towards the design of profitable MG in industrial environments
[29]	2 & 4	MG	NITT	2012	Algorithm and method description for the transformation of a traditional power grid into MGs.
[30]	2 & 4	MG	BCIT	2012	Detailed approach of the planning problems of a campus MG. Simulation of operational conditions using software PSCAD/EMTDC
[31]	0	SG	ALACATEL-LUCENT	2012	Presentation of guidelines to smart grid planning

Table 2. Publications Focused on Community Energy Systems Planning Methods

12. Individual Approaches to Power Systems Planning Problems

The planning process of power systems has been traditionally divided into two different problems: Economic Load Dispatch (ELD) and Optimal power flow (OPF). While the ELD problem is to define a power equipment layout able to cover the power demand at the minimum cost (including distribution and transmission losses), the most common objective of the OPF problem is usually focused in the study of electrical parameters, quality keeping, and power grid configuration. These problems have been widely studied by many researchers for decades, but they have also evolved into different approaches. This evolution will be studied through a review of the research literature.

12.1. Power Systems Sizing and Scheduling

Defining the optimal technology and size of a power system (also known as sizing) is one of the most common problems found in research literature and power systems design books. While and oversized power system would face high operational costs, and undersized power systems would be prone to experience blackouts and other quality-related problems. Cost efficiency, quality, and reliability are among the main competitive advantages of a commercial power system. Reliability and quality in power systems are usually achieved through generation unit redundancy. However, redundancy increases the initial investment and eventually the payback period of the system.

The scheduling problem focuses on scheduling a set of selected generation units to cover the power demand at the minimum cost. Both problems, sizing and scheduling, are the basis of modern power systems planning processes. Traditional approaches to solving these problems are still valid in many cases, despite being in the technical literature for more than 40 years.

As shown in Figure 13, the ELD problem is still a trending problem thanks to the update and migration of techniques from traditional power grids to microgrids planning. Unlike the OPF problem, the ELD problem has not suffered considerable changes in their objectives, constraints and uncertainties. The ELD problem is not as affected by the size of the system such as the OPF problem where distances between generators and customers between them are quite different for traditional power grids and microgrids. Three different approaches to the sizing and scheduling problem in power systems have been identified as part of this literature review.

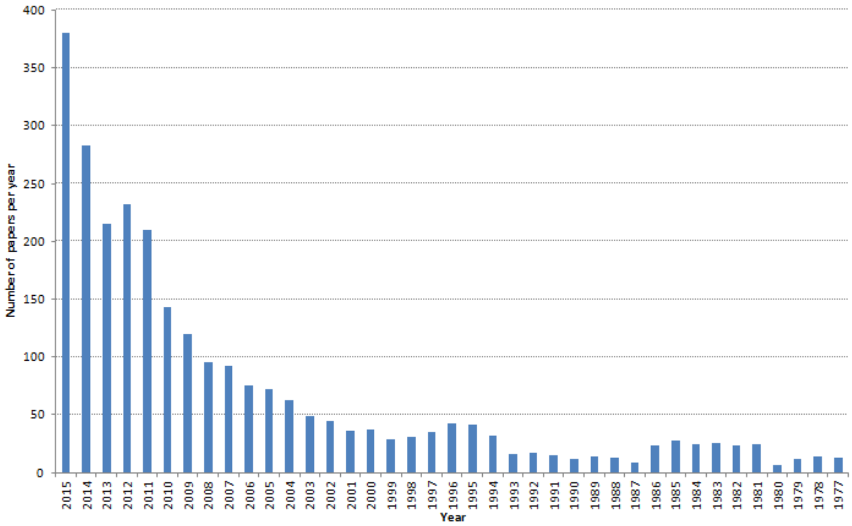

Figure 13 References Found Under the Term "Economic Load Dispatch" per year. Source: SCOPUS

The **first approach**, which could be considered the most traditional one, and has already been presented as the **Economic Load Dispatch Problem**. This problem was designed for conventional power sources and is the most common approach in the technical literature. The basic objective of ELD in the electric power systems field is to schedule the outputs of the committed generating units in such a manner so as to meet the load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints [32–34]. Some authors also consider demand response strategies in economic dispatch problem such as Huang et al. and Xing et al. do in [35] and [36].

The nature of the solution methodologies has shifted in recent years from centralized to distributed ones [37] due to the evolution of power technologies. Some of the same techniques used for solving the ELD problem in power systems planning are still suitable for architectures based on distributed energy resources, such as microgrids. But in some occasions, the approach cannot be the same since, for example, size and control strategies are usually not the same. Here is where the **second approach appears**. When it comes to power systems based on distributed generation, such as microgrids, this problem has been divided into two different problems:

- *Sizing*: is the problem that includes the modeling, analysis, and selection of different technologies for power generation, energy storage and different kind of fuels. The outcome of this problem is a layout of different power generation and energy storage units with different and defined sizes. [38–50]
- *Scheduling* is the problem in which power and energy storage equipment is scheduled in order to minimize the cost of the system [51–57]. Some of the scheduling problems also consider demand management strategies such as demand response and demand-side management [58,59].

The **third approach** is similar to the second approach but considering additional goals or constraints for the microgrid. For instance, the synergies and potential methods to integrate microgrid systems into industrial processes management are described in [28]. In this paper, the microgrid is not just designed to follow the demand but scheduled in coordination with the rest of the manufacturing process. The authors review the applicability of knowledge discovery in database techniques to manufacturing processes and study innovative approaches to the sizing and scheduling problems in data-intensive environments.

Abouheaf et al. introduce in [60] traditional mathematical techniques used to solve the ELD and OPF problems, including Newton-based and gradient methods, lambda iteration method, base point and participation factors method, interior point algorithm, linear programming, dynamic programming, and dual quadratic programming, where the generation cost functions are assumed to be monotonically increasing piece-wise linear functions. Also, fuzzy optimization has been proposed to solve the same problem in [5-7]. Lo and Anderson combine in [61] multi-pass dynamic programming (MPDP) with a time-shift technique to sizing and calculate the economic dispatch of energy storage systems. Traditional methods are compared with the most modern ones, such as Prabhakar et al., Xu et al., and S. Mishar in [62–65], including heuristic and metaheuristic algorithms.

Heuristic and metaheuristic methods were designed to find a good solution in large search spaces with less computational effort than optimization techniques. Besides, they also solve some of the limitations cited for traditional methods [66]. The point of metaheuristics is that they can combine more than one heuristic method: the first one can be used to find a primary solution while a second heuristic can be used to find a better solution. A brief review of heuristic methods applied to solve the ELD problem is introduced in Tables 3, 4 and 5. **Genetic Algorithms, PSO, and their variations are among the most popular heuristic algorithms.**

Table 3. Sizing and Scheduling Approaches for Traditional Power Systems 1

FIRST AUTHOR	YEAR	PROBLEM	ALGORITHM	SIZE (NODES, UNITS)	OBJECTIVES AND APPROACH
Ouyang	1991	ELD	Self-Designed Heuristic	4 units	To develop a multi-area generation scheduling scheme that can provide the proper unit commitment in each area, and effectively preserve the tie line constraints
Wang	1992	ELD	Self-Designed Heuristic d	4 buses 26 units	A multi-area generation scheduling problem is proposed which enhances the transportation problem with the non-linear optimization procedure
Kumar	1995	ELD	ANN	6 buses 3 units	ANN applied to real-time economic power dispatch
Demartini	1996	ELD	Self-Designed Heuristic	20 and 389 units	To provide ELD with the look-ahead capability of the advanced demand procedures based on dynamic dispatch models
Song	1997	ELD	GA	6 units	Fuzzy logic controlled genetic algorithms for environmental/economic dispatch
Das	1998	ELD	MOSST (GA and SA)	30 and 57 units	Multi-objective economic-emission-dispatch problem
Jabr	2000	ELD	HIP	14, 30, 57 and 118 units	Economic dispatch with network constraints, ramping constraints, and transmission losses as a single convex optimization problem
Ling	2003	ELD	GA	13 units	An improved genetic algorithm for economic load dispatch with valve-point loadings
Dos Santos	2006	ELD	DE	13 and 40 units	Economic load dispatch problems with valve-point effect.
Thitithamrongchai	2006	ELD	SADE-ALM	10 units	Hybrid self-adaptive differential evolution with augmented Lagrange multiplier method
Saber	2007	ELD	SA	100 units	Stochastic simulated annealing algorithm for unit commitment problem.
Sinha	2007	ELD	NSDE	15 units	Non-dominated sorting differential evolution algorithm for solving optimal economic emission dispatch problem as a multi-objective problem.
Ling	2007	ELD	HPSOWM, HPSOM, HGAPSO, HGPSO, SPSO	40 units	A new hybrid particle swarm optimization (PSO) that incorporates a wavelet theory-based mutation operation for solving economic load dispatch is proposed.

Table 4. Sizing and Scheduling Approaches for Traditional Power Systems 2

FIRST AUTHOR	YEAR	PROBLEM	ALGORITHM	SIZE (UNITS OR BUSES)	OBJECTIVES AND APPROACH
Vanaja	2008	ELD	AIS	3, 13 and 40 units	A clonal selection based AIS technique has been applied to solve ELD problem with the valve-point effect.
Vlachogiannis	2009	ELD	ICA-PSO	6, 13, 15 and 40 units	An improved coordinated aggregation-based particle swarm optimization (ICA-PSO) algorithm is introduced
Zaraki	2009	ELD	PSO	3, 6, 15 and 40 units	The ELD problem has also been solved by quadratic programming, genetic algorithm, and particle swarm optimization methods for 4 various test cases and load demands.
Affijulla	2011	ELD	GSA, PSO, DE, and GA	3, 6, 13 and 40 units	Gravitational Search Algorithm (GSA) is applied to the economic load dispatch problem with valve point loading and Kron's loss. It is compared with PSO, DE, and GA.
Kannan	2011	ELD	FA and PSO	26 and 30	The proposed algorithm utilized firefly's food searching mechanism to optimize the economic load dispatch problem in the power system.
Apostolopoulos	2011	ELD	FA	6	A general formulation of this algorithm is presented together with analytical mathematical modeling to solve this problem by a single equivalent objective function.
Kumar	2012	ELD	DE and PSO	14 buses 4 units	Optimal locations and sizes, which are independent of CHP-based DERs types, are selected, here, by loss sensitivity index (LSI) and by loss minimization using particle swarm optimization (PSO) method, respectively.
Jadhav	2012	ELD	PGSA	6, 15 and 40 units	The generation scheduling for an overall system comprising coal-based units and a wind farm is delivered by solving an objective function using plant growth simulation algorithm
Rahmat	2012	ELD	DEACO	6 units 26 buses	Differential Evolution Ant Colony Optimization to optimize Economic Load Dispatch in power system
Singh	2012	ELD	MRPSO	6 units	Moderate-random particle swarm optimization (MRPSO) is used for solving ELD problem with emission as constraints.

Table 5. Sizing and Scheduling Approaches for Traditional Power Systems 3

FIRST AUTHOR	YEAR	PROBLEM	ALGORITHM	SIZE (UNITS OR BUSES)	OBJECTIVES AND APPROACH
Bulbul	2014	ELD	QOGSA	10 and 40	This paper proposes an extension of the gravitational search algorithm (GSA) to solve nonlinear ELD optimization problems by considering valve point loading effects.
Loganathan	2014	ELD	PSO	3, 13 and 20	PSO solves economic practical economic load dispatch problem (with valve point effect) with better-optimized results in a little fraction of seconds.
Orike	2014	BBDELD	IFEP, ABC, PSO, DE, BBO, HS, MGSO and SA	40	The bid-based dynamic economic load dispatch problem involves matching bids from competing generating companies to the demands of consumers
Suresh	2015	ELD	UDTPSO	30 and 62 units	Analyze the effect of multi-fuel and practical constraints on economic load dispatch problem using a novel uniform distributed two-stage particle swarm optimization
Khosa	2015	ELD	GA	6 units	The economic load dispatch model is developed, considering thermal and wind power plants.
Dash	2015	ELD	SA	30, 57 and 118 buses	Multi-objective Economic Emission Load Dispatch with Nonlinear Fuel Cost and non-inferior Emission Level Functions

12.2. Sitting Resources in Power Systems

Resource allocation has always been one of the main optimization problems in power systems planning. Geospatial constraints, such as altitude and distances between generation units and customers, can influence the performance of the systems and their associated costs. As shown in Figure 14, many authors have studied this problem under different approaches from 2000 to 2015.

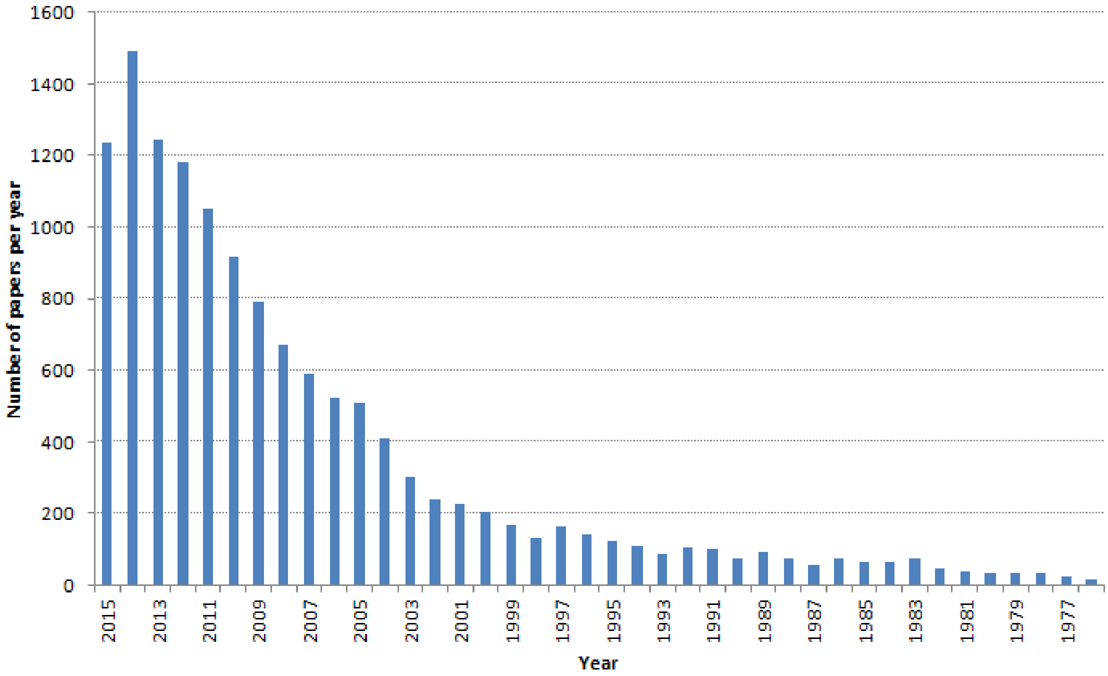

Figure 14. References Found Under the Search Term "Optimal Power Flow" per Year. Source: SCOPUS

The main objective of this problem is to optimize the economic performance of the system, while quality parameters are fulfilled. The main approaches discovered during a review of technical literature are described below.

The first approach has been commonly known as the **Optimal Power Flow** (OPF) problem. As Niu et al. assert in [67], that *the OPF problem adjusts the continuous control variables (e.g., real power outputs and voltages) and discrete control variables (e.g., transformer tap setting, phase shifters, and reactive injections) to reach the optimal objective function while satisfying a set of physical and operational constraints.* This problem is not defined as a strictly resource location-based problem, but the results of this approach are dependent on the location of the resources. **This approach allows planning engineers to simulate and benchmark different network architectures and control strategies in order to find the most optimal one.** The most common objective is to minimize the active power losses. However, several other objectives can be optimized such as bus voltage deviation or environmental emissions. Reconfiguration of traditional power grids has been considered for existing conventional power grids in different papers [68–72]. Since this first approach is characterized by providing energy to big areas and a large number of buses from distant power generation sources, the progressive apparition of new concepts related to power systems (including distributed generation and microgrid) and new mathematical techniques caused slight modifications in the approach different authors followed.

The second approach to the location of power resources can be named as the **siting** problem. **This problem is based on determining the optimal power line layout of the elements taking part in smaller power systems like microgrids**, **given their potential locations and ways to be interconnected** (e.g. location and connection of micro-sources and load points)**.** This specific problem, as OPF, is constrained basically by geospatial, economic, and power quality requirements. The sitting approach is more likely to be found in papers about microgrids, trying to define the optimal location of power lines, power generation, and energy storage equipment. Some authors have reviewed the approaches followed to solve the sitting problem during the last decades [62].

A third approach has been studied by authors like Kirthiga et al. [73] and Ghiani et al. [74]. They study the advantages of the reconfiguration of traditional power grids, dividing them into different microgrids.

The fourth approach to microgrid siting could be proposed from the application of the OPF problem to microgrid architectures [75,76]. Distances between nodes are shorter, and fewer nodes, buses, and switches are considered in microgrids than in conventional power grids. That is the reason why the OPF problem in the microgrid world is sometimes oriented towards sizing and siting the power lines in order to reach a trade-off solution between a power network with low capital expenses and or with low power losses.

New mathematical techniques and algorithms have evolved the approach of the sitting problem from a mathematical point of view. A brief list of OPF focused papers, including their main objectives, has been presented in Tables 6 and 7. The OPF problem can be defined as a highly constrained, non-linear, and non-convex optimization problem [77]. Thus, conventional techniques as linear programming (LP), quadratic programming (QP), non-linear programming (NLP), and mixed-integer linear programming (MILP) have been applied under different theoretical assumptions and problem constraints. As N. Ming et al. cited in [67], *conventional techniques such as linear programming (LP), quadratic programming (QP), and non-linear programming (NLP), were developed to solve optimal power flow problems (OPF), with some theoretical assumptions, such as convexity, differentiability, and continuity, which may not be suitable for the actual OPF conditions. Since continuous LP, QP, and NLP formulations cannot accurately model discrete control variables, such as transformer tap ratios or switched capacitor banks, Mixed-integer linear programming (MILP) techniques were introduced to* *solve this problem. However, the nonlinearity of the power system cannot be fully represented by MILP formulations, and therefore cause inherent inaccuracy.*

In this scenario, heuristic methods have been applied to find an optimal solution among a broad set of feasible solutions with less computational effort than optimization techniques. Its application also resolves some of the limitations cited for traditional methods [66]. Besides heuristics, the point of metaheuristics is that they can combine more than one heuristic method: the first one can be used to find a primary solution, and later another heuristic method can help find a better solution. Metaheuristic methods can be classified following [62] into:

- Trajectory meta-heuristics use a single-solution approach focused on modifying and improving a single candidate solution during the search process. The outcome is also a single optimized solution. The main meta-heuristic methods in this category include SA, TS, GRASP, VNS, and ILS.
- Population-based meta-heuristics use a population of solutions, which evolve during a previously fixed number of iterations, returning a population of solutions when the stop condition is fulfilled. Perhaps GA and PSO are the most popular algorithms in this category.
- Bio-inspired metaheuristics are metaheuristics that mimic nature for solving optimization problems. These techniques have been divided by Binitha and Shatia [78] into three main types: Evolutionary algorithms, Swarm intelligence, and Ecology-based algorithms. Such as Zeng et al. review evolutionary, swarm intelligence, and hybrid algorithms in their application to optimization problems in the field of sustainability [66].

Other classifications have been developed for these methods, as the one developed in [67], which included the following categories:

- ✓ Genetic algorithm (GA) based approach
- ✓ Particle swarm optimization (PSO) based approach
- ✓ Differential evolution (DE) based approach
- ✓ Evolutionary programming (EP) based approach
- ✓ Other techniques: including ant colony optimization (ACO), Simulated annealing (SA), and Artificial bee colony (ABC) techniques.

The authors also cite other different approaches using metaheuristics that could be considered in a microgrid planning process, such as hybrid (combining them with traditional techniques) and parallel approaches, (an algorithm that runs multiple metaheuristic searches in parallel by using parallel computing techniques).

Table 6. Siting Approaches for Traditional Power Systems 1

FIRST AUTHOR	YEAR	PROBLEM	ALGORITHM	SIZE (NODES)	OBJECTIVES AND APPROACH
Shirmohanunadi	1.989	OPF	Self-designed heuristic	56	Reconfiguration of distribution networks in order to reduce their resistive line losses under normal operating conditions.
Wu	1.991	OPF	Heuristic search	9	Heuristic search approach to feeder switching operations for overload, faults, unbalanced flow and maintenance
Abido	2.001	OPF	PSO	3	Fuel cost minimization, voltage profile improvement and stability enhancement.
Celli	2.001	OPF and ELD	GA	148	Mono-objective function to be optimized within the technical constraints refers to the total cost of the network
Miranda	2.002	OPF	EPSO	24	Loss minimization and voltage control are solved.
Celli	2.003	Siting and sizing	GA	102	A multi-objective approach towards determining the best locations and sizes of EG.
Parada	2.004	Siting and sizing	SA	315	Minimizing the investment cost for feeders and substations, and the power-loss cost.
Nallagownden	2.006	OPF	GA	34	Reduction of Reactive Power Losses in Radial Distribution System
Vallem	2.006	Siting and sizing	SA	6	The siting problem considers factors like deployment costs and savings gained using CHP units
Srinivasa	2.009	OPF	Not mentioned	33	Optimal reconfiguration of radial distribution systems: determine the best switching combinations and optimum power loss calculation
Basu	2.009	OPF	PSO	6 and 14	Cost minimization of the integration of CHP units in a power grid, considering optimal sizing and location.

Table 7. Siting Approaches for Traditional Power Systems 2

FIRST AUTHOR	YEAR	PROBLEM	ALGORITHM	SIZE (NODES)	OBJECTIVES AND APPROACH
Mulyawan	2.010	OPF	GA	30	Optimal setting of OPF control variables which include generator active power output, generator bus voltages, transformer tap setting, and shunt devices with the objective function of minimizing the fuel cost.
Ayan	2.011	OPF	GA	9	Sequential load flow analysis of integrated AC/DC systems
Amanifar	2.011	OPF and ELD	PSO	15	Determine optimal DG allocation and sizing
Shrawane	2.013	OPF	GA	3	Line losses minimization. Comparison it with Gauss-Seidel method
Tan	2.013	OPF and ELD	GA, PSO, AIS, VAIS	33	ELD and OPF problems integration into a network reconfiguration algorithm.
Cabadaj and Turkay	2.013	OPF	PSO and GA	14 and 30	Total hourly generation cost of generator units are minimized as an objective function to meet the load demand and system losses

13.State of The Art of Microgrid Planning Problems.

Even though each microgrid planning process has its own constraints and specific goals, the same planning problems are present in every microgrid. These planning problems can be defined as:

- ***Power generation mix selection and sizing:*** Microgrid design engineers are responsible for choosing the best available power system to satisfy demand requirements. Power source selection requires an analysis of suitable power generation alternatives in the influence area. Power generation and energy storage equipment must be sized according to the minimum and peak-load demand and cost-effectiveness criteria. The most common objectives to fulfill at this planning stage are high cost-effectiveness, low environmental impact, and high reliability.

- **The siting problem takes care of** power resources allocation and power lines layout design in order to keep quality constraints. In this process, not only confirmed consumers but also potential and future customers might be considered. This problem must also be considered among the strategic problems. As in the sizing problem, the initial investment and long-term performance of the system are highly dependent on the results. In this planning stage, it is not only necessary to provide high cost-effectiveness and high reliability as in the previous one, but also low power losses are required.

- ***Scheduling*** is focused on optimizing the dispatch of the available resources, such as generators and storage devices. The scheduling problem tries to minimize the operational costs, but other objectives can be incorporated, such as the environmental impact. Optimal operational conditions for different microgrid configurations are defined using different **single or multi-objective optimization techniques.**

These are the typical stages in a microgrid feasibility analysis. A survey of optimization techniques taking part in these stages is presented in this section. Besides, the application of some related mathematical techniques such as simulation, fuzzy logic, and forecasting, including uncertainty management will be discussed.

13.1. Power Generation Mix Selection and Sizing

Optimization problems like power source selection [79] and sizing [80] and energy storage devices selection and sizing [81] are common problems to every microgrid according to the technical literature. **The goal of the economic load dispatch** problem is to determine the real power outputs for the generators so that the total cost of the system is minimized.

Traditional optimization techniques are used in [42] by M. Vafaei and M. Kazerani, to select and size different power generation technologies and storage devices for a microgrid from an operational cost perspective. The optimization model is formulated as a MIP (Mixed Integer Programming) problem in the GAMS environment. Also, a classical optimization method is reviewed towards microgrid modeling purposes in [82] by Augustine *et al*. They perform the power mix selection of four different types of microgrids by using the *Reduced-Gradient Method for Economic Dispatch* algorithm and MATLAB software in order to simulate the system. In this paper, the final selection is based on economic dispatch costs, considering renewable energy sources penetration, costs, and receipts associated.

Y. Han et al. solve the ELD problem using the Karush-Kuhn-Tucker (KKT) conditions in [83]. Allowing inequality constraints, the KKT approach to nonlinear programming generalizes the method of Lagrange multipliers, which allows only equality constraints. The KKT approach guarantees to find the true optimum (versus heuristic search approaches) but is also readily capable of being extended with further realistic constraints/costs, versus purely analytic approaches.

In [48], T. Logenthiran compares a classical Integer Minimization Problem (IMP) with Evolutionary Strategy (ES) method (a generic population-based optimization metaheuristic algorithm) in order to size power equipment for an islanded microgrid. The optimization aim is to minimize the sum of the total capital, operational, and maintenance costs of DERs.

Heuristics are widely used in sizing and power generation mix selection. Erdinc in [80] highlights some heuristic optimization techniques for hybrid renewable energy systems sizing, such as GA, PSO, SA, and some promising techniques such as Ant Colony and AIS. In [50], S.M.M. Tafreshi et al. model a microgrid using MATLAB and GA to solve the sizing problem. They evaluate the system considering costs and benefits such as the cost function annualized capital, replacement, operational, maintenance, fuel costs, and annual income by selling power to the grid. SA algorithm is used to solve the optimal sizing problem for renewable energy generations and combined heat and power (CHP) units in a hybrid energy microgrid in [84]. Stochastic variability of renewable energy resources and the heat and power requirements are considered in order to meet customer requirements with minimum system annual cost.

Energy efficiency and renewable power sources are nowadays the main tools to minimize the environmental impact of a microgrid. However, since renewable power sources are not always ready to produce energy at their peak power, energy storage becomes an important topic in microgrids. This topic is introduced by S. Bahramirad et al. in [40] in which the optimal ESS sizing problem is proposed both for initial investment and expansion problems. The problem is analyzed from an economic point of view, using a MIP approach in order to minimize investment in storage devices and microgrid operational costs. S.X. Chen et al. propose in [81] a method based on the cost-benefit analysis for optimal sizing of an energy storage system in a microgrid. *Time series* and *Feed-forward neural network* techniques are used for forecasting the wind speed and solar radiation, respectively. The main problem is formulated as a MILP, which is solved in AMPL *(A Modelling Language for Mathematical Programming*). A specific Artificial Neural Network algorithm is used for production forecasting. Meanwhile, a classical approach is used for the optimization problem. A heuristic method is again used in [85] by Navaeefard *et al*. They introduce uncertainty in a microgrid sizing problem that includes photovoltaic PV/wind hybrid system with storage energy systems. Wind power uncertainty is considered, and the reliability index is introduced as a constraint. The PSO algorithm is implemented in MATLAB script and able to obtain global optimal solutions.

In [38] O. Menniti et al. describe a **methodology** based on simulation techniques to determine the optimum sizing and configuration of a grid-connected hybrid Photovoltaic/Wind system, including energy storage systems and ensuring that the system total cost is minimized while guaranteeing a highly reliable source of load power.

Some of these mathematical programming methods **have been developed into commercially available software tools**. ETAP is introduced in [86] as a software tool which, although it was not initially designed for microgrids, has been adapted to handle selection and sizing problem in microgrids. A comparison between two different technology selection and sizing software such as HOMER and WEBOPT is made by A. Litchy et al. in [87]. While WebOpt is based in a MILP optimization, HOMER is based on alternatives simulation, creating a list of feasible configurations sorted by net present cost. DER-CAM software is the tool used for technology selection and simulating the operations of a microgrid for a commercial building in [88].

HOMER software is widely used with microgrid modeling purposes. It is used by C. Nayar et al. in [89] in order to define a layout of power plants for a hybrid microgrid in remote islands in the Republic of Maldives. A stand-alone microgrid is also designed in [90] for Pulau Ubin Island of Singapore. In this paper, authors simulate different systems using HOMER in order to fit the needs with optimum cost and available renewable sources, including storage units sizing. Similar work is presented in [91], selecting and sizing power generators for a rural microgrid in India. Environmental objectives can also be considered using this modeling software. In [92] W. Su et al. study the planning and operation of micro-source generators to accommodate the high demand of renewable energy systems due to a change in the environmental policy.

13.2. Siting

There exist many papers on the allocation of energy resources, not only for DERs and RES but also for energy community systems, such as district heating [93]. However, two main approaches have been identified, and both are focused on minimum power losses under quality constraints: power lines layout and equipment siting (power and storage equipment).

Q. Cui et al. present in [94] **a traditional approach** to design cost-optimized microgrid architectures subject to reliability constraints. The method is based on DP and consists of determining the optimal power line layout between micro sources and load points, given their locations and the rights of way for possible interconnections.

A. Khodaei presents in [95] an algorithm for microgrid planning as an alternative to the optimization of traditional electric power systems regarding generation and transmission. The optimization problem is decomposed into a planning problem and an annual reliability problem. The objective is to minimize the total system planning cost, and a software tool called *Versatile Energy Resource Allocation* (VERA) is used. A prediction of demand coverage based on local weather conditions is also performed. Nonlinear aspects of the problem are solved with a Sequential Quadratic Programming technique (SQP).

In [96] V. Verda and C. Ciano deal with the choice of the optimal configuration of a district heating network to be built in an urban area. Users to be connected to the network are determined and an economic objective function is optimized using Simulated Annealing (SA). Despite this is not a specific microgrid planning problem, a similar method can be applied to microgrids in competitive environments. The technique *Modified Discrete Particle Swarm Optimization* is used in [97] by M.T. Wishart et al. to plan a distribution system upgrade over 20 years. The objective is to minimize the system's total lifetime cost regarding line loss, reliability costs, and investment needed in DGs, capacitors, lines, and transformers. The bus voltage, feeder current, and the DG output power are incorporated in the optimization procedure as constraints. M.V. Kirthiga et al. propose in [73]a methodology to transform an existing radial distribution network into an autonomous microgrid, in which sizing and siting strategies for distributed generators and structural modifications for autonomous microgrids are developed. The optimal sites and corresponding sizes of renewable resources for autonomous operation are obtained using PSO and GA. An optimization problem for system losses and costs is formulated, considering quality constraints.

Some **multi-objective optimization** algorithms are combined with sensitivity analysis in microgrids siting problems. For example, in [98], K. Buayai et al. carry out a two-stage multi-objective optimization process for MG planning in two primary distribution systems using MATLAB. In the first stage, the loss sensitivity factor is proposed to identify the MG area in a primary distribution system. In the second stage, a Pareto-based NSGA-II is proposed to find locations and sizes of a specified number of distributed generators within microgrids. Multi-objective functions include system real power loss, load voltage deviation, and annualized investment cost. A fuzzy decision making analysis is used to obtain the final trade-off optimal solution. Another multi-objective method is proposed by G. Celli et al. in [99] to solve sizing and siting problems in distribution networks. The objective is to achieve the best alternative between the cost of network upgrading, the cost of power losses, the cost of energy not supplied, power quality costs, and the cost of energy required by the served customers. Using a GA, they apply the *$\mathcal{E}$-constrained* technique to obtain a compromised non-inferior solution.

As it has been described in [99], **heuristics** have also been applied to siting problems. A. Basu et al. select in [100] bus locations by loss sensitivity analysis. PSO is implemented using MATLAB in order to maximize the value of the B*enefit to Cost Ratio* (BCR). The cost of electricity generation is minimized, not only using CHP-based DER technology but also deploying them in the microgrid system regarding their type, capacity-size, and bus-location. G. Celli et al. propose in [101] a new software procedure based on a GA, capable of establishing the optimal distributed generation allocation on an existing medium voltage (MV) distribution network, considering technical constraints of real size scenarios with several hundreds of nodes. In [102], G. Carpinelli presents a three-step procedure, based on GA, applied to establish the best-distributed generation siting and sizing on an MV distribution network.

M.R. Vallem et al in [103,104] describe a method for siting of DER within the framework of an optimal microgrid architecture regarding minimum cost interconnection, sizing, and siting of DER subject to stipulated global and local reliability criteria. The siting problem considers factors like deployment costs and savings gained by the use of CHP, and it is formulated as a SA optimization problem. An optimal economic and allocation model of an industrial photovoltaic microgrid is proposed in [105] by M. Mao. The economic indexes analyzed include energy cost, emission reduction benefits, and payback period. The optimization problem is solved using PSO. S.Tan considers necessary in [106] to integrate microgrid load dispatch and network reconfiguration, resulting into a non-convex non-linear problem. Four evolution computational optimization methods are compared in that paper, such as *GA, PSO, AIS, and Vaccine-AIS.*

13.3. Operations Scheduling: the Economic Load Dispatch Problem

The control strategy of each microgrid has a significant impact on its operational costs. The Economic Dispatch Problem is usually solved by mathematical computing techniques and specific computer software, but it is crucial to be able to develop an accurate estimation during the feasibility analysis stage. The scheduling problem must fulfill system goals in the framework shaped by demand, operational, and system constraints of the available resources and corresponding transmission capabilities. C. Colson and M. Nehrir review In [53] some microgrid management challenges, emphasizing tasks in DER and CHP integration, power management, and control as the main fields of development.

A **classical approach** for other energy community systems is presented in [56]. A Combined Cooling and Heating Power model of a rural microgrid is built and optimized by using a MINLP optimization process to improve system efficiency of energy utilization and other goals with a BONMIN solver. The whole system model is mathematically programmed into the platform of GAMS. Again MINLP is used in [107]. C.A. Hernandez-Aramburo et al. try to minimize the fuel consumption rate for a two-generation unit microgrid, while constraining it to fulfill the local energy demand (both electrical and thermal) and provide a guaranteed minimum power reserve. P. Stluka et al. solve in [108] the problem of powering a set of buildings through a microgrid, formulating a cost-minimizing problem. Load forecasting and sitting problems are solved using a MINLP approach with the optimization software VERA. Other classic optimization methods such as IP and LP are still a valid approach depending on the problem definition, and GAMS a widely used modeling system [109,110]. The optimization model for a microgrid based in a CHP generation unit operation is formulated in both papers. LP is also used in [111] by D. Quiggin et al. to model a microgrid, including a mix of renewable generation technologies, energy storage, and DR, based on real-world data of residential energy consumption and weather variables. DP is used to solve optimization problems in [112] by A. Sobu and in [113] by M.Y. Nguyen, et al.. A. Sobu defines a dynamic optimal schedule management method for an isolated or grid-connected microgrid system, considering forecast errors with uncertainties of solar radiation, wind speed, and local user demand. Nguyen et al. try to maximize the profit that the owner might achieve from energy trading in a day, either in isolated or grid-connected microgrids. C. Huang et al. consider tariffs inside the ELD problem in [114]. A power-scheduling problem, solved by a MPDP approach, and considering load/generation changes and TOU tariff for a low voltage DC microgrid is developed.

F. Mohamed and H. Koivo propose in [115–118] different **multi-objective algorithms**, which are also used to determine the optimal operating strategy for a microgrid such as SQP, GA, and MADS. MADS is a generalization of the pattern search algorithm. The aim of these papers is to minimize the cost function of the system. Multi-objective optimization based on modified game theory is applied in [117] to the environmental and economic problems of the MG. T.S. Mahmoud introduces in [119] **fuzzy logic techniques** for scheduling storage devices. A fuzzy logic-based adaptive charging price is set for charging the storage device based on the microgrids local generation price at the time of charging, and the amount of daily storage device participation in the microgrid dispatch. A combination of **fuzzy**

logic theories and multi-objective PSO is applied to optimize the energy dispatch for the managed microgrid. H. Kanchev et al. [120] present a microgrid energy tactical optimization in the presence of PV-based active generators. The optimization objective function is focused on the CO_2 equivalent emissions (environmental criteria), the fuel consumption (economic criteria), or a trade-off between these two. Tools as MATLAB, TRNSYS, GenOpt, and TRNOPT are proposed to solve this kind of problems [46,86]

T. Niknam et al propose in [122] a probabilistic approach for economic/emission management of microgrids from a **probabilistic optimization method**, including uncertainties covering and a modified multi-objective algorithm based on the MGSA to find Pareto-optimal front of the operation management problem.

Forecasting techniques have been introduced in optimization problems due to the stochastic nature of demand and renewable energy resources. R.Y. Jaganmohan et al., design in [123] a system that forecasts the short (daily), medium (seasonal) and long term (yearly) load demand and the availability of energy resources at the microgrids. They use ANN to forecast both load and availability of energy resources at microgrids in different scenarios like daily, seasonal, and yearly. The layered ANN architecture is developed and trained with Levenberg-Marquardt Back Propagation Algorithm. Other authors use in [124,125] forecasting techniques based on ANN. Although forecasting technique changes from some papers to others, the most common objective of these techniques is to forecast both load and availability of energy resources, as in [126].

In [127] C. Chen et al. propose one unified model so that smart management of ESS, economic load dispatch, and operation optimization of distributed generation are simplified into a single-objective optimization problem. They use an improved GA to solve the problem. C. Chansong et al. use in [93] the same algorithm to determine an optimal schedule of all available units over a planning horizon to meet all system, plant, and unit constraints, as well as the load and ancillary service demands. An ANN power forecasting is used to predict hourly power outputs. A GA is developed to make proper operation and trading decisions while meeting constraints.

S. Obara and E.G. El-Sayed in [128] develop an optimal operation algorithm of a compound microgrid using publicly available numerical weather information (NWI), and a **GA is developed to minimize system fuel consumption**. L Ricalde et al. introduce in [129] some forecasting methods depending on the temporal range of look-ahead times, and they address ANN as excellent approximations for nonlinear and stochastic models.

Trends in microgrid control have been pointed out by D. Olivares et al. in [130]. They also present a brief review of the existing **Energy Management Systems** (EMSs) architectures for microgrids in [131], identifying the main advantages of each approach, and have proposed a centralized EMS architecture for implementation on isolated microgrids in a stand-alone mode of operation. D. Olivares D. y C.A. Cañizares search for a proper dispatch of the energy power and storage units, designing a centralized energy management system in [132]. In this paper, the energy management problem is decomposed into unit commitment and optimal power flow problems in order to avoid a mixed-integer non-linear formulation.

Some authors look for new approaches for power source scheduling in microgrids. M. Chen et al. propose a calculation method of microgrid surplus load, and the features and influencing factors of its ultra-short-term forecasting are discussed in [133]. A simulation model of microgrid with wind farms, micro-turbines, and fuel cells is established. A similar vision of the same problem, including demand-side management, is introduced by R. Palma-Behnke et al. in [58]. An energy management system (EMS) minimizes the operational costs while supplying the load demands. Also, a neural network method for a two-day ahead electric consumption forecasting is presented. G. Celli et al. in [134] develop a novel EMS that uses a Multi-Layer Perceptron Neural Network for the optimal scheduling of generators in an industrial park. They train the Neural Network by using information about energy price, weather conditions, and the forecasts on the energy and thermal load demand.

H. Kanchev in [135] proposes a deterministic EMS for a microgrid, including advanced PV generators with embedded storage units and a gas microturbine. A. Borghetti describes in [136] the functions of an energy resources scheduler implemented in a microgrid management system. The scheduler periodically updates the set points of DERs regulators in order to achieve economic, reliability, and power quality objectives, starting from the load and renewable production forecasts, and the results of the system state estimation.

S. Chakraborty and M.G. Simoes in [137] and in [138], focus on renewable energy sources integration in a distributed generation system, implementing a distributed intelligent EMS to optimize operating costs. A Fuzzy ARTMAP Neural Network is used to predict hourly day-type outputs, based on which generation can be forecasted. The same authors introduce in [139] a Distributed Intelligent Energy Management System (DIEMS) to optimize operating costs of a representative PV-based microgrid.

A probabilistic EMS based on an efficient Point Estimate Method is proposed in [51] by S. Mohammadi. This method models the uncertainty in the power generation of the wind farms and the PV systems, the market prices, and the load demands. Moreover, an AMFA is employed to identify the optimal operational conditions with regard to cost minimization. Niknam et al. introduce in [140,141] two different probabilistic algorithms in order to optimize a microgrid operation: a self-adaptive mutation technique of the GSA and a self-adaptive Charged System Search called SCSS, devised to upgrade the original CSS algorithm.

H. Vahedi et al. study in [142], the optimal operating strategy and cost optimization scheme using the Bacterial Foraging Algorithm (BFA). L. Lu et al. study in [143] propose a class of competitive online algorithms, called CHASE, which tracks the offline optimal in an online fashion. They also extend these algorithms to intelligently leverage on a limited prediction of the future, such as near-term demand or wind forecast.

S. Tan et al. [144] search for an integrated solution that takes care of both microgrid load dispatch and network reconfiguration problems. The stochastic nature of wind, PV, and load are taken into consideration, and the bio-inspired optimization scheme Vaccine-AIS is adopted to solve the problem. A bio-inspired algorithm description is elaborated by S. Binitha and S. Sathya in [78]. A new bi-level prediction strategy is proposed for short-term load forecasting of microgrids by N. Amjady et al. in [145]. They propose a strategy composed of a feature selection technique and a forecast engine (including NN and EA) in the lower level as the forecaster and an enhanced differential evolution algorithm in the upper level for optimizing the performance of the forecaster.

Multi-agent systems in microgrid applications are reviewed by A. Kulasekera y K. Hemapala in [146]. N. Hatziargyriou develops in [147] a centralized control for optimizing microgrids operation regarding information exchange, market policies, demand-side bidding and security, and quantifies economic, environmental, and operational benefits for centralized controlled-microgrids in [148]. The same authors have also published some papers about agent-based control for virtual power plants [149] and microgrids [150–153]. They present in a MAS-based control architecture for an islanded microgrid and compares it with a centralized approach. Along with these papers, these authors developed an agent control structure focused on allowing the agents to learn and adapt to the environment based on a reinforcement learning algorithm. Agents should be capable of learning to cooperate and to solve a problem that requires planning for the future in a stochastic environment without the existence of a central controller. T. Funabashi et al. [154] propose a microgrid control system using multi-agent technologies. In this control system, operation planning is realized based on the generation and load forecasting by using ANN and fuzzy systems.

14.Software Tools Applicable to MG Planning

One of the factors pushing forward the next generation of planning software tools is the adoption of new computational optimization methods and algorithms. As mentioned above, a microgrid planning process can be approached as a combination of optimization problems [11]. Different optimization techniques applied to specific technologies, usually included in microgrids such as renewable energy systems, have been reviewed [80,155,156]. R. Baños et al. review in [155] optimization methods applied to wind power, solar energy, hydropower, bioenergy, geothermal energy, and hybrid systems, and also different approaches to design hybrid renewable energy systems have been reviewed in [80] by O. Erdinc et al.. M. Iqbal et al. present in [156] a generic list of inputs, outputs, objectives, and constraints for the resource allocation problem (also known as siting) of renewable energy sources. They also introduce a list of optimization tools, a conflicting objective matrix, and a short review of the optimization techniques.

Different authors have reviewed commercially available microgrid planning tools. For example, G. Mendes et al. present in [157] the most commonly available tools for Community Energy Systems planning. They include a survey of these tools, qualifying them as bottom-up, simulation, equilibrium, operation optimization, and investment optimization tools. Some of these tools are suitable for microgrid planning, such as HOMER, DER-CAM, ReOpt, MARKAL/TIMES, RETScreen, and H2RES. Also, D. Conolly et al. presents in [158] an in-depth comparison of 37 different analysis software tools used to evaluate renewable energy sources integration projects. This paper also includes HOMER, MARKAL/TIMES, RETScreen, and H2RES.

The information in these papers has been reviewed and updated in Table 8, presenting 17 software tools and the specific optimization problems they can solve in this context. A question mark means that the ability to solve that problem is mentioned among the capabilities of the tool, but it could not be verified.

	PLANNING PROBLEM				
TOOL	ED or Sizing	OPF or Siting	Scheduling	Economic Feasibility and/or Pricing	LINK
COMPOSE	✓		✓	✓	www.energianalyse.dk/index.php/software
DER-CAM PLUS	✓		✓	✓?	building-microgrid.lbl.gov/projects/der-cam
ENPEP-BALANCE	✓?	✓		✓?	ceeesa.es.anl.gov/projects/Enpepwin.html
ETAP Microgrid	✓	✓	✓		etap.com/microgrid/etap-microgrid.htm
GTMAX		✓?	✓	✓	ceeesa.es.anl.gov/projects/Gtmax.html
HOMER	✓		✓	✓?	www.homerenergy.com
H2RES	✓		✓		h2res.fsb.hr
MARKAL/TIMES/ETEM	✓		✓?	✓?	www.etsap.org
MATLAB	✓	✓	✓	✓	www.mathworks.com
NEPLAN		✓	✓?	✓?	www.neplan.ch
NETPLAN	✓		✓	✓	www.ece.iastate.edu/~vkrish/software.html
PALADIN DESIGNBASE	✓?		✓	✓	www.poweranalytics.com/
PALADIN SMARTGRID			✓		www.poweranalytics.com/
REopt	✓		✓	✓?	www.nrel.gov/tech_deployment/tools_reopt.html
RETSCREEN	✓		✓	✓	www.nrcan.gc.ca/energy/software-tools/7465
SICAM MICROGRID			✓		www.siemens.com
TRNSYS17	✓	✓	✓	✓	www.trnsys.com/tess-libraries/
VPOWER			✓	✓?	viridityenergy.com
THIS THESIS	✓	✓	✓	✓	

Table 8. Software Tools and Their Potential to Solve MG Planning Problems

This information has been obtained from the cited research papers, additional web pages, technical brochures, and manuals. Software available at no cost has been downloaded and installed to verify its capabilities. Additional information about these software tools is available in [157] and [158].

Both publications classify these tools into similar categories that could also be defined as:

- Bottom-up tool: identify and analyze specific energy technologies, finding investment options, and alternatives.
- Simulation tool: simulates the operation of an energy system supplying the correspondent energy demand needs. Simulation tools normally operated in hourly time-steps over a one-year time-period
- Scenario tool: usually combines a series of annual results into long- term scenarios, typically 20 to 50 years.
- Equilibrium tool: explains the behavior of supply, demand and prices, normally in the whole or in part of an economy, with several or many markets.
- Operation optimization tool: optimize the operation of some given energy system. It is common that operation optimization tools are also simulation tools, simulating the operation of the same system for attaining optimal results.
- Investment optimization tool: optimize investments in an energy system in study. Typically, optimization tools are also scenario tools.
- Top-down tool: macroeconomic tool using general macroeconomic data to determine growth in energy prices and demands. Typically, top-down tools are also equilibrium tools.

Eighteen software tools are classified in Table 9 into these categories, describing the problems they address, techniques, and algorithms. Some of the software tools used by engineering companies to design microgrids have evolved from power systems design tools such as SICAM Microgrid, ETAP, or DER-CAM Plus. Other tools such as HOMER or REOpt focus on single-user or single building microgrids. Of all these tools, only DER-CAM can develop the feasibility analysis of multi-building microgrids from a techno-economic perspective. A description of the capabilities of DER-CAM can be found on Berkley´s lab website[30]. The key inputs for DER-CAM are:

- *Site's hourly end-use load profiles for a typical year (electric, cooling, refrigeration, space heating, hot water, and natural gas loads)*
- *Site's default electricity tariff, natural gas prices, and other relevant price data*
- *Capital, operating and maintenance (O&M), and fuel costs of the various available technologies, together with the interest rate on customer investment*

[30] https://building-microgrid.lbl.gov/projects/der-cam

- *Basic physical characteristics of alternative generating, heat recovery and cooling technologies, including the thermal-electric ratio that determines how much residual heat is available as a function of generator electric output*
- *Information on the site's topology and distributed heating infrastructure (only for multi-node models)*

Table 9. Problems, Techniques and Solutions Methods per Software Tool

TOOL	Simulation	Scenario	Equilibrium	Top-down	Bottom-up	Operation optimization	Investment optimization	TECHNIQUES INVOLVED	SOLUTION METHOD
COMPOSE					YES	YES	YES	Model, Sim, Fore, Opt, Risk	MILP
DER-CAM PLUS						YES	YES	Model, Sim, Fore, Opt	MILP/GAMS-CPLEX
ENPEP-BALANCE		YES	YES	YES			YES	Model, Sim, Fore	Jacobi method
ETAP Microgrid	YES					YES		Moni, Cont, Sim, Fore, Opt	Not declared
GTMAX	YES		YES			YES	YES	Model, Sim, Fore, Opt	Not declared
HOMER	YES				YES	YES	YES	Model, Sim, Fore, Opt, Risk	Accounting
H2RES	YES	YES				YES		Model, Sim, Fore	Energy balancing
MARKAL/TIMES/ETEM		YES	YES			YES	YES	Model, Sim, Fore, Opt	MILP/GAMS-CPLEX
MATLAB	YES	YES	YES	YES	YES	YES	YES	Model, Sim, Fore, Opt	Programmable
NEPLAN	YES	YES			YES		YES	Model, Sim, Fore, Opt	Not cited
NETPLAN	YES	YES			YES	YES	YES	Model, Sim, Fore, Opt	NSGA-II & LP
PALADIN DESIGNBASE	YES				YES	YES	YES	Model, Sim, Fore, Opt	Time-series analysis
PALADIN SMARTGRID	YES					YES		Moni, Cont, Opt	Time-series analysis
REOpt	YES				YES	YES	YES	Model, Fore, Opt	MILP
RETSCREEN		YES					YES	Model, Fore, Opt	Accounting
SICAM MICROGRID	YES					YES		Moni, Cont, Sim, Fore	Not declared
TRNSYS17	YES	YES			YES	YES	YES	Model, Sim, Fore, Opt	Programmable
VPOWER	YES					YES		Moni, Cont	Not declared
THIS THESIS	**YES**	**YES**			**YES**	**YES**	**YES**	**Model, Sim, Opt, Risk**	**GA y MC SIMULATION**

Model= Modeling; Sim= Simulation;Fore=Forecasting; Opt= Optimization; Risk= Risk analysis; Moni= Monitoring; Cont= Control

The outputs determined by DER-CAM include:

- *Optimal selection and capacity of DER to be installed*
- *Optimal placement of DER inside the microgrid (for multi-node models)*
- *When and how the available DER should be dispatched (both to maximize economic performance and meet resiliency and reliability targets)*
- *Detailed cost breakdown of supplying end-use loads*
- *Detailed breakdown of carbon emissions associated with supplying end-use loads*

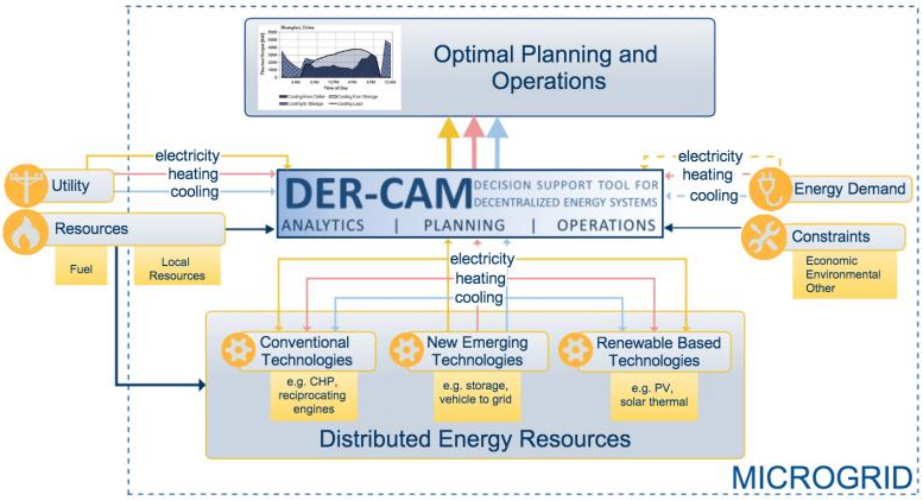

Figure 15. Inputs and Outputs by DER-CAM[31]

DER-CAM is probably one of the commercially available tools for single and multi-building microgrids that better fits the requirements of a microgrid feasibility analysis. The main limitation of DER-CAM when it comes to feasibility analyses is its limited potential to assess future scenarios of sensitive variables in an agile way. DER-CAM's calculations engine follows a deterministic approach and does not allow probabilistic approaches to profitability.

Some of the main challenges software companies and developers face in the present in this field are:

- ✓ To develop holistic approaches to the MG planning process, allowing users to complete the sizing, siting, scheduling, and pricing problems at least at a feasibility level.
- ✓ To improve the existing methods and algorithms, allowing planning teams and stakeholders to model more complex planning scenarios such as future market and weather conditions.
- ✓ To introduce innovative optimization, forecasting, simulation, and uncertainty analysis, among others, while competing in performance with existing tools.
- ✓ To implement sophisticated feasibility analysis methods into fast and user-friendly software.

[31] https://building-microgrid.lbl.gov/projects/der-cam

✓ To integrate intuitive ways to collect data, such as GIS-based interfaces.

15.Conclusions

The trends in the application of optimization algorithms to individual microgrid planning problems have been reviewed in this chapter. Table 10 presents a different single and multi-objective optimization algorithm classified per planning problem developed by this author in [11]. This table has been extracted from that publication, and the references in the right column match the references in that paper, but not in this one.

MG planning problems, methods and references regarding single or multiple objective optimization.

Approach	Method-algorithm	Main problem	References
Single-objective optimization	MILP	Power generation mix selection and sizing	[32,43,44]
	Lagrange multipliers-KKT conditions	Power generation mix selection and sizing	[35]
	Reduced Gradient Method	Storage devices mix selection and sizing	[34]
	MIP	Power generation mix selection and sizing	[33,36]
		Storage devices mix selection and sizing	[39]
	SQP	Siting	[51]
		Operation scheduling	[77]
	DP	Siting	[50]
		Operation scheduling	[71,72]
	MINLP	Operation scheduling	[65,66,67]
	IP	Operation scheduling	[68]
	LP	Operation scheduling	[69,70]
	MPDP	Operation scheduling	[73]
Multi-objetive optimization	NSGA-II	Siting	[55]
	Simulation-accounting	Power generation mix selection and sizing	[41,42,45,46,47,48]
		Storage devices mix selection and sizing	[41]
		Operation scheduling	[42,96,97,98,99,100,101,102]
	Game theory	Operation scheduling	76

Table 10. MG Planning Problems, Methods, And References Per Optimization Technique. Source [11]

As it has been described in this table, algorithms based on Linear Programming are a useful and popular approach depending on the objective and constraints. As shown in Table 11, a growing number of research papers are looking into heuristic optimization to solve microgrid scheduling, sizing, and siting problems. This table has also been extracted from [11], and the references in the right column match the references in that paper.

MG planning problems, methods and references using heuristic optimization.

Heuristic and metaheuristic optimization	EA	Power generation mix selection and sizing	[36]
	GA	Power generation mix selection and sizing	[37]
		Siting	[54,56,58,59,63]
		Operation scheduling	[75,88,89,90]
	SA	Power generation mix selection and sizing	[38]
		Siting	[52,60,61]
	PSO	Storage devices sizing	[40]
		Siting	[54,57,62,63]
		Operation scheduling	[77,79,80]
	AIS	Siting	[63]
	VACCINE-AIS	Siting	[63]
		Operation scheduling	[107]
	MDPSO	Siting	[53]
	MADS	Operation scheduling	[74,78]
	MGSA	Operation scheduling	[82]
	AMFA	Operation scheduling	[102]
	GSA	Operation scheduling	[103]
	SCSS	Operation scheduling	[103]
	BFA	Operation scheduling	[105]
	CHASE	Operation scheduling	[106]

Table 11. MG Planning Problems, Methods, and References Using Heuristic Optimization. Source [11]

Heuristics as GA, PSO, and SA have become very popular in energy planning and designing problems due to the increasing amount of candidate technologies available that leads to bigger search spaces. Some new bio-inspired heuristics have also been applied to microgrid planning such as AMFA, BFA, AIS, and Vaccine-AIS. **GA and PSO are widely used algorithms for planning purposes in microgrids.**

References per planning problem and optimization approach.

Approach	Main problem	Papers
Single objective optimization	Power generation mix selection and sizing	[32,33,35,36,43,44]
	Storage generation mix selection and sizing	[34,39]
	Siting	[50,51]
	Operation scheduling	[65,66,67,68,69,70,71,72,73,77]
MO optimization	Power generation mix selection and sizing	[41,42,45,46,47,48]
	Storage generation mix selection and sizing	[41]
	Siting	[55]
	Operation scheduling	[42,76,96,97,98,99,100,101,102]
Heuristic optimization	Power generation mix selection and sizing	[36,37,38]
	Storage generation mix selection and sizing	[40]
	Siting	[52,53,54,56,57,58,59,60,61,62,63]
	Operation scheduling	[74,77,78,79,82,102,103,105,106,107]

Table 12. References per planning problem and optimization approach. Source [11]

Regarding the problems solved, scheduling is the most prevalent problem when it comes to feasibility analysis for microgrids, as it has been summarized in Table 12. Again the references in the right column match with the references in [11]. The development of more advanced Energy Management Systems for microgrids has increased the interest of researchers in this specific problem. Regarding modern mathematical techniques, it can be highlighted that parallel processing has not been deeply explored for microgrid planning purposes yet.

The second conclusion is about planning methodologies. In this chapter, four common problems have been identified for an economic feasibility approach to microgrids: *power mix selection and sizing, siting, and scheduling.* Most researchers propose techniques to solve these individual problems, but real-world planning problems require a holistic approach to the whole microgrid planning process. These microgrid planning problems must be solved in a coordinated way. Planning and feasibility guidelines have been proposed for some specific islanded microgrid scenarios with defined constraints and uncertainties, such as military bases [24]. In [159] Stewart points out the potential of existing diesel generators to develop microgrids in India and Southeast Asia with uneconomical capital costs or complexity . He suggests an *anchor-business-community model* for microgrids as a way to capitalize on existing gensets in large enterprises to create affordable community microgrids. The author also points out to potential barriers such as grid-interconnection policies, design, and financing mechanisms for microgrids to ultimately help in proliferating the technology to areas of critical importance. Solar-based microgrids have been widely studied by different authors. Kirchhoff et. al. proposes in [160] an approach for renewable energy-based electrification. This approach is based on a bottom-up microgrid concept framed as "Swarm Electrification" and discussed in the paper as a sharing-based electrification scheme. They present nine success factors for renewable-powered microgrid implementation *based on lessons learned that microgrids in the Global South and 100%-RE communities in Germany share*. These factors cover categories such as ownership and participation, technology and system design, as well as policy and financing. They do not develop and actual analysis in this paper but provide the guidelines of a potentially successful deployment strategy for solar microgrids.

Eales et.al. provide in [161] a summary of the process and key findings in assessing technical and financial feasibility of single-user microgrids in Malawi, including PV and battery storage design, business model discussion and sensitivity analysis of key parameters through techno-economic modelling. The author uses HOMER Pro and simulates three potential combination of PV and battery storage going from 2 to 10 kW capacity and from 11.52 to 57.6 kWh respectively.

Optimal campus microgrid designs have been developed in [162–164]. In these papers, the authors propose studies optimal designs for a campus microgrid at Seoul National University. The analysis considers single building microgrids combining PV and battery storage. No power distribution systems or any other power generation technology than PV solar are considered. The authors use their own microgrid planning model (MDSTool) to simulates the optimal operation of different sizes of photovoltaic plants with and without energy storage. The main contribution of the analysis is to study the profitability of higher penetration rates of solar in campuses, considering various incentives and *particularly the incentive for Energy Storage Systems (ESS) to discharge their energy during on-peak hours on weekdays*.

No methodologies combining current design conditions and long-term feasibility of a commercial microgrid have identified during this search on the state of the art of microgrid planning. More holistic approaches towards market-oriented solutions are needed, dealing with the increasing complexity that different business models, weather patterns, market trends, and regulatory policies bring to the microgrid market.

Finally, some trends in microgrid planning are described. Some of these new approaches to the planning process may include GIS-based techniques [94,98,165,166] and new algorithms associated with optimization, forecast, and other microgrid related aspects. Other energy community systems, such as virtual power plants or district heating, have many points in common with microgrids. Design and establishment processes of DH systems have been studied for a long time, and multi-node microgrids planning can benefit from the results of that research. Technical literature previously applied to district heating systems has been considered in this paper. Regarding microgrid distributed control and operation, MAS are a hot topic in microgrids scheduling [53,167–170] and have a high potential to link GIS, forecasting, optimization, risk analysis, and decision-making methods. They can also address different objectives such as cost-effectiveness, reliability, environmental, quality, protection, and interaction with other microgrids.

Microgrids can also be designed for supplying ancillary services. Indeed voltage support, reactive power support, peak load reduction, spinning reserve provision, and thermal energy supplying are considered in some papers as [171–173]. A real microgrid planning process can be described as a multi-objective, constrained, and stochastic optimization problem. **That is the reason why sensitivity and risk analysis has been revealed as a critical step in microgrid planning.**

Commercially available tools have been also reviewed in this chapter. Most of the existing software tools for microgrid feasibility analysis have evolved from power systems design tools such as SICAM Microgrid, ETAP, or DER-CAM. Other tools such as HOMER or REOpt focus on single-user or single building microgrids. Of all these tools, only DER-CAM is able to develop a complete feasibility analysis of multi-building microgrids from a techno-economic perspective.

New methods and tools are needed to study feasibility scenarios under a more significant number of complex variables: not only enabling an optimal selection of technical alternatives but also assessing future scenarios of long-term feasibility. New software tools can help identify business opportunities for multi-node microgrids. It is essential to put in the hands of microgrid planners the right tools to design efficient, clean and reliable microgrids, but also to estimate the potential impact of uncertainties on the economics of the project like, for instance, quantifying the probability of their design to be profitable in future scenarios.

No methodology term has been found during this review process able to combine a technical and economical approach for multi-node microgrid planning (sizing, siting, and scheduling problems) and **to study the impact of oscillations in the design framework conditions in the long-**. As mentioned before, since most of the feasibility analysis tools in the market have evolved from power systems design tools, risk analysis is barely considered among the existing multi-building microgrid planning tools.

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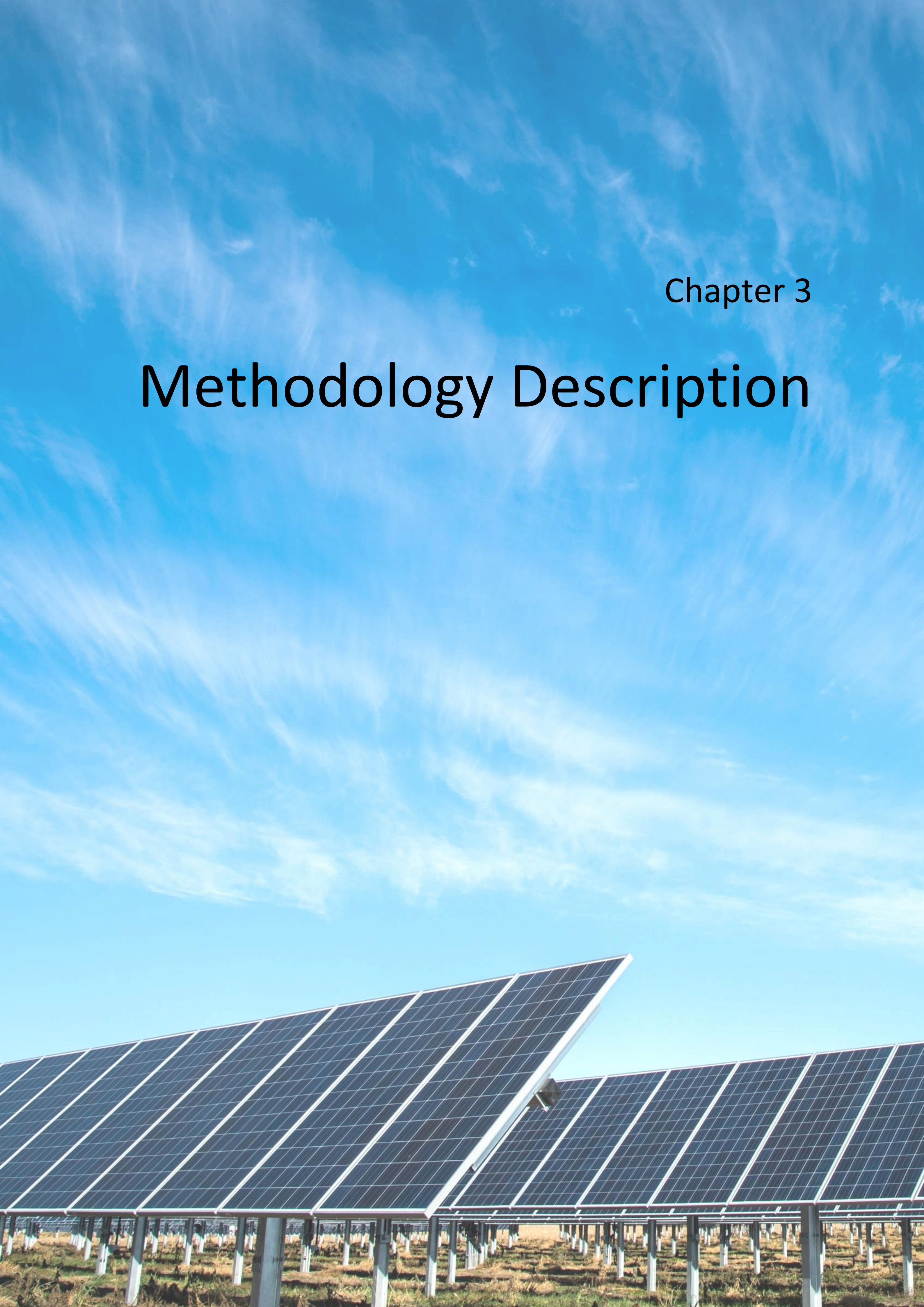
Chapter 3

Methodology Description



17.Introduction

As discussed in Section 2, microgrids have been frequently presented as the future of the power systems, taking part in the future smart power grids. However, there are still gaps between the research advances and a more intensive microgrid deployment. Some authors [1,2] discuss these gaps and identify innovative planning and control techniques, technological advances, and standardization as solutions to fill them.

In the end, the successful deployment of a microgrid depends on the proper identification of its long-term profitability scenarios. Like district heating systems in the 1970s, microgrids must expect to have to compete against power grids and future decentralized power systems or solutions. During their lifespan. Therefore, it is essential to develop innovative methodologies allowing microgrid planners not only to design, but also to know if their designs are going to be able to compete in the market. Both the technologies and the opportunities exist, but more work has to be done on developing tools to expedite the identification of long-term profitability conditions for microgrids.

Assessment technique for energy projects have been widely studied. Authors such as Sims et al. have studied in [3] the process of project evaluation for different applications, and Mahmoud and Ibrik at [4] apply some of these criteria to power systems. Dilworth describes in [5] some common indicators to evaluate projects from a financial standpoint, being that approach not very common among microgrid research papers, as it has been described in chapter 2. Most of the existing microgrid planning tools are engineering tools that analyze the project strictly from a deterministic point of view, basing their calculations on current costs and not considering deviations from those values. New methodologies are needed not to define the project from a technological point of view, but also to study long-term feasibility scenarios, and to provide more accurate information on the probability of the project to fulfill its economic goals.

Modern computational optimization techniques have been developed during the last decades and have been successfully applied to different stages of the microgrid planning process [6]. However, as discussed in chapter 2, **none of the documented methods and algorithms combine a technical and an in-depth economic approach to the whole planning process (sizing, siting, scheduling and prizing different microgrid alternatives) studying how the uncertainties of the framework conditions might affect the long-term profitability of the project in competitive power markets.**

Thus, economic indicators will become the center of the method presented in this chapter, with the specific goal to provide stakeholders with the critical technical and economic information they need to make decisions at the feasibility analysis level.

This method benchmarks the long-term profitability indicators of the optimal designs identified by the algorithms, but also of other designs of the interest of the user. Beyond quantifying profitability for the optimal designs and operating conditions, this method will allow planners to quantify how changes in sensitive project variables will impact the economics of the optimal designs, such as:

- Electricity, natural gas, and fuel prices
- Installation, replacement, and O&M costs
- Potential incentives

To sum up, this chapter presents a methodological approach to search for profitable microgrid designs. Some of the questions that this research considers are described as follows:

- ✓ Should an owner of multiple buildings think about microgrids to power his/her new or existing facilities? Can a microgrid fulfill his/her economic constraints?
- ✓ What are the most profitable combinations of technologies for a microgrid in this area?
- ✓ Will a defined microgrid be profitable in the long term?
- ✓ Which kind of incentives or savings might the project need to achieve the profitability goals demanded by the investors?

18. Objectives and Scope

The goal of this method is to expedite the feasibility analysis of multi-building microgrids in competitive markets, supporting the decision-making process for investors during the early stages of the project. The intrinsic characteristics of the method are:

- ✓ *Competitive markets*: the microgrid is not established as the only power system in the area. The existing power grids and also new initiatives could be considered as competence of the microgrid.
- ✓ *Profitability conditions:* profitability can be defined as the state or condition of yielding a financial profit or gain. This is, in essence, a relative term since one solution can be considered profitable depending on the solutions it is compared with. The focus of this project is to let planners define which their own profitability conditions are, defining among others, the Internal Rate of Return (IRR) they consider profitable for a defined interest rate.
- ✓ *Long-term:* the life cycle of these systems is usually longer than 20 years, but electricity and natural gas prices change at least annually for every user. Besides energy prices, there exist other uncertainties in a microgrid planning process to avoid, or at least to control. [7–9]. In addition to the high initial investment of a microgrid, sequential investment strategies might be needed in order to keep the system competitive (such as equipment replacement,

additional maintenance, or capacity expansions). Quantifying the cost of keeping the system generating power at competitive rates will help define it as feasible or not in the long term

Uncertainties are perhaps one of the main concerns of projects with a long lifespan and high initial capital expenses such as microgrids. Following this procedure, planners will be able to find the most profitable microgrid designs in the long term and the probability of these designs to fulfill the economic goals of the project. The environmental impact (CO_2 emissions) of each solution will be assessed too.

The results of this method will be classified into two main categories:

- ✓ Profitable solutions: those designs that fulfill the economic goals defined for the project by the investors.
- ✓ Potentially profitable solutions: those designs that initially do not fulfill the economic goals defined for the project by the stakeholders. The main incentives and cost savings that would make these designs fulfill the profitability thresholds defined by the stakeholder will be quantified.

A schematic of the method has been illustrated in Figure 16. The planning framework is shaped by different data such as energy demand and energy prices, in addition to regulation and policies, and energy resources technologies available.

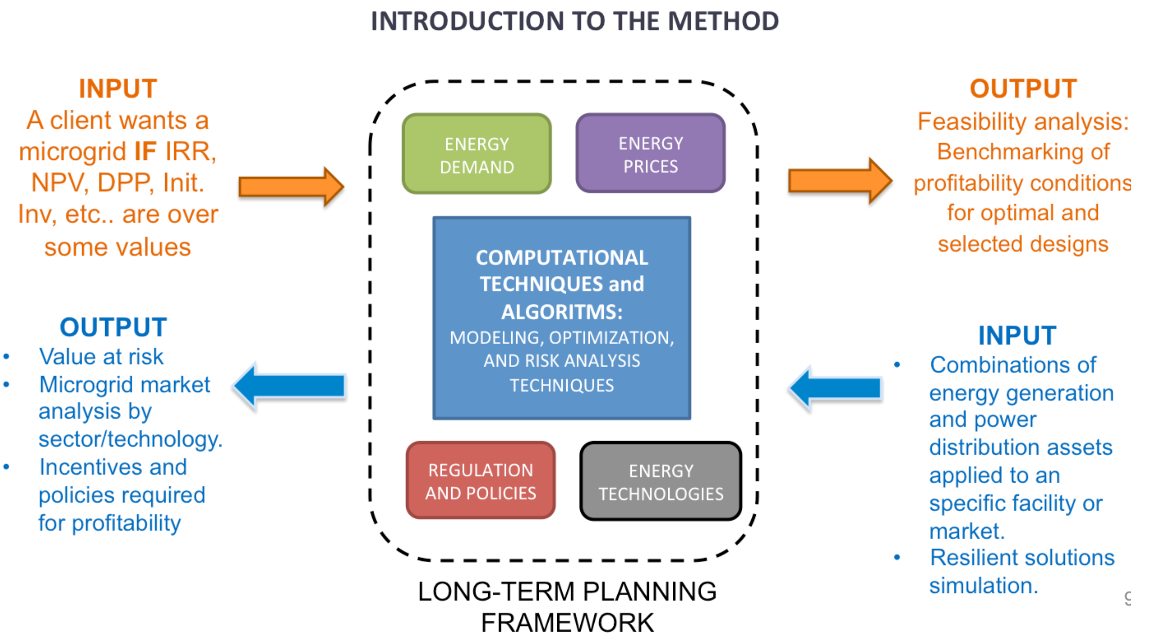


Figure 16. Schematic of the Method

In this method, the optimization algorithms will explore the long-term planning framework looking for optimal solutions, which will be combined with other solutions suggested by the user before moving into the risk analysis stage. A detailed explanation of the algorithms developed for the method and their interactions is presented below.

19. Description of the Proposed Algorithms

Every microgrid planning process is built around specific goals and constraints, being the economic constraint common to all of them. **Feasibility analyses are focused on exploring economic and technical aspects of the project**, incorporating additional goals into the analysis process such as environmental emissions, resiliency, energy quality, or even social goals such as generating qualified employment locally. Sometimes these objectives can be opposed to the others. For instance, it is generally accepted that minimizing the environmental impact of a microgrid requires higher investments in renewable energy and efficient technologies. Additional energy generation or storage capacity will also increase the initial investment if among the design goals.

In general, every relevant design and operating aspect of a microgrid project can be translated into costs and savings, and every stakeholder has economic goals in mind when it comes to approving a microgrid project. That is the reason why the algorithms proposed for this method will focus on identifying optimal microgrid designs and benchmarking them based on profitability indicators.

The proposed feasibility analysis method has four main stages:

1. Data Collection and Planning Framework Modeling.
2. Power flow optimization algorithm.
3. Power generation optimization algorithm.
4. Risk analysis and profitability scenarios assessment algorithm.

Their execution sequence is described in Figure 17. Their operative and main functions are presented below.

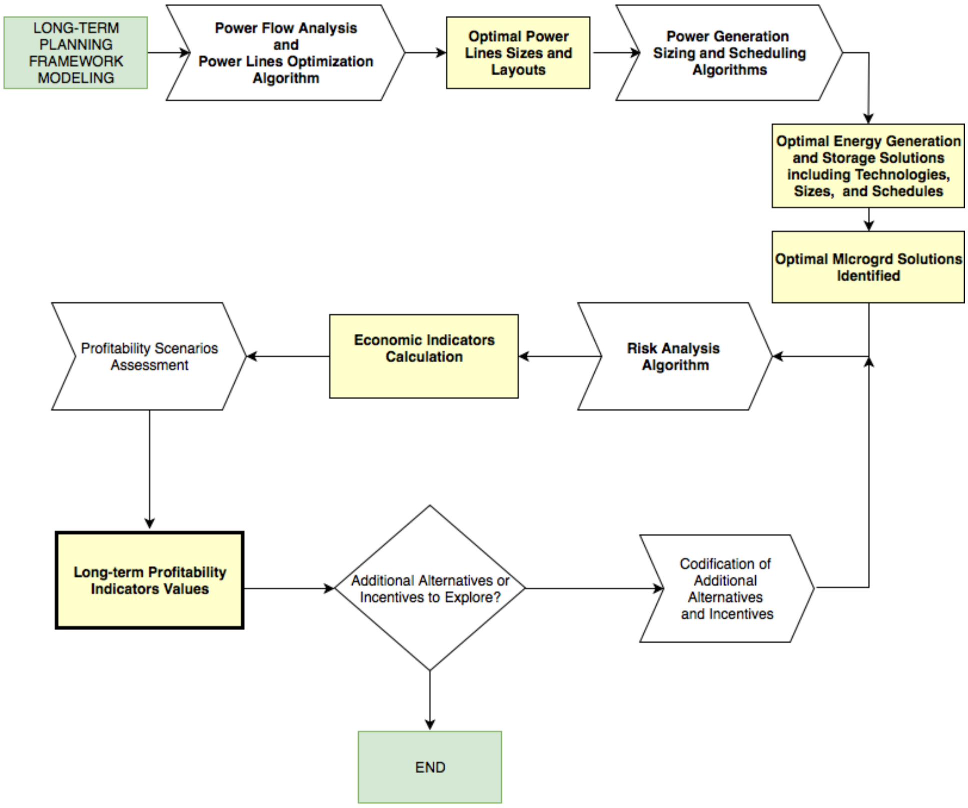


Figure 17. Algorithm Execution Sequence

19.1. Data Collection and Planning Framework Modeling

The planning framework modeling stage focuses on collecting the input data required for the analysis to be developed by the optimization and risk analysis algorithms. The main data to be collected on the microgrid's influence area for the planning process at a feasibility analysis level is:

- Existing energy infrastructures owned by the promoter, local utilities, or other owners, including power generation plants, power lines, load centers, and substations.
- Location and hourly power demand data of the nodes.
- Thermal energy demand per node and other related data.
- Availability and characterization of space, schedule of the existing buildings
- Renewable power sources availability (solar irradiation, wind, biomass)
- Local fuels availability and costs
- Electricity costs for final customers (tariffs of energy companies in the area).
- Air quality indicators
- Power generation technologies available locally, considering technical and social constraints in developing areas.
- Local installation, replacement, operation, and maintenance costs of load centers, substations, and power lines according to total and individual nodes' energy demand.

- Local installation, replacement, operation, and maintenance costs of the power generation and energy storage systems, according to total and individual nodes' energy demand.
- Aerial images of the influence area

Historic and forecasted data must be collected for some variables such as electricity and natural gas prices in order to model their future probabilistic scenarios.

19.2. Power Flow Analysis and Power Lines Optimization Algorithm

The goal of this algorithm is to size, site, schedule, and price the power distribution system connecting the nodes of the microgrid. The optimization algorithm selected is a **real-coded Genetic Algorithm** (GA). A GA is a *heuristic search method used for finding optimized solutions to search problems based on the theory of natural selection and evolutionary biology*[32]. GAs were initially developed in the 1960s and have been widely used to solve power flow analysis problems and power systems design since the 1980s [10–14]. Some of the advantages of genetic algorithms are their speed and their random crossovers and mutations, guaranteeing to some extent a wide exploration of the search space. They are also easy to understand and easy to code compared to other algorithms. Perhaps the main disadvantage of genetic algorithms is that, as other heuristic algorithms, they might not find the most optimal solution in all cases. GAs are fast searching through large and complex data sets and highly capable of solving unconstrained, and constrained optimization problems, which makes them great candidates for microgrid feasibility analyses where thousands of combinations of technologies and their sizes are available, and more detailed analyses have to be developed in further stages.

The steps followed by the GA are presented in Figure 18 below.

[32] https://www.techopedia.com/definition/17137/genetic-algorithm

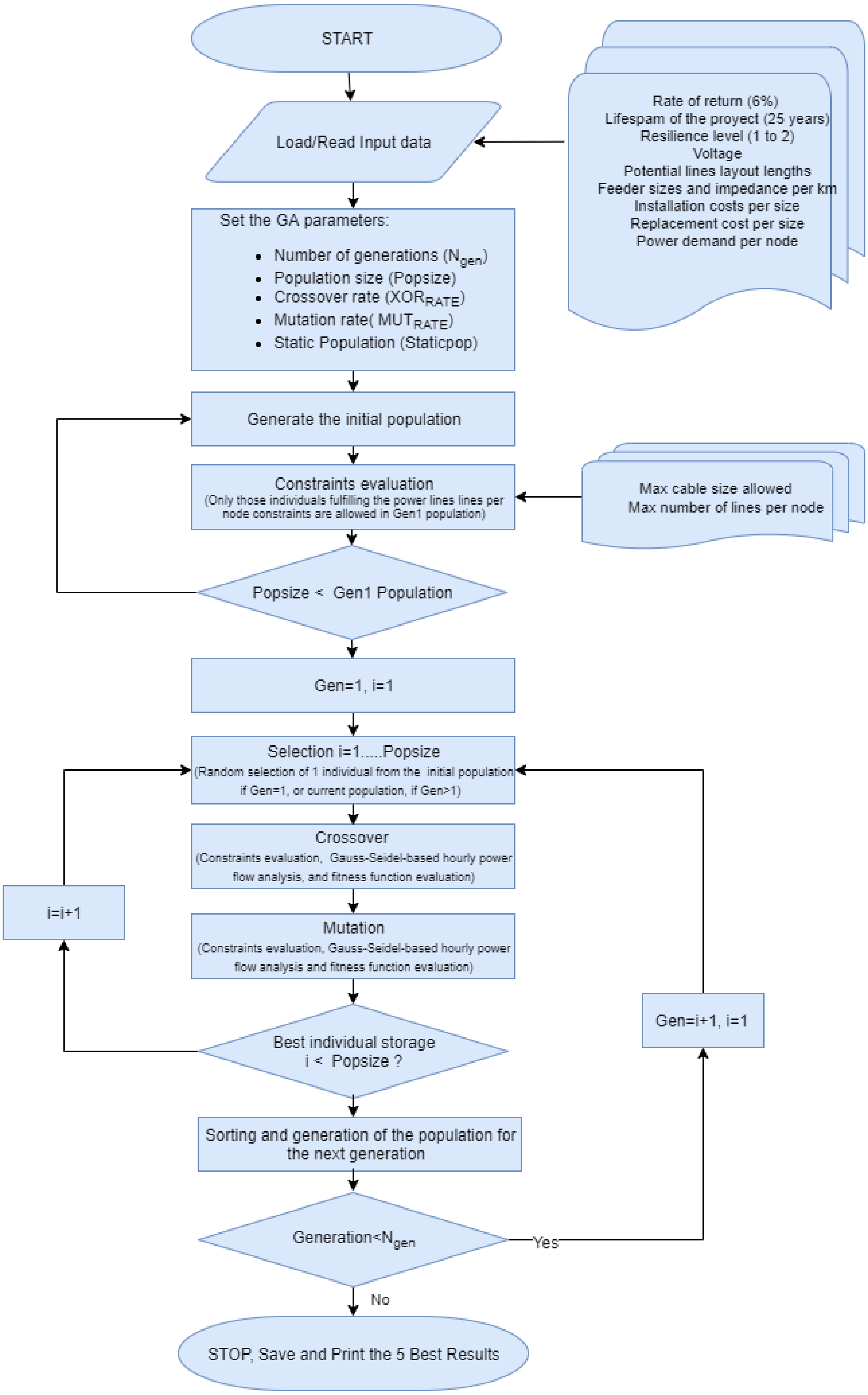


Figure 18. Flow Chart for the Genetic Algorithm used for the Selection, Sizing, and Scheduling of the Power Generation Systems.

As shown in Figure 18, the interest rate and the lifespan considered by the investors for the project are important inputs of the algorithm. Information on local installation, replacement, operation, and maintenance (O&M) costs must be also gathered for power lines, load centers, and substations. The fitness function is based on the Newton-Raphson method for power flow analysis. It calculates power losses, capital, replacement, and O&M costs of the layouts selected by the algorithm. The main inputs for the power flow analysis are:

- ✓ Grid voltage
- ✓ 1-hour interval power demand data for each node for an entire year (8,760 values)
- ✓ Technical specifications for normalized overhead or underground power lines: sizes and impedances per Km.
- ✓ Available routes between nodes in kilometers (line impedances according to the short line model).

The outputs of the algorithm are the best five power grid configurations with the highest Present Value (NPV). This algorithm looks for a list of solutions rather than one optimal solution because of the importance of giving different options to the engineering team, especially at the early stages of the feasibility analysis level. The secondary outputs of this algorithm are the active and reactive power and the voltage profiles per node. These profiles show 1-hour interval data calculated by the algorithm for those variables.

The goal of the fitness function is to calculate the Present Value (PV) of the solutions selected from the search space by the algorithm. Many authors as G.Celli et al. [15,16], G. Carpinelli et al. [17], and M. Kirthiga et al. [18] have presented the objective function they use in their algorithms for similar problems. In order to be accurate, the fitness function must calculate the estimated costs of the network based on the information available for:

- Geospatial and urbanistic constraints of the area of influence of the microgrid.
- Potential sites of the substations and loads previously defined by planners.
- Technical and regulatory constraints.
- Power demands of the nodes and their potential growth during the planning period.
- Local construction and maintenance costs of feeders of different cross-sections and for different types of lines (overhead, underground).
- Local construction and maintenance costs of different sizes, technologies, and configurations of electrical substations and load centers.
- Hourly electricity prices to estimate the cost of energy losses.

The fitness function in the GA algorithm incorporates the calculated capital, replacement, operating, maintenance and salvage costs into a cash flow vector (CF) with N+1 values, calculating the present value of the project according to the formulation below:

$$PV_{PDS}(i,N) = C^{0}_{CAP\ pds} - \left(\frac{SAV^{N+1}_{PDS}}{(1+i)^{N+1}}\right) + \sum_{N=1}^{N}\left(\frac{C^{A}_{REP\ PDS} + C^{A}_{O\&M\ PDS} + C^{A}_{PWLOSS}}{(1+i)^{N}}\right)$$

Where

- ✓ PV_{PDS} represents the present value of the power distribution system of the microgrid
- ✓ i represents the interest rate considered for the project
- ✓ N represents the lifecycle of the project in years
- ✓ $C^{0}_{CAP\ PDS}$ represents the fixed costs incurred on construction, installation, and commissioning works required to bring power lines, load centers, and substations to a commercially operable status. Local costs will be calculated per kilometer for power lines, and per unit for substations and load centers.
- ✓ SAV^{N+1}_{PDS} includes the salvage value of load centers, substations, and power lines at the end of the lifecycle of the project based on a linear depreciation and calculated at the end of the project (year N+1).
- ✓ $C^{A}_{REP\ PDS}$ represents the annual cost of replacement of load centers, substations, and power grids when they reach the end of their lifespan based on a percentage of their respective installation costs.
- ✓ $C^{A}_{O\&M\ PDS}$ includes the annual operation and maintenance costs of load centers, substations, and power grids. They are calculated as an annual fixed cost per unit for the load centers and the substations, and as an annual cost per kilometer for the power lines.
- ✓ C^{A}_{PWLOSS} represents the costs associated with power losses based on the hourly electricity price and the total power losses in the microgrid. The power losses in power lines are calculated using the Newton-Raphson algorithm for power flow analysis, while the power losses in substations and load centers are calculated as a fixed percentage of the power in the node.

The constraints applied by the algorithm avoid identifying non-feasible solutions as optimal solutions. Since most of the terms of the fitness functions are costs, the PV of the solutions will be negative. The algorithm looks for the highest present value. Therefore, a microgrid layout not connecting all the nodes would have a higher present value than one connecting all the nodes, but that design would not be acceptable.

The quality constraints for an eligible design are:

a. $V^{h}_{MAX\ k} \geq V^{h}_{NODE\ k} \geq V^{h}_{MIN\ k}$, the voltage at the nodes is between upper and lower limits.

b. $P^h_{NODE\,k} \geq P^h_{MAX\,DEM\,k}$, power demand at nodes is lower than the nominal capacity of the load centers

c. $I_{ij} \leq I_{max}$, current in feeders is lower than their nominal capacity

d. *Power lines per node > 1*, every node must be connected by at least one power line.

e. *Radial Index> Power lines per node*, the maximum number lines per node will define the topology of the final design as radial, meshed, or loop system.

f. *Maximum cable size*, the maximum cable size allowed by the utility can be constrained.

Conditions a, b and c have been met, allowing only power lines and load centers of defined sizes, and are validated through the power demand and voltage profiles presented in the solutions. Conditions d and e have been incorporated as constraints of the GA to limit the search space and allow the user to explore different topologies. But the higher the number of power lines per node, the lower the PV of the solution making the design less optimal.

The candidate solutions are coded using a string of real numbers. Each position of the string represents one potential power line to be built between two specific nodes. The length of the vector will be the maximum number of power lines for an N-node grid calculated according to the following formula:

$$MaxPL = \sum_{i=1}^{N}(N-i) = \frac{N^2 - N}{2}$$

Integer numbers will represent the standard feeder sizes allowed. For example, integer numbers from one to five represent 70, 90, 120, 150, and 240 mm^2 cables, respectively, and zero represents there is no power line between two nodes. Different cables can have the same size, and all sizes are allowed for all cables. Thus, the search space of the problem depends on the maximum number of power lines and the number of nodes to connect, calculated as follows:

$$Search\ Space\ Size = s^{MaxPL}$$

Where

- ✓ $MaxPL$ is the maximum number of power lines in the microgrid.
- ✓ *s* represents the number of the standardized cabled sizes to be considered.

For instance, a 5-node power grid would admit a maximum of 10 power lines to explore with six potential cable alternatives per line (five actual cable sizes plus no cable). In this case, the number of potential configurations available would be 60,466,176. As mentioned above, some constraints must be applied to speed up the execution time of the algorithm, excluding those solutions that will not work such as, for example, those leaving nodes unconnected to the grid. An example of the algorithm´s codification and solutions will be presented in chapter 4.

19.3. Power Generation Sizing and Scheduling Algorithm

The goal of this algorithm is to select, size, schedule, and price the power generation systems connected to the nodes of the microgrid. The optimization algorithm selected is a **binary-coded genetic algorithm** (GA) combined with a **Linear Programming** (LP) algorithm. GAs have already been presented in sections 2 and 3.2. LP algorithms were initially developed in the 1940s[33] , and they still play an essential role optimization problems for single and multi-building energy systems design, including microgrids and district heating and cooling systems [19–24]. LP algorithms can be very efficient in identifying possible and practical solutions, such as defining the optimum use of productive resources like power generation and energy storage assets. They are also fast and easy to code, but they can have some limitations too, such as:

- ✓ Only one objective is considered, allowing the rest to be incorporated as constraints.
- ✓ The objective function and the constraint equations or inequalities must be linear or linearized.
- ✓ Modifications of the optimal solutions might be required when translating from the computational to the real world since there might be other constraints operating outside the problem unable to be modeled or just to be considered because they haven't happened yet.
- ✓ LP model does not take into consideration the effect of uncertainty. The LP model should be defined in a way that changes due to internal and external factors can be incorporated. Risk analysis techniques can also help to fill this gap.

The speed and accuracy of the LP algorithm make them very convenient for feasibility analyses when combined with other algorithms. A combination of GA and LP has been selected for selecting, sizing, scheduling, and pricing power generation assets for the microgrid. The steps followed by the GA algorithm associated with this part of the method are presented below in Figure 19.

The GA algorithm selects random combinations of technologies and sizes of power generators and the LP optimization algorithm calculates the optimal schedule to meet the power demand of the system, and also the costs associated with the operations of those generators. LP optimization occurs during the initial population generation, mutation, and crossover stages of the GA.

The fitness function of the GA algorithm includes the calculation of the capital, replacement, operating, maintenance, salvage and miscellaneous costs of the power generation system in a cash flow vector with N+1 values, to finally calculate the Present Value of the project according to the formulation below:

[33] https://cs.nyu.edu/overton/g22_lp/encyc/article_web.html

$$PV_{MG}(i,N) = PV_{PDS} + C_{CAPg}^{0} + C_{MISCmg}^{0} - \left(\frac{SAV_g^{N+1}}{(1+i)^{N+1}}\right) + \sum_{N=1}^{N}\left(\frac{C_{REPg}^{A} + C_{O\&Mg}^{A}}{(1+i)^{N}}\right)$$

Where

- ✓ PV_{MG} is the present value of the microgrid in euros. (€)
- ✓ PV_{PDS} is the present value of the power distribution system of the microgrid, calculated by the algorithms described in section 19.2.
- ✓ i is the interest rate defined for the project by the stakeholder
- ✓ N is the lifespan in years of the project selected by the stakeholder
- ✓ C_{CAPg}^{0} represents the fixed costs incurred on construction, installation, and commissioning works required to bring the power generation and energy storage systems to a commercially operable status. Local costs will be calculated per technology and size based on publicly available data.
- ✓ $C_{MISC\,MG}^{0}$ represents the miscellaneous costs incurred on different aspects of the project before it starts operating, such as the energy management system, insurances and other costs required for the project to start operating. It is calculated as a percentage of C_{CAPg}^{0}.
- ✓ SAV_g^{N+1} is the salvage value of the power generation systems at the end of the lifecycle of the project (year N+1) based on a linear depreciation.
- ✓ C_{REPg}^{A} is the annual cost of replacement of the power generation systems once they reach the end of their lifespan, calculated as a fixed percentage of their installation costs.
- ✓ $C_{O\&Mg}^{A}$ includes the annual operation and maintenance costs of the power generation systems in the microgrid. **The input for this calculation is the annual schedule calculated by the LP optimization algorithm,** in addition to local average performance and maintenance costs per technology.

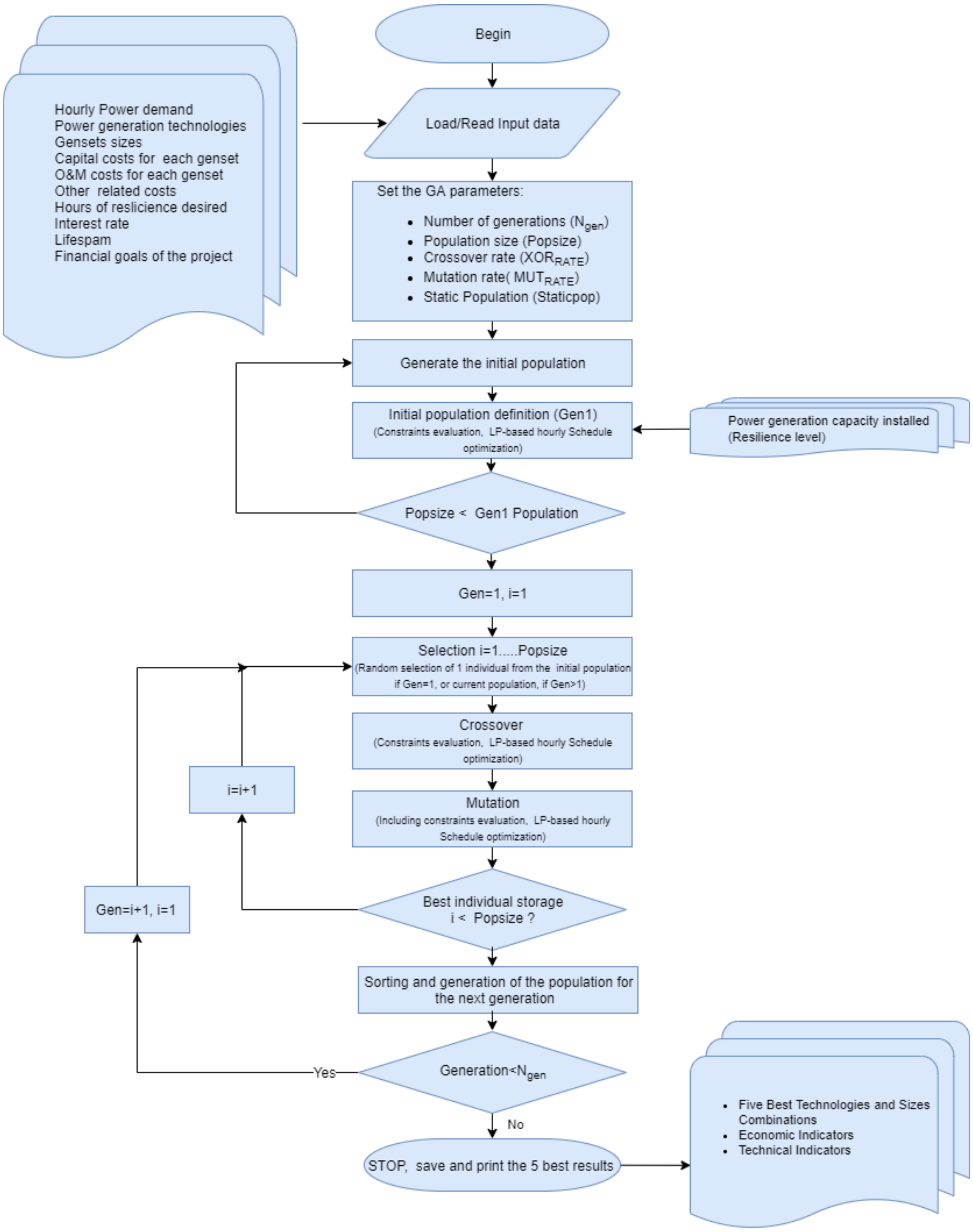


Figure 19. Flow Chart for the Genetic Algorithm Used for Power Lines Sizing, Siting and Scheduling

The formulation of the scheduling problem that leads to the calculation of $C^{A}_{O\&Mg}$ is described below. The goal of the linear programming algorithm is to minimize the operation and maintenance costs of the power generation equipment:

$$Min \sum_{h=1}^{8,760} PW_g^h \times PR_{ELEC,g}^h \qquad [€]$$

where

- PW_g^h is the hourly power generation capacity per generator, in KW

- $PR^{h}_{ELEC,g}$ is the hourly electricity cost per generator. The value of this factor is the fuel cost per hour per generator except for the power grid, which is the electricity price per hour. The units are euros per kWh

The constraints applied to the linear programming algorithm are:

- Hourly power generation values must be lower than or equal to the maximum power capacity of the generator, and always higher or equal to zero

$$PW_{g\ MAXi} \geq PW^{h}_{gi} \geq 0,$$

- The addition of the hourly power generation values per generator must be higher than or equal to the addition of the power demand and the power losses for every hourly interval.

$$\sum_{\mathrm{h}=0}^{8760} \left(PW^{h}_{gi}\right) \geq \sum_{\mathrm{h}=0}^{8760} \mathrm{PW}^{\mathrm{h}}_{\mathrm{DEM}} + PW^{h}_{LOSS}$$

Where

- ✓ $PW_{g\ MAXi}$ represents the nameplate capacity of the generator in KW.
- ✓ PW^{h}_{DEMj} represents the hourly power demand values in KW.
- ✓ PW^{h}_{gi} represents the power generation per generator in KW.
- ✓ $\mathrm{PW}^{\mathrm{h}}_{\mathrm{LOSS}}$ represents the hourly power losses in the power distribution system in KW.

Other relevant aspects of this algorithm are its codification and the size of the search space generated through it.

The search space will be formed by strings of values. The length of the string will be equal to the number of candidate power generators: for 20 candidate generators, each potential solution will be represented by a string of 20 numbers. The values in the string follow binary code, so the size of the search space can be determined by the following formula:

$$Soss = 2^{G}$$

Where,

- Soss is the size of the search space
- G is the number of candidate generators

For example, for a set of 20 candidate generators, the number of alternatives or size of the search space would be 1,048,576. Examples of this coding strategy will be presented in chapter 4 as part of the case study.

The main inputs of this algorithm are

- The solutions of the Power Flow Analysis and Power lines Optimization Algorithm described in section 19.2 including the hourly power demand per node (PW_{NODE}^{h}), the cash flow associated with the solutions (CF_{PLLC}), and the interest rate (ir), the lifespan of the project (N), and the maximum initial investment defined by the investors.
- Energy models of the power generators to be studied for the project, including power and thermal generation capacity, fuel consumption, and CO_2 production at full and partial loads for different technologies and sizes.
- Local installation, replacement, and O&M costs of the power generation technologies and sizes studied by the algorithm, including fuel costs.
- Resilience level required for the microgrid in hours of operation with the power grid down (RL).

According to mathematical theory, the most common output of an optimization algorithm is one only optimal solution. However, following a more realistic approach for a feasibility analysis method**, it is important to consider a group of optimal solutions instead of just one in order to allow the user to choose among them in case one becomes not available later in the process. This strategy of looking for multiple solutions will allow the algorithm to explore the search space under different constraints and help the user to answer more complex questions**.

The main outputs of the method are the economic indicators. The following indicators have been selected:

a) Key Economic Indicator 1 (KEI1): Initial investment. This indicator defines the *out-of-pocket* contribution of the stakeholder in order to bring a project to a commercially operable status. If the stakeholder does not need loans to pay the project in full, this indicator could also be defined as the value resulting from de addition of the costs of the project at the zero hour.
b) Key Economic Indicator 2 (KEI2): Loan. The algorithm allows the stakeholder to set a maximum initial investment, being all the costs over that amount covered by a loan. This indicator calculates the loan required to leave the microgrid project in a fully operational status.

$$Loan = C_{CAP} - I_{INV}$$

c) Key Economic Indicator 3 (KEI3): Annual Savings. The annual savings per year the system is expected to achieve in comparison with the baseline, calculated as follows:

$$Annuals\ Savings = Cost_{OPTIMAL}^{A} - Cost_{BASELINE}^{A}$$

d) Key Economic Indicator 4 (KEI4). Net Present Value. The present value (PV) condenses all the costs associated with the power distribution, power generation, and energy storage assets that occur within the project lifetime into a single lump sum in year-zero dollars, with future cash flows discounted back to year zero using the interest rate. Costs may include capital costs, replacement costs, operating and maintenance costs, the cost of buying electricity from the grid, and other miscellaneous costs such as the microgrid management system, and insurance policies. If the costs of the baseline project (typically the costs of the existing systems) are subtracted from the PV, the result is the Net Present Value.

$$NPV(i,n) = PV^{A}_{BASELINE} - PV^{A}_{MICROGRID}$$

The NPV is the variable to maximize in order to find the best solution that fulfills the design constraints.

e) Key Economic Indicator 5 (KEI5): Internal rate of return (IRR). IRR computes for what interest the NPV will be zero, so it expresses the achievable interest tied-up in the investment. IRR should be higher than the selected interest rate. Otherwise, it could be more profitable to put the money in the bank.

$$0 = NPV(IRR, n)$$

Where

- N is the life cycle of the project in years.
- IRR, Internal Rate of Return to be calculated.

f) Key Economic Indicator 6 (KEI6): Discounted Payback Period (DPP). The payback period could be defined as *the length of time that it takes for the cumulative gains from an investment to equal the cumulative cost*[34]. Thus, Discounted Payback Period (DPB) is the period after which the capital invested has been recovered by the discounted net cash inflows from the project. The DPP is different from the simple payback period because it considers not only capital needs to be recovered but also the maximum interest acceptable. The formula is shown below. The capital cost of the project is divided by the mean yearly discounted cash flow. DPP values must be shorter than the lifespan of the project and the sorter the DPP, the most interesting the investment is.

$$DPP = \frac{C_{CAP}}{\sum_{n=0}^{N}\left(\frac{NCF_t^A}{(1+i)^n}\right) \Big/ N} \quad [years]$$

[34] https://www.investopedia.com/terms/d/discounted-payback-period.asp

g) Key Economic Indicator 7 (KEI7): Equivalent Annuity (A). This indicator converts all net cash flows connected with an investment project into a series of annual payments of equal amount, as follows:

$$Equivalent\ Annuity = NPV \times CRF(i, N)$$

$$CRF(i,t) = \frac{i \times (i+1)^N}{(i+1)^N - 1}$$

The microgrid designs with the highest equivalent annuity are the most favorable ones.

An additional set of indicators provides detailed information on the technical solutions calculated by the two optimization algorithms. The indicators selected for these sets are briefly described below:

a) Power demand (KTI1), is the total power demand of the system calculated in the power flow analysis. This indicator includes power losses in the distribution system.

$$\sum_{g}\sum\nolimits_{h=0}^{H}(P_g^h + PW_{LOSSES}^h) \quad [KWh]$$

b) Energy Generated on-site (KTI2), is the addition of the power generated on-site, not purchased from the local utility.

$$KTI2 = \sum_{\text{h}=0}^{8{,}760}\left(PW_{g\ ONSITE}^{h}\ \right) \quad [KWh]$$

c) Energy purchased from the grid (KTI3) is the energy purchased from the local power utility.

$$KTI3 = \sum_{\text{h}=0}^{8{,}760}\left(PW_{GRID}^{h}\right)\ [KWh]$$

d) Renewable energy fraction (KTI4) is the percentage of the demand supplied by clean sources such as solar.

$$KTI4 = \frac{\sum_g \sum_{h=0}^{8{,}760}(PW_{g\ SOLAR}^h)}{KTI1}\ [\%]$$

e) Environmental emissions (KTI5) is the total CO_2 emissions generated to cover the power demand. It is the total amount of emissions in a year (Kg of CO_2/year) for the whole microgrid calculated as follows:

$$KTI5 = \sum_{\text{h}=0}^{8{,}760}\left(PW_{gi}^h \times EF_g^h + PW_{GRID}^h \times EF_{GRID}^h\right)$$

Where:

- PW_{gi}^h is the hourly power rating of the on-site g_{th} generator.

- EF_{gi}^{h} is the hourly emission factor for each KWh supplied by the g_{th} generator.
- $PW_{\mathrm{GRID}}^{\mathrm{h}}$ is the hourly power capacity purchased to an external power grid.
- EF_{GRID}^{h} is the hourly emission factor for each KWh supplied by the power grid.

f) Overall efficiency (KTI6) is calculated as the total energy generated on-site (including thermal) divided by the total energy in the fuel consumed by the generators. The result is a percentage (%).

$$KTI6 = \frac{KTI2 + \sum_g \sum_{h=0}^{8,760}(ThE_g^h)}{\sum_g \sum_{h=0}^{8,760}(Fuel_g^h)} \; [\%]$$

Where:

- ThE_{gi}^{h} is the hourly thermal energy per generator.
- $Fuel_g^h$ is the hourly fuel consumption per generator.

g) Levelized Cost of Energy (LCOE, KTI7) is a ratio frequently used to compare different architectures of microgrids. It is an economic assessment of the annual cost to operate a generation asset divided by its useful energy output for the same period.

$$LCOE = \frac{\mathrm{C}_{\mathrm{O\&M}}^{\mathrm{A}}}{\sum_{\mathrm{h=0}}^{8,760}\left(\mathrm{PW}_{\mathrm{g}}^{\mathrm{h}} + PW_{PUR}^{h} - PW_{LOSS}^{h}\right)} \quad \left[\frac{€}{KWh}\right]$$

Where:

- ✓ PW_{PUR}^{h} is the amount of energy purchased to a power grid.
- ✓ $\mathrm{PW}_{\mathrm{g}}^{\mathrm{h}}$ is the amount of energy generated by the on-site power generators.
- ✓ PW_{LOSS}^{h} is the amount of kWh lost in the power distribution system.

h) Breakeven point (KTI8) refers to the power demand that would break-even the project. Provides valuable information on how much demand the system can accommodate or needs to reduce to change its profitability status

$$Breakeven = \frac{\mathrm{PR}_{\mathrm{ELEC}}^{\mathrm{Ave}} \times \mathrm{KTI1}}{\mathrm{KTI7}} \quad [kWh]$$

Where:

- ✓ $\mathrm{PR}_{\mathrm{ELEC}}^{\mathrm{Ave}}$ is the baseline average electricity price.

A last set of indicators provides detailed information on the performance of the individual generators. This information is essential to validate the optimal design and also to help make decisions about potential adjustments in the final design. The indicators selected described below:

a. KTch1, Rated capacity of each individual generator in kW.

b. KTch2, Peak-load of each individual generator in kW.

c. KTch3, Minimum load of each individual generator in kW.

d. KTch4, Annual operating hours.

e. KTch5, Estimated lifespan is calculated dividing the lifespan of the technology by the annual operating hours. Its units are years.

f. KTch6, Number of starts per year, is calculated counting the times the power output of the generator changes from zero to a different value.

g. KTch7, Power generated is the addition of the hourly power generation values in a year per generator, calculated as follows:

$$KTch7 = \sum_{g=i}^{i} \sum_{h=0}^{8,760} (PW_g^h) \ [kWh]$$

h. KTch8, Thermal output is the addition of the hourly thermal energy generation values in a year per generator, calculated as follows:

$$KTch8 = \sum_{g=i}^{i} \sum_{h=0}^{8,760} (ThE_g^h) \ [kWh]$$

i. KTch9, Fuel is the addition of the hourly thermal energy generation values in a year per generator, calculated as follows

$$KTch9 = \sum_{g=i}^{i} \sum_{h=0}^{8,760} (Fuel_g^h) \ [kWh]$$

j. KTch10, Environmental emissions are the annual CO_2 emissions of each generator according to its emission factor (kg of CO2 per kWh) and calculated as follows.

$$KTch10 = \sum_{\mathrm{h}=0}^{8,760} \left(PW_{gi}^h \times EF_g^h\right) \ [kg\ CO2]$$

The results will be summarized in different tables and figures, as shown in chapter 4.

19.4. Risk Analysis and Profitability Scenarios Assessment Algorithm

The optimization algorithms used in the previous stages of the method follow a deterministic approach, considering fixed values for sensitive variables such as energy prices, and installation or O&M costs. But the truth is that some variables like the electricity or the natural gas price change at least once a year, and their future values are uncertain, especially over the, at least, 20 years of lifespan of a microgrid.

Uncertainties are a critical factor in microgrid planning processes, a source of risk that system planners need to avoid, or at least to control. Stewart, motivated in [25] by practical needs for modeling a decision-making problem, classifies every uncertainty under two categories:

- External uncertainty: related to the lack of knowledge (about the consequences of an action) and to the nature of the environment (outside of the control of the decision-maker).
- Internal uncertainties: presented in the process of identification, structuring and analysis of the decision-maker (depending on the decision-maker).

A probabilistic approach can help assess risk at a feasibility level, and that is the goal of this algorithm. Some of the most popular techniques to choose are scenario analysis, decision trees, and simulations. The selected technique will depend on how the output is used, and on the risks the project is expected to deal with [35].

Table 13. Risk Type and Probabilistic Approaches. SOURCE: www.coursehero.com, Course FIN 400 from National Economics University of Hanoi

Table 6.4: Risk Type and Probabilistic Approaches

Discrete/Continuous	*Correlated/Independent*	*Sequential/Concurrent*	*Risk Approach*
Discrete	Independent	Sequential	Decision Tree
Discrete	Correlated	Concurrent	Scenario Analysis
Continuous	Either	Either	Simulations

The best-case/worst-case scenario analysis looks at only three scenarios (the best case, the most likely case, and the worst case) and ignores all other scenarios. This technique will not allow a complete assessment of all possible outcomes from risky investments or assets, even when multiple scenarios are considered.

Scenario analysis and decision trees are generally built around discrete outcomes whereas simulations are better suited for continuous risks and concurrent risks.[36] Simulations allow for explicitly modeling correlations among the various sensitive variables that affect the investment, assuming that those values can be forecasted. The evolution of sensible variables considered in the model will be studied and fitted to standard or customized probability distributions, following a similar approach to the one presented in Figure 20.

[35] https://www.coursehero.com/file/p7kjdi0/2-Discrete-versus-Continuous-Risk-As-noted-above-scenario-analysis-and-decision/

[36] http://people.stern.nyu.edu/adamodar/pdfiles/papers/probabilistic.pdf

Figure 6A.15: Distributional Choices

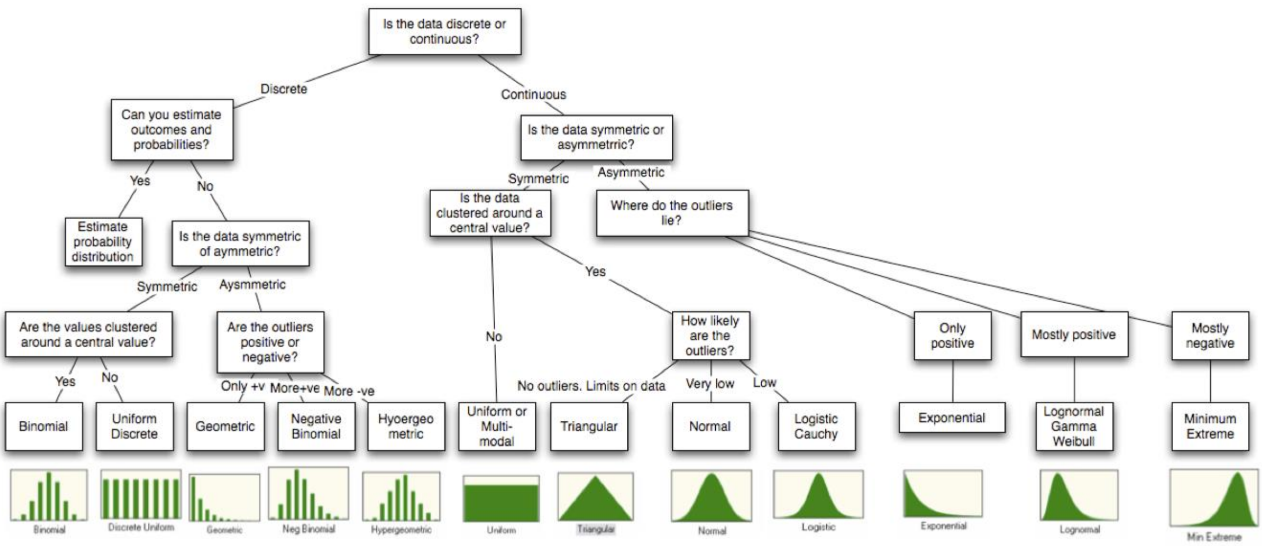


Figure 20 Decision Tree Diagram for Statistical Distributions Fitting. Source: Figure 6.A.15 of Probabilistic Approaches to Risk by Aswath Damodaran[37]

The algorithm chosen to implement uncertainties management in this method is the Monte Carlo Simulation. Monte Carlo simulations are used to model the probability of different outcomes in a process that cannot easily be predicted due to the intervention of random variables[38]. It is a technique used to understand the impact of risk and uncertainty in prediction and forecasting models.

The concept is to use randomness to solve problems that might be deterministic in principle. Developed in 1946[39], it has been widely used in power systems planning [16,26–28]. One of the main uses that Kroese et al. highlight in [29] for Monte Carlo methods are optimization problems. Savvide presents in [30] the methodology and uses of the Monte Carlo simulation technique as applied in the evaluation of investment projects to analyze and assess risk. The flow chart presented in Figure 21 illustrates the steps followed by the risk analysis algorithm of the methodology described in this section.

[37] http://people.stern.nyu.edu/adamodar/pdfiles/papers/probabilistic.pdf

[38] https://www.investopedia.com/terms/m/montecarlosimulation.asp

[39] http://www.phys.ubbcluj.ro/~zneda/edu/mc/mcshort.pdf

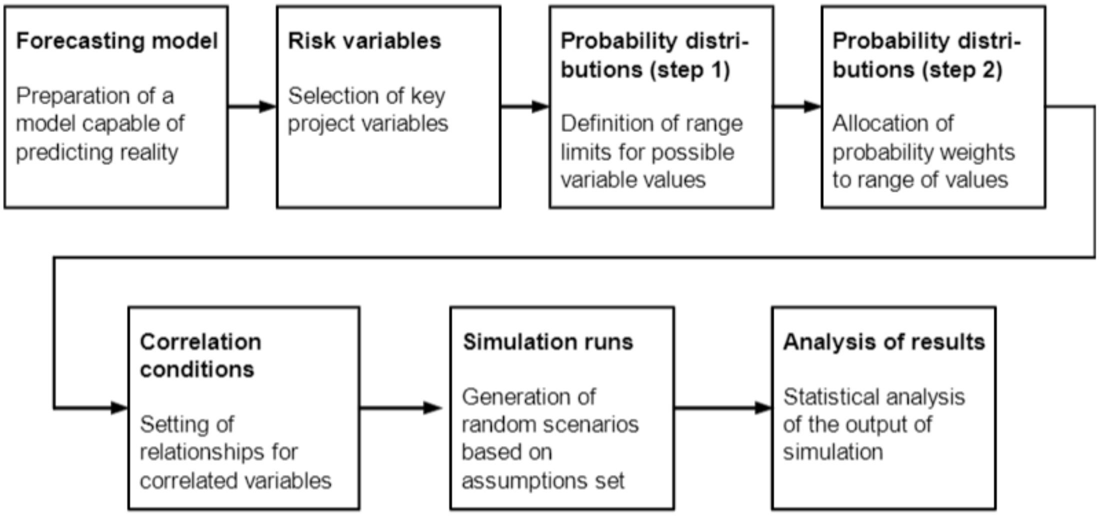


Figure 21. Risk Analysis Process Flow Chart in Investment Appraisal by Savvakis C. Savvides [30]

The goal of this third algorithm is to calculate the probability of the optimal solutions to fulfill the economic goals by studying the simultaneous influence of the sensitive input variables on the profitability indicators. This part of the method uses the same fitness functions as the algorithms described in sections 19.2 and 19.3 but in a matrix form. For instance, the table below compares the deterministic and the probabilistic calculations over the same formula in GAs and the Monte Carlo simulation.

Table 14. Matrix Dimensions for the $C^{A}_{O\&Mg}$ Formula Using Probabilistc and Deterministic Calculations (Monte Carlo Simulation vs. Genetic Algorithm)

$C^{A}_{O\&Mg} = \sum_{h=1}^{8{,}760} PW^{h}_{g} \times PR^{h}_{g}$	
Genetic Algorithm	Monte Carlo Simulation
$\sum_{h=1}^{8{,}760} [hxg] \times [gx1] = [1x1]$	$\sum_{h=1}^{8{,}760} [hxg] \times [gx1000] = [1x1000]$

The main inputs of the Monte Carlo simulation algorithms are the same as for the GAs in addition to:

- the solution of the power flow analysis (Newton-Raphson algorithm) consisting of a matrix of 8,760 hourly power demand values per nodes→ $[8{,}760, number\ of\ nodes]$
- the solution of the scheduling problem (LP algorithm) consisting of 8,760 values of power generation capacity per generator → $[8{,}760, number\ of\ generators]$

Sets of one thousand values for the sensitive input variables are defined and fitted to a probabilistic function following the scheme in Figure 21. Examples of the functions used, and the fitting process will be presented in chapter 4. **The sensitive input variables selected from the algorithms in section 19.2 and 19.3 are**:

- $PR^{h}_{ELEC\ GRID}$, hourly price of the kWh of electricity supplied by the local utility in euros per kWh.
- PR^{h}_{NG} , price of the kWh of natural gas supplied by the local utility in euros per kWh
- PR^{h}_{DIESEL} price of the kWh of diesel supplied by local distributors in euros per kWh.
- $C^{0}_{CAP\ PDS}$, fixed costs incurred on construction, installation, and commissioning works required to bring power lines, load centers, and substations to a commercially operable status.
- SAV^{N+1}_{PDS} , salvage value of load centers, substations, and power lines at the end of the lifecycle of the project.
- $C^{A}_{REP\ PDS}$, the annual cost of replacement of load centers, substations, and power grids when they reach the end of their lifespan.
- $C^{A}_{O\&M\ PDS}$ annual operation and maintenance costs of load centers, substations, and power grids.
- C^{0}_{CAPg}, fixed costs incurred on construction, installation, and commissioning works required to bring the power generation and energy storage systems to a commercially operable status.
- $C^{0}_{MISC\ MG}$, miscellaneous costs incurred on different aspects of the project before it starts operating, such as the energy management system, insurances and other costs required for the project to start operating.
- SAV^{N+1}_{g} , salvage value of the power generation systems at the end of the lifecycle of the project (year N+1).
- C^{A}_{REPg} , the annual cost of replacement of the power generation systems once they reach the end of their lifespan.
- $C^{A}_{O\&Mg}$, annual operation and maintenance costs of the power generation systems in the microgrid.

These variables will be transformed from single values to sets of 1,000 alternatives and combined randomly in order to simulate 1,000 scenarios. Once applied to the fitness functions of the optimization problems described in sections 19.2 and 19.3, they will generate one set of 1,000 cash flows per optimal solution. Those cash flows will be used to calculate the probabilistic economic indicators described below:

a) Value at Risk (VaR): represents the potential savings calculated as the subtraction of the probabilistic Present Values of the optimal solutions and the baseline or existing solutions as shown in the formula below:

$$VaR = PV^{PROB}_{OPTIMAL} - PV^{PROB}_{BASELINE} \quad [1x1000]$$

This indicator is very appropriate to identify the maximum, median, and minimum values the savings could reach, and also to analyze how the probability of different values is distributed. Positive values of VaR mean that the analyzed optimal solution is generating savings while negative values highlight scenarios in which the baseline is more profitable than the optimal solution. The outputs associated with this variable are:

$$\boldsymbol{KRI3 = Max\ (VaR)}$$

$$\boldsymbol{KRI2 = Median\ (VaR)}$$

$$\boldsymbol{KRI3 = Min\ (VaR)}$$

b) Probability of obtaining savings: the probability of VaR's cumulative distribution function of having positive values.

$$\boldsymbol{KRI4 = \mathrm{p}(cdf(VaR) > 0)} \quad [\%]$$

c) IRR over X% at 90% probability: identifies the IRR value of the optimal solution at a 10% probability.

$$\boldsymbol{KRI5 = min\ IRR\ value\ for\ \mathrm{p}(cdf(IRR) \geq 10\%)} \quad [\%]$$

d) DPP under Y years at 90% probability: identifies DPP values of the optimal solution at a 90% probability.

$$\boldsymbol{KRI6 = max\ DPP\ value\ for\ \mathrm{p}(cdf(DPP) \geq 90\%)} \quad [years]$$

After the risk analysis is completed, some of the optimal solutions might fulfill the profitability goals, and some might not. Those that fulfill the goals defined by the stakeholder should be considered in further stages of the project. Those that do not fulfill the requirements will be studied further in order to define which costs savings or incentives would help make them profitable from the decision-makers' perspective. Four parameters will be calculated for these variables:

a) Incentives for IRR goal: one-time incentive (year 0) required for the optimal design to achieve the IRR goal set by the stakeholder, calculated as follows.

$$\boldsymbol{KRI7 = \mathrm{CIRR}_{GOAL} - \mathrm{CIRR}_{OPTI}} \quad [€]$$

$$\mathrm{CIRR}_{OPTI} = C^{0}_{CAP\ PDS} + C^{0}_{CAPg} + C^{0}_{MISC\ MG}$$

$$\mathrm{CIRR}_{GOAL} = -\left(C^{A}_{O\&M\ PDS} + C^{A}_{O\&Mg}\right) \times \frac{(1 + IRR_{GOAL})^{N} - 1}{IRR_{GOAL} \times (1 + IRR_{GOAL})^{N}}$$

Where:

- CIRR_{GOAL}, initial investment calculated for the project to meet the IRR goal, in euros.
- CIRR_{OPTI}, initial investment of the optimal solution to be analyzed, in euros.
- N, lifespan of the project
- IRR_{GOAL}, IRR goal set by the investors for the project

- $C^0_{CAP\ PDS}$, fixed costs incurred on construction, installation, and commissioning works required to bring power lines, load centers, and substations to a commercially operable status.
- $C^A_{O\&M\ PDS}$ annual operation and maintenance costs of load centers, substations, and power grids.
- C^0_{CAPg}, fixed costs incurred on construction, installation, and commissioning works required to bring the power generation and energy storage systems to a commercially operable status.
- $C^0_{MISC\ MG}$, miscellaneous costs incurred on different aspects of the project before it starts operating, such as the energy management system, insurances and other costs required for the project to start operating.
- $C^A_{O\&Mg}$, annual operation and maintenance costs of the power generation systems in the microgrid.

b) Savings for IRR goal: annual savings or annual incentive required for the optimal design to achieve the IRR goal set by the stakeholder, calculated as follows.

$$\boldsymbol{KRI}\mathbf{8} = \mathbf{AnnIRR}_{\boldsymbol{GOAL}} - \mathbf{AnnCIRR}_{\boldsymbol{OPTI}} \quad [€]$$

$$\mathrm{AnnIRR}_{OPTI} = \mathrm{CF}_{OPTI}\,(2)$$

$$\mathrm{AnnIRR}_{GOAL} = -CF_{OPTI}(1) \times \frac{IRR_{GOAL} \times (1 + IRR_{GOAL})^N}{(1 + IRR_{GOAL})^N - 1}$$

Where:

- AnnIRR_{GOAL}, annual costs calculated the project to achieve the IRR goal, in euros.
- AnnIRR_{OPTI}, annual costs of the optimal solution to be analyzed, in euros.
- CF_{OPTI}, cash flow vector of the optimal solution to be analyzed.
- N, lifespan of the project
- IRR_{GOAL}, IRR goal set by the investors for the project

c) Incentive for DPP goal: one-time incentive (year 0) required for the optimal design to achieve the DPP goal set by the investors, calculated as follows.

$$\boldsymbol{KRI}\mathbf{9} = \mathbf{CDPP}_{\boldsymbol{GOAL}} - \mathbf{CDPP}_{\boldsymbol{OPTI}} \quad [€]$$

$$\mathrm{CDPP}_{OPTI} = \mathrm{CF}_{OPTI}\,(1)$$

$$\mathrm{CDPP}_{GOAL} = -\sum_{s=2}^{DPPgoal+1} \frac{\mathrm{CF}_{OPTI}\,(s)}{(1 + ir)^{s-1}}$$

Where

- CDPP_{GOAL}, initial investment calculated for the project to achieve the DPP goal, in euros.
- CDPP_{OPTI}, initial investment of the optimal solution to be analyzed, in euros.
- ir, interest rate defined by the investors for the project analysis.
- DPP_{GOAL}, DPP goal set by the investors for the project in years.
- CF_{OPTI}, cash flow vector of the optimal solution to be analyzed.

d) Savings for DPP goal: annual savings or annual incentive for the optimal design to achieve the DPP goal set by the stakeholder, calculated as follows.

$$\boldsymbol{KRI10} = \mathbf{AnnDPP}_{\boldsymbol{GOAL}} - \mathbf{AnnCDPP}_{\boldsymbol{OPTI}} \quad [€]$$

$$\mathrm{AnnCDPP}_{OPTI} = \mathrm{CF}_{OPTI}\,(2)$$

$$\mathrm{AnnDPP}_{GOAL} = \mathrm{CF}_{OPTI}\,(1) \times \frac{ir \times (1+ir)^{DPPGOAL}}{(1+ir)^{DPPGOAL} - 1}$$

Where

- AnnDPP_{GOAL}, annual savings or annual incentive that the project should have to meet the DPP goal, in euros.
- AnnDPP_{OPTI}, annual costs of the optimal solution to be analyzed, in euros.
- CF_{OPTI}, cash flow vector of the optimal solution to be analyzed.
- ir, interest rate defined by the investors for the project analysis
- DPP_{GOAL}, DPP goal set by the investors for the project in years

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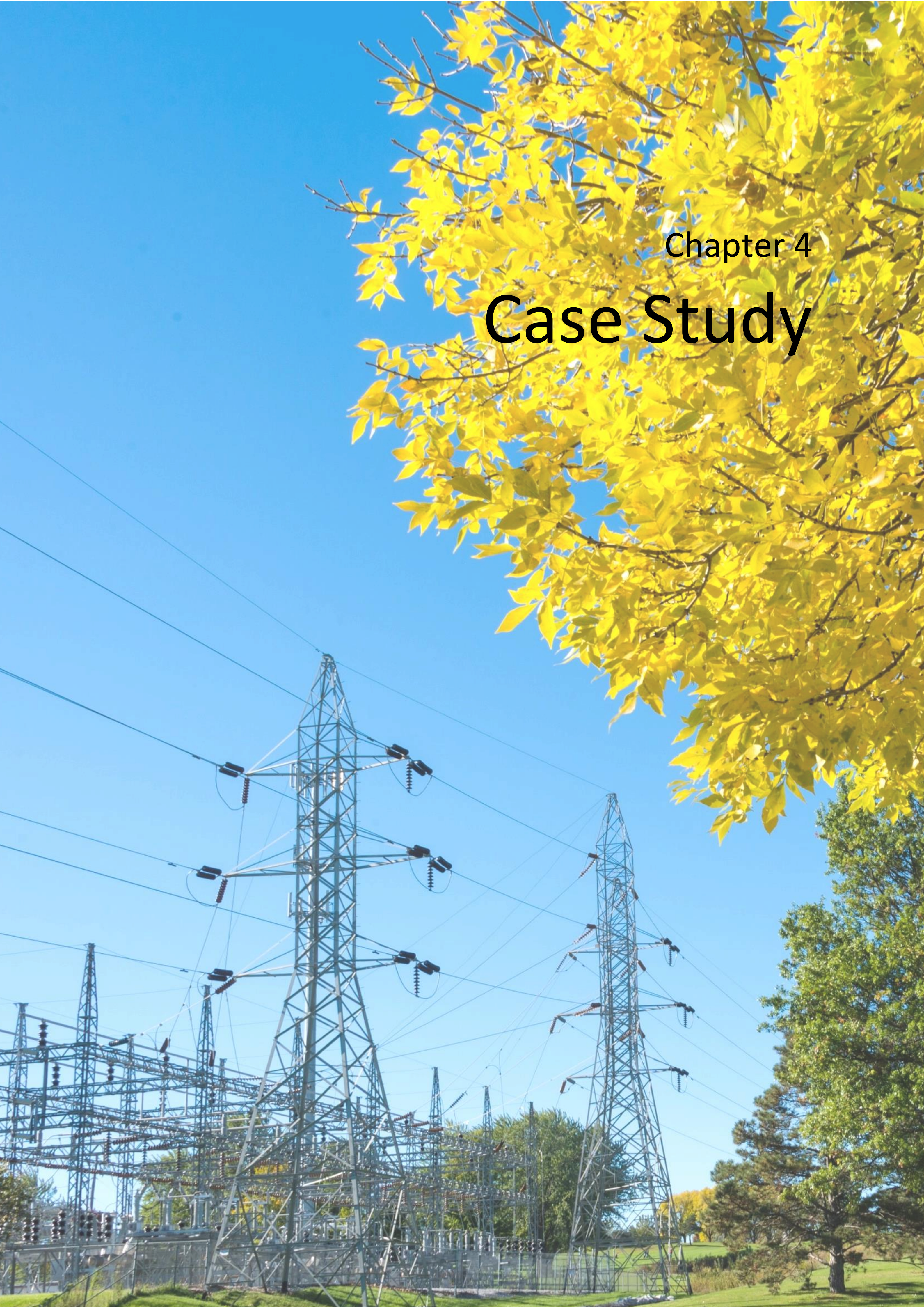
Chapter 4

Case Study



21.Introduction to the Case Study

The method described in section 3 will be tested on a real facility: a university campus owned and operated by the University of Burgos. UBU is a public university in the Spanish city of Burgos.

Established in 1990, the UBU currently has almost 10,000 students distributed among at six centers: the Science Faculties, the Faculty of Economics and Business Studies, the Faculty of Humanities and Education, the Faculty of Law, and the Higher Polytechnic School, as well as at three associated schools, the School of Nursing, the School of Labor Relations and the School of Tourism. It currently offers over 30 different undergraduate degrees and over 20 Ph.D. programs, as well as several Official Masters and other graduate courses. UBU has education agreements with over 100 international academic institutions[40].

Image 2. Administrative Services Building. University of Burgos

UBU has its centers divided among different campuses around the city, but the highest concentration of buildings is located West from the historic city center. The Science Faculties, the Faculty of Economics and Business Studies, the Faculty of Humanities and Education, the Faculty of Law, and the Higher Polytechnic School are located in that area. These sets of buildings are owned and operated by UBU and have different uses such as academic buildings, sports centers, student housing, libraries, and research facilities. They scope of this study is highlighted in orange in Image 2. The influence area of the microgrid is also represented in that image.

The rest of the buildings in the influence area are mainly single and multi-family residential buildings nor owned or neither operated by the UBU. They have not been included in this study due to the difficulty of collecting accurate energy demand data from them. These buildings will be good candidates to be connected to the microgrid in the future.

[40] https://www.ubu.es/english-version/courses-spanish-language-and-culture-foreigners/introduction

Image 3. Microgrid's Influence Area and Location of UBU’s buildings

Besides, it is a common practice in community energy systems to start engaging the highest energy consumer in the area and try to incorporate the rest of the users in successive stages, and that is precisely the approach this study will follow: only UBU’s buildings inside the influence area (dashed area in Image 3) have been considered.

22. Data Collection and Candidate Technologies Definition

The data collection stage requires intensive research on the existing facilities inside the influence area.

22.1. Energy Technologies Available in the Area.

Beyond the distribution power grid, owned and operated by Iberdrola Distribucion Electrica, all the distributed generation technologies available in any developed country are available in the area, such as, for example:

- Photovoltaic solar panels
- Wind power generators
- Natural gas and diesel power generators
- Combined Heat and Power (CHP) technologies
- Diesel, natural gas, propane, and biomass boilers
- Geothermal systems

However, some of these technologies cannot be considered due to different constraints:

- Several wind power plants surrounding the city of Burgos show the potential of this resource in the area, but the university is located in an urban area, and the urbanistic regulation limits the height of the new constructions. Other concerns, such as the noise levels, make this technology not good for this case study.

- Biomass is a popular fuel in the area, but there is no additional space available inside the mechanical rooms of the university, neither to expand them.
- Geothermal might be considered in the design of new buildings, but just for heating and cooling applications. There is not enough geothermal potential for power generation in the area.
- Currently, there are no economic incentives for the installation of renewable energy systems or other specific technologies.

22.2. Air Quality

The air quality indicators in 2018, presented in Table 15, shows 46 days with ozone values higher than the ones recommended by the World Health Organization. There are has no issues with PM10. PM2.5, NO_2 and SO_2 levels in the area so far . No constraints will be considered in that regard at the feasibility analysis level.

Table 15. Air Quality in Burgos in 2018. Source: Ecologistas en Accion[41]

Castilla y León 1/2

ZONA / AGLOMERACIÓN	SUPERFICIE	POBLACIÓN	ESTACIONES	PM10 (partículas menores de 10 micras) Valor diario — Nº días > 50 ug/m3 Normativa: máx=35 OMS: máx=3	PM10 Media anual — ug/m3 Normativa: máx=40 OMS: máx=20	PM2,5 (partículas menores de 2,5 micras) Valor diario (OMS) — Nº días > 25 ug/m3 OMS: máx=3	PM2,5 Media anual — ug/m3 Normativa: máx=25 OMS: máx=10	NO2 (dióxido de nitrógeno) Media anual — ug/m3 Normativa y OMS: máx=40	O3 (ozono troposférico) Octohorario (Normativa) — Nº días > 120 ug/m3 Normativa: máx=25	O3 Octohorario (OMS) — Nº días > 100 ug/m3 OMS: máx=25	O3 AOT40 (Normativa) — Normativa: máx=18000	SO2 (dióxido de azufre) Valor diario (OMS) — Nº días > 20 ug/m3 OMS: máx=3
AGLOMERACIÓN DE BURGOS	281	186.698	BURGOS 1 (PLAZA DE LOS LAVADEROS)	2	16			17				0
			BURGOS 4 (FUENTES BLANCAS)	1	15	0	5	8	7	46	nd	0
			MEDIA	**2**	**16**	**0**	**5**	**13**	**7**	**46**	**nd**	**0**

22.3. Existing Power supply and interval data

All the buildings are supplied of electricity by the local utility, Iberdrola Distribucion Electrica. The electric market is de-regulated, and UBU can choose its own Retail Electricity Provider (REPs). The buildings considered in this study are equipped with eight 20kV transformer centers owned and operated by UBU as described in Table 16.

Table 16. Transformers, Sizes, and Locations

	Facility	TRANSFORMERS AND SIZES
A	EPS D (POLITECNICA SAN AMARO)	2x630 KVAS
B	Fª DERECHO	1x630 KVAS
C	BIBLIOTECA	Supplied from Fª DERECHO
D	Fª HUMANIDADES Y EDUCACION	2x400 KVAS
E	POLIDEPORTIVO	Supplied from Fª HUMANIDADES
F	Fª ECONOMICAS Y EMPRESARIALES	1x1000 KVAS
G	Fª CIENCIAS Y TECNOLOGIA DE LOS ALIMENTOS	1x630 KVAS
H	I+D+I	1x630 KVAS
I	EDIFICIO DE SERVICIOS ADMINISTRATIVOS	2x630 KVAS

[41] https://www.ecologistasenaccion.org/wp-content/uploads/2019/06/informe-calidad-aire-2018.pdf

The location of the different transformer centers is presented in Image 4.

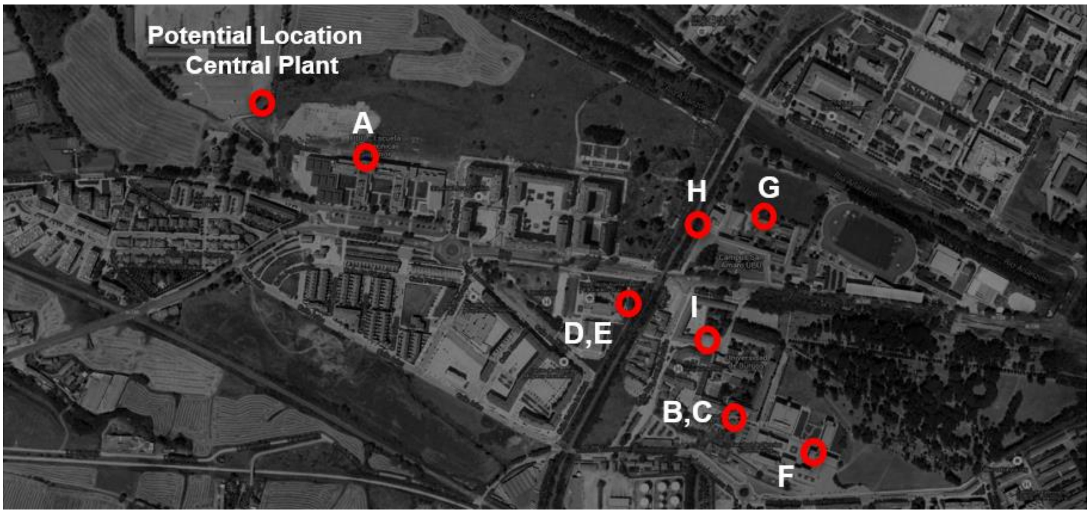


Image 4. Transformer Centers' Location, Nodes of the Potential Microgrid

The electricity bills and 15-minute interval data have been collected from the UBU. The annual electricity demand in 2015 was 5,347,781 KWh, with a cost of 610,289 euros before taxes, resulting in an average electricity price of 0.1141 euros per kWh. UBU has a three-period time-of-use tariff.

The monthly aggregated energy demand per buildings is presented in Figure 22.

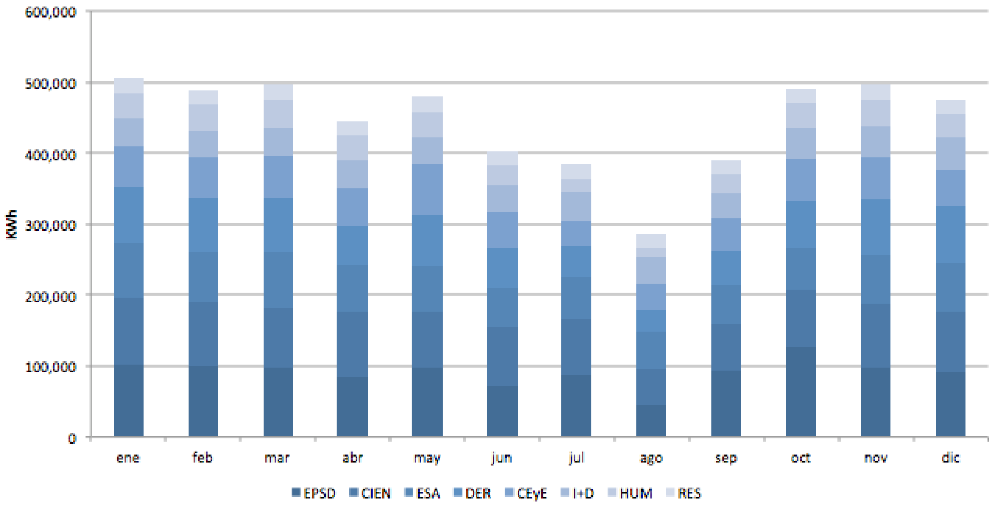


Figure 22. Electricity Demand per Building Aggregated per Month

The annual power demand oscillates between 1,821 and 244 KW. The maximum, average and minimum hourly values are presented in Figure 23.

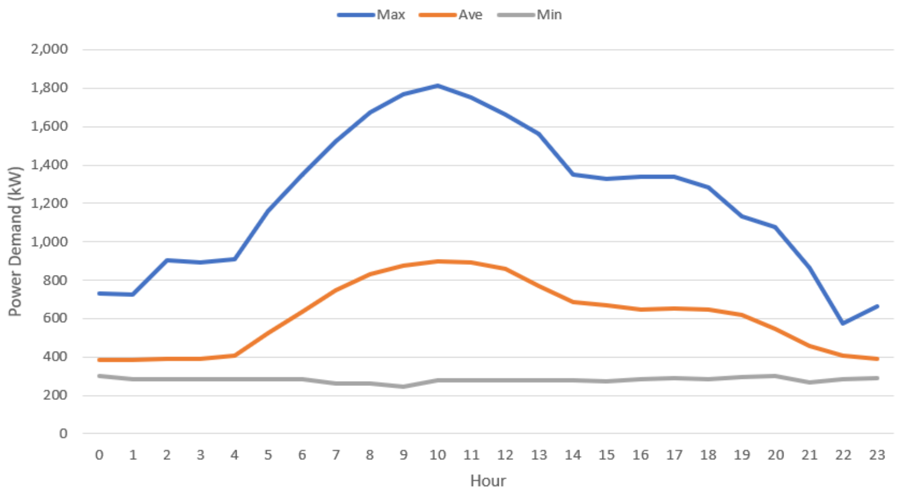


Figure 23. Aggregated Maximum, Minimum, and Average Power Demand.

The minimum hourly values are low for a set of nine buildings with so many different uses. The reason is that most of the buildings are closed to the public during August and come back to the normal schedule in September, and most of the minimum hourly values are from that month.

22.4. Existing Thermal Energy Supply and Demand Data

The thermal supply is decentralized. Each building has its dedicated thermal systems, as described in Table 17. The predominant heating technology is natural gas boilers, but there are also absorption and electric heat pumps. The Higher Polytechnic School, the Administrative Services Building, and the R&D building (I+D+i) are the buildings equipped with heat pumps.

Table 17. Thermal Energy Generation Systems per Building

	Facility	Technolgy	Capacity
A	EPS D (POLITECNICA SAN AMARO)	Absorption Heat Pump	2x969 KW Heating 2x1,160 KW Cooling
B	Fª DERECHO	Natural Gas Boiler	2x895 KW
C	BIBLIOTECA	Natural Gas Boiler	2x370 KW
D	Fª HUMANIDADES Y EDUCACION	Natural Gas Boiler	1x895 KW
E	POLIDEPORTIVO	Natural Gas Boiler	1x385 KW
F	Fª ECONOMICAS Y EMPRESARIALES	Natural Gas Boiler	2x460 KW
G	Fª CIENCIAS Y TECNOLOGIA DE LOS ALIMENTOS	Natural Gas Boiler	2x895 KW
H	I+D+I	Heat Pumps	96 KW Cooling
I	EDIFICIO DE SERVICIOS ADMINISTRATIVOS	Heat Pumps	875 KW Cooling

The local utility supplies natural gas to the individual buildings. The total annual natural gas consumption is 8,175,522 KWh with and annual cost before taxes of 515,525 euros. The average cost of natural gas is 0,063 euros per kWh.

The monthly aggregated thermal energy consumption per building is presented in Figure 24.

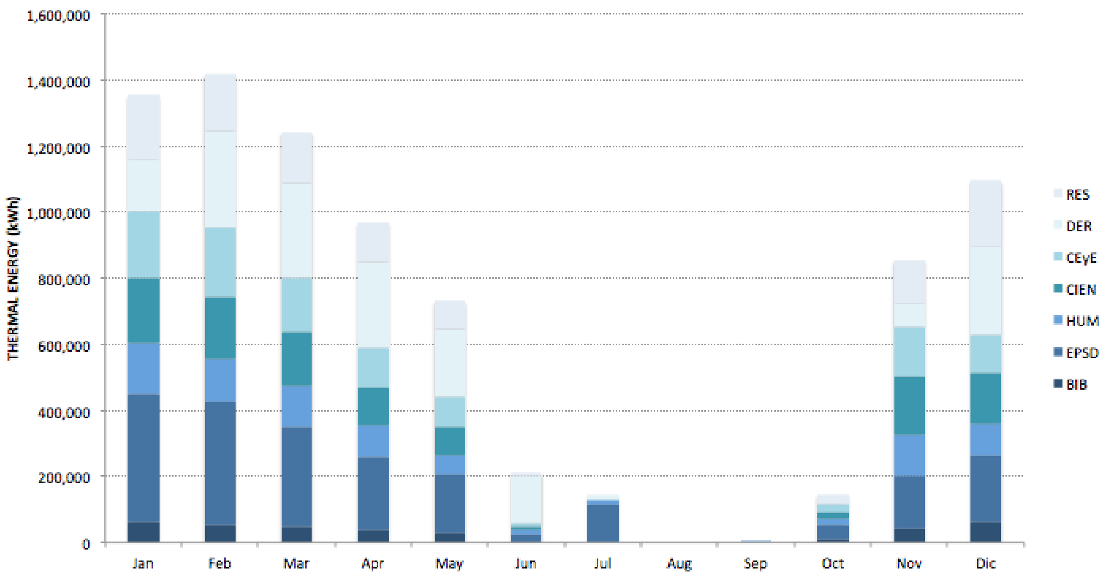


Figure 24. Thermal Demand per Building Aggregated per Month

The heating demand decreases considerably from June to October, reaching zero in August and values close to zero in September. Most of the buildings are closed to the public during August and come back to normal activity levels in mid or late September. The building with the highest thermal demand is the Higher Polytechnic School with 2,002,384 kWh per year.

22.5. Existing Energy Infrastructure

The area has an underground medium voltage distribution system (20 kV). The local utility has been able to share data on this and other existing underground facilities, including natural gas distribution pipelines, optic fiber, and other communication services, water supply, and sewerage systems. This information will be used to find out the routes available to connect the nodes of the microgrid.

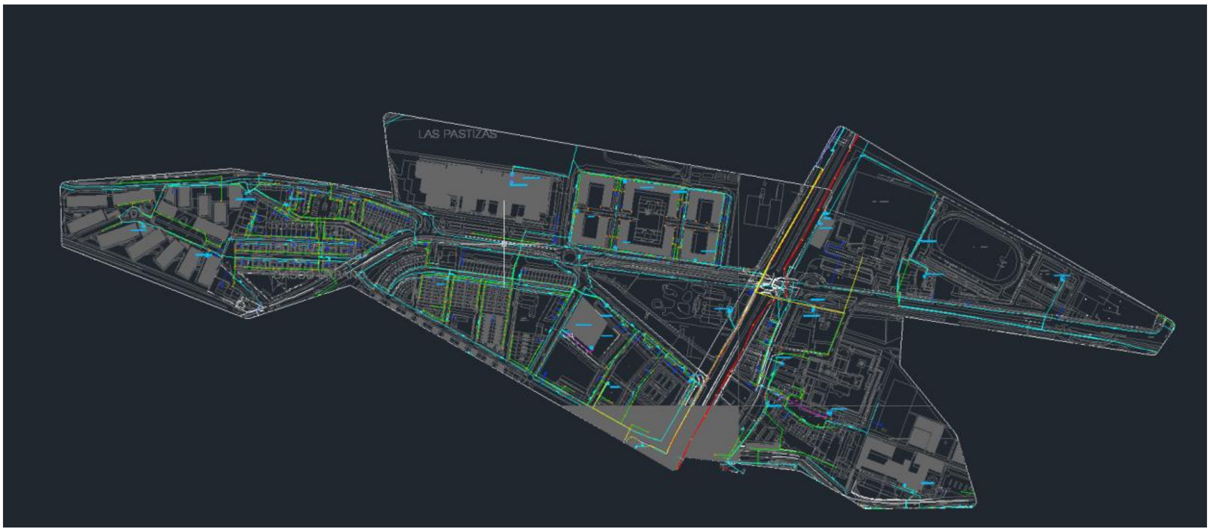


Image 5. Underground Facilities Map of the Influence Area. Source: Iberdrola Distribucion Electrica

22.6. Fuels Availability and Costs

Different fuels are available in the area such as diesel, natural gas (local utility), and biomass:

- Biomass will not be considered for this project due to the reasons mentioned in section 22.1.
- The average natural gas price for UBU has been calculated from the natural gas bills: 0.063 euros per kWh.
- The local price of diesel is 0.081 euros per kWh.

22.7. Space Availability

There is no available room in the existing buildings for new generation assets neither in the transformer centers nor in the mechanical rooms. Only the roof of the High Polytechnic School and its surroundings will be considered suitable for installing solar plants. Additional information is required to figure out if the structure would stand the weight of the panels in the rest of the buildings. Due to space availability, a potential new node has been defined in Image 3 as *Potential Location for Central Plant*.

22.8. Candidate Technologies (Search Space) Definition

Power generation Sizing and Scheduling. According to the energy and power capacity demand data presented above, the following set of power generation technologies and sizes will be considered for this project.

- Photovoltaic plants: 150, 300 and 450 kW
- Diesel generators: 400, 630, 1,000 kW
- Natural gas generators: 400, 630, 1,000 kW
- Combined Heat and Power, Reciprocating Engines: 299 kW, 635 KW, 847, KW, and 1,067 kW
- Power grid: 2,000 kW
- Battery storage will not be considered this time due to its high investment. In case CHP is selected as part of the potential design, a thermal storage tank will be customized for the hours of resilience defined for the project.

The following set of power distribution technologies and sizes will be considered for this case study.

- Substations. Due to the space constraints only one new substation will be considered. It will be located in the spot described in Image 3 as *Potential Location for Central Plant*. The minimum capacity required for the substation is 2.5 MVA.
- Transformer centers/Nodes. All the transformers in Table 17 have the same configuration: one input, one measurement, and one protection 20 kV gas-insulated switchgear. Different

microgrid configuration might require this configuration to be modified, including additional input or output switchgears per transformer center/node, but not the capacity or number of transformers per center. Every node will be treated as PQ (loads) except the potential central plant location, which will be considered as a node with voltage regulation capacity (PV). Interval data per existing node is collected and used as node power demand.

- Power lines. Five different wire sections have been considered for this problem: 70, 90, 120, 150, 240 mm^2. All these correspond to aluminum underground wire sizes normalized by the local utility. In addition to the sizes of the feeders, length has also been estimated, measuring one feasible path from each node to the rest, resulting in the following distances in kilometers.

Table 18. Distances Between Nodes in Kilometers

	SLACK New Subs	PQ EPSSAN	PQ I+D+I	PQ CIENCIAS	PQ ESA	PQ DRCHO	PQ CEyES	PQ HUMAN
Node	1	2	3	4	5	7	8	9
1		0.213	0.942	0.992	0.928	1.388	1.145	0.843
2	0.213		0.745	0.795	0.715	1.175	1.323	0.616
3	0.942	0.745		0.05	0.427	0.561	0.838	0.21
4	0.992	0.795	0.05		0.2	0.611	0.888	0.26
5	0.928	0.715	0.427	0.2		0.46	0.74	0.192
6	1.388	1.175	0.561	0.611	0.46		0.26	0.2
7	1.145	1.323	0.838	0.888	0.74	0.26		0.21
8	0.843	0.616	0.21	0.26	0.192	0.2	0.21	

23.Inputs Coding and Algorithms Execution Sequence

Genetic Algorithms are intuitive and effective when it comes to exploring the search space, allowing the user to ask different questions with minimum changes in the code. The number of scenarios modeled in this case studied will be defined by the number of times each algorithm is run. For this case study, the algorithms will be looking at eight different optimal solutions based on four different constrains and two additional solutions introduced by the user. They will be coded using the following constraints:

a. Maximum feeder size 150 mm^2: only 0 to 4 coding values allowed per line.
b. No constraints: Sum of all the values in the array different than zero.
c. *What is the best power generation technology mix considering Combined Heat and Power?* The addition of all the values in the array is different from zero, and the addition of the array positions from 10 to 13 is equal or higher than two.
d. Options minimizing local environmental emissions: PV and grid. The addition of all the values in the array is different than zero, the addition of the positions 1 to 3 is different than zero and position 14 equals to 1.

e. Islanded microgrid: the sum of all the values in the array is different than zero, and position 14 equal to 1.

f. Additional resilience: What is the cost of adding power capacity for additional reliability/resilience in case of a power blackout?

```
%% Resilience level
if sum(Yg.*Aux2)>RL*max(PdUBU)
correcto=1;
return;
end
```

g. Example of a customized solution to be benchmarked 1. *The shortest ring bus possible with the largest standard wire size allowed*

Zija=[4 0 0 0 0 4 0 0 0 4 0 0 0 4 0 0 0 4 0 4 0 0 0 0 4 4 0 0];

h. Example of customized solution to be benchmarked 2. *A design the investors or the engineering team might be interested in.*

Zija=[4 0 0 0 0 0 4 4 0 0 0 0 0 4 0 0 0 0 4 0 0 0 4 0 0 4 0 4];

i. Example of customized solution to be benchmarked 3. *How would a solution with three PV plants 150, 300 and 450 kW, a 1 MW natural gas, a 1MW diesel genset and the power grid would look like?*

Yg=[1 1 1 0 0 1 0 0 1 0 0 0 0 0 1];

j. Example of customized solution to be benchmarked 4. *How would a solution with three PV plants of 150, 300 and 450 kW, a 1 MW natural gas, a 1MW CHP system, and the power grid look like?*

Yg=[1 1 1 0 0 1 0 0 0 0 0 0 0 1 1];

The sequence the algorithm will follow in their execution is described in Figure 25.

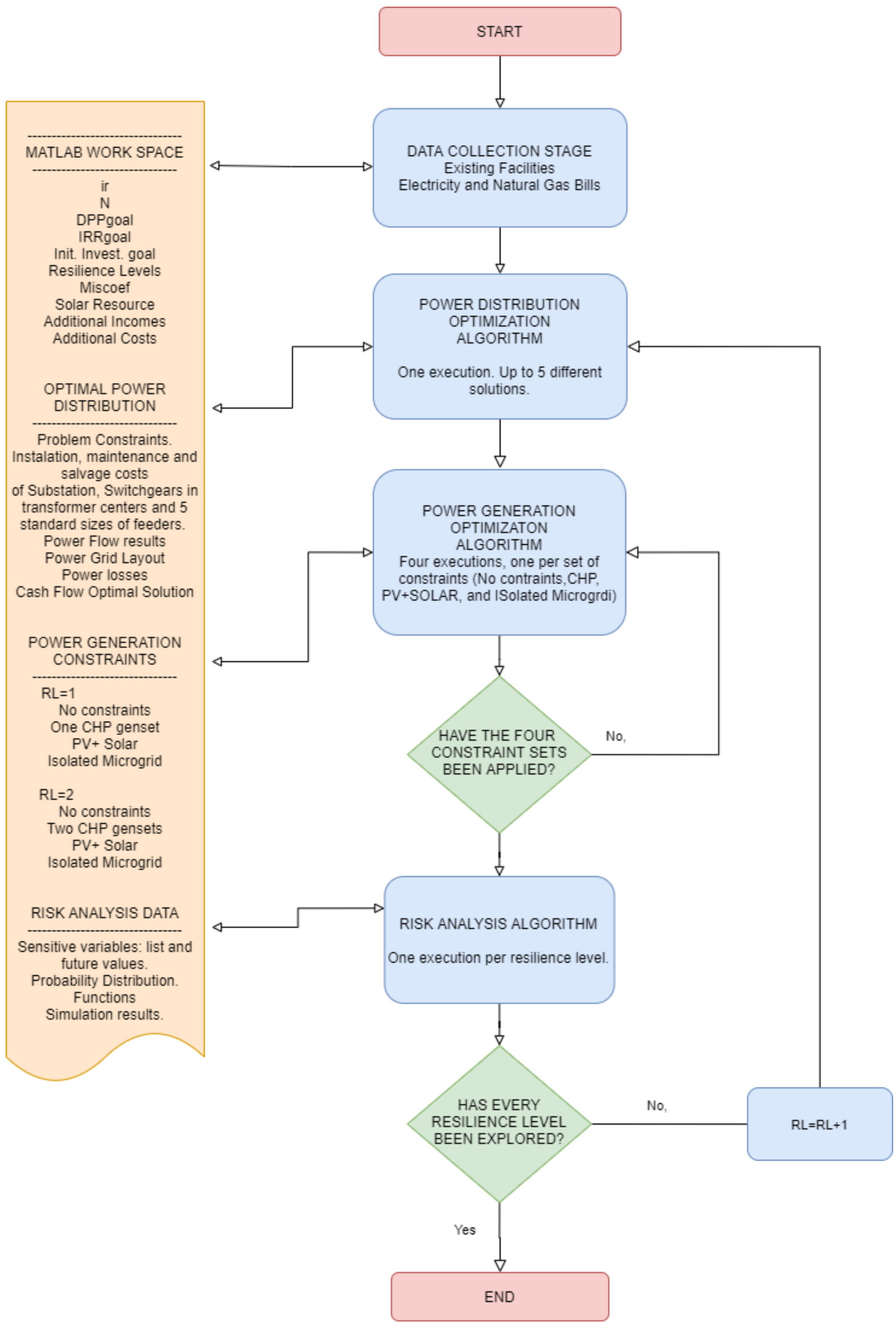


Figure 25. Sequence of Algorithms Executed in the Case Study

The specifications of the computer and MATLAB version used in the execution of these algorithms is presented below in Image 6.

Manufacturer:	Dell
Model:	Latitude E5470
Rating:	5,8 Your Windows Experience Index needs to be refreshed
Processor:	Intel(R) Core(TM) i5-6440HQ CPU @ 2.60GHz 2.60 GHz
Installed memory (RAM):	32.0 GB (31.7 GB usable)
System type:	64-bit Operating System

MATLAB

R2016B STUDENT LICENSE

Image 6. Specifications of the Computer and MATLAB License Used

24. Power Distribution System Sitting, Sizing and Scheduling

The power distribution optimization algorithm described in Chapter 3 has been adapted to accommodate a central plant in an additional node. The locations and sizes of the transformer centers operating inside the buildings presented in section 22 have also been considered. Besides the GA algorithm parameters described below, the most relevant inputs of the algorithm at this point are:

- Interest Rate (*ir*): defined by the investors, this value will be the same during the whole method.
- Lifespan of the project (N): will be considered as 25 years. Although the main infrastructure of the microgrid is designed to last at least 50 years, power generation technologies will need major investment after 25 years, or more effective technologies could replace them even before.
- *Power lines per node*: every node must be connected by at least one power line and by a maximum of four. There is not enough room in the transformer centers to accommodate more than three additional medium-voltage switchgears.
- *Maximum cable size*, the maximum cable size allowed will be 150 mm^2. Underground 240 mm^2 aluminum cables are hard to install un urban environments. That is the reason why they are usually avoided for these applications.
- *Radial Index*, the maximum number of power lines in the system has been set to 11 in order to expedite the execution time of the algorithm. The rationale behind this reduction is that the shorter the grid, the lower the power losses and the installation costs.

For this input parameters and constraints, the length of the vector describing a solution will be the maximum number of power lines for an 8-node grid calculated according to the following formula:

$$MaxPL = \sum_{i=1}^{8}(8-i) = \frac{8^2-8}{2} = 28\, power\ lines$$

The standard feeder sizes allowed are 0, 70, 90, 120, and 150mm^2. Different cables can have the same size, and all sizes are allowed for all cables. The size of the search space will be simplified by reducing the maximum number of power lines from 28 to 11 and the cable sizes allowed, from 6 to 5, and calculated as follows:

$$Search\ Space\ Size = 5^{11} = 48{,}828{,}125\ alternatives$$

24.1. GA Parameters Configuration and Performance

The configuration parameters of a GA are the number of generations, population size, and crossover and mutation rates. However, the user could not be familiar with how to configure a GA. In this case, different values have been tested for these parameters in order to find a trade-off solution between accuracy and limited execution time. As mentioned in sections 2 and 3, heuristic algorithms cannot guarantee they always find the optimal solution. The optimal parameters of a GA depend on the specific problem. Some authors have proposed different methods to estimate the best parameters [42], but a sensitivity analysis is a simple and commonly accepted way to identify the values for the number of generations, size of the population, crossover, and mutation rates. Once the problem is coded in the algorithm, the user carries out multiple runs of the algorithms with different values comparing the outcome. The results have been benchmarked based on the best solution found by the algorithm (maximum Present Value) and presented in Table 19

Table 19. GA Performance of MATLAB code for Power Distribution System Optimization

Dev percent %	Generations	Population Size	XORrate %	MUTrate %	**Evaluations** Times	**Exec. Time** Seconds	**Per Eval** Seconds
0%	30	100	16	4	**1,266**	**2,572**	**2.03**
-4%	50	100	4	16	**2,158**	**4,333**	**2.01**
-6%	50	100	16	4	**2,110**	**4,261**	**2.02**
-7%	50	100	16	4	**2,064**	**4,151**	**2.01**
-8%	30	100	16	4	**1,328**	**2,673**	**2.01**
-9%	15	60	10	4	**344**	**983**	**2.86**
-10%	10	60	10	4	**222**	**634**	**2.86**
-10%	50	100	4	16	**1,992**	**4,008**	**2.01**

A higher value for the population size would guarantee that a higher number of potential solutions are included in the initial population. However, the higher the number, the longer it would take for the algorithm to complete the initial population. A higher number of generations would increase the total execution time, but it would also help the algorithm to find the best solutions in the search space.

In GA, mutation operators are used to providing exploration, and cross-over operators are used to leading the population to convergence on the optimal solutions. Consequently, while crossover tries to converge to a specific point of the search space, the mutation does its best to avoid convergence and explore more areas[43]. Thus, high mutation rates combined with low crossover rates would reduce the search ability of the GA to a simple random selection. On the other hand, high crossover rates combined with low mutation rates would result in premature convergence of the algorithm, identifying local optimums as the global optimum.

In this specific problem, the evaluation of the fitness function takes around two seconds. The total number of executions of the fitness function is highly dependent on the population size, the number of generations, the crossover, and mutation rates. It is common practice in the industry that after a feasibility analysis level, the initial design is refined in an investment-grade audit and in the

[42] http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.423.586&rep=rep1&type=pdf

[43] https://www.researchgate.net/post/Why_is_the_mutation_rate_in_genetic_algorithms_very_small

engineering studies. That means accuracy is important, but a trade-off solution between accuracy and execution time is a proper criterion to follow.

As seen in Table 19, crossover rates of 16% and mutation rates of 4% are the best combination. The algorithm has proven to be capable of finding good results in 30 generations. Running the algorithm for 50 generations will almost double the execution time. Populations under 60 individuals seem to generate higher deviations from the best-identified solutions. The final parameters for this algorithm are selected among the options studied in Table 19, considering a trade-off solution between accuracy and execution time:

- Generations: 30
- Population Size: 100
- Crossover Rate: 16%
- Mutation rate: 4%

As shown in Figure 26, the value of the fitness function has been improved four times during the 30 generations for a cost of 1.1 million euros.

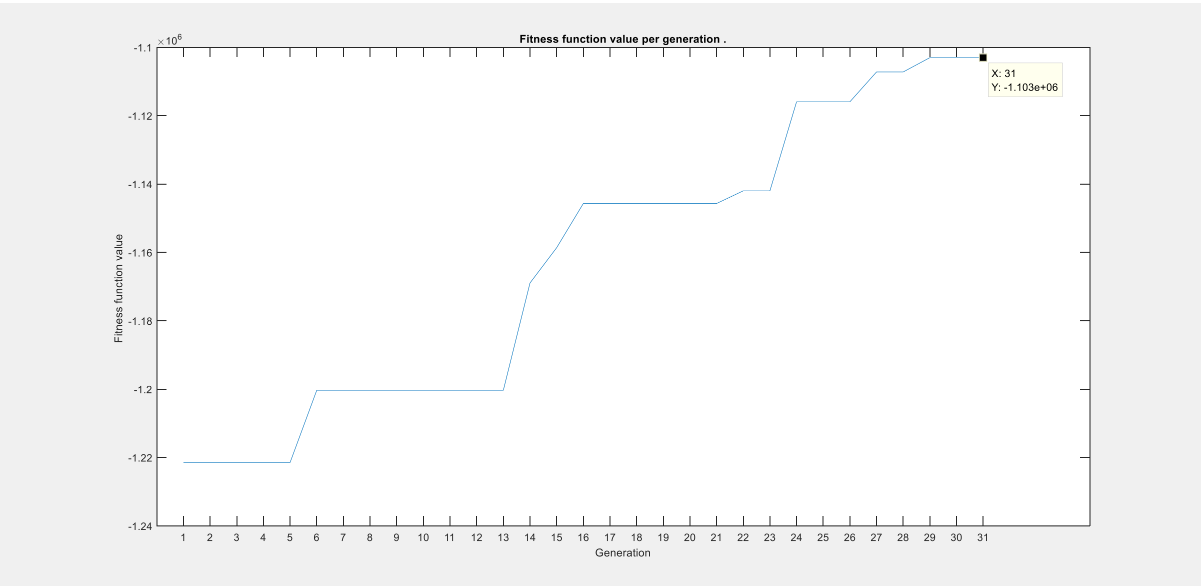


Figure 26. Evolution of the Fitness Function Value for the Power Distribution Grid Optimization Problem

The MATLAB script has performed 1,328 fitness function evaluations in 2,631 seconds. The execution time is reduced to half once the code is specifically compiled for Windows 64-bit architectures. A compiled version of the code is estimated to reach a solution in 22 minutes for this algorithm.

24.2. Algorithm Results

As described in Figure 6, the algorithm has found one optimal solution to the problem with a fitness function value of 1,103,032 euros

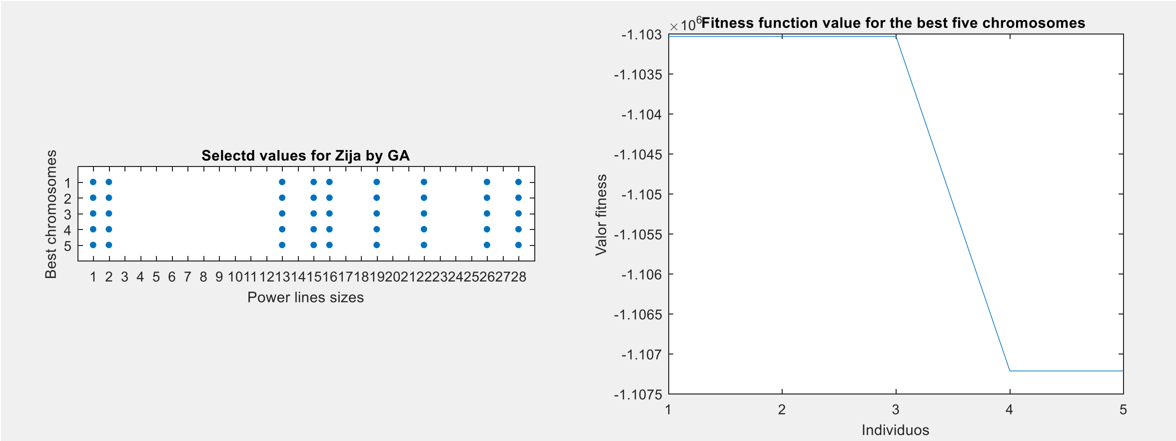


Figure 27. Best Five Solutions of the Power Grid Optimization Algorithm

The optimal solutions' codes and layouts are presented below and in Image 7.

Pgrid Opti1= [4 4 0 0 0 0 0 0 0 0 0 0 4 0 2 2 0 0 2 0 0 2 0 0 0 3 0 3]

Pgrid Opti2= [4 4 0 0 0 0 0 0 0 0 0 0 4 0 4 2 0 0 2 0 0 2 0 0 0 3 0 3]

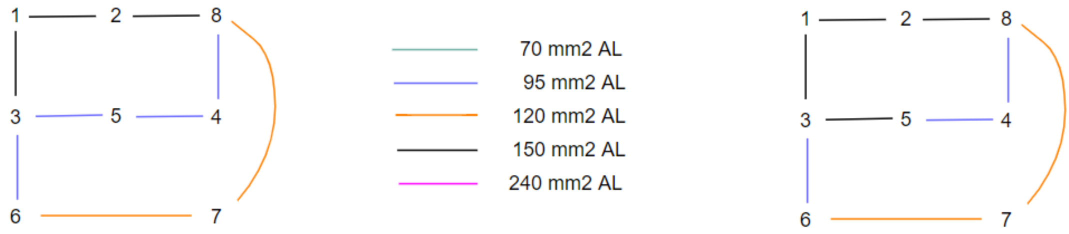


Image 7. Optimal Power Dristribution Grid Layouts

The selected layout is a meshed power grid with the same number of power lines, and just one difference: the size of the feeder connecting nodes 3 and 5. Out of the 9 power lines forming these microgrid, the maximum allowed feeder size in recommended for two of them and 120 mm^2 is the size chosen for another three or four. This solution fulfills the technical constraints of the problem. Table 20 present the main economic indicators of the optimal solution.

Table 20. Economic Indicators of the Optimal Power Grid Layouts

	Present Value KPI (€)	Present Value (€)	PW Losses
Pgrid Opti1	1,103,033 €.	1,041,846 €	57,664
Pgrid Opti2	1,107,212 €.	1,049,716 €	54,193

Present Value KPI is the indicator used to benchmark the alternatives. The main difference between *Present Value KPI* and *Present Value* is the cost of power losses incurred through the lifespan of the project. Including power losses in the fitness function is critical because otherwise, the algorithm would always select the smallest feeders due to its lower costs. Additional outputs of this algorithm are included in the Appendix.

25. Power Generation and Thermal Storage Technology Selection, Sizing and Scheduling

The code of the algorithm has been adapted to the specific conditions of this project, such as the installation of a central substation and the lack of room for installing other equipment than additional switchgear in the transformer centers, if needed. The problem is then limited to select, size and schedule power generation technologies.

Fourteen generators have been pre-selected and modeled. The search space will be formed by strings of 14 binary values, with zero meaning a generator is not considered and 1 meaning that the generator is included in that specific solution.

Table 21. Codification of the Power generation Technologies in the Solution

[1 0 0 0 0 0 0 0 0 0 1 0 0 0 1]

Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Technology	PV PLANT	PV PLANT	PV PLANT	NG Genset	NG Genset	NG Genset	Diesel Gen.	Diesel Gen.	Diesel Gen.	CHP	CHP	CHP	CHP	Pow. Grid
Size	150 KW	300 KW	450 KW	400 KW	630 KW	1000 KW	400 KW	630 KW	1000 KW	299 KW	635 KW	847 kW	1067 KW	2000 KW

The size of the search space will be determined by the following formula:

$$2^{14} = 16{,}384 \; alternatives$$

Besides the GA algorithm parameters defined in the next section, the most relevant inputs of this algorithm are:

- Interest Rate (ir): defined by the investors, this value will be the same during the whole method.
- Lifespan of the project (N): will be considered 25 years. Although the main infrastructure of the microgrid is designed to last at least 50 years, power generation technologies will need a significant investment after 25 years, or more effective technologies could replace them before 25 years.
- *Hourly power demand at the central plant node* calculated in the previous algorithm. It includes power distribution losses.
- *Resilience Level (RL)*: For energy generation, the resilience level will influence the maximum capacity installed in the system and the usage of the thermal storage tank.

- ✓ RL=1 means the generation capacity installed must be higher than the maximum demand and no thermal storage tank is considered. Power generation by CHP is limited by thermal demand.
- ✓ RL=2 means the generation capacity installed must be at least twice the maximum demand and a thermal storage tank will be installed. CHP will be allowed to run when there is no thermal demand by storing the excess thermal in the tank.

- Thermal storage size: power outages are not frequent in the area, and investment in resilience need to make sense. The tank is sized by the algorithm with enough capacity to cover the highest 8-hour thermal demand of the year. A tank will only be size when CHP is part of the solution.
- Initial investment: the out-of-pocket money the investors are willing to contribute with. A bank loan should be obtained for the rest of the investment, if any.
- IRR Goal: Internal rate of return defined by the investors as one of the thresholds to pass the feasibility analysis.
- DPP Goal: Discounted Payback Period defined by the investors as one of the thresholds to pass the feasibility analysis.

25.1. Genetic Algorithm Parameters Configuration and Performance

As discussed before, the main parameters of a genetic algorithm are the number of generations, population size, and crossover and mutation rates. Different values have been tested for these parameters searching for the fastest and closest value to the optimal solution. Results have been benchmarked based on the maximum Present Value found by the algorithm and presented in Table 22

Table 22. GA Performance of MATLAB Script for Power generation Sizing and Scheduling

Dev percent	Generations	Population	XORrate	MUTrate	**Evaluations**	**Exec. Time**	**Per Eval**
%		Size	%	%	Times	Seconds	Seconds
0%	15	60	4	10	**292**	**6,661**	**22.8**
0%	15	75	5	3	**269**	**6,347**	**23.6**
-1%	15	75	5	3	**269**	**6,238**	**23.2**
-1%	30	50	5	3	**278**	**6,921**	**24.9**
-1%	30	50	5	3	**344**	**8,422**	**24.5**
-1%	45	60	5	3	**530**	**12,075**	**22.8**
-1%	5	100	5	3	**178**	**4,614**	**25.9**
-1%	5	100	10	4	**274**	**6,647**	**24.3**

While the evaluation of the fitness function takes around 24 seconds, the number of executions of the fitness function is highly dependent on the population size, the number of generations, the crossover and mutation rates. As described in section 24.1, the parameters of genetic algorithms depend on the specific problem. As mentioned before, some authors have proposed different methods to estimate the best parameters, but a sensitivity analysis is a simple and commonly accepted way to identify the values for the number of generations, size of the population, crossover, and mutation

As discussed before, at a feasibility level finding the solution closest to the global minimum is important, but a trade-off solution between accuracy and execution time is the best criteria to follow when it comes to exploring large search spaces for the first time. According to the results in Table 22, the deviation of the results for different configurations are low. A mutation rate of 10% can provide similar solutions than mutation rates of 3% with bigger population sizes (75 instead of 60), resulting into similar execution times. However, populations of 75 with low mutation and crossover rates are more frequent among the best results. The final values selected for the parameters of this algorithm are:

- Generations: 15
- Population Size: 75
- Crossover Rate: 5%
- Mutation rate: 3%

The same algorithms will be run under different constraints for a resilient and a no resilient design, following the execution sequence described in Chapter 3, and resulting in eight potential solutions. The performance of the algorithm is similar in both cases, as shown in Tables 23 and 28 and Figures 28 and 34. As shown in Figure 28, the value of the fitness function has been improved from zero to four times per solution, identifying optimal values from 8.22 to 8.86 million euros.

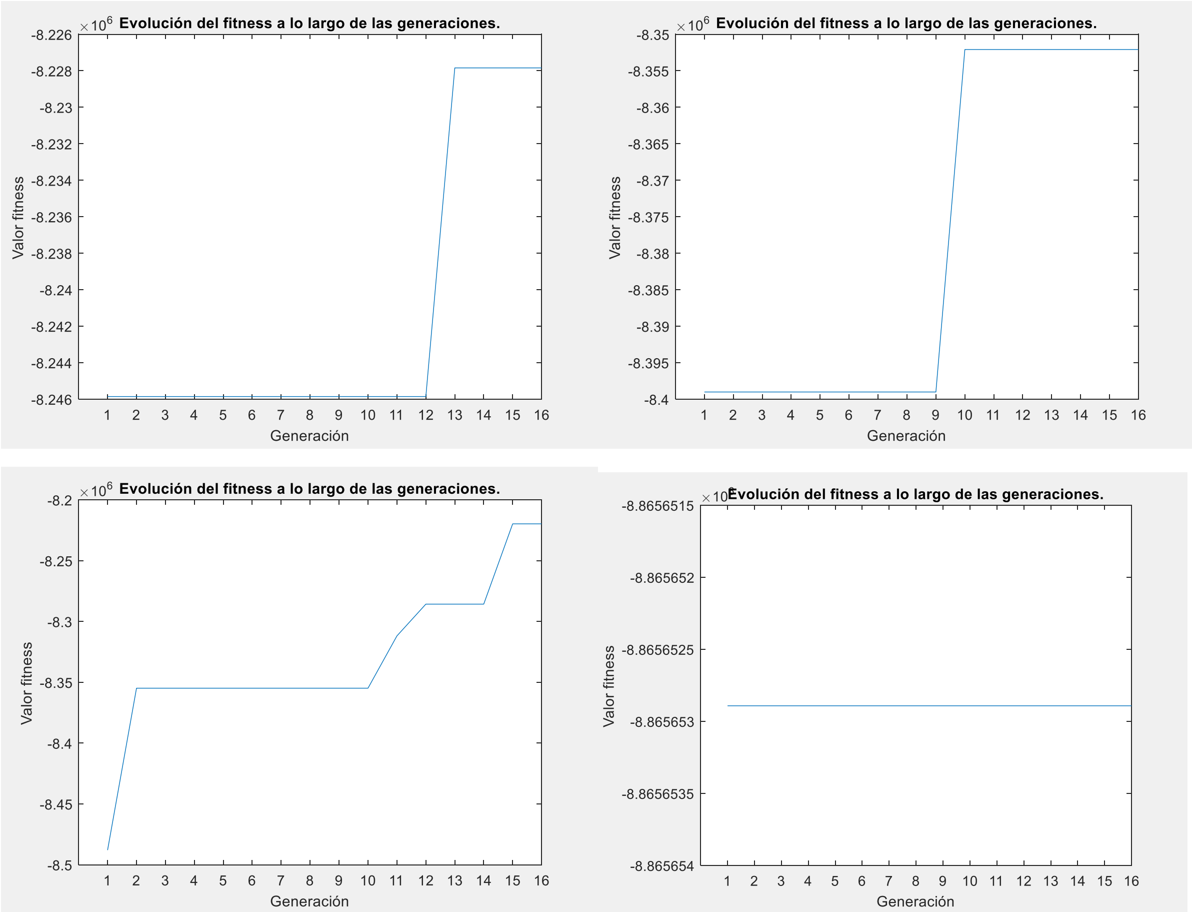


Figure 28. Fitness Function Value Evolution for No Additional Resilience Alternatives

The execution times presented in Table 9 oscillate between 6,675 and 5,040 seconds for a number of executions between 279 and 243, respectively.

Table 23. Optimization Algorithms Performance for the No Additional Resilience Case

	NO ADDITIONAL RESILIENCE					
	Power Dist.	**Pow. Gen. No Constraint**	**Pow. Gen. CHP**	**Pow. Gen. PV + Grid**	**Pow. Gen. Isolated MG**	**TOTAL**
Total Execution Time (secs)	2,631	6,675	4,881	5,040	5,061	24,288
Number of executions	1,304	279	243	254	256	2,336
Per Annual Solution (secs)	2.02	23.92	20.09	19.84	19.77	
Per Hourly Interval (secs)	0.00023	0.00273	0.00229	0.00227	0.00226	

The aggregated execution time of the MATLAB code for all the optimization algorithms is 6.75 hours (24,288 seconds). However, one compiled for a Windows 64-bit architecture, the time to evaluate the fitness function is reduced to a half. That means the time to explore 1,033 alternatives can be reduced to less than 3.4 hours using a laptop computer with the specifications described in Image 6.

25.2. Algorithm Results: No Additional Resiliency

Figures 29 to 32 present the results of the optimization algorithm for the four different constraint sets. These results are de-coded below in Table 24.

Table 24. No Additional Resilience Solutions per Constraint

Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Technology	PV PLANT	PV PLANT	PV PLANT	Diesel Gen.	Diesel Gen.	Diesel Gen.	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Pow. Grid
Size	150 KW	300 KW	450 KW	400 KW	630 KW	1000 KW	400 KW	630 KW	1000 KW	299 KW	635 KW	847 kW	1067 KW	2000 KW
No Constraint	X													X
2 CHP Systems	X		X		X					X				X
PV+Grid	X				X					X				X
Isolated MG			X		X	X				X				

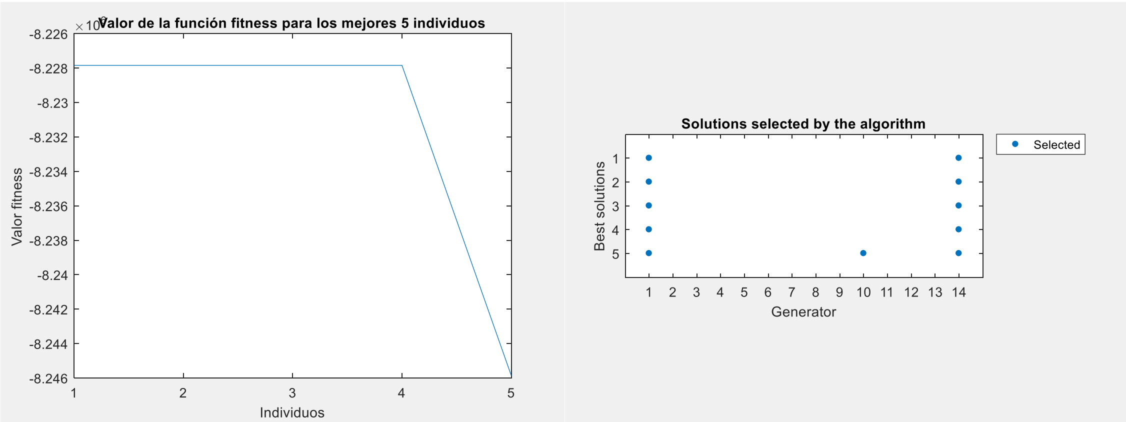


Figure 29. Fitness Functions and Generators of the Five Best Solutions. No Constraints

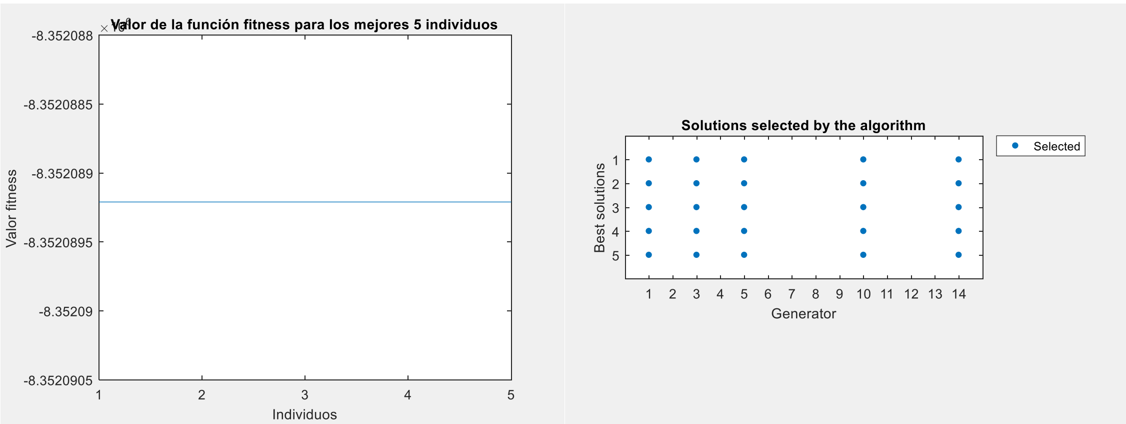


Figure 30. Fitness Functions and Generators of the Five Best Solutions. CHP Constraint

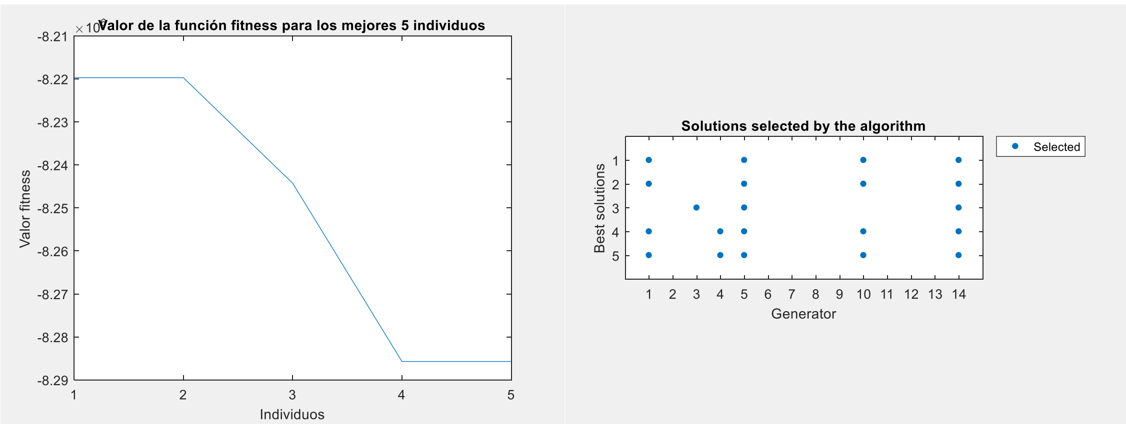


Figure 31. Fitness Functions and Generators of the Five Best Solutions. PV + Grid Constraint

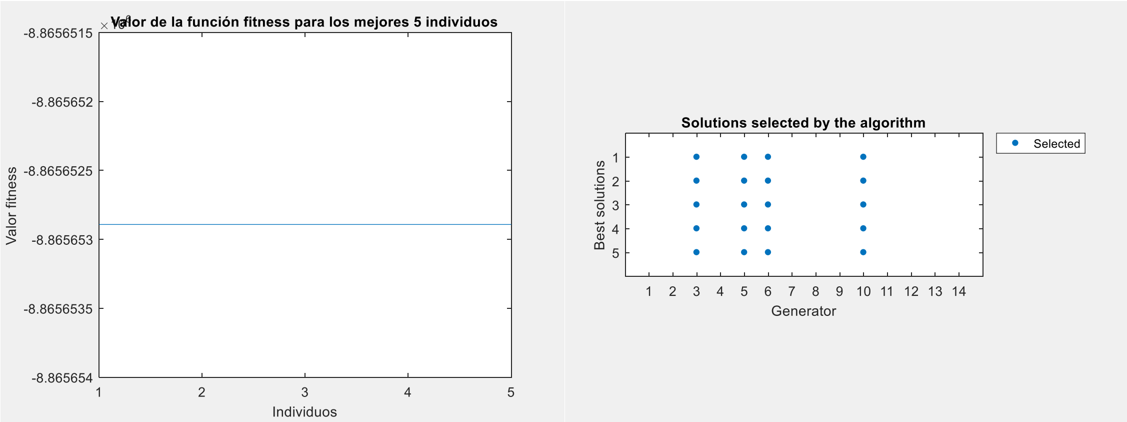


Figure 32. Fitness Functions and Generators of the Five Best Solutions. Isolated MG Constraint

The profitability of these solutions, identified as optimal by the algorithms, is revealed when compared with the current costs of the power supply, as described in section 3. As presented in Table 25, the four solutions have a positive Net Present Value, which means they are more profitable than the existing power supply. Payback periods of the solutions with a positive NPV oscillate between 7.89 and 21.66 years.

Table 25. Summary of Key Economic Indicators of the Algorithm per Solution: No Additional Resilience

	No Constraint		One CHP System		PV+GRID		ISOLATED GRID	
Initial Invest.	€	(1,185,224)	€	(2,870,338)	€	(2,129,473)	€	(2,875,449)
Loan	€	-	€	-	€	-	€	-
Annual Savings	€	215,666	€	320,048	€	266,720	€	242,767
NPV	€	1,620,403	€	1,314,323	€	1,429,930	€	238,671
IRR		17.93%		10.25%		11.98%		6.75%
DPP		7.89		14.43		12.34		21.66
Equiv. Annuity	€	236,962	€	353,435	€	300,626	€	263,018

Different technical indicators have been presented per solutions in Table 26 and Figure 33. The fraction of energy produced by renewable energy or the environmental emissions can help identify which option is the one with the lowest environmental impact, for example.

Table 26. Summary of Key Technical Indicators Per Optimal Solution: No Additional Resilience

		No Constraint	At least 1 CHP	PV+Grid	Isolated MG
Demand	kWh	5,397,863	5,397,863	5,397,863	5,397,863
Generated ON site	kWh	258,907	1,789,994	1,147,472	5,397,863
From the Utility	kWh	5,138,956	3,607,869	4,250,391	-
Renewable Fraction	%	4.8	19.2	4.8	14.4
Environ. Emissions	TnCo2	1,233	1,624.0	1,877	3,761
Onsite Fuel to Power Eff	kWhe/kWh Fuel (%)	Inf	89%	48%	43%
Energy to Fuel Ratio	Kwhe+th/kWH Fuel	Inf	2.95	2.50	0.54
LCOE	$ per kWh	0.103	0.081	0.091	0.087
Breakeven Point	kWh	5,972,218	7,615,200	6,780,066	7,087,687

Other indicators of Table 26 provide additional insights about the solutions, such as the:

- *Onsite Fuel to Power Efficiency (%)*, which presents the aggregated efficiency of the on-site generation.
- *Energy to Fuel ratio (kWh/kWh)*, which presents the ratio between the total energy generated by the microgrid (thermal energy plus electricity) and the fuel burned onsite.
- *Breakeven Point (kWh),* which shows how much energy would each solution generate to even the annual cost of the existing system.

The fifteenth column in each chart of Figure 33 represents the thermal energy generated by the existing broilers to meet the thermal demand. Those solutions with more active CHP systems will require less support from the existing boilers.

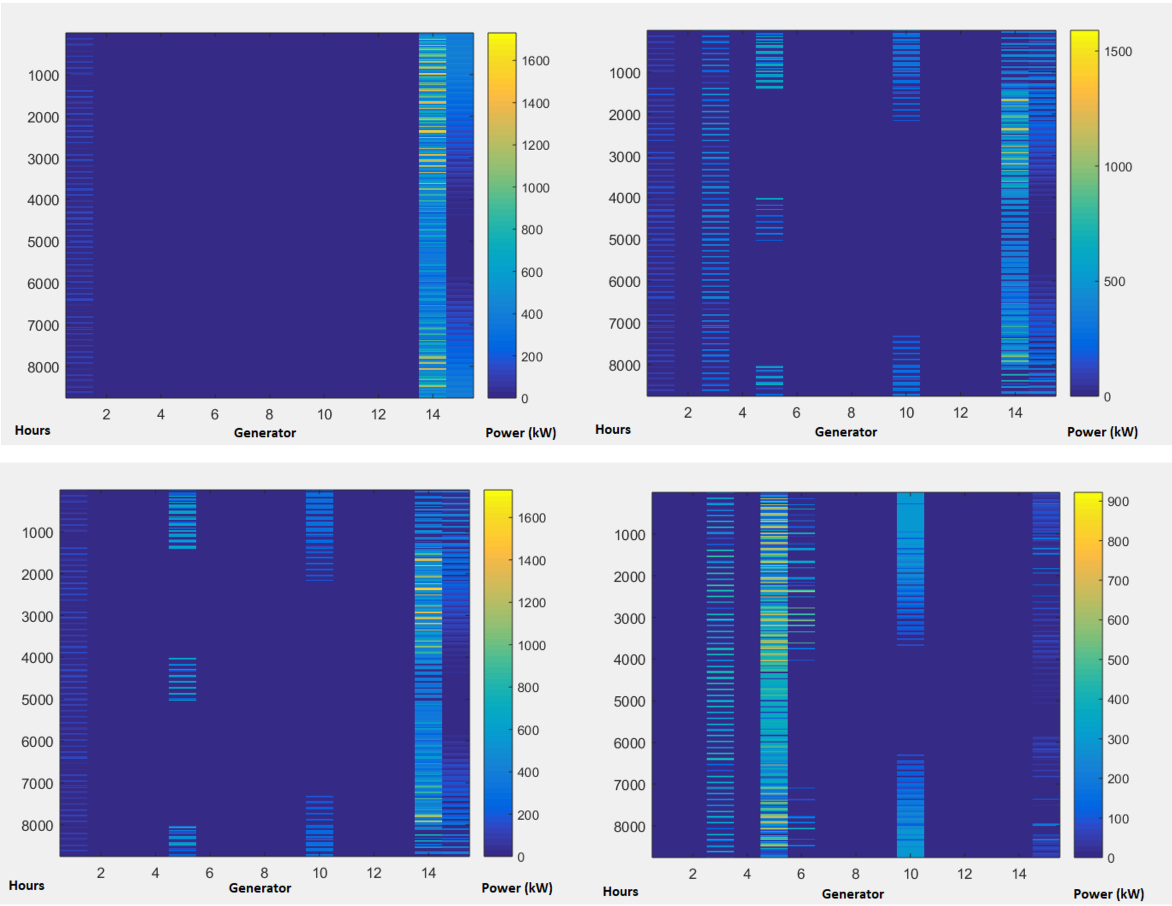


Figure 33. Annual Hourly Schedule Per Generator and No Additional Resilience cases, in KW

Table 27 presents the values of the technical indicators developed per generator. When allowed in the solution, the power grid supplies from 67 to 95% of the energy demanded by the UBU. All the different technologies have been selected at least once in the four solutions.

Table 27. Key Technical Performance Indicators per Generator

NO CONSTRAINTS	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	2,000
Max. Capacity (kW)	150	-	-	-	-	-	-	-	-	-	-	-	-	1,731
Ave. Capacity (kW)	58	-	-	-	-	-	-	-	-	-	-	-	-	587
Annual Operating hours	4,484	-	-	-	-	-	-	-	-	-	-	-	-	8,760
Lifespam Based on Operating Hours (Years)	39	-	-	-	-	-	-	-	-	-	-	-	-	34
Starts	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Energy generated (kWh per year)	258,907	-	-	-	-	-	-	-	-	-	-	-	-	5,138,956
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Fuel (kWh per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	
Efficiency (%)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	1,233

COMBINED HEAT AND POWER	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	2,000
Max. Capacity (kW)	150	-	450	-	630	-	-	-	-	299	-	-	-	1,589
Ave. Capacity (kW)	58	-	173	-	384	-	-	-	-	262	-	-	-	461
Annual Operating hours	4,484	-	4,484	-	798	-	-	-	-	1,795	-	-	-	7,823
Lifespan Based on Operating Hours (Years)	39	-	39	-	165	-	-	-	-	98	-	-	-	38
Starts	-	-	-	-	448	-	-	-	-	313	-	-	-	506
Energy generated (kWh per year)	258,907	-	776,721	-	283,477	-	-	-	-	470,889	-	-	-	3,607,869
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	538,608	-	-	-	-
Fuel (kWh per year)	-	-	-	-	778,482	-	-	-	-	1,236,280	-	-	-	
Efficiency (%)	-	-	-	-	36.4%	-	-	-	-	81.7%	-	-	-	-
Env. Emmisions (Tons of CO2 per year)	-	-	-	-	195	-	-	-	-	563	-	-	-	866

PV + GRID	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	2,000
Max. Capacity (kW)	150	-	-	-	630	-	-	-	-	299	-	-	-	1,731
Ave. Capacity (kW)	58	-	-	-	446	-	-	-	-	269	-	-	-	517
Annual Operating hours	4,484	-	-	-	905	-	-	-	-	1,806	-	-	-	8,222
Lifespan Based on Operating Hours (Years)	39	-	-	-	145	-	-	-	-	97	-	-	-	36
Starts	-	-	-	-	450	-	-	-	-	301	-	-	-	312
Energy generated (kWh per year)	258,907	-	-	-	403,409	-	-	-	-	485,156	-	-	-	4,250,391
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	554,927	-	-	-	-
Fuel (kWh per year)	-	-	-	-	1,107,840	-	-	-	-	1,273,736	-	-	-	-
Overall kWH to Fuel Ratio (%)	-	-	-	-	36.4%	-	-	-	-	81.7%	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	277	-	-	-	-	580	-	-	-	1,020

ISLANDED MICROGRID	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	2,000
Max. Capacity (kW)	-	-	450	-	630	922	-	-	-	299	-	-	-	-
Ave. Capacity (kW)	-	-	173	-	361	124	-	-	-	213	-	-	-	-
Annual Operating hours	-	-	4,484	-	8,561	3,021	-	-	-	5,419	-	-	-	-
Lifespan Based on Operating Hours (Years)	-	-	39	-	15	43	-	-	-	32	-	-	-	-
Starts	-	-	-	-	138	846	-	-	-	174	-	-	-	-
Energy generated (kWh per year)	-	-	776,721	-	3,093,642	372,078	-	-	-	1,155,421	-	-	-	-
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	1,321,585	-	-	-	-
Fuel (kWh per year)	-	-	-	-	8,495,750	1,018,444	-	-	-	3,033,464		-	-	-
Efficiency (%)	-	-	-	-	36.4%	36.5%	-	-	-	81.7%	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	2,124	255	-	-	-	1,382	-	-	-	-

25.3. Algorithm Results for the Additional Resilience Case

This section evaluates the performance of the power generation optimization algorithm for the additional resilience case and its solutions. As shown in Figure 34, the costs calculated for the optimal solutions oscillate between 8.05 and 9.09 million euros. The full set of charts and tables presenting the technical indicators of the solutions is available in the Appendix.

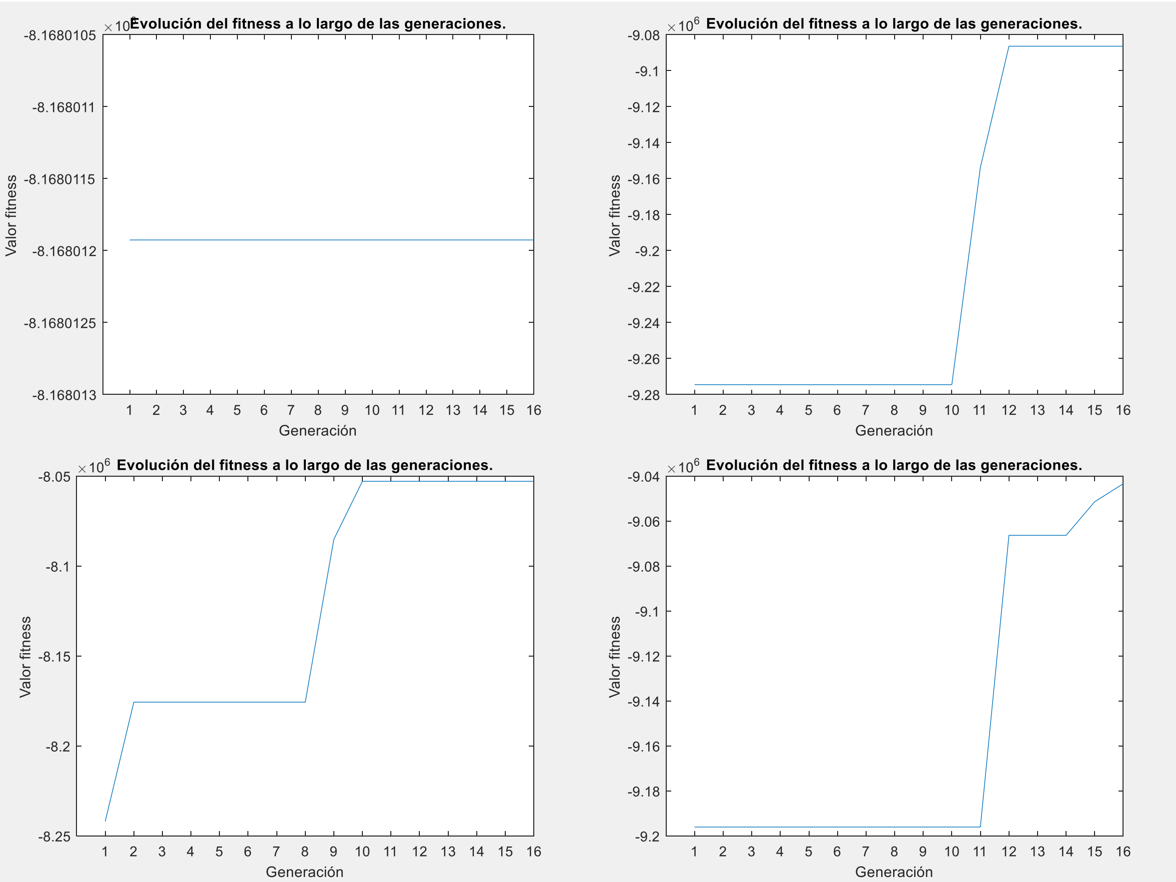


Figure 34. Fitness Function Values Evolution for Additional Resiliency Alternatives

Execution times presented in Table 28 oscillate from 4,529 to 6,465 seconds for a number of executions between 228 and 278, respectively.

Table 28. Optimization Algorithms Performance for the Additional Resilience Alternatives

	ADDITIONAL RESILIENCE					
	Power Dist.	Pow. Gen. No Constraint	Pow. Gen. CHP	Pow. Gen. PV + Grid	Pow. Gen. Isolated MG	TOTAL
Total Execution Time (secs)	2,631	4,529	6,465	5,583	5,220	24,428
Number of executions	1,304.00	228	278	236	264	
Per Annual Solution (secs)	2.02	19.86	23.26	23.66	19.77	
Per Hourly Interval (secs)	0.00023	0.00227	0.00265	0.00270	0.00226	

The average execution time per annual solution is 21.6 seconds. The aggregated execution time of the MATLAB code for all the optimization algorithms is 6.79 hours (24,428 seconds). Once compiled for a

Windows 64-bit architecture, the time to assess the fitness function 980 times is reduced to a half (3.39 hours) using the same computer.

The generators selected per solution are presented in Table 29 and Figures 35 to 38. More or bigger generators are selected per solution than in the no resilience case, as it could be expected when the strategy to achieved resilience is to install additional power generation assets.

Table 29. Solutions Selected by the Algorithm for the Additional Resilience Alternatives

Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Technology	PV PLANT	PV PLANT	PV PLANT	Diesel Gen.	Diesel Gen.	Diesel Gen.	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Pow. Grid
Size	150 KW	300 KW	450 KW	400 KW	630 KW	1000 KW	400 KW	630 KW	1000 KW	299 KW	635 KW	847 kW	1067 KW	2000 KW
No Constraint	X	X			X			X						X
2 CHP Systems				X	X					X	X			X
PV+Grid			X		X	X								X
Isolated MG	X	X		X	X	X			X	X				

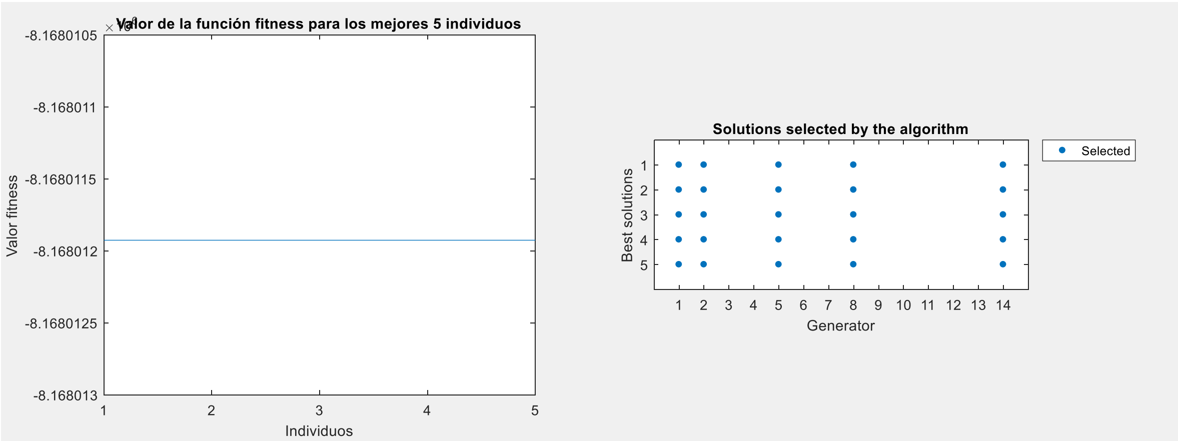


Figure 35. Fitness Functions and Generators of the Five Best Solutions. No Constraints

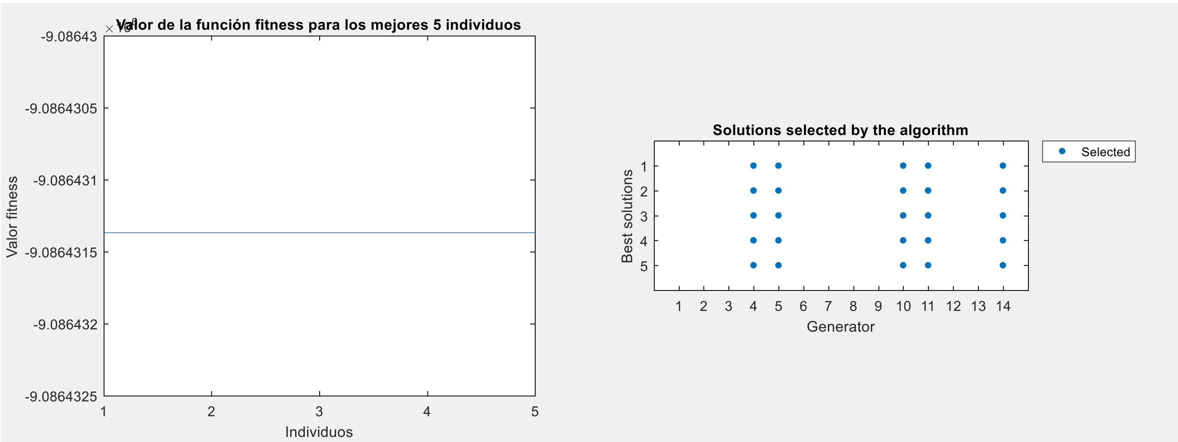


Figure 36. Fitness Functions and Generators of the Five Best Solutions. At least Two CHP Systems

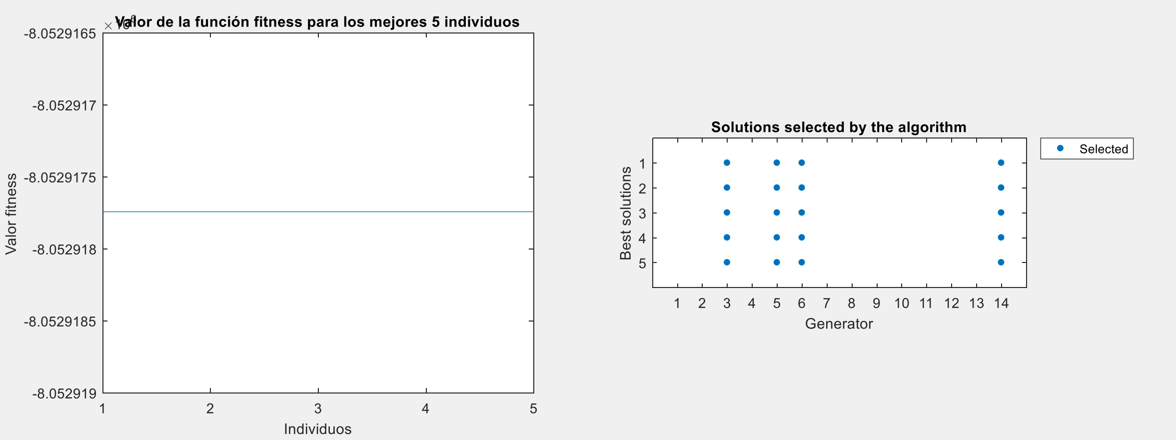


Figure 37. Fitness Functions and Generators of the Five Best Solutions. PV + Grid Constraint

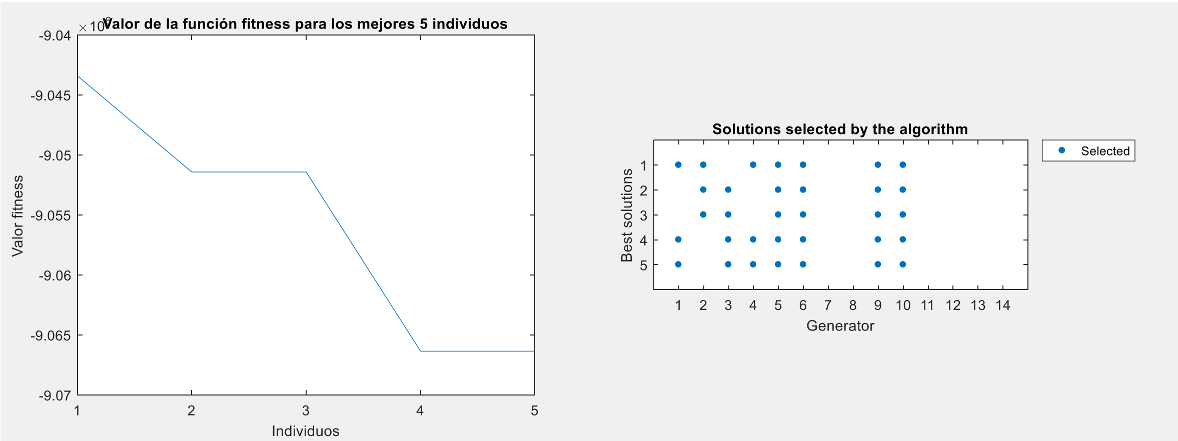


Figure 38. Fitness Functions and Generators of the Five Best Solutions. Isolated MG Constraint

As described in chapter 3, the profitability of the solutions identified as optimal by the algorithms is not revealed until it is compared with the current costs of the power supply. Table 30 shows that three out of the four 4 solutions have a positive Net Present Values, meaning they are more profitable than the existing power supply. Discounted Payback periods of the solutions with a positive NPV oscillate between 12.28 and 24.65 years.

Table 30. Key Economic Indicators of the Algorithm Solutions for Additional Resilience

	No Constraint	Two CHP Systems	PV+GRID	ISOLATED GRID
Initial Invest.	€ (2,080,781)	€ (3,000,000)	€ (2,031,287)	€ (3,000,000)
Loan	€ -	€ 928,307	€ -	€ 617,768
Annual Savings	€ 255,455	€ 284,903	€ 255,152	€ 229,627
NPV	€ 1,216,363	€ 227,597	€ 1,314,134	€ (465,515)
IRR	11.45%	6.62%	11.87%	4.50%
DPP	12.63	24.27	12.28	24.65
Equiv. Annuity	€ 278,476	€ 272,602	€ 282,553	€ 214,062

As it has been mentioned before, the complete set of results has been included in the Appendix.

26. Risk Analysis Results

The optimization algorithms used in the previous stages of the method follow a deterministic approach considering fixed values for sensitive variables such as energy prices, and installation or O&M costs. However, some variables like the electricity or the natural gas price change at least once a year, and their future values are uncertain, especially over the 25 years of lifespan of a microgrid. **The goal of using a risk analysis algorithm at this stage is to minimize the uncertainties around the designs with the potential to pass the feasibility analysis by studying the same economic indicators in a probabilistic way. The method selected for this analysis is the Monte Carlo Simulation**. The analysis starts the selection of the risk variables and their probability distributions.

26.1. Sensitive Variables and Probability Distributions

Sets of one thousand values for the sensitive input variables are defined according to a probabilistic function. The variables identified as sensitive have been pointed out in chapter 3:

- $PR_{ELEC\ GRID}^{h}$, hourly price of the kWh of electricity supplied by the local utility in euros per kWh.
- PR_{NG}^{h} , price of the kWh of natural gas supplied by the local utility in euros per kWh
- PR_{DIESEL}^{h} price of the kWh of diesel supplied by local distributors in euros per kWh.
- $C_{CAP\ PDS}^{0}$, fixed costs incurred on construction, installation, and commissioning works required to bring power lines, load centers, and substations to a commercially operable status.
- SAV_{PDS}^{N+1} , salvage value of load centers, substations, and power lines at the end of the lifecycle of the project.
- $C_{REP\ PDS}^{A}$, annual cost of replacement of load centers, substations, and power grids when they reach the end of their lifespan.
- $C_{O\&M\ PDS}^{A}$ annual operation and maintenance costs of load centers, substations, and power grids.
- $C_{REP\ g}^{A}$, annual cost of replacement of power generators when they reach the end of their lifespan.
- C_{CAPg}^{0}, fixed costs incurred on construction, installation, and commissioning works required to bring the power generation and energy storage systems to a commercially operable status.
- $C_{CAP\ Tank}^{0}$ fixed costs incurred on construction, installation, and commissioning of the thermal storage tank.
- $C_{MISC\ MG}^{0}$, miscellaneous costs incurred on different aspects of the project before it starts operating, such as the energy management system, insurances, and other costs required for the project to start operating.

- SAV_g^{N+1}, salvage value of the power generation systems at the end of the lifecycle of the project (year N+1).
- C_{REPg}^{A}, annual cost of replacement of the power generation systems at the end of their lifespan.
- $C_{O\&Mgen}^{A}$, annual operation and maintenance costs of the power generation systems in the microgrid.

Future values of every sensitive variable are fitted into a probability distribution. In that regard, the strategy followed for construction, installation, and replacement costs is to increase their variability depending on how far in time are they from the moment the decision is made, such as:

- +/- 10 deviation of the current cost will be considered for capital costs, because they are usually-well defined at the moment the decision of building the system is made.
- +/-15% will be considered for replacement costs since no equipment is supposed to be replaced before year 10 and costs o generation assets might have changed in ten years.
- +/-50% will be considered for the salvage value of the equipment since it is difficult to predict how valuable will those materials or equipment be in year 25.
- A +/-5% variation will be considered for the O&M costs.

Forecasting energy prices is a complex task that will not be covered in this work, but information from different energy price forecasts will be considered to define the probabilistic distributions of natural gas, electricity and diesel. Energy price forecasts oscillate considerably depending on the source.

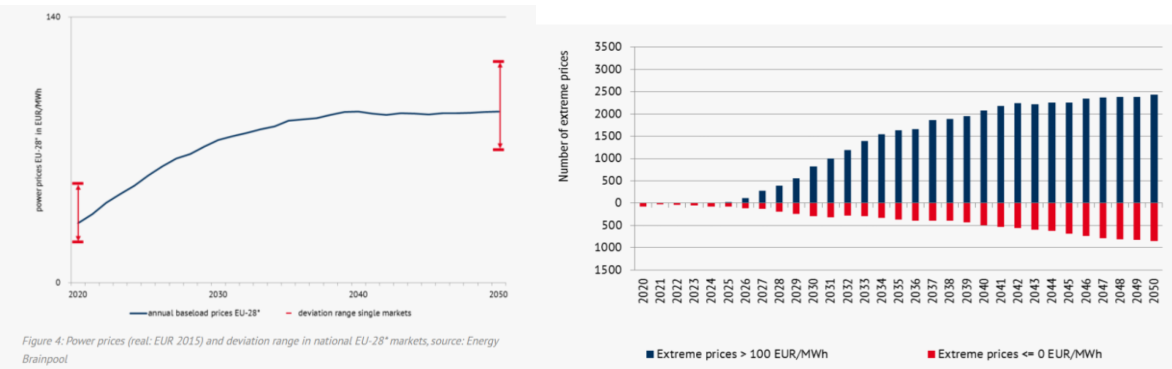
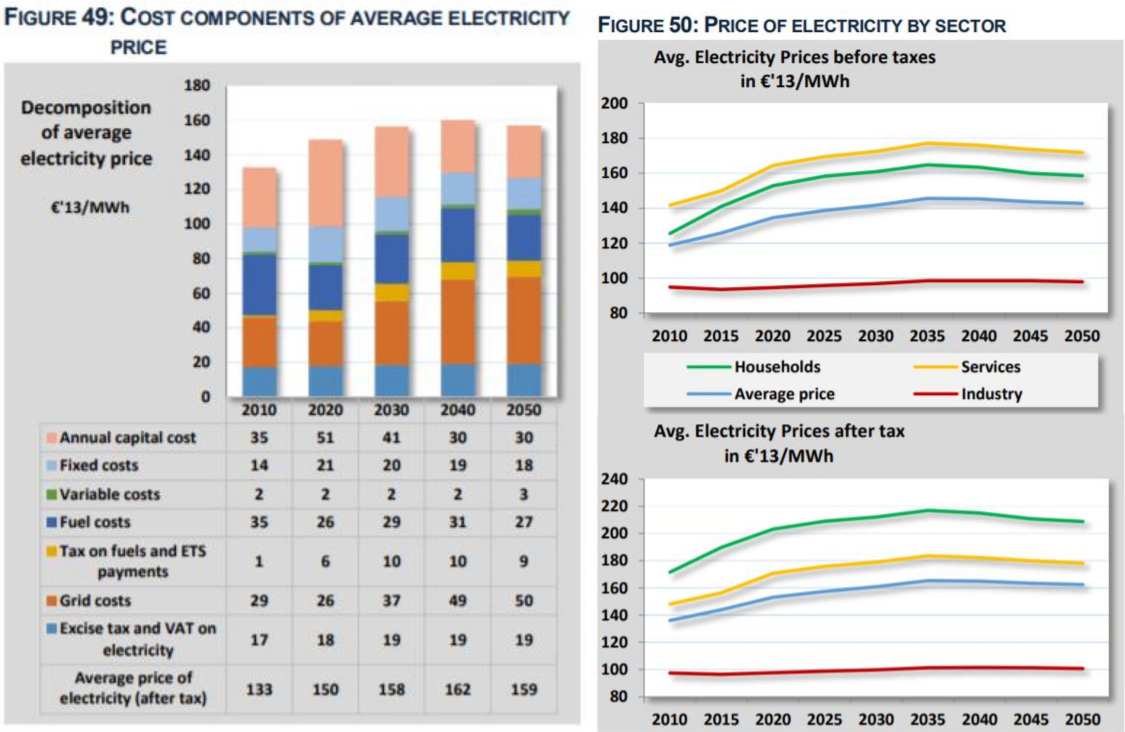


Figure 39. Future Electricity Prices in Europe. Source: Energy Brainpool GmbH, “Trends in the development of electricity prices – EU Energy Outlook 2050”. June 2017

While, for instance, Energy Brain Pool estimates in Figure 39 an increase in the electricity price of 275% by 2050 [44] (from 30.7 to 84.5 Euros per MWh generated), the European Commission forecasts an

[44] https://blog.energybrainpool.com/en/trends-in-the-development-of-electricity-prices-eu-energy-outlook-2050/

increase of 20% for the same period (from 133 to 159 euros per MWh before taxes), as shown in Figure 40.



	2010	2020	2030	2040	2050
Annual capital cost	35	51	41	30	30
Fixed costs	14	21	20	19	18
Variable costs	2	2	2	2	3
Fuel costs	35	26	29	31	27
Tax on fuels and ETS payments	1	6	10	10	9
Grid costs	29	26	37	49	50
Excise tax and VAT on electricity	17	18	19	19	19
Average price of electricity (after tax)	133	150	158	162	159

Figure 40. Electricity Price Forecast for the EU. Source:European Commission, 2016. EU Reference Scenario 2016 Energy, transport and GHG emissions Trends to 2050

The US Energy Information Administration (EIA) predicts a lower variation in the United States than the European Commission does in Europe, as shown in Figure 41.

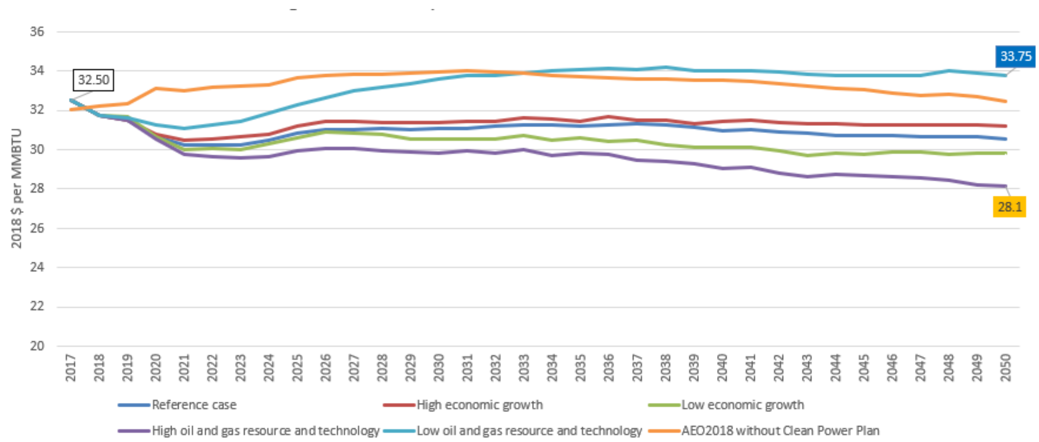


Figure 41. Electricity Price Forecast for the US. Source: US Energy Information Administration

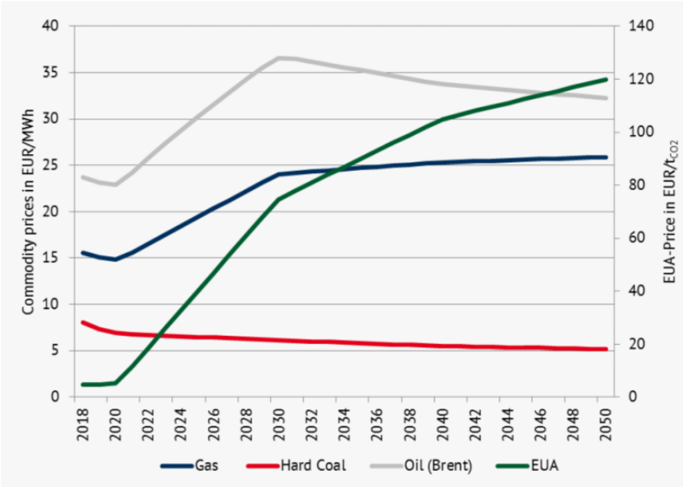


Figure 3: Commodity prices (real: EUR 2015), source: Energy Brainpool

Figure 42. Natural Gas and Oil prices Forecast by Energy Brainpool. Source: Energy Brainpool GmbH, "Trends in the development of electricity prices – EU Energy Outlook 2050". June 2017:

According to the information in Figure 42, natural gas price forecasts are still showing a price increase (+62%) in the next 30 years despite (or probably due to) the de-carbonization policies announced by different states of the USA and the European Union. Oil price trends are also uncertain, showing increases and decreases. In the end, the most important thing is to involve the stakeholder in the process and to select energy price forecasts he/she is comfortable with. The probability functions assigned to each of these variables is presented in Table 31.

Table 31. Probability Distribution Applied per Variable

PROB. DIST.	VARIABLES
Normal 5%	$C_{O\&M\ gen}^{A}$
Normal 10%	$C_{CAP g}^{0}, C_{CAP\ Tank}^{0}, C_{CAP\ PDS}^{0}, C_{MISC\ MG}^{0}$
Triangular 15%	$C_{REP\ g}^{A}, C_{REP\ PDS}^{A}$
Triangular 25%	$C_{O\&M\ PDS}^{A}$
Triangular 50%	$SAV_{g}^{N+1}, SAV_{PDS}^{N+1}$
Triangular Diesel	$PR_{DIESEL}^{h}, C_{O\&M gen}^{A}$
Normal Electricity	$PR_{ELEC\ GRID}^{h}, C_{O\&M gen}^{A}$
Normal Natural Gas	$PR_{NG}^{h}, C_{O\&M gen}^{A}$

The cumulative probability distribution applied to the cited costs for the probabilistic analysis are in presented Figure 43. No potential correlations between the variables have been considered.

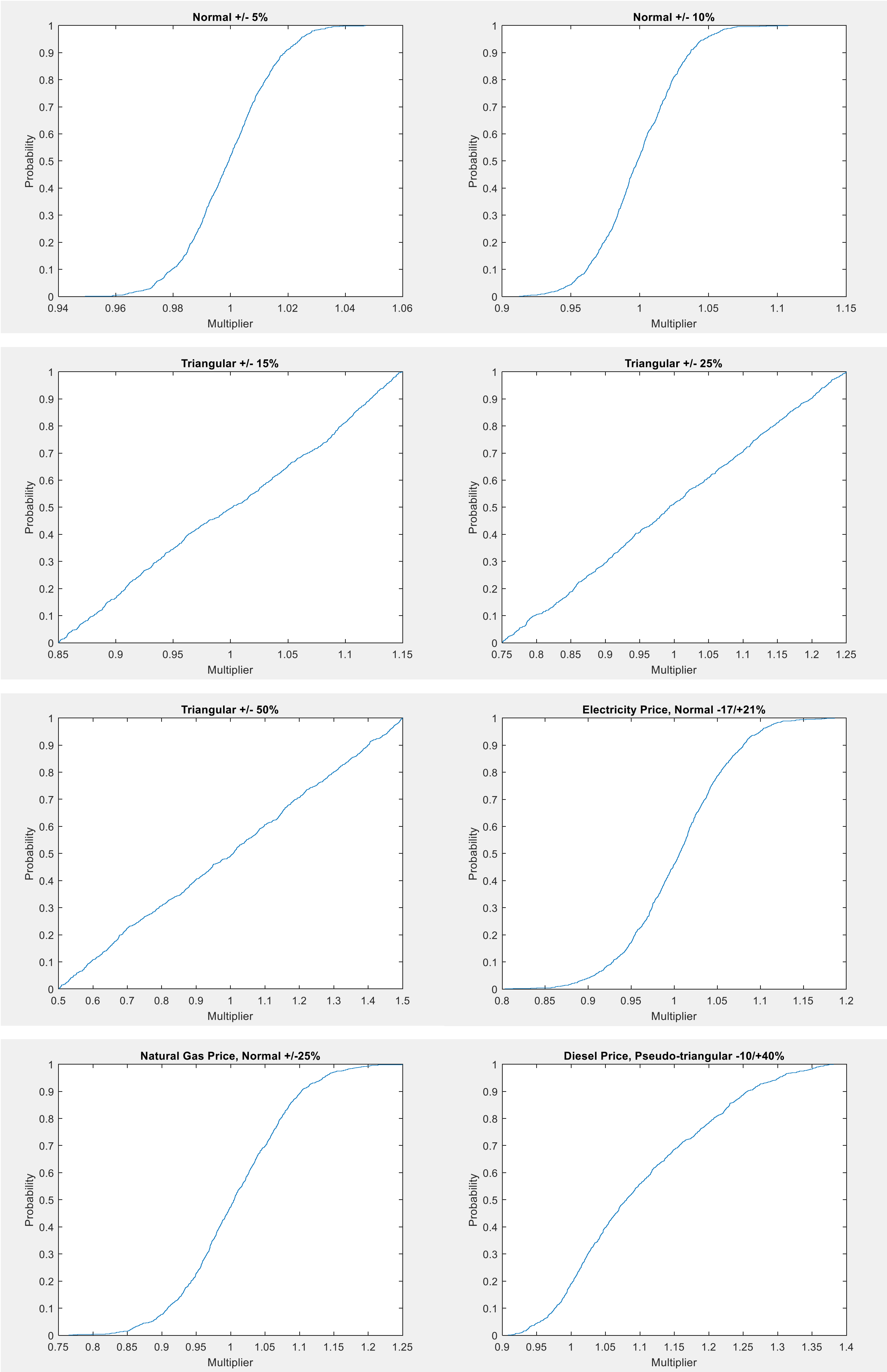


Figure 43. Cumulative Probability Distributions Applied in the Monte Carlo Simulation

26.2. Results for the Alternatives and Customized Solutions for the No Additional Resilience Option.

The Monte Carlo Simulation algorithm analyzes the four optimal solutions per case (No additional and additional resilience) plus two customized solutions introduce by the stakeholder. The two additional customized solutions simulated in this algorithm are:

a) Customized power distribution 1: The shortest layout with the minimum number of 150 mm^2 feeders.

b) Customized power distribution 2: A 150 mm^2 ring layout connecting the nodes clockwise.

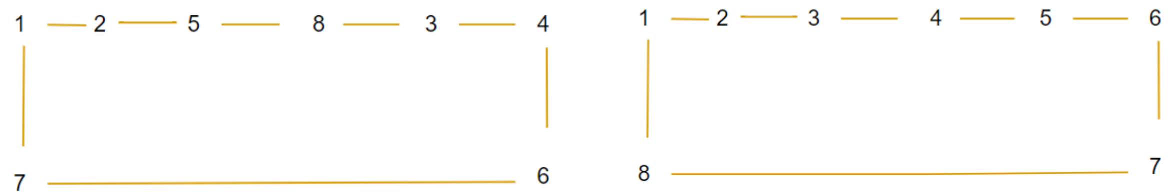


Figure 44. Proposed Power Grid Layouts: Shortest (Left) and Ring (Right)

a) Customized power generation 1: The goal is to minimize local environmental emissions with the maximum solar capacity installable and the utility's power grid.

b) Customized power generation 2: The goal is to allow some fuel consumption with the highest efficiency possible. Two solar plants (150 and 450 KW), the utility's power grid and the 299-CHP system to provide cost-effective thermal energy and water.

Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Technology	PV PLANT	PV PLANT	PV PLANT	Diesel Gen.	Diesel Gen.	Diesel Gen.	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Pow. Grid
Size	150 KW	300 KW	450 KW	400 KW	630 KW	1000 KW	400 KW	630 KW	1000 KW	299 KW	635 KW	847 kW	1067 KW	2000 KW
No Constraint	x													x
1 CHP System	x		x		x					x				x
PV+Grid	x				x					x				x
Isolated MG			x		x	x				x				
Customized 1	x	x	x											x
Customized 2	x		x							x				x

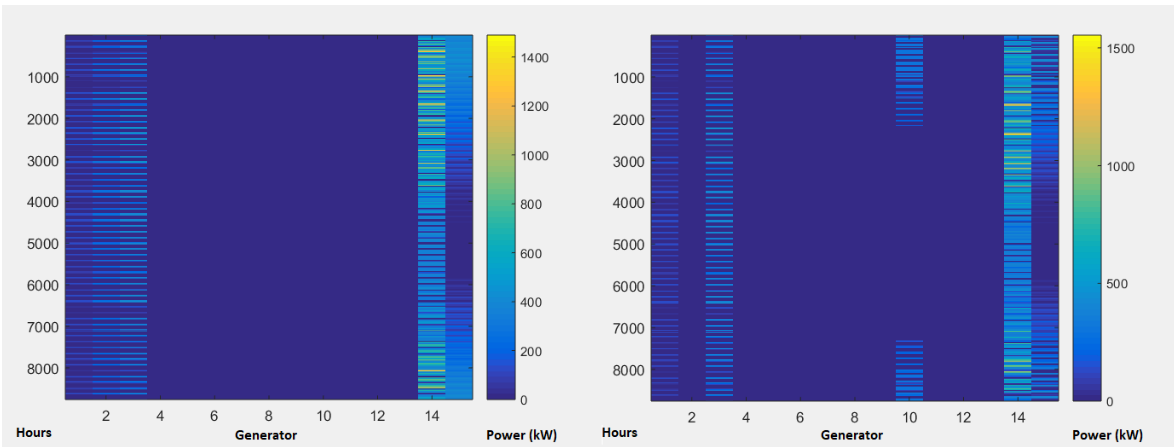


Figure 45. Generators per Solution and Scheduling for Customized Solutions 1 and 2. No Additional Resilience

The execution time of the MATLAB code to run the risk analysis algorithm is 57.2 seconds, simulating six solutions. The *No Additional Resilience* Key Economic Indicators are presented in Table 32.

Table 32. Key Economic Indicators of the No Additional Resilience Solutions

	No Constraint	One CHP System	PV+GRID	ISOLATED GRID	CUSTOMIZED 1	CUSTOMIZED 2
Initial Invest.	€ (1,185,224)	€ (2,870,338)	€ (2,129,473)	€ (2,875,449)	€ (2,387,418)	€ (2,694,473)
Loan	€ -	€ -	€ -	€ -	€ -	€ -
Annual Savings	€ 215,666	€ 320,048	€ 266,720	€ 242,767	€ 272,240	€ 299,190
NPV	€ 1,620,403	€ 1,314,323	€ 1,429,930	€ 238,671	€ 1,048,052	€ 1,203,209
IRR	17.93%	10.25%	11.98%	6.75%	10.24%	10.17%
DPP	7.89	14.43	12.34	21.66	14.02	14.48
Equiv. Annuity	€ 236,962	€ 353,435	€ 300,626	€ 263,018	€ 290,159	€ 329,197

Following a deterministic analysis, all the solutions are profitable with IRRs oscillating from 6.75 to 17.93%, and DPPs oscillating from 7.89 to 21.66 years. A probabilistic analysis will identify which systems can fulfill the profitability conditions defined by the stakeholder:

- IRR over 12% at 90% probability
- DPP under 15 years at 90% probability

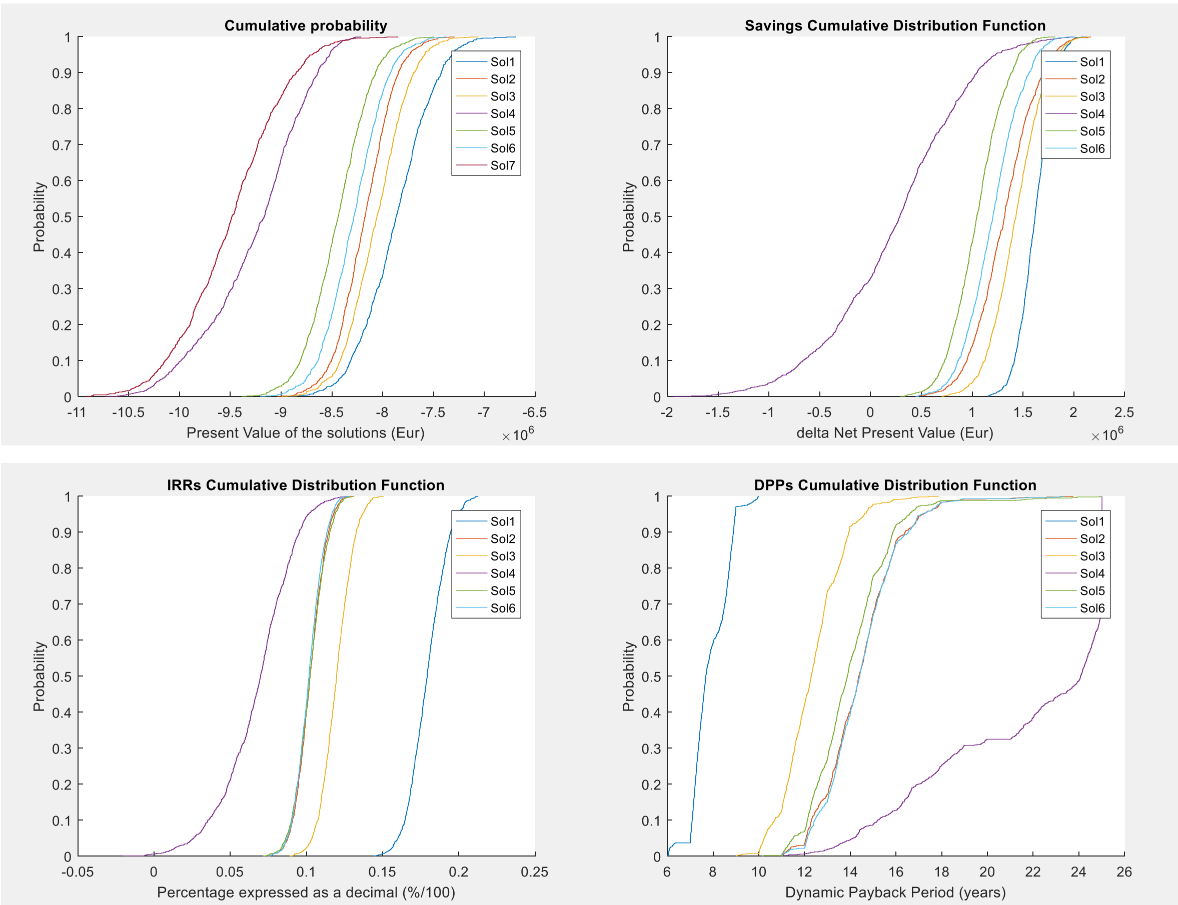


Figure 46. Cumulative Probability Distributions of Risk Analysis Indicators No Additional Resilience Solutions

The cumulative probability distributions are calculated by Monte Carlo Simulation and presented in Figure 46. The Present Value of the existing power supply is presented as *Sol 7* in the first chart of Figure 46. *Sol 7* is subtracted from the rest of the solutions to calculate the NPV in the second chart of the same figure to calculate savings and the rest of the profitability indicators.

Table 33 shows the results of the probabilistic analysis based on the goals defined by the investors. Since none of the solutions fulfill the two initial goals (IRR over 12% and DPP under 15 years at 90% probability), a sensitivity analysis has been performed to identify the incentives required to achieve the initial and also lower financial goals such as:

- IRR over 10% and DPP under 17.5 years at 90% probability
- IRR over 8% and DPP under 20 years at 90% probability

Table 33. Risk Analysis Indicators of the No Additional Resilience Solutions

NO ADD RL, IRR 12% DPP 15 yrs	No Constraints	At least 1 CHP System	PV+GRID	ISOLATED GRID	CUSTOMIZED 1	CUSTOMIZED 2
Value at Risk (Savings) MAXdNPV	€ 2,127,242	€ 2,165,496	€ 2,154,507	€ 1,998,483	€ 1,814,695	€ 2,009,586
Value at Risk (Savings) MEANdNPV	€ 1,618,269	€ 1,317,934	€ 1,429,416	€ 287,725	€ 1,045,311	€ 1,203,658
Value at Risk (Savings) MINdNPV	€ 1,158,446	€ 452,478	€ 702,250	€ (1,936,551)	€ 294,002	€ 446,630
Probbaility of obtaining savings	100.0%	100.0%	100.0%	67.0%	100.0%	100.0%
IRR over X% at 90% probability	16.46%	9.09%	10.75%	3.53%	9.00%	9.06%
DPP under Y years at 90% probability	8.89	16.38	13.94	25.01	15.86	16.54
IRR goal (Over X at 90%)	12%	12%	12%	12%	12%	12%
Incentive for IRR goals	€ -	€ 588,323	€ 199,520	€ 1,514,204	€ 442,711	€ 513,263
Additional Annual Savings for IRR goals	€ -	€ 75,011	€ 25,439	€ 193,061	€ 56,446	€ 65,441
DPP goal (Under Y at 90%)	15	15	15	15	15	15
Incentive for DPP goals	€ -	€ 69,857	€ -	€ 1,269,540	€ 91,466	€ 50,334
Additional Annual Savings for DPP goals	€ -	€ 7,193	€ -	€ 206,468	€ 9,418	€ 5,183
IRR goal (Over X at 90%)	10%	10%	10%	10%	10%	10%
Incentive for IRR goals	€ -	€ 210,149	€ -	€ 1,190,807	€ 113,491	€ 186,734
Additional Annual Savings for IRR goals	€ -	€ 23,152	€ -	€ 131,189	€ 12,503	€ 20,572
DPP goal (Under Y at 90%)	17.5	17.5	17.5	17.5	17.5	17.5
Incentive for DPP goals	€ -	€ -	€ -	€ 665,433	€ -	€ -
Additional Annual Savings for DPP goals	€ -	€ -	€ -	€ 144,955	€ -	€ -
IRR goal (Over X at 90%)	8%	8%	8%	8%	8%	8%
Incentive for IRR goals	€ -	€ -	€ -	€ 967,030	€ -	€ -
Additional Annual Savings for IRR goals	€ -	€ -	€ -	€ 90,590	€ -	€ -
DPP goal (Under Y at 90%)	20	20	20	20	20	20
Incentive for DPP goals	€ -	€ -	€ -	€ 607,180	€ -	€ -
Additional Annual Savings for DPP goals	€ -	€ -	€ -	€ 128,098	€ -	€ -

26.3. Results for the Additional Resilience and Customized Solutions

The same customized power grid solutions (presented in Figure 44) have been considered for the additional resilience alternatives but incorporating new customized power generation solutions:

a) Customized power grid 1. The shortest layout with the minimum number of 150 mm^2 lines.

b) Customized power grid 2. A 150 mm^2 ring layout is connecting the nodes clockwise.

a) Customized power generation 1. The goal is to allow some fuel consumption with the highest efficiency possible. Two solar plants (150 and 450 KW), the utility's power grid and the 299-CHP system to provide cost-effective thermal energy and water.

b) Customized power generation 2. The goal is to minimize local environmental emissions with the maximum solar capacity installable incorporating a 630-kW diesel generator, the efficiency of a 299 kW CHP system and the utility's power grid.

Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Technology	PV PLANT	PV PLANT	PV PLANT	Diesel Gen.	Diesel Gen.	Diesel Gen.	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Pow. Grid
Size	150 KW	300 KW	450 KW	400 KW	630 KW	1000 KW	400 KW	630 KW	1000 KW	299 KW	635 KW	847 kW	1067 KW	2000 KW
No Constraint	X	X			X			X						X
2 CHP Systems				X	X					X	X			X
PV+Grid			X		X	X								X
Isolated MG	X	X		X	X	X			X	X				
Customized 1	X	X	X		X		X							X
Customized 2	X	X	X		X					X				X

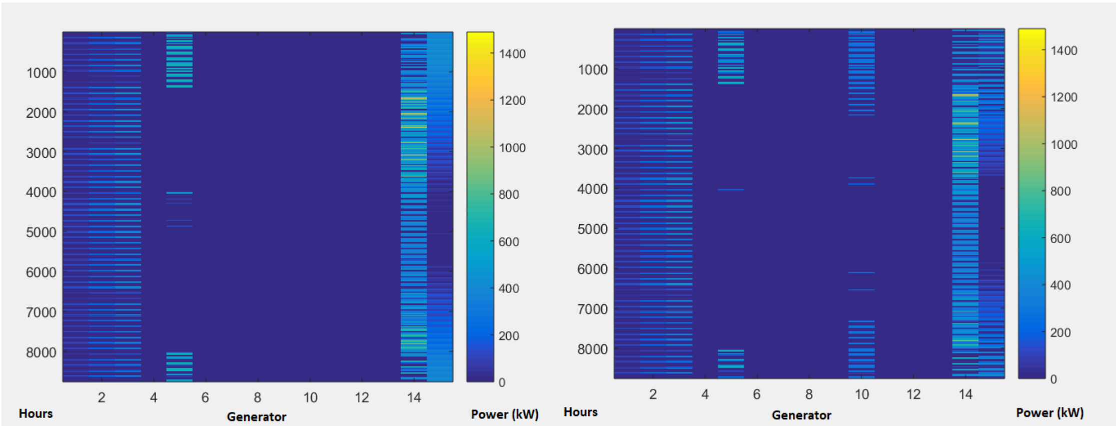


Figure 47. Generators per Solution and Scheduling for Customized Solutions 1 and 2. Additional Resilience

The execution time of the MATLAB code to run the risk analysis algorithm is 51.94 seconds, simulating 6 solutions. The *Additional Resilience* Key Economic Indicators are presented in Table 34.

Table 34. Key Economic Indicators of Additional Resilience Solutions

	No Constraint	Two CHP Systems	PV+GRID	ISOLATED GRID	CUSTOMIZED 1	CUSTOMIZED 2
Initial Invest.	€ (2,080,781)	€ (3,000,000)	€ (2,031,287)	€ (3,000,000)	€ (2,737,700)	€ (3,000,000)
Loan	€ -	€ 928,307	€ -	€ 617,768	€ -	€ 500,457
Annual Savings	€ 255,455	€ 284,903	€ 255,152	€ 229,627	€ 305,003	€ 358,051
NPV	€ 1,216,363	€ 227,597	€ 1,314,134	€ (465,515)	€ 1,137,795	€ 1,238,469
IRR	11.45%	6.62%	11.87%	4.50%	10.00%	9.69%
DPP	12.63	24.27	12.28	24.65	14.52	15.80
Equiv. Annuity	€ 278,476	€ 272,602	€ 282,553	€ 214,062	€ 327,323	€ 357,980

Following a deterministic analysis, 5 out of 6 solutions result to be profitable with IRRs going from 6.62 to 11.45% and DPPs from 12.28 to 24.65 years. A probabilistic analysis will identify which systems can fulfill the profitability conditions defined by the stakeholder:

- IRR over 12% at 90% probability
- DPP under 15 years at 90% probability

The cumulative probability distributions of the risk analysis indicators are presented in Figure 48.

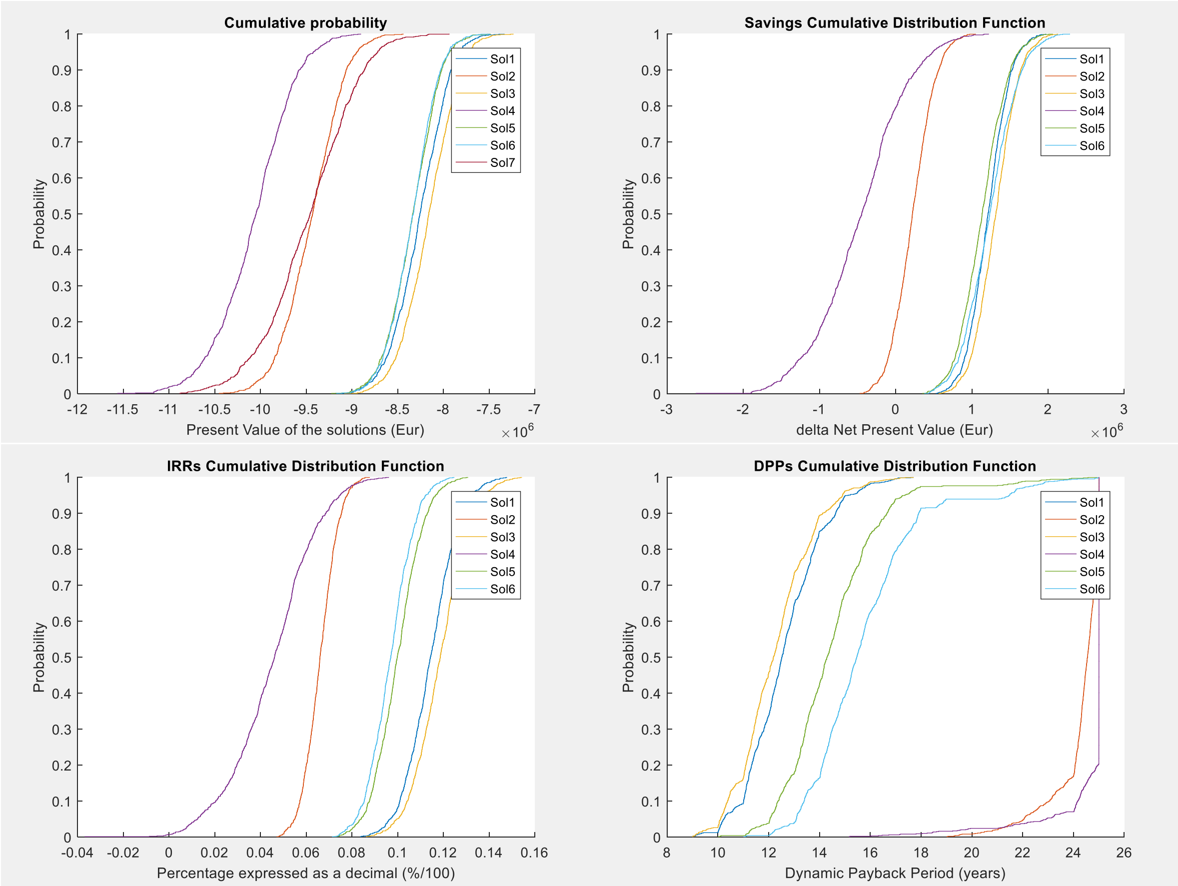


Figure 48. Cumulative Probability Distributions of the Risk Analysis Indicators for Additional Resilience Solutions

Table 35 shows the results of the probabilistic analysis based on the goals defined by the stakeholder. Since none of the objectives fulfills the two initial goals at a time (IRR over 12% and DPP under 15 years at 90% probability), a sensitivity analysis has been performed to calculate the incentives that would help achieve lower goals such as:

- IRR over 10% and DPP under 17.5 years at 90% probability
- IRR over 8% and DPP under 20 years at 90% probability

Table 35. Risk Analysis Indicators of Solutions with Additional Resilience

ADD RL, IRR 12% DPP 15 yrs	No Constraint	Two CHP Systems	PV+GRID	ISOLATED GRID	CUSTOMIZED 1	CUSTOMIZED 2
Value at Risk (Savings) MAXdNPV	€ 1,971,040	€ 1,047,410	€ 2,127,464	€ 1,218,896	€ 2,058,823	€ 2,283,974
Value at Risk (Savings) MEANdNPV	€ 1,211,421	€ 220,157	€ 1,314,794	€ (445,477)	€ 1,133,721	€ 1,234,953
Value at Risk (Savings) MINdNPV	€ 531,548	€ (467,368)	€ 566,552	€ (2,618,692)	€ 354,479	€ 380,894
Probbaility of obtaining savings	100.0%	79.9%	100.0%	20.3%	100.0%	100.0%
IRR over X% at 90% probability	10.1%	5.7%	10.4%	2.0%	8.8%	8.5%
DPP under Y years at 90% probability	14.64	25.00	14.12	25.01	16.66	17.91
IRR goal (Over X at 90%)	12%	12%	12%	12%	12%	12%
Incentive for IRR goals	€ 244,979	€ 1,585,606	€ 233,509	€ 2,290,965	€ 576,515	€ 798,529
Additional Annual Savings for IRR goals	€ 31,235	€ 202,165	€ 29,772	€ 292,098	€ 73,506	€ 101,812
DPP goal (Under Y at 90%)	15	15	15	15	15	15
Incentive for DPP goals	€ -	€ 1,062,211	€ -	€ 1,362,448	€ 37,231	€ 143,772
Additional Annual Savings for DPP goals	€ -	€ 31,119	€ -	€ 85,729	€ 3,833	€ 62,006
IRR goal (Over X at 90%)	10%	10%	10%	10%	10%	10%
Incentive for IRR goals	€ -	€ 1,561,254	€ -	€ 2,224,103	€ 222,509	€ 587,746
Additional Annual Savings for IRR goals	€ -	€ 172,000	€ -	€ 245,025	€ 24,513	€ 64,751
DPP goal (Under Y at 90%)	17.5	17.5	17.5	17.5	17.5	17.5
Incentive for DPP goals	€ -	€ 1,006,455	€ -	€ 1,242,918	€ -	€ 108,157
Additional Annual Savings for DPP goals	€ -	€ 18,907	€ -	€ 58,928	€ -	€ 27,710
IRR goal (Over X at 90%)	8%	8%	8%	8%	8%	8%
Incentive for IRR goals	€ -	€ 1,080,985	€ -	€ 1,779,869	€ -	€ -
Additional Annual Savings for IRR goals	€ -	€ 101,265	€ -	€ 166,736	€ -	€ -
DPP goal (Under Y at 90%)	20	20	20	20	20	20
Incentive for DPP goals	€ -	€ 810,369	€ -	€ 1,116,237	€ -	€ -
Additional Annual Savings for DPP goals	€ -	€ 6,579	€ -	€ 34,332	€ -	€ -

27. Results Discussion

27.1. Deterministic Results

a) Design Guidelines based on the Technical Solutions

Eight of the twelve solutions have been selected by the algorithms while four have been proposed by the user. Besides, Figures 45 and 47 present the customized power generation sets selected per solution. The most frequent power generator of the eight optimal solutions is the 630-kW diesel generation set, followed by the power grid. There is at least one photovoltaic plant in every solution, six out of the eight solutions include the 299-kW CHP reciprocating engine. The algorithm has selected the smallest CHP unit in every solution unless it was forced to select a second unit, suggesting that there is not enough thermal demand to operate two CHP systems in a cost-effective manner.

The grid has been selected in every solution it was allowed, with a contribution to UBU's annual demand between 57.6 and 95.2%. Isolating the microgrid from the local utility's power grid, while feasible, does not seem to be the most profitable solution. The solution with the highest NPV combines just two units: a 150 kW PV plant and the utility grid.

The installation of two CHP units does not look like the best solutions either, based on the low NPV obtained. This low NPV is due to a relatively high cost for a small contribution to the energy demand (under 9.3 % for the current thermal demand of the UBU). This result suggests that not only there might not be enough thermal load at the High Polytechnic School, but also the installation of a storage tank does not provide enough value to this solution.

Additional resilience does not necessarily require a considerable additional investment when it is based on diesel and natural gas generators. The algorithm has selected at least one of them in 11 out of 12 solutions. They contribute to the system during high electricity cost periods (no additional resilience) and back-up the system in case other power generators have to stop (additional resilience). However, the usage of natural gas and diesel generators also increase the fuel consumption threefold and, consequently, the environmental emissions especially for the isolated microgrid design. The combination of photovoltaic plants and the power grid is the one with the lowest CO_2 emissions, the best option to take if more restrictive environmental policies are expected to be approved during the lifespan of the project.

The algorithm has found better solutions than the ones suggested by the user. The customized solutions turn out to be reasonable solutions but are less profitable due to the cost associated with installing additional generators.

b) Economic Insights

Eleven out of the twelve solutions selected by the algorithm and the user are more profitable than the baseline, in which the local power utility is the only supplier. An *out-of-pocket* investment threshold of 3 million euros has been defined by the stakeholder, allowing any additional quantity to be provided through a bank loan. All the solutions not requiring additional resilience have initial investments under the 3 million euros threshold. On the contrary, three out of six solutions able to provide additional resilience require a loan to cover the additional capital investment required.

If we compare the optimal solutions per constraint, it can be asserted that natural gas and diesel generators can provide resilience at a low economic cost, but these technologies operate at a higher environmental cost. Thus, if the project does not have any environmental constraints the cheapest way to achieve additional resilience is to install diesel and natural gas fueled generation sets.

The cost achieving of additional resilience through cleaner or more efficient technologies oscillate between 350,282 and 1,057,969 euros, with an average cost of 625,654 euros per solution.

As shown in Tables 32 and 34, eleven out of the twelve solutions selected by the algorithm and the user are more profitable than the baseline, but none of them fulfill the profitability goals established by the investors: IRR over 12% and DPP under 15 years. However, there are four solutions with a DPP under 15 years and four solutions with an IRR equal or over 10%. **That means the goals were realistic and eventually, some incentives or savings can help the project reach its economic goals**. A sensitivity analysis has analyzed the incentives required to make those solutions profitable.

27.2. Risk Analysis or Probabilistic Results

As has been described in Chapter 3, one thousand values of each sensitive variable described in Table 31 will be combined and applied to the optimal solutions: the power distribution and the power generation equipment selected, and their optimal schedules. The results will be sets of 1,000 values for each of the profitability indicators: Present Value, NPV, IRR and DPP. The deterministic goals set by the investors are be translated to probabilistic goals as follows:

- 100% probability of obtaining savings
- IRR over 12% at 90% probability
- DPP under 15 years at 90% probability

According to the results of the risk analysis presented in Tables 33 and 35, only one solution fulfills all the profitability criteria, but there are three more that fulfill at least one of them. A sensitivity analysis has been performed to analyze which solutions could be considered profitable, if the profitability conditions determined by the user are softened to DPPs of 17.5 and 20 years and IRRs of 10 and 8% respectively. Besides, the one-time or annual incentives (also called savings) which could help the system achieve these goals have been calculated. The results of this analysis are presented in Figures 49 to 52.

According to Figure 49, an initial incentive of 1,514,204 euros would make all the N*o Additional Resilience* solutions fulfill the profitability goals.

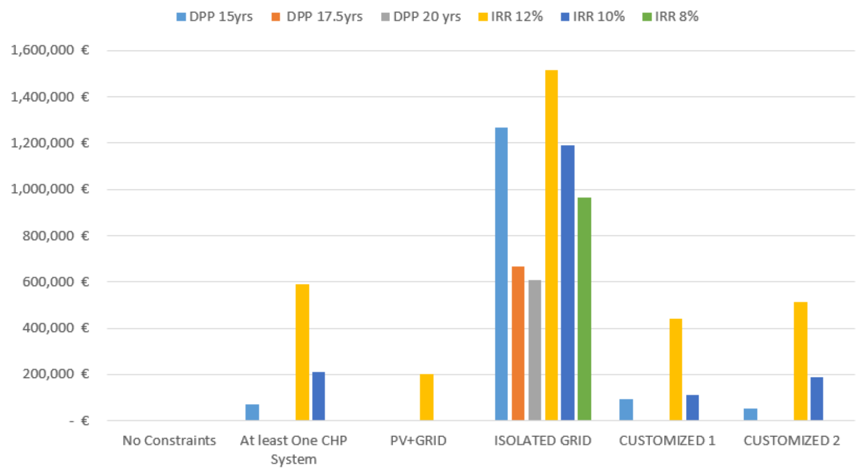


Figure 49. Incentives to Fulfill the Goals for No Additional Resilience Solutions

The *Additional Resilience solutions* represented in Figure 50 would require an incentive of over 1,585,606 euros for five out of six solutions to fulfill the goals.

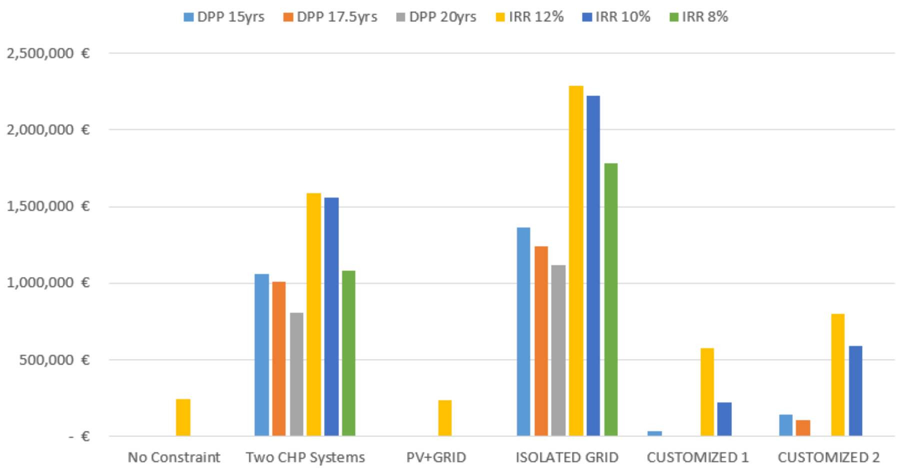


Figure 50. Incentives to Fulfill the Goals for Additional Resilience Solutions

These are high incentives since they represents from 39 to 132% of the initial investment of the solutions. However, an initial incentive of 600,000 euros would make 9 out of the 12 solutions achieve the most restrictive profitability goals (IRR over 12% and DPP under 15 years), and there are even lower incentives that might help some of these solutions pass the feasibility threshold.

The DPP goals have proven to be easier to achieve that the IRR goals, according to the information in Table 36. This table presents the total number of solutions requiring one-time or annual cost savings or incentives to achieve each profitability goal. The number of solutions per goal requiring incentives to be considered profitable do not change too much per incentive type

Table 36. Total Solutions Requiring Incentives per Goal and Type of Incentive

	Incentives over Initial Investment	Annual Incentives
IRR 12%	11	11
IRR 10%	8	8
IRR 8%	3	3
DPP 15 years	7	8
DPP 17.5 years	4	4
DPP 20 years	3	3

According to Table 33 and Figure 51, an annual incentive of 206,468 euros (or the same amount in annual cost savings) would make all the N*o Additional Resilience* solutions fulfill the profitability goals.

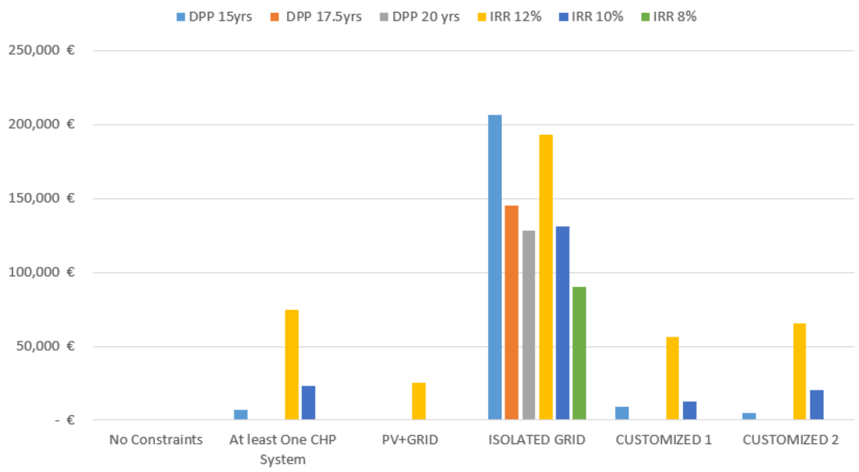


Figure 51. Savings to Fulfill the Goals for No Additional Resilience Solutions

The annual incentives or cost savings for the A*dditional Resilience solutions* are represented in Figure 52. Any incentive over 292,098 euros would make all of them fulfill the goals too.

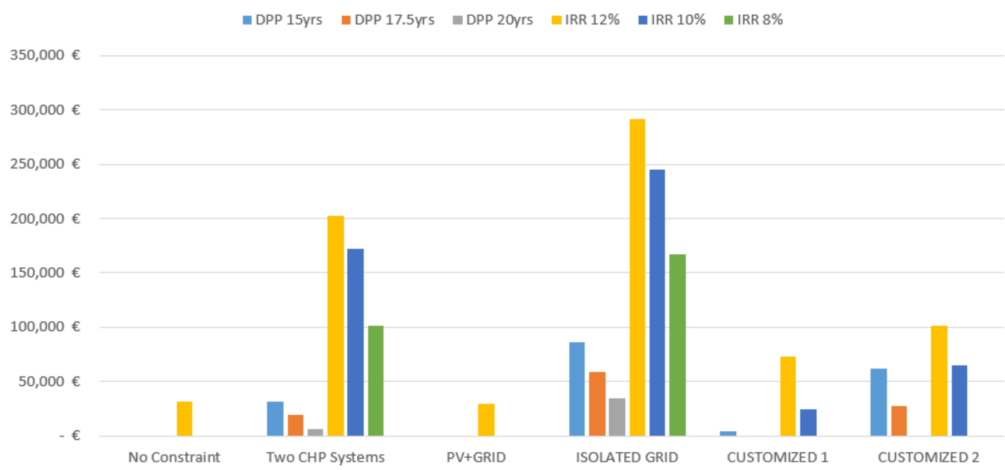


Figure 52. Savings to Fulfill the Goals for Additional Resilience Solutions

These are high incentives since they represent around 50% of the annual operating costs of many of the solutions. However, an annual incentive or cost savings of 75,000 euros would make 8 out of the

12 solutions achieve the most restrictive profitability goals (IRR over 12% and DPP under 15 years). As shown in Tables 33 and 35, and Figures 49 to 52, there are even lower incentives that might help some of the solutions pass the feasibility analysis.

The information provided by this risk analysis is considered essential to help users make decisions when the results are close but do not fulfill the profitability goals refined. If incentives are not available, the investors could consider more flexible thresholds for the profitability indicators if they feel comfortable the results estimated by this method. **For instance, if an IRR of 9% is targeted instead of 10%, seven potential solutions would pass the feasibility analysis instead of the one passing it initially.**

27.3. Deterministic Vs. Probabilistic Results

This method allows the user to benchmark the deterministic and the probabilistic results, which should be similar but not necessarily the same.

According to the deterministic analysis, eleven out of the twelve solutions selected by the algorithm and the user are more profitable than the baseline. This data matches the results of the probabilistic analysis presented in Tables 33 and 35, where eleven out of the twelve solutions have a positive Net Present Value, meaning that they are profitable. However, just nine of these twelve solutions have a 100% probability of obtaining savings under the analyzed scenarios, **meaning that 3 out of 12 might experience economic losses, despite the results of the deterministic approach.**

Another example is the oscillation of the values of the profitability indicators. An Internal Rate of Return of 11.98% calculated following a deterministic approach is very close to the 12% set as the goal by the stakeholder. However, as shown in Figure 53, following a probabilistic approach, IRR might range from 8.9 to 15.03%, with a 50% probability of being under 12%, not fulfilling the profitability goals.

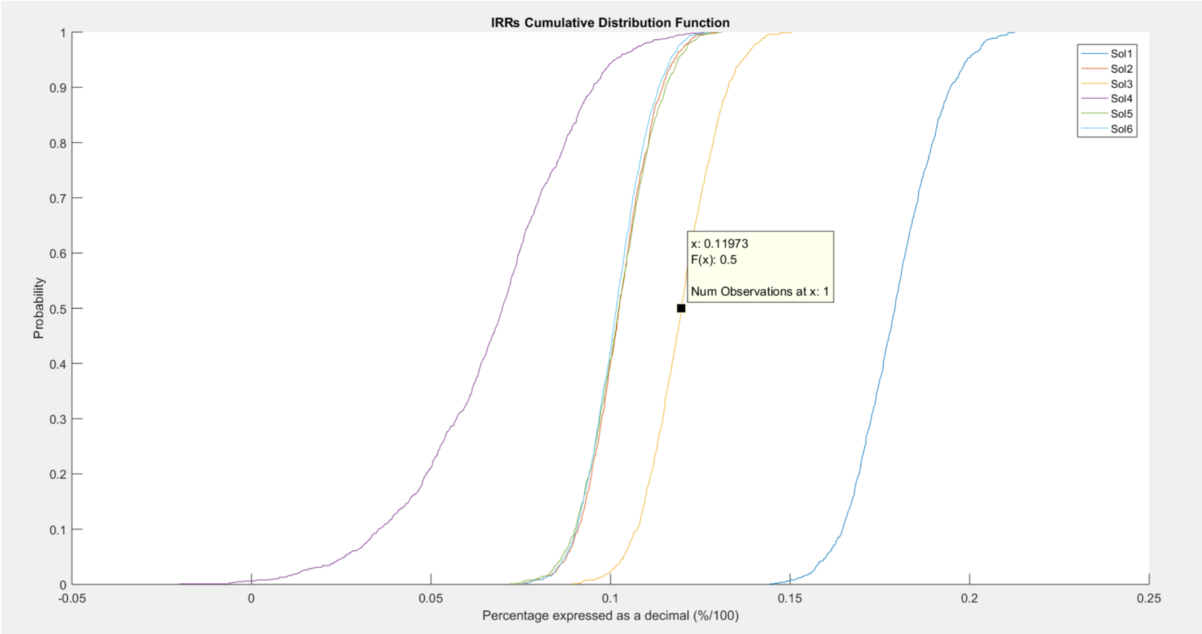


Figure 53. Detail 1 of the Risk Analysis Results for the IRRs. No Additional Resilience Solutions

More realistic results can be obtained by selecting a probability for the profitability thresholds to be satisfied. For instance, Figure 54 shows that the IRR of Solution 3 that its IRR would be over 10.63% at a 90% probability.

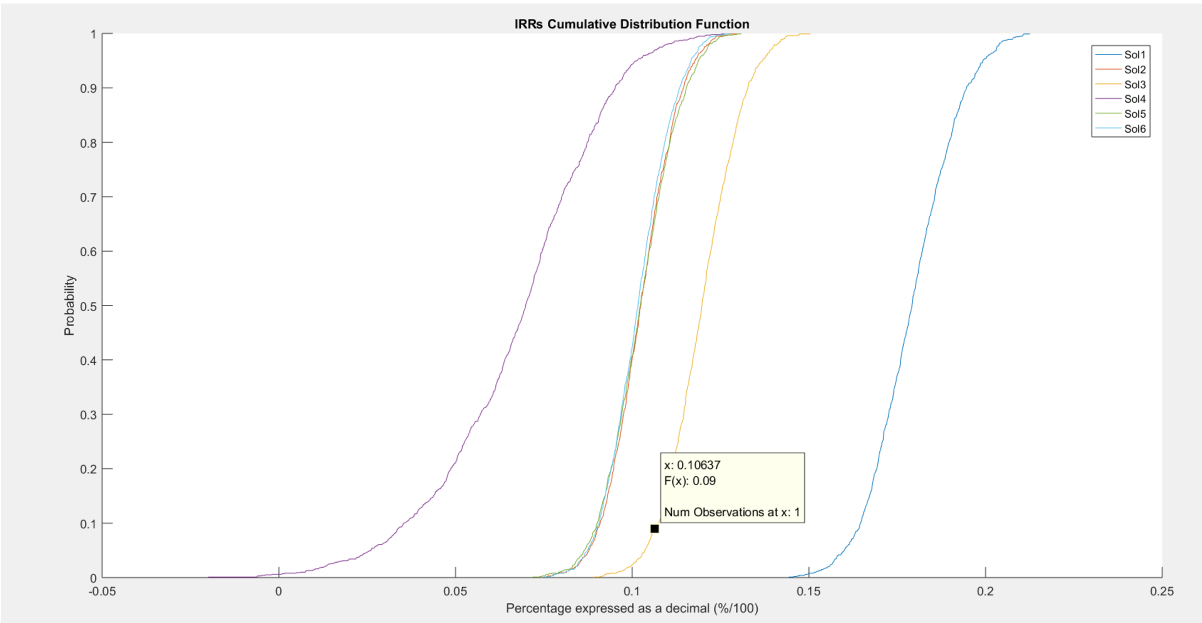
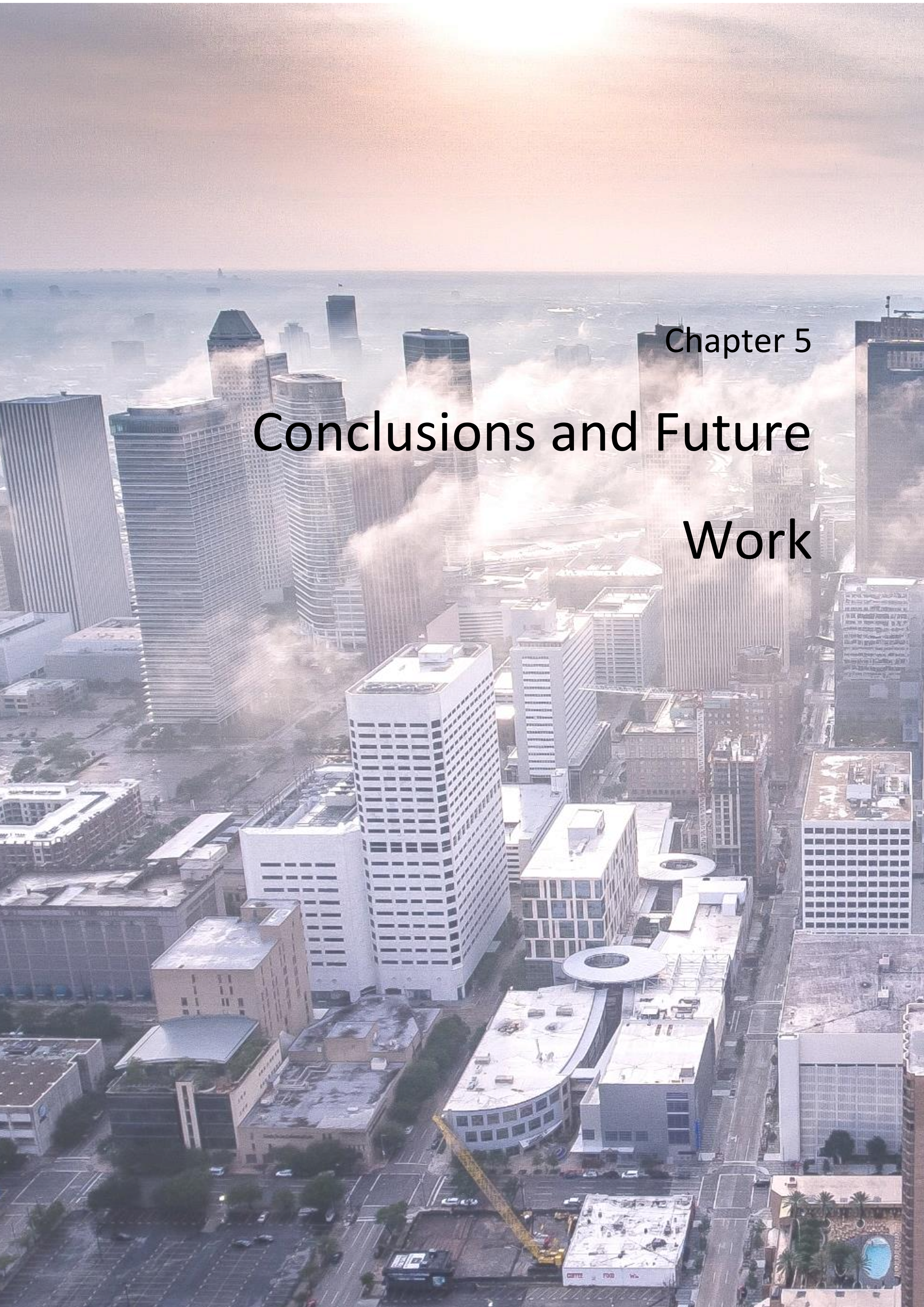


Figure 54. Detail 1 of the Risk Analysis Results for the IRRs. No Additional Resilience Solutions

This method and tool can obtain valuable insights, such as if the solutions would fulfill the goals of the stakeholders under 1,000 different future price scenarios. Chapter 5 will present the discussion of the main goals and the conclusions of this work.

Chapter 5

Conclusions and Future Work



28. Conclusions

Microgrids have been frequently presented as the future of the energy systems, taking part in the future smart grids, as discussed in Chapter 2. However, there are still gaps between the research advances and patents on one side, and the technology, regulations, business models, and market conditions on the other side, which are preventing a more intensive microgrid deployment to happen. As in other types of projects, profitability is the most common reason for users to adopt complex energy solutions such as a microgrid. Currently microgrid feasibility analysis are based in past and present values for weather, market and energy demand among others. Since microgrids have long lifespans (usually over 25 years) studying the profitability of a microgrid is not just a matter of studying present or past scenarios. The profitability of a microgrid depends on a considerable number of variables which combined evolution needs to be assessed in the long term.

In this Thesis, the microgrid design process has been modeled as a sequence of optimization algorithms. According to the information in Chapter 2, optimization algorithms have been successfully applied to different stages of the microgrid planning process. However, **none of the documented methods and algorithms develops a holistic approach to the planning process, combining in-depth technical and economic problems (sizing, siting, scheduling and prizing different microgrid alternatives) and studying how the uncertainties of the framework conditions might affect the long-term profitability of the project in competitive power markets.**

Thus, economic indicators are the center of the method presented in this Thesis and developed with the specific goal to provide stakeholders with additional information about how the values of those indicators might oscillate in the long-term to help them make better decisions at a feasibility analysis level.

In this Thesis, the state of the art of microgrid planning techniques has been reviewed, identifying past, present, and future trends at the algorithm, method, methodology, and commercial software levels. A set of optimization and risk analysis algorithms able to fit into the guidelines of the methodology designed has been identified and selected. That methodology has been developed and documented, and its corresponding method has been implemented into a MATLAB tool.

This method and tool integrate an innovative combination of three consolidated optimization algorithms and risk analysis techniques to solve feasibility analyses for multi-building microgrids. The method can design a multi-building microgrid from a decision-maker standpoint, outperforming the existing tools in the market when it comes to the number of alternatives explored per time ratio and the information provided at the economic feasibility level.

This method will help decision-makers:

- To be aware of the uncertainties of the project by exploring thousands of configurations and scenarios instead of the less than ten alternatives covered by a traditional microgrid feasibility analysis.
- To become less dependent on external expertise, and to develop a personal point of view on how the system should look like before involving other entities in the process.
- To limit the biased information that they might receive during the early stages of the project from different sources, and its impact in the final configuration of the microgrid.

The main contributions of this Thesis are presented below based on the goals stated in Chapter 1:

1. *To research the state of the art of microgrid planning algorithm, methods, methodologies, and tools.*

The exhaustive review developed on the state of the art of microgrid planning has led to two publications in research journals cited by 140 and 15 authors, respectively as of February 2020, and different conference papers and presentations, as described in Chapter 6. This review allowed:

- The identification of past, present, and future trends in microgrid planning at the methodology, method, algorithm, and commercial software tool levels.
- The selection of a research problem for this Thesis.
- The selection of a case study to apply the method and tools developed.

2. *To create a fast and innovative multi-user microgrid feasibility analysis method oriented to the multi-building microgrid sales process.*

The method presented in this Thesis provides a holistic approach to the microgrid planning process at the feasibility analysis stage. The method and the tool can size, site, and schedule power distribution and power generation systems based on an innovative combination of optimization algorithms such as GA and LP, and risk analysis techniques as the Monte-Carlo simulation. The algorithms are intuitive and easy to configure in order to answer feasibility questions such as:

- *Can a microgrid be a solution for the facilities considering the economic constraints and goals?*
- *What is the probability of a microgrid to achieve the economic goals in the long-term?*
- *How far is a microgrid from fulfilling our economic goals? Can incentives help? How much should the energy costs change to fulfill the profitability goals?*

- *The facility at the other side of the street has a CHP system with thermal storage. Is CHP a suitable technology for my microgrid? Does it make sense to install the thermal storage?*

A probabilistic analysis complements the results of the deterministic analysis, providing the stakeholder with additional information on the probability of the economic goals to be fulfilled by studying 1,000 combinations of future prices and costs for the most sensitive variables.

3. *To reduce the modeling time and costs for the same number of scenarios analyzed per time unit by other software tools in the market.*

A traditional feasibility analysis for a multi-building microgrid usually relies on single building microgrid design tools, engineering tools, or a combination of both. It can take between 100 and 400 hours to develop a microgrid feasibility analysis, depending on the number of nodes, technologies, and scenarios to model. Around 30% of that time is dedicated to the initial data collection and another 50% to modeling and data analysis, leaving a 20% for the development of the final report. The final reports analyze less than six alternatives in detail due to time constraints, providing one or two alternatives to the client.

The MATLAB script developed in this work has evaluated in detail 2,631 potential power grid designs and 2,038 configurations of power generation and thermal storage assets in 12.80 hours, as shown in Table 37.

Table 37. Execution Times of the Method

	NO ADDITIONAL RESILIENCE					
		Pow. Gen.	Pow. Gen.	Pow. Gen.	Pow. Gen.	
	Power Dist.	**No Constraint**	**CHP**	**PV + Grid**	**Isolated MG**	**TOTAL**
Total Execution Time (secs)	2,631	6,675	4,881	5,040	5,061	24,288
Number of executions	1,304	279	243	254	256	
Per Annual Solution (secs)	2.02	23.92	20.09	19.84	19.77	
Per Hourly Interval (secs)	0.00023	0.00273	0.00229	0.00227	0.00226	

	ADDITIONAL RESILIENCE					
		Pow. Gen.	Pow. Gen.	Pow. Gen.	Pow. Gen.	
	Power Dist.	**No Constraint**	**CHP**	**PV + Grid**	**Isolated MG**	**TOTAL**
Total Execution Time (secs)	2,631	4,529	6,465	5,583	5,220	24,428
Number of executions	1,304	228	278	236	264	
Per Annual Solution (secs)	2.02	19.86	23.26	23.66	19.77	
Per Hourly Interval (secs)	0.00023	0.00227	0.00265	0.00270	0.00226	

It has been verified that, once compiled into a Windows executable program, the execution time of the fitness function can be reduced to a half. Under those conditions, the execution time of the case study presented in Chapter 4 would be 6.4 hours. During that time, the algorithm would have analyzed 2,038 potential microgrid configurations (11.3 seconds per solution). At the end of the process, eight solutions have been selected by the algorithms and four more by the user, and these solutions are benchmarked in detail, taking this new analysis less than 60 seconds using the MATLAB script on the laptop with the specifications described in Chapter 5.

This method uses linearized models of power generation technologies that can be re-utilized: once a power generator is modeled, it can be considered in further studies. Same as with other microgrid analysis tools such as HOMER, modeling time will cut shorter in each project as models of different power generation systems and manufacturers are incorporated, and less customized modeling is required.

4. *To benchmark the results of the economic indicators obtained by deterministic and probabilistic approaches and identifying the probability (risk) of optimal and user-selected solutions to fulfill the economic goals of the project.*

Project developers usually will not consider risks during the feasibility analysis of the project, but stakeholders need to have that information in order to control the uncertainties both in the long and in the short term. As shown in Chapter 4, the risk analysis can define the probability of the project to be profitable under different future cost scenarios. However, for the analysis to be valid, it is crucial that the stakeholder understands and agrees with the future price scenarios that the risk analysis will consider. The probability distribution functions used by this method have been presented in Chapter 4. Additional probability functions can be incorporated.

This method allows the user to benchmark the deterministic and the probabilistic results, which should be similar but not necessarily the same. For example:

- According to the deterministic approach, 11 out of the 12 solutions has a positive Net Present Value, meaning that it is profitable. However, following the probabilistic approach, 9 of the 12 solutions have a 100% probability of obtaining savings under the analyzed scenarios. That means 3 out of 12 might experience economic losses, despite the results of the deterministic approach.
- An Internal Rate of Return of 11.98% calculated following a deterministic approach is very close to the 12% set as the goal by the stakeholder. However, following a probabilistic approach, it shows a range from 8.9 to 15.03%, with a 49.5% probability of being over 12% for the scenarios analyzed.

The tool can define if the solutions fulfill the goals of the stakeholders, but more importantly, provides valuable information about the probability for it to happen under future scenarios.

5. *Reducing the engineering skills required by the final user of the tools to allow non-technical users to develop independent analyses.*

The method can be customized for the project topology and the inputs adapted for users with any level of technical background and skills: from microgrid engineers to stakeholders with just a few economic goals in mind for the project. Stakeholders can opt for hiring a company to develop a feasibility analysis with this method and tool but can also adapt it to the skills their own staff has or can learn to use it by themselves.

In Chapter 4, the method has successfully proven its capabilities to perform the tasks presented in Chapter 1:

- ✓ To benchmark, the optimal designs calculated based on quantitative project profitability indicators, and the profitability thresholds defined by the stakeholders at the beginning of the project.
- ✓ To provide detailed information on the technical solutions behind the economic results, including a one-hour interval schedule for each asset of the microgrid.
- ✓ To solve sizing, siting, scheduling, and pricing problems and to identify the best solutions under different design constraints such as technologies and fuels involved, or hours of resilience required by the facilities.
- ✓ To model long-term profitability results through optimization and risk analysis techniques, based on current and future market conditions, and allowing the user to consider potential changes in regulation and policies.

There are advantages and disadvantages of using this specific combination of algorithms. For instance, although heuristic algorithms do not guarantee to find the global optimum, they are fast when it comes to analyzing a high number of potential solutions. Deviations observed in this case study are lower than 10% of the minimum, a level acceptable at a feasibility study stage. Besides, cost uncertainties are also covered by the risk analysis, resulting in an excellent combination of algorithms to explore potential multi-building microgrid solutions at the feasibility analysis level.

As described in the review of the state of the art, Genetic Algorithms and Linear Programming have proven to be good candidates to solve microgrid optimization problems, exploring big search spaces, and giving a good level of accuracy with low execution times. Thanks to them, the method presented in this Thesis can help:

- The promoter have a detailed view of the probability of the project to fulfill its profitability goals.
- The design team decides which alternatives should they look at for the engineering analysis

As described in Chapter 2, Linear Programming algorithms have been reported as part of microgrid design tools and are well-known for the role they play in microgrid energy management systems. On the other hand, and despite being fast, intuitive to code, and their ability to avoid local minimums, GAs have not been reported as part of professional microgrid planning tools. A potential reason for that is related with the way it is configured.

- In case the constraints are not adequately configured, a GA might be evaluating non-feasible solutions such as a power distribution system with zero power lines or with nodes left disconnected.
- If, for instance, the crossover or mutation rates are not correctly configured, a GA might become a random simulation algorithm, failing to identify optimal solution.

There is always a randomness component in a GA. For example, it cannot be guaranteed that the algorithm has analyzed 2,038 **different** solutions in Chapter 4. Some potential solutions might have been analyzed from one up to eight times since the power generation optimization algorithm has been run eight times.

One of the limitations of this approach is the size of the problem that can be solved. For instance, the size of the search space in a power distribution design problem strongly depends on the number of nodes, as shown in Table 38.

Table 38. Size of the Search Space for Power Distribution Systems

Power Line Sizes Allowed	Number of Nodes	Power lines Allowed	Search Space Size
3	3	3	27
3	4	6	729
3	5	10	59,049
3	6	15	14,348,907
3	7	21	10,460,353,203
3	8	28	2.28768E+13
3	9	36	1.50095E+17
3	10	45	2.95431E+21
3	15	105	1.25237E+50
3	20	190	4.4982E+90

Thus, a bigger microgrid would require a more significant initial population in order to improve the probability of the GA to find the optimal solution. However, increasing the population size would also increase the execution time, as discussed in Chapter 4.

The MATLAB tool can be compiled into a customized Windows executable solution to cut this time, but still, advanced knowledge of MATLAB and basic knowledge of GA, LP, and Monte Carlo simulations are required to customize the original script to different microgrid projects. A user with MATLAB skills will require a brief training on where in the code are inputs and outputs located. In its current state, the MATLAB tool is not as intuitive as an engineering software tool.

As discussed in Chapter 1, the ultimate goal of the approach started by this Thesis is to make microgrid feasibility analyses more accessible to people without advanced technical skills in the field of microgrids or even with no engineering background. That means a more intuitive interface than MATLAB is required, making of other algorithms more complex good candidates for further versions of this method. It would be useful for those sets of algorithms to keep some of the competitive advantages of the genetic algorithm, such as its ability to explore big search space in a reduced amount of time.

29.Future Work

The work developed in this Thesis has evolved to become the initial step of a project to develop a commercial tool for multi-building microgrid feasibility analysis. The focus of this project has been to develop the computational or calculations engine presented in Figure 55.

Some of the next steps to be considered in the development of this project idea are described below:

- The code might need to be adapted to a different programing language to be determined.
- The execution time of the algorithms can be optimized following a similar approach. As mentioned in Chapter 4, preliminary compilations of the fitness function have shown that the execution time is reduced to a half. That time represents 99.5% of the execution time of the algorithm in it the current version.
- Additional strategies can be applied if required, such as using cloud services to minimize the execution time no matter what the performance of the user's computer is.
- This method can be easily expanded to cover both microgrids and district energy systems (district heating and district cooling systems).
- The data collection stage can be expedited through Geographical Information Systems (GIS) tools, which would also diminish the technical skills required by the user.

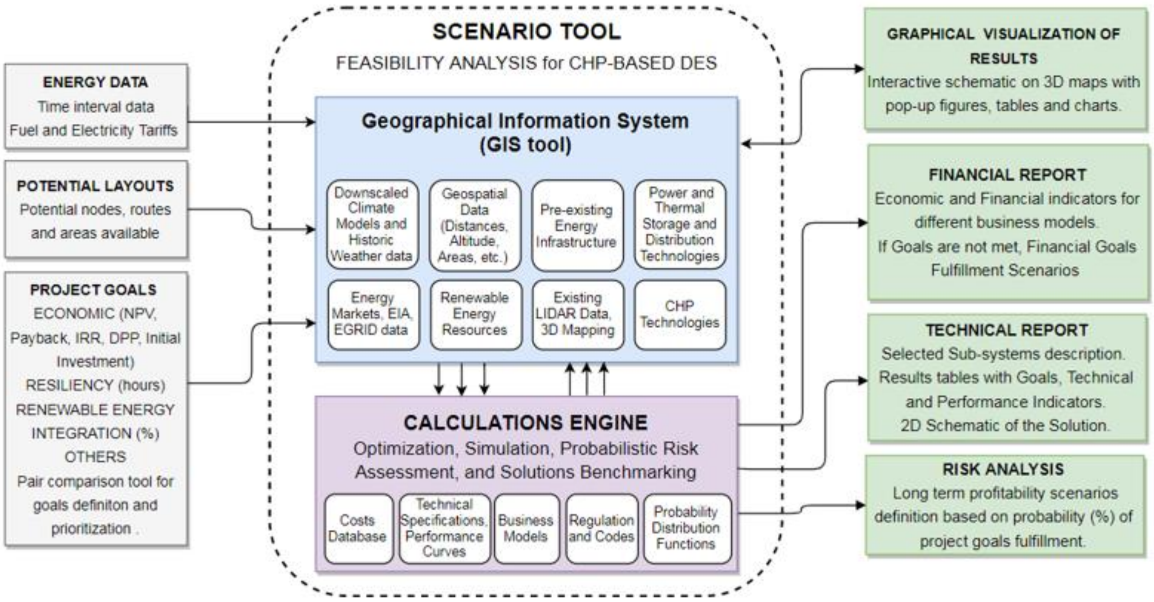


Figure 55. Proposed Main Components and Information Flow for Software Tool

There are other opportunities and trends in the microgrid planning market. One of them is related with the amount of data available during the design stage. The Internet of Things (IoT) is increasing the amount of data available in all kinds of facilities. As shown in Figure 56, IoT is a trending topic in research publications. Machine Learning (ML) techniques lead the way when it comes to extracting valuable information from those data sets.

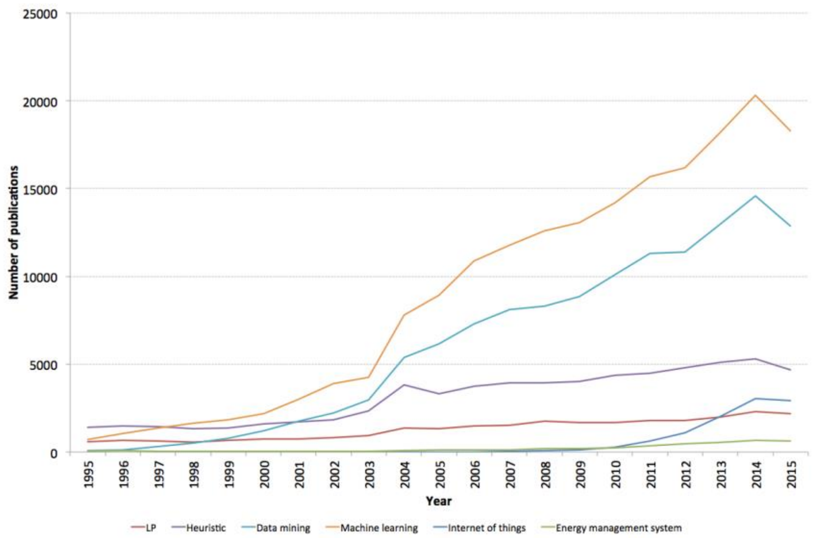


Figure 56.. Papers per Search Term from 1995 to 2015. Source: SCOPUS

With many techniques and algorithms already available, data-intensive environments will enable the incorporation of techniques such as data mining and machine learning to the microgrid planning process (i.e., in manufacturing processes), easily overperforming the capabilities of the existing software tools at a feasibility analysis level. Figure 57 presents a preliminary description of a microgrid planning methodology in data-intensive environments developed by this author[1].

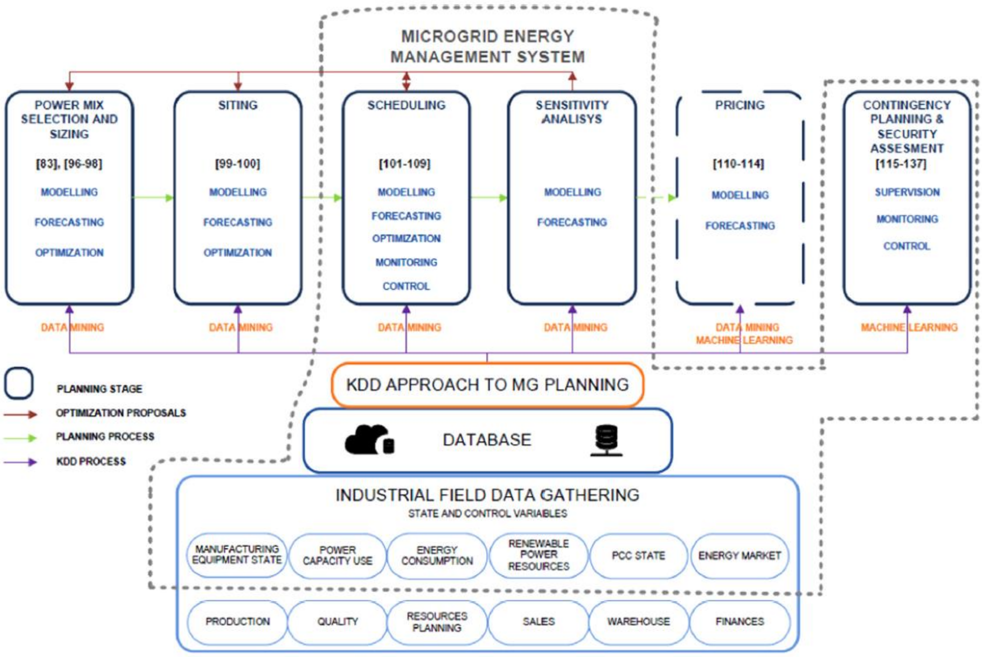


Fig. 3. A KDD-based approach to microgrid planning process scheme.

Figure 57. Innovative Microgrid Planning Process in Data-Intensive Environments. Source[45]

Currently, microgrids are designed based on average historical climate patterns, not considering any future weather conditions they would to operate under. This fact adds uncertainty to power generation plants, and especially to those based on wind and solar energy. Downscaled climate data can help incorporate future weather variability to the existing microgrid planning methodologies and represents another trend. Downscaled climate data can help better select, size, and operate future power generation systems, and the microgrid planning process can benefit from the valuable information they provide.

Downscaled climate models are becoming more popular among power utilities mainly because they allow future climate patterns to be forecasted, enabling new capabilities such as:

- To forecast power operations both for renewable and dispatchable power generation systems.
- To respond to strategic questions such as, *What is the best power generation portfolio under climatic uncertainty?*

[45] Gamarra C, Guerrero JM, Montero E. *A Knowledge Discovery In Databases Approach For Industrial Microgrid Planning*. Renew Sustain Energy Rev 2016;60:615–30. DOI:10.1016/j.rser.2016.01.091

Capítulo 5

Conclusiones y Líneas de Trabajo Futuro

30.Conclusiones

Las microrredes se han presentado con frecuencia como el futuro de los sistemas energéticos, participando en las futuras redes de energía inteligente, como se ha presentado en el Capítulo 2. Sin embargo, aún existen lagunas entre los avances de la investigación y las patentes, por un lado, y el desarrollo de la tecnología, modelos de negocio y condiciones de mercado por el otro las cuales ralentizan el nivel de adopción de microrredes por parte de los propietarios. Al igual que la mayoría de los proyectos, la rentabilidad es la razón más común para que los usuarios adopten soluciones energéticas complejas, como una microrred. Actualmente los estudios de viabilidad de microrredes se basan en análisis determinísticos que usan valores pasados y presentes de variables climáticas, de mercado y de demanda energética entre otras. Dado que las microrredes tienen una larga vida útil (generalmente más de 25 años), estudiar la rentabilidad de una microrred no es solo una cuestión de considerar condiciones pasadas o presentes. La rentabilidad de una microrred depende de un amplio número de variables cuya evolución combinada necesita ser evaluada a largo plazo.

En esta tesis, el proceso de diseño de microrredes se ha modelado como una secuencia de algoritmos de optimización. De acuerdo con la información presentada en el Capítulo 2, los algoritmos de optimización se han aplicado con éxito a diferentes etapas del proceso de planificación de microrredes. Sin embargo, ninguno de los métodos y algoritmos documentados considera un enfoque holístico del proceso de planificación: combinando problemas técnicos y económicos en profundidad (dimensionamiento, ubicación, programación y valoración de diferentes alternativas de microrredes) y estudiando como las incertidumbres de las condiciones marco del proceso de diseño podrían afectar a la rentabilidad del proyecto a largo plazo en mercados de energía competitivos.

Por lo tanto, los indicadores económicos son el centro del método presentado en este trabajo, desarrollado con el objetivo específico de proporcionar a los promotores y usuarios finales de microrredes información sobre posibles variaciones a largo plazo de los indicadores de rentabilidad que les ayuden a tomar mejores decisiones sobre la viabilidad del proyecto.

En esta Tesis se ha revisado el estado del arte de las técnicas de planificación de microrredes, identificando tendencias pasadas, presentes y futuras a nivel de algoritmo, método, metodología y software comercial. Se ha identificado y seleccionado un conjunto de algoritmos de optimización y análisis de riesgos capaces de adaptarse a las directrices de la metodología diseñada. También se ha desarrollado y documentado dicha metodología y su método correspondiente ha sido implementado en una herramienta MATLAB.

Este método y herramienta integran una innovadora combinación de dos algoritmos de optimización y una técnica de análisis de riesgos para resolver los análisis de viabilidad de microrredes multi-edificio. El método permite diseñar una microrred desde el punto de vista del promotor, superando a las herramientas existentes en el mercado en lo referente al número de alternativas exploradas por unidad de tiempo y a la información proporcionada a nivel de viabilidad económica.

Este método ayudará a los promotores del proyecto a:

- Conocer las incertidumbres del proyecto mediante la exploración de miles de configuraciones y escenarios en vez de las menos de diez alternativas cubiertas por un análisis de viabilidad tradicional.
- Ser menos dependientes del conocimiento externo a su organización y desarrollar un punto de vista personal sobre cómo debería ser la microrred antes de involucrar a otras entidades en el proceso.
- Limitar la influencia de la información sesgada que podrían recibir durante las primeras etapas del proyecto en la configuración final de la microrred.

Las principales contribuciones de esta Tesis se presentan a continuación en función de los objetivos establecidos en el Capítulo 1:

1. *Investigar el estado del arte de algoritmos, métodos, metodologías y herramientas de planificación de microrredes.*

La revisión exhaustiva desarrollada sobre el estado del arte de la planificación de microrredes ha llevado a dos publicaciones en revistas de investigación citadas por 140 y 15 autores, respectivamente hasta febrero de 2020, como se describe en el Capítulo 6. Esta revisión ha permitido:

- La identificación de tendencias pasadas, presentes y futuras en la planificación de microrredes a nivel de metodología, método, algoritmo y herramienta de software comercial.
- La selección de un problema de investigación para esta Tesis.
- La selección de un caso de estudio para aplicar el método y las herramientas desarrolladas.

2. *Crear un método rápido e innovador de análisis de viabilidad de microrredes multi-edificio orientado al proceso de venta de microrredes.*

El método presentado en esta Tesis sigue un enfoque holístico del proceso de planificación de microrredes en la etapa de análisis de viabilidad. El método y la herramienta pueden dimensionar, ubicar y programar sistemas de distribución de energía y generación de energía basados en una combinación innovadora de algoritmos de optimización como GA y LP, y técnicas de análisis de riesgos como la simulación de Monte-Carlo. Los algoritmos son intuitivos y fáciles de configurar para responder preguntas sobre viabilidad como:

- ¿Puede una microrred ser una solución para las instalaciones considerando las limitaciones y objetivos económicos?
- ¿Cuál es la probabilidad de que una microrred alcance los objetivos económicos fijados a largo plazo?
- ¿Cómo de lejos está una microrred de cumplir con los objetivos económicos propuestos? ¿Pueden ayudar los incentivos? ¿Cuánto deberían cambiar los costes de energía para cumplir con los objetivos de rentabilidad?
- Las instalaciones al otro lado de la calle tienen un sistema de cogeneración con almacenamiento térmico. ¿Es la cogeneración una tecnología adecuada para mi microrred? ¿Tiene sentido instalar el almacenamiento térmico en mis instalaciones?

Un análisis probabilístico complementa los resultados del análisis determinístico, proporcionando al promotor información adicional sobre la probabilidad de que se cumplan los objetivos económicos mediante el estudio de 1,000 combinaciones de precios y costes futuros para las variables más sensibles.

3. *Reducir el tiempo y los costes de modelado para el mismo número de escenarios analizados por unidad de tiempo respecto al resto de herramientas software en el mercado.*

Los análisis de viabilidad para una microrred de múltiples edificios normalmente se realizan con software de diseño de microrredes de un solo edificio, software de ingeniería o una combinación de ambos. El desarrollo de un análisis de viabilidad de una microrred multi-edificio puede llevar entre 100 y 400 horas, dependiendo del número de nodos, tecnologías y escenarios a modelar. Alrededor del 30% de ese tiempo se dedica a la recopilación inicial de datos y el otro 50% a la modelización y el análisis de soluciones, dejando un 20% para la elaboración del informe final. Los informes finales analizan menos de diez alternativas en detalle debido básicamente a limitaciones de tiempo o de presupuesto, presentando solo una o dos alternativas al cliente.

El código de MATLAB desarrollado en este trabajo ha evaluado en detalle 2.631 diseños potenciales de la red eléctrica y 2.038 configuraciones de activos de generación de energía y almacenamiento térmico en 12.80 horas, como se muestra en la Tabla 37.

Table 37. Tiempos de ejecución del código MATLAB

	NO ADDITIONAL RESILIENCE					
		Pow. Gen.	Pow. Gen.	Pow. Gen.	Pow. Gen.	
	Power Dist.	No Constraint	CHP	PV + Grid	Isolated MG	TOTAL
Total Execution Time (secs)	2,631	6,675	4,881	5,040	5,061	24,288
Number of executions	1,304	279	243	254	256	
Per Annual Solution (secs)	2.02	23.92	20.09	19.84	19.77	
Per Hourly Interval (secs)	0.00023	0.00273	0.00229	0.00227	0.00226	

	ADDITIONAL RESILIENCE					
		Pow. Gen.	Pow. Gen.	Pow. Gen.	Pow. Gen.	
	Power Dist.	No Constraint	CHP	PV + Grid	Isolated MG	TOTAL
Total Execution Time (secs)	2,631	4,529	6,465	5,583	5,220	24,428
Number of executions	1,304	228	278	236	264	
Per Annual Solution (secs)	2.02	19.86	23.26	23.66	19.77	
Per Hourly Interval (secs)	0.00023	0.00227	0.00265	0.00270	0.00226	

Se ha comprobado que, una vez compilado en un programa ejecutable de Windows, el tiempo de ejecución de la función fitness se reduce a la mitad. Bajo esas condiciones, el tiempo de ejecución del código para el caso de estudio presentado en el Capítulo 4 sería de 6.4 horas. Durante ese tiempo, el algoritmo habría analizado 2.038 configuraciones potenciales de microrred (11.3 segundos por solución). Al final del proceso, ocho soluciones han sido seleccionadas por los algoritmos y cuatro más por el usuario, y estas soluciones se comparan en detalle, tomando este nuevo análisis menos de 60 segundos ejecutando el código MATLAB desarrollado en el ordenador portátil cuyas especificaciones se han descrito en Capítulo 5.

Este método utiliza modelos linealizados de tecnologías de generación de energía que se pueden reutilizar: una vez que se modela un generador, se puede considerar en estudios posteriores. Al igual que con otras herramientas de análisis de microrredes como HOMER, el tiempo de modelado se acortará en cada proyecto a medida que se incorporen nuevos modelos de diferentes sistemas de generación y fabricantes.

4. *Comparar los resultados de los indicadores económicos obtenidos mediante enfoques determinísticos y probabilísticos e identificar la probabilidad (riesgo) de que las soluciones óptimas y seleccionadas por el usuario cumplan con los objetivos económicos del proyecto.*

Las empresas encargadas del estudio técnico generalmente no consideran los riesgos del proyecto durante el análisis de viabilidad, pero es importante que las partes interesadas tengan esa información para controlar las incertidumbres tanto a largo como a corto plazo. Como se muestra en el Capítulo 4, el análisis de riesgos puede definir la probabilidad de que el proyecto sea rentable para diferentes escenarios de costes futuros. Sin embargo, para que el análisis sea válido, es crucial que el promotor comprenda y esté de acuerdo con los escenarios de precios futuros que el análisis de riesgo considerará. Las funciones de distribución de probabilidad utilizadas por este método se han presentado en el Capítulo 4. Al igual que con los modelos de las tecnologías, se pueden incorporar y reutilizar funciones de probabilidad adicionales.

Este método permite al usuario comparar los resultados determinísticos y probabilísticos, que deberían ser similares, pero no necesariamente los mismos. Por ejemplo:

- De acuerdo con el enfoque determinístico, 11 de las 12 soluciones tienen un valor presente neto positivo (NPV>0), lo que significa que son rentables. Sin embargo, siguiendo el enfoque probabilístico, solo 9 de las 12 soluciones tienen un 100% de probabilidad de obtener ahorros en los escenarios analizados. Eso significa que 3 de cada 12 podrían experimentar pérdidas económicas, a pesar de los resultados del enfoque determinístico.
- Un IRR del 11,98% calculado siguiendo un enfoque determinístico está muy cerca del 12% establecido como objetivo por el promotor. Sin embargo, siguiendo un enfoque probabilístico el mismo indicador presenta un rango de 8.9% a 15.03%, con solo una probabilidad de 49.5% de ser superior al 12% para los escenarios analizados.

La herramienta puede definir si las soluciones cumplen los objetivos del promotor y, lo que es más importante, proporciona información valiosa sobre la probabilidad de que eso ocurra en los escenarios futuros simulados.

5. *Reducir los conocimientos de ingeniería requeridos con el fin de permitir a los usuarios no técnicos desarrollar análisis de viabilidad más independientes.*

El método se puede personalizar para la topología del proyecto y las entradas adaptadas para usuarios con cualquier nivel de conocimientos técnicos y habilidades: desde ingenieros de microrredes hasta para promotores que centran el análisis en los objetivos económicos que tienen en mente para el proyecto. Los promotores pueden optar por contratar una empresa para desarrollar un análisis de viabilidad con este método y herramienta, pero también podrían adaptarlo a las habilidades que tiene su propio personal o incluso aprender a usarlo por sí mismos.

En el Capítulo 4, el método ha demostrado sus capacidades para realizar las tareas presentadas en el Capítulo 1 como:

1. Comparar los diseños óptimos calculados en base a indicadores cuantitativos de rentabilidad del proyecto y los umbrales de rentabilidad definidos para ellos por el promotor del proyecto.
2. Proporcionar información detallada sobre las soluciones técnicas detrás de los resultados económicos, incluyendo una programación horaria de las operaciones anuales de cada activo de la microrred.

3. Resolver los problemas de dimensionamiento, localización, programación y cálculo de costes identificando las mejores soluciones bajo diferentes restricciones de diseño basadas en tecnologías, combustibles, o las horas de resistencia a problemas en la red eléctrica requeridas por las instalaciones entre otras.
4. Modelar los resultados del análisis de rentabilidad a largo plazo a través de técnicas de optimización y análisis de riesgos, basadas en las condiciones actuales y previsiones futuras del mercado, y permitiendo al usuario considerar posibles cambios en la normativa y en las políticas que pudieran afectar a la microrred.

Existen ventajas y desventajas de usar esta la combinación de algoritmos adoptada en este trabajo. Por ejemplo, aunque los algoritmos heurísticos no garantizan encontrar el óptimo global, son rápidos cuando se trata de analizar una gran cantidad de posibles soluciones. Las desviaciones observadas en el caso de estudio son inferiores al 10% del optimo global encontrado, un nivel aceptable para un estudio de viabilidad. Además, las incertidumbres de costes están cubiertas por el análisis de riesgos, lo que resulta en una excelente combinación de algoritmos para explorar la viabilidad de posibles diseños de microrredes.

Como se describe en el Capítulo 2, los Algoritmos genéticos y la Programación lineal han demostrado ser buenos candidatos para resolver problemas de optimización de microrredes, explorando grandes espacios de búsqueda y proporcionando un buen nivel de precisión con bajos tiempos de ejecución. Gracias a ellos el método presentado en esta Tesis puede ayudar a que:

- El interesado tenga una visión detallada de la probabilidad de que el proyecto cumpla con sus objetivos de rentabilidad.
- El equipo de diseño decida qué alternativas deberían considerar para el análisis de ingeniería básica y de detalle.

Como se describe en la revisión el estado del arte, los algoritmos de programación lineal han probado su valía como herramientas de diseño de microrredes y son conocidos por el papel que desempeñan en la gestión energética de microrredes. Por otro lado, y a pesar de ser rápidos, intuitivos para codificar, y de su capacidad para evitar los mínimos locales, los GA no se han consolidado entre las herramientas software comerciales. Una razón potencial para eso está relacionada con la forma en que se configuran.

- En caso de que las restricciones no estén configuradas adecuadamente, un GA podría estar evaluando soluciones no viables, como un sistema de distribución de energía con cero líneas de energía o con nodos que quedan desconectados.

- Si las tasas de cruce o mutación no estan configuradas correctamente, un GA podría convertirse en un algoritmo de simulación aleatorio y no identificar las soluciones optimas.

Siempre hay un componente de aleatoriedad en un GA. Por ejemplo, no se puede garantizar que el algoritmo del caso de estudio haya analizado 2.038 soluciones diferentes en el Capítulo 4. Algunas soluciones potenciales podrían haberse analizado entre una y ocho veces ya que el algoritmo de optimización de generación de energía se ha ejecutado ocho veces.

Una de las limitaciones de este enfoque es el tamaño del problema que se puede resolver. Por ejemplo, el tamaño del espacio de búsqueda en un problema de diseño de distribución de energía depende en gran medida del número de nodos, como se muestra en la Tabla 38.

Tabla 38. Tamaño del espacio de búsqueda de sistemas de distribución eléctrica

Power Line Sizes Allowed	Number of Nodes	Power lines Allowed	Search Space Size
3	3	3	27
3	4	6	729
3	5	10	59,049
3	6	15	14,348,907
3	7	21	10,460,353,203
3	8	28	2.28768E+13
3	9	36	1.50095E+17
3	10	45	2.95431E+21
3	15	105	1.25237E+50
3	20	190	4.4982E+90

Por lo tanto, una microrred más grande requeriría una población inicial más amplia para mejorar la probabilidad de que el GA encuentre la solución óptima. Pero al aumentar el tamaño de la población también aumentaría el tiempo de ejecución, como se demuestra en el capítulo 4.

La herramienta MATLAB se puede compilar en una solución ejecutable de Windows personalizada para reducir el tiempo de ejecución, pero para ello se requieren conocimientos avanzados de MATLAB y conocimientos básicos sobre GA, LP y simulación de Monte Carlo con el fin de el código original a diferentes proyectos. En su estado actual, la herramienta MATLAB no es intuitiva y dista mucho de la facilidad de manejo de una herramienta software para un usuario no entrenado. Como se ha comentado en el Capítulo 1, el objetivo final del camino iniciado por esta Tesis es hacer que los análisis de viabilidad de microrredes sean más accesibles para personas sin habilidades técnicas avanzadas en este campo o incluso sin experiencia alguna en ingeniería. El desarrollo de una interfaz más intuitiva que MATLAB, convertiria otros algoritmos más complejos pudieran convertirse en buenos candidatos para futuras revisiones de este método. Sería útil para esos conjuntos de algoritmos mantener algunas de las ventajas competitivas de este método, como su capacidad para explorar grandes espacios de búsqueda en un período de tiempo reducido.

31.Futuras Líneas de Trabajo

Este trabajo desarrollado en esta tesis ha evolucionado en un paso preliminar al desarrollo de una herramienta comercial para el análisis de viabilidad de microrredes multi-edificios. Esta tesis desarrolla una version preliminar del módulo denominado *computational or calculations engine* de la figura 55. Algunos de los siguientes pasos a considerar en el desarrollo de esta línea de trabajo se describen a continuación:

- El código podria tenr que ser convertido a un lenguaje de programación por determinar.
- El tiempo de ejecución de los algoritmos se puede optimizar siguiendo un enfoque similar. Como se mencionó en el Capítulo 4, se ha comprobado que una compilación de la función de fitness reduce su tiempo de ejecución a la mitad. Ese tiempo representa el 99.5% del tiempo de ejecución del algoritmo completo en la versión actual.
- Se pueden aplicar estrategias de ejecución adicionales, como el uso de servicios en la nube, limitando la influencia del rendimiento de la computadora del usuario sobre el tiempo de ejecución.
- Este método puede expandirse fácilmente para cubrir tanto microrredes como sistemas district heating o district cooling.
- La recogida de datos se puede acelerar a través de herramientas basadas en Sistemas de Información Geográfica (SIG), que también disminuiría las habilidades técnicas requeridas por el usuario.

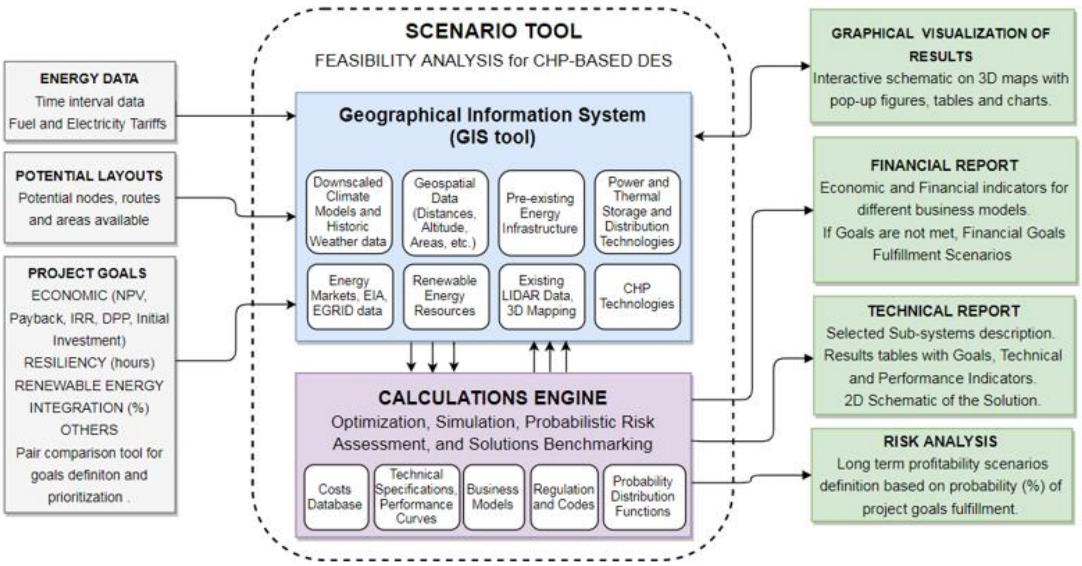


Figure 55. Principales componentes y flujos de información propuestos para una herramienta profesional

Existen otras oportunidades y tendencias en el mercado de planificación de microrredes. Una de ellas está relacionada con la cantidad de datos disponibles durante la etapa de diseño. El *Internet de las* *cosas o Internet of Things* (IoT) está aumentando la cantidad de datos disponibles en todo tipo de instalaciones.

Como se muestra en la figura 56, IoT es un tema de tendencia en publicaciones de investigación, mientras que las técnicas de Machine Learning (ML) destacan en lo que se refiere a extraer información valiosa de los conjuntos de datos generados por los sistemas basados en IoT.

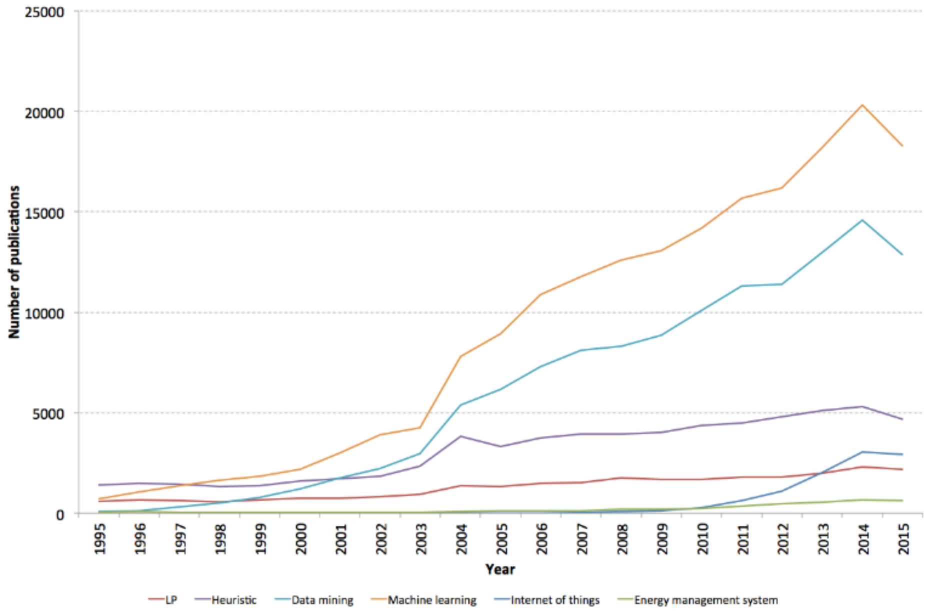


Figure 56. Artículos por termino de búsqueda entre 1995 y 2015. Fuente: SCOPUS

Los algoritmos ya disponibles permitirán la incorporación de técnicas como la minería de datos y el ML al proceso de planificación de microrredes en entornos intensivos en datos (como por ejemplo en los procesos de fabricación), superando fácilmente las capacidades de las herramientas de software existentes a nivel de análisis de viabilidad y diseño.

La figura 57 presenta una descripción preliminar de una metodología de planificación de microrredes en entornos de uso intensivo de datos desarrollada por este autor.

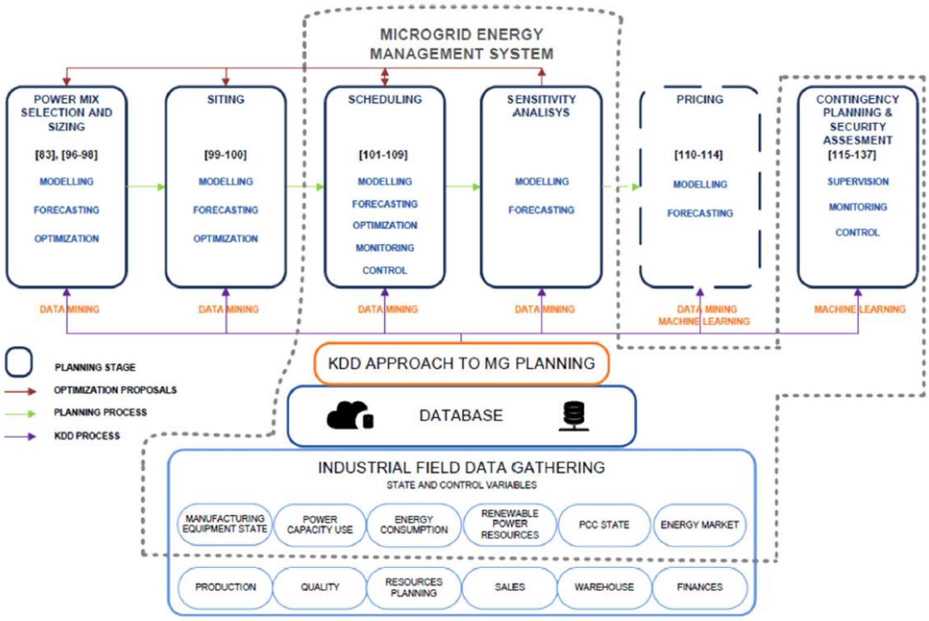


Fig. 3. A KDD-based approach to microgrid planning process scheme.

Figura 57. Proceso de planificación de microrredes eléctricas en entornos intensivos en datos. Fuente[46]

Actualmente, las microrredes son diseñadas en base a patrones climáticos históricos medios, sin tener en cuenta las condiciones climáticas futuras en las que tendrían que operar. Esto añade incertidumbre al rendimiento por ejemplo de las plantas de generación de energía, y especialmente a aquellas basadas en energía eólica y solar. **Los modelos climáticos localizados pueden ayudar a incorporar las predicciones reales de variabilidad climática en las metodologías de planificación de microrredes existentes y constituyen otra tendencia en este campo**. Los modelos climáticos localizados pueden ayudar a una selección, dimensionamiento y programación más precisas, de los sistemas de generación beneficiándose el proceso de planificación de las microrredes de la valiosa información que proporcionan.

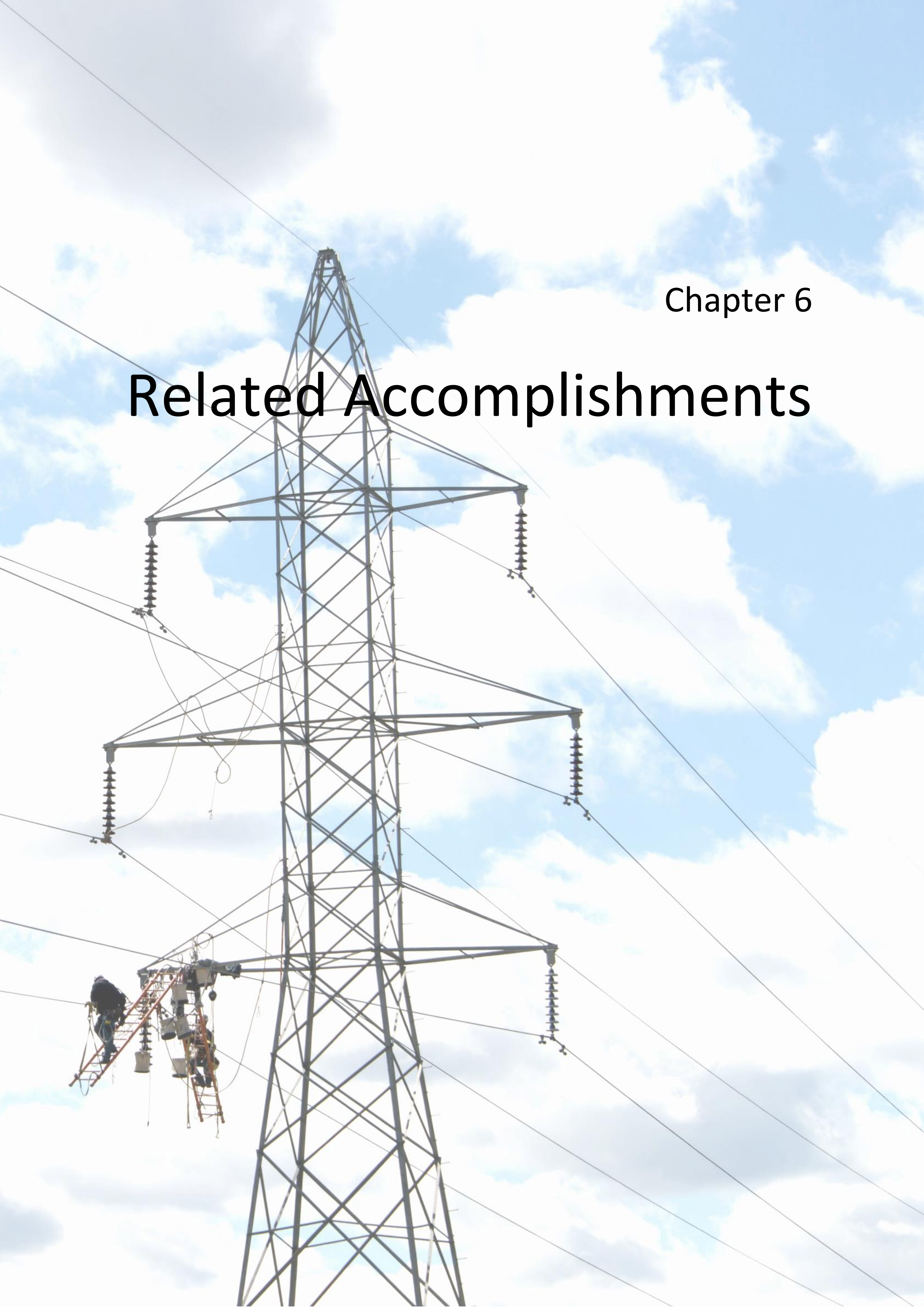
Dichos modelos se ganando popularidad especialmente entre las empresas de generación energética y compañías eléctricas porque permiten pronosticar futuros patrones climáticos a nivel local o regional, habilitando nuevas capacidades como:

- Pronosticar de manera más precisa la generación de energía en plantas basadas en energías renovables y en consecuencia también en las basadas en combustibles tradicionales.
- Responder a preguntas estratégicas como: ¿Cuál es el mejor mix de generación de energía para los futuros patrones climáticos?

[46] Gamarra C, Guerrero JM, Montero E. *A knowledge discovery in databases approach for industrial microgrid planning*. Renew Sustain Energy Rev 2016;60:615–30. DOI:10.1016/j.rser.2016.01.091

Chapter 6

Related Accomplishments



This document presents the most relevant accomplishment during the time the author has been enrolled as a Ph.D. student at the Doctorate program.

32. Publications on Research and Peer-Reviewed Journals

Gamarra C, Guerrero JM. ***Computational optimization techniques applied to microgrids planning: A review***. Renew Sustain Energy Rev 2015;48:413–24. DOI:10.1016/j.rser.2015.04.025.

- Quality Indicator: *Journal Citation Reports*
- Impact Index (2015): 6.798. Quartile: Q1 (6/88). Category: Energy&Fuels.
- Cited 140 times as of February 2020

Gamarra C, Guerrero JM, Montero E. ***A knowledge discovery in databases approach for industrial microgrid planning***. Renew Sustain Energy Rev 2016;60:615–30. DOI:10.1016/j.rser.2016.01.091.

- Quality Indicator: Journal Citation Reports
- Impact Index (2016): 8.050. Quartile: Q1 (5/90). Category: Energy&Fuels.
- Cited 15 times as of February 2020,

C.Gamarra and J.Ronk. ***Floating Solar: An Emerging Opportunity at the Energy-Water Nexus***., Texas Water Resources Institute. Texas Water Journal, Vol. 10, Number 1, March 25, 2019 Pages 32-45

C. Gamarra, M. Ortega, E. Montero, and J.M. Guerrero ***Innovative planning synergies between manufacturing processes and microgrids*****.** International Conference on Renewable Energies and Power Quality (ICREPQ'16). Madrid (Spain), 4th to 6th May 2016. Renewable Energy and Power Quality Journal (RE&PQJ). ISSN 2172-038 X, No.14 May 2016

33. Doctoral Stays and Collaborations

Nov 2013	Center for Research on Microgrids, University of Aalborg, Denmark. Professor Josep M. Guerrero, Director. One-month stay and later collaboration in two research papers and two conference papers.
Sep 2015-Present	Center for Electromechanics, University of Texas at Austin, USA. Dr. Robert Hebner, Director. **Co-director of this Ph.D. Thesis**. Three meetings per year on average to discuss advances and collaborations.

34. Participation in Conferences

2018

Title	***Profitability Thresholds of Resilient Microgrids (And How to Exceed Them)***
Author(s)	C. Gamarra
Type of Contribution	Presentation
Conference Name	Microgrid 2.0
City and Dates	Baltimore, MD (USA), Oct 27, 2018

Title	***Combined Heat and Power as A Source of Resilience in Microgrids***
Author(s)	C. Gamarra
Type of Contribution	Panel Session
Conference Name	USGBC Texas Energy Summit
City and Dates	Houston, TX (USA), Oct 11, 2018

2017

Title	***Designing Microgrids For Resilience***
Author(s)	C. Gamarra
Type of Contribution	Presentation
Conference Name	CATEE 2017 Texas Energy Summit
City and Dates	Dallas, TX (USA), Nov 15, 2017

Title	***Long-Term Profitability of CHP-Based Microgrids***
Author(s)	C. Gamarra
Type of Contribution	Presentation
Conference Name	IDEA 2017
City and Dates	Scottsdale, AZ (USA), June 27, 2017

2016

Title	***Impact of Research on the Planning of Community Energy Systems***
Author(s)	C. Gamarra, E. Montero, and R. Hebner
Type of Contribution	Poster
Conference Name	Smart Cities Innovation Summit
City and Dates	Austin, TX (USA), June 13-15, 2016

Title	***Innovative planning synergies between manufacturing processes and microgrids***
Author(s)	C.Gamarra, Ortega, J.M. Guerrero, and E. Montero
Type of Contribution	Poster
Conference Name	Int. Conf. on Renewable Energies and Power Quality ICREPQ'16
City and Dates	Madrid (Spain), May 4-6, 2016

2015

Title	***Evolution and Trends of Industrial Energy Management Systems***
Author(s)	C.Gamarra, Ortega, J.M. Guerrero, and E. Montero
Type of Contribution	Poster
Conference Name	IX Congreso de Ingeniería Termodinámica
City and Dates	Cartagena (Spain), Jun 3-5, 2015

2013

Title	***Success Factors in A District Energy System Establishment Process***
Author(s)	C.Gamarra and E. Montero
Type of Contribution	Poster
Conference Name	VIII Congreso de Ingeniería Termodinámica
City and Dates	Burgos (Spain), Jun 19-21, 2013

35.Related Awards

2020

Title	***Advances on CHP District Energy and Microgrids Deployment: Simplified Tool for Rapidly Deploying Feasibility Analytics for the Non-Technical User***
Funder	US Department of Energy's Advanced Manufacturing Office
Performance Period	Sept 2020-Sept 2023
Budget	1.9 Million Dollars

2013

Title	***Excellent Youth Program. Doctoral Stay with the Center for Research on Microgrids at the University of Aalborg (Denmark)***
Funder	Fundación Gutierrez Manrique (www.fundaciongutierrezmanrique.es/)
Performance Period	November 2013
Budget	2,000 €

36.Related Work Experience

Feb 2017-Current

Senior Research Associate at Houston Advanced Research Center. Assistant Director for the US Department of Energy´s South Central CHP TAP (TX, NM, OK, AR, LA).

Microgrid Feasibility Analysis

- 40 MW Microgrid feasibility analysis for an International Airport
- 3.3 MW Microgrid feasibility analysis for a university campus

R&D project development: climate change's impact on present and future power systems. Energy planning projects: Energy infrastructure and energy systems, from a district-scale to individual solutions including microgrids and district energy.

Energy manager of HARC's NET ZERO, LEED PLATINUM, and ENERGY STAR certified building: 21.9% energy savings in the last 12 months, increasing the Energy Star score from 93 to 99.

Feb 2011-May 2015

Research Associate and Project Manager at R&D Unit in Energy Technologies. Instituto Tecnológico de Castilla y Leon

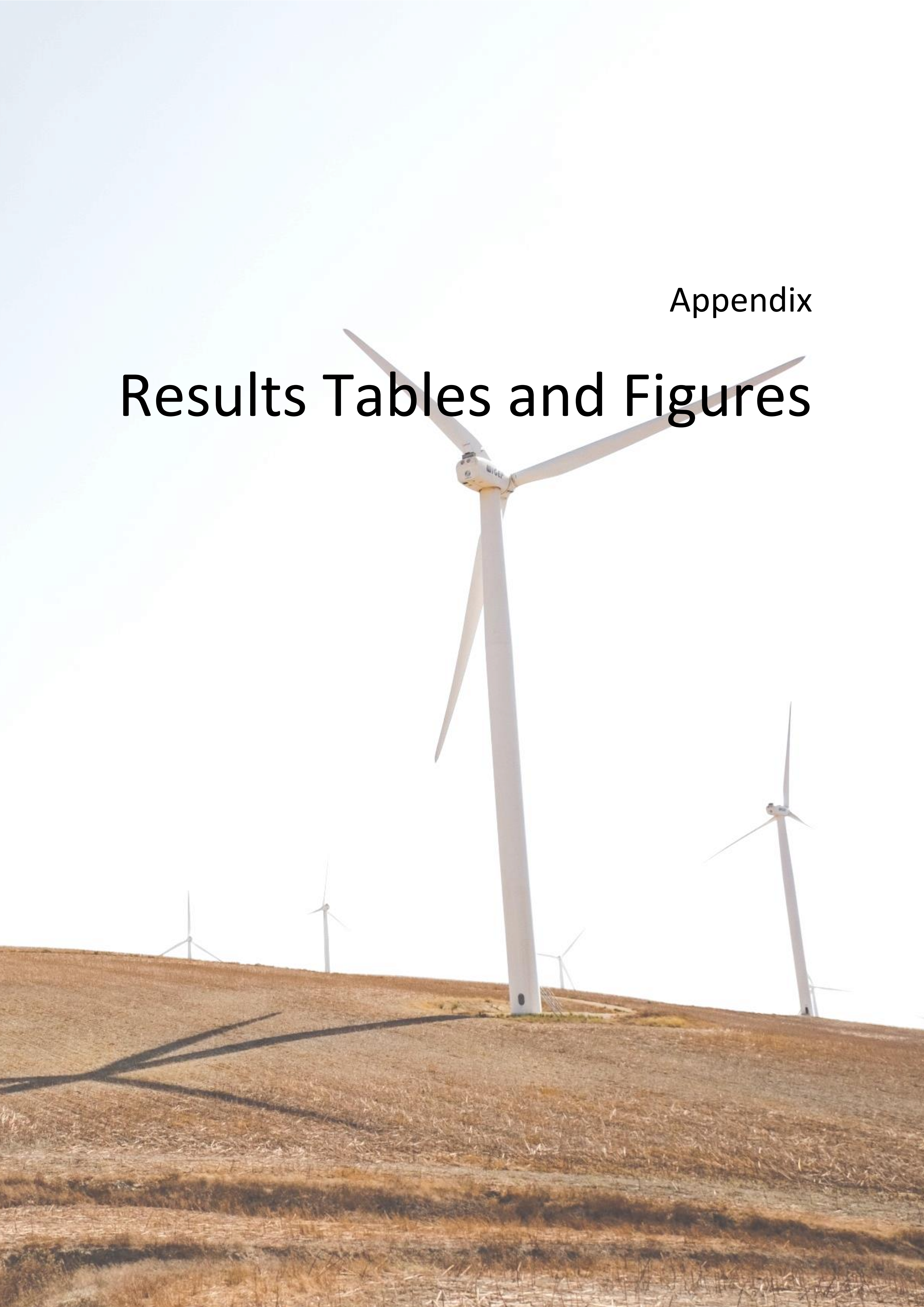
R&D project technician working on industrial energy systems modeling, data collection, and analysis for DHEMOS and IDECOBIEN (1.25 MM euros).

Electric systems specialist: design, integration, and prototyping of renewable energy systems for other research units.

Energy efficiency specialist: Project Manager in more than 30 energy audits and Energy Management Systems (EMSs) developed for more than 20 different industrial processes (+ 1,000 field measurements). 17% savings per project on average.

Appendix

Results Tables and Figures



1. Algorithms Execution Sequence

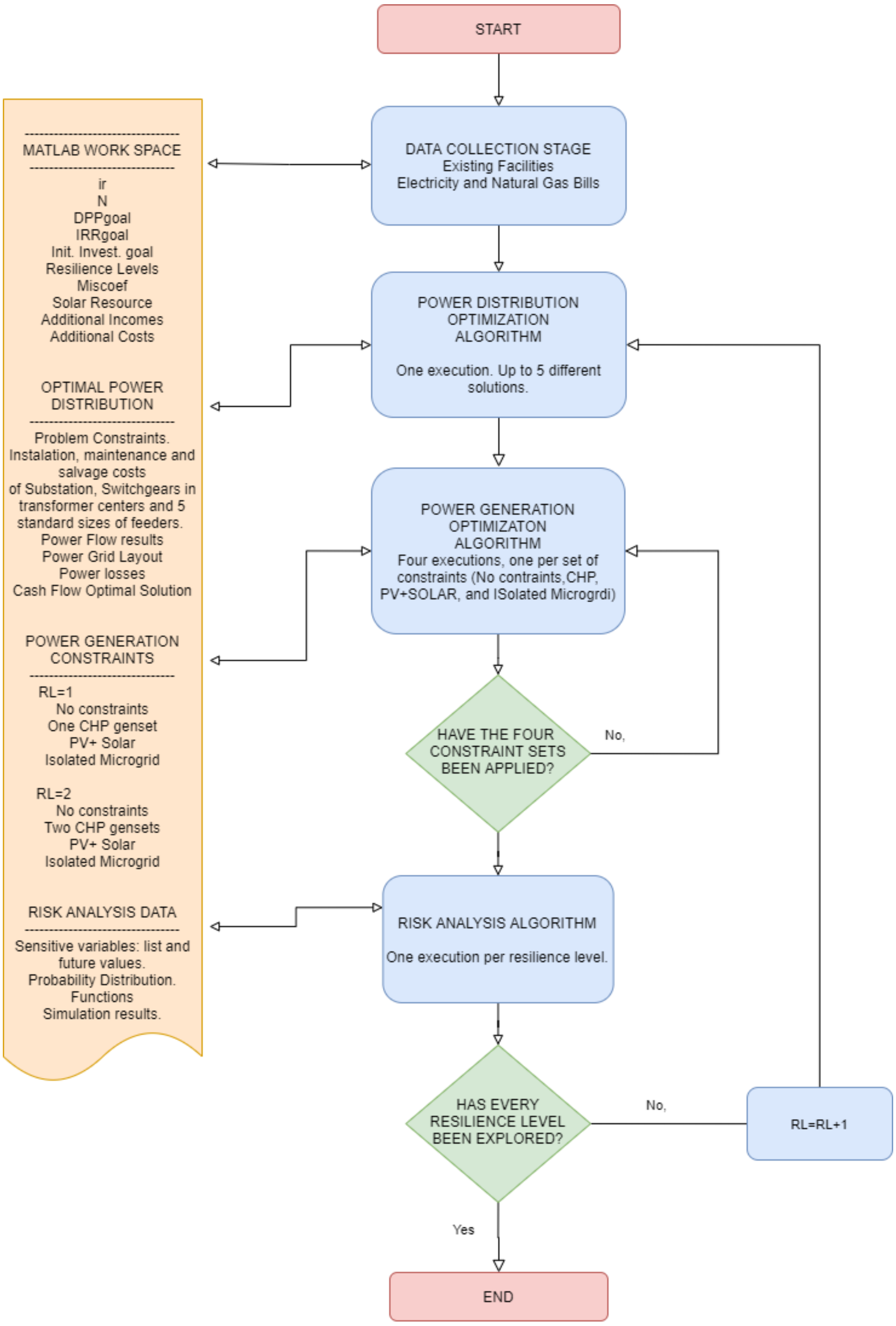


Figure 58 AP. Sequence of Algorithms Executed in the Case Study

2. Results of the Power Distribution System Optimization Algorithm

Table 39 AP. GA Performance of MATLAB script for Power Distribution System Optimization

Dev percent %	Generations	Population Size	XORrate %	MUTrate %	**Evaluations** Times	**Exec. Time** Seconds	**Per Eval** Seconds
0%	30	100	16	4	**1,266**	**2,572**	**2.03**
-4%	50	100	4	16	**2,158**	**4,333**	**2.01**
-6%	50	100	16	4	**2,110**	**4,261**	**2.02**
-7%	50	100	16	4	**2,064**	**4,151**	**2.01**
-8%	30	100	16	4	**1,328**	**2,673**	**2.01**
-9%	15	60	10	4	**344**	**983**	**2.86**
-10%	10	60	10	4	**222**	**634**	**2.86**
-10%	50	100	4	16	**1,992**	**4,008**	**2.01**

Table 40 AP. Economic Indicators of the Optimal Power Grid Layouts

	Present Value KPI (€)	Present Value (€)	PW Losses
Pgrid Opti1	1,103,033 €.	1,041,846 €	57,664
Pgrid Opti2	1,107,212 €.	1,049,716 €	54,193

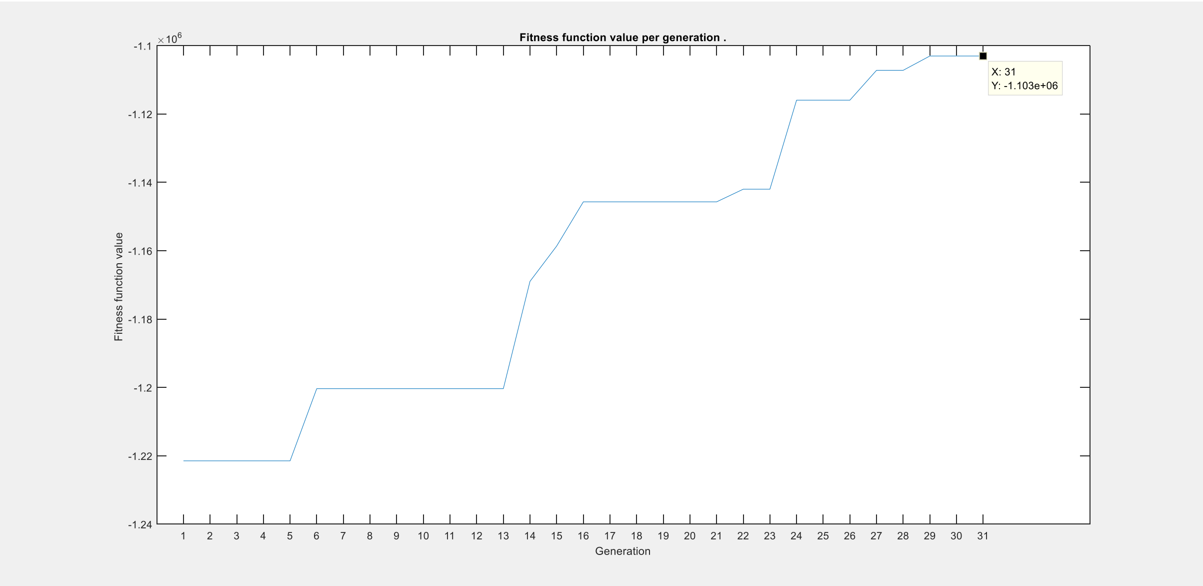


Figure 59 AP. Evolution Pgrid Opti1's Fitness Function Value

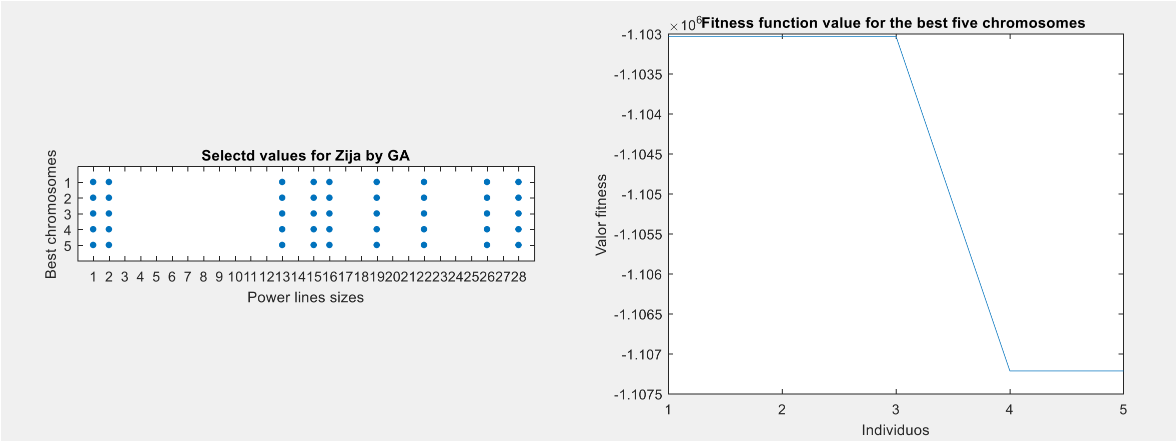


Figure 60 AP. Best Five Solutions of the Power Grid Optimization Algorithm

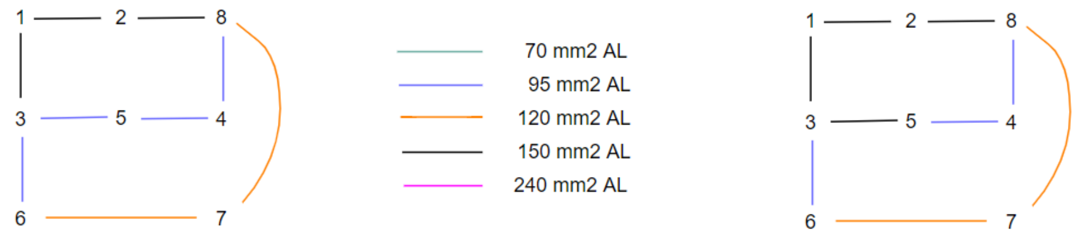


Image 8 AP. Optimal Power Distribution Grid Layouts Pgrid Opti1 and Pgrid Opti12

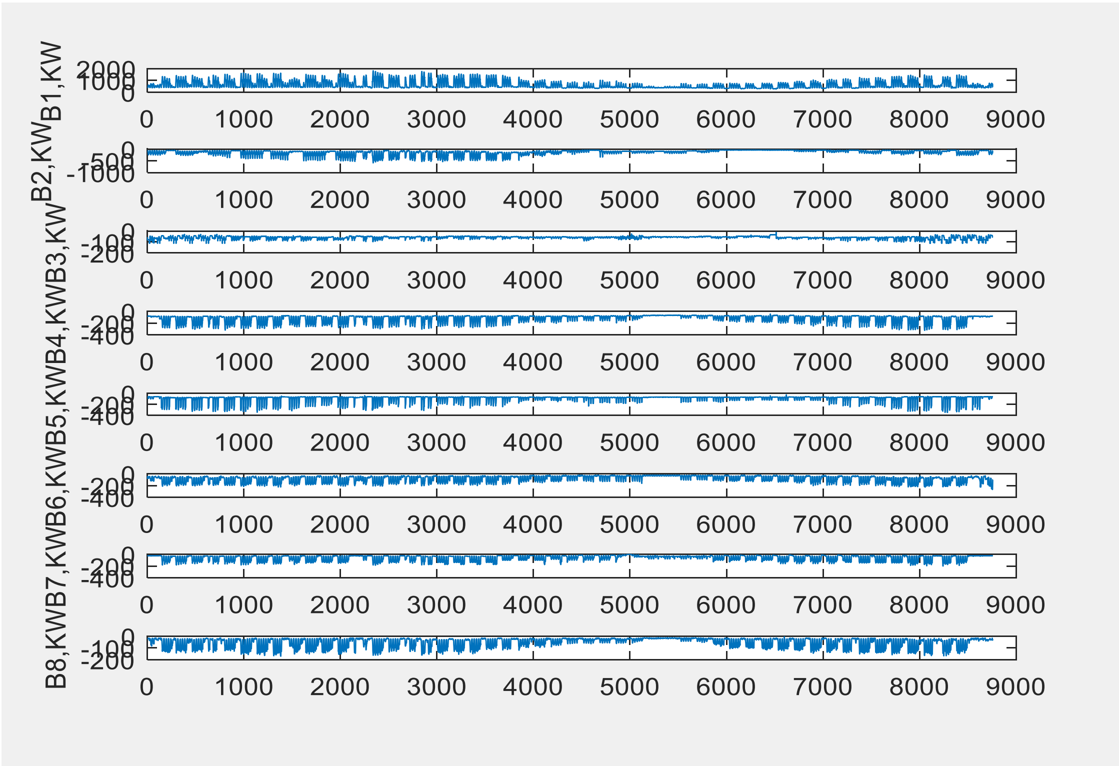


Figure 61 AP. Active Power per Node Pgrid Opti1, in kW

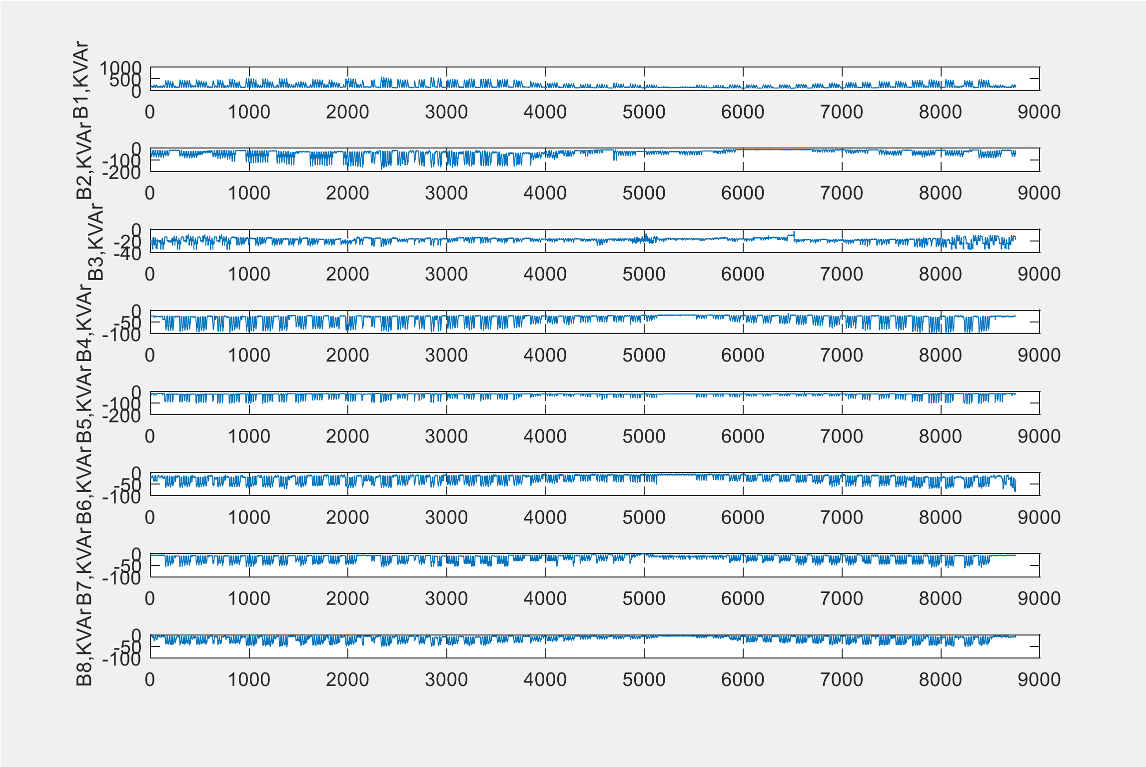


Figure 62 AP. Reactive Power per Node Pgrid Opti1, in kW

3. Results of the Power Generation Optimization Algorithm

3.1. Algorithm Configuration and Performance

Table 41 AP. Example of Codification of the Power generation Technologies in the Solution

[1 0 0 0 0 0 0 0 0 1 0 0 0 1]

Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Technology	PV PLANT	PV PLANT	PV PLANT	Diesel Gen.	Diesel Gen.	Diesel Gen.	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Pow. Grid
Size	150 KW	300 KW	450 KW	400 KW	630 KW	1000 KW	400 KW	630 KW	1000 KW	299 KW	635 KW	847 kW	1067 KW	2000 KW
	x									x				x

Table 42 AP. GA Performance of MATLAB Script for Power generation Sizing and Scheduling

Dev percent %	Generations	Population Size	XORrate %	MUTrate %	**Evaluations** Times	**Exec. Time** Seconds	**Per Eval** Seconds
0%	15	60	4	10	**292**	**6,661**	**22.8**
0%	15	75	5	3	**269**	**6,347**	**23.6**
-1%	15	75	5	3	**269**	**6,238**	**23.2**
-1%	30	50	5	3	**278**	**6,921**	**24.9**
-1%	30	50	5	3	**344**	**8,422**	**24.5**
-1%	45	60	5	3	**530**	**12,075**	**22.8**
-1%	5	100	5	3	**178**	**4,614**	**25.9**
-1%	5	100	10	4	**274**	**6,647**	**24.3**

3.2. Optimal Solutions: No Additional Resilience

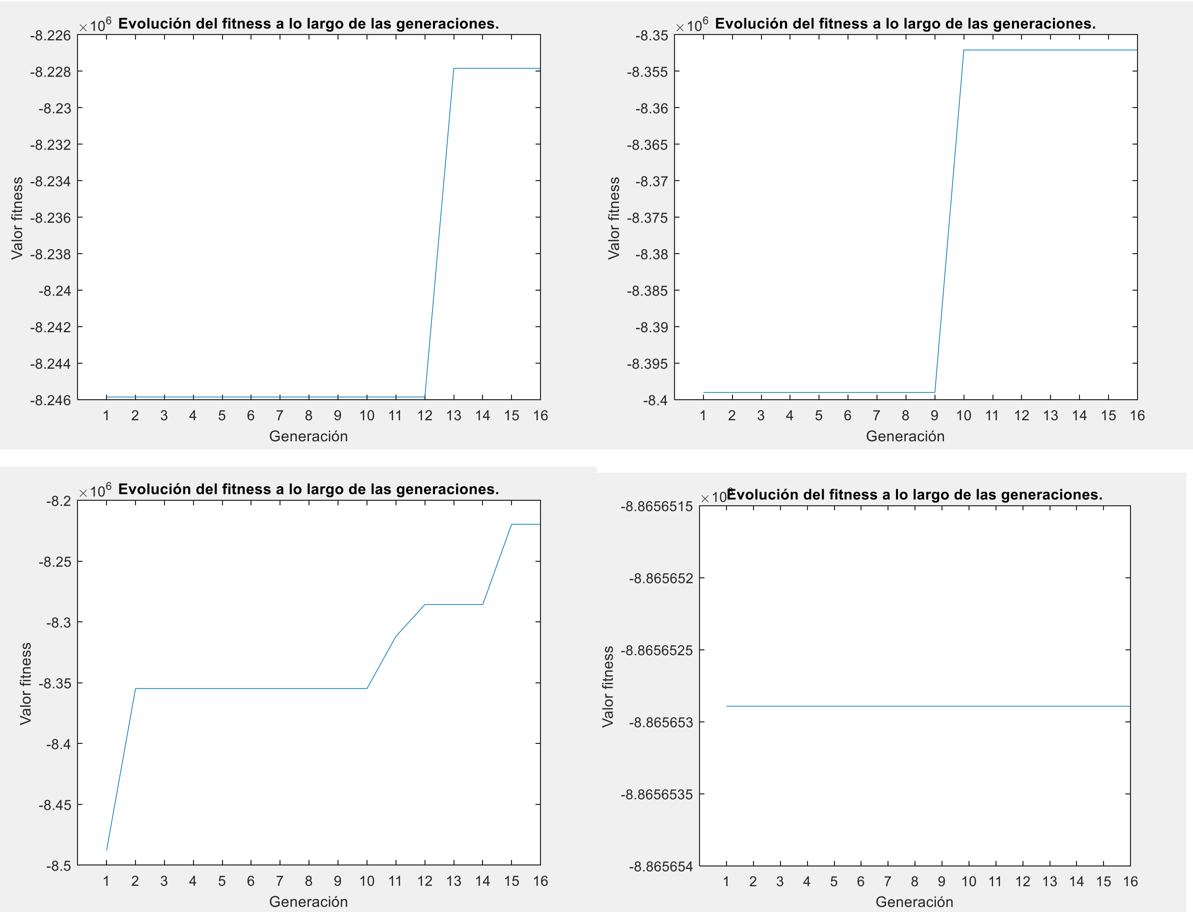


Figure 63 AP. Fitness Function Value Evolution for No Additional Resilience Alternatives

Table 43 AP. Optimization Algorithms Performance for the No Additional Resilience Case

	NO ADDITIONAL RESILIENCE					
		Pow. Gen.	Pow. Gen.	Pow. Gen.	Pow. Gen.	
	Power Dist.	**No Constraint**	**CHP**	**PV + Grid**	**Isolated MG**	**TOTAL**
Total Execution Time (secs)	2,631	6,675	4,881	5,040	5,061	24,288
Number of executions	1,304	279	243	254	256	2,336
Per Annual Solution (secs)	2.02	23.92	20.09	19.84	19.77	
Per Hourly Interval (secs)	0.00023	0.00273	0.00229	0.00227	0.00226	

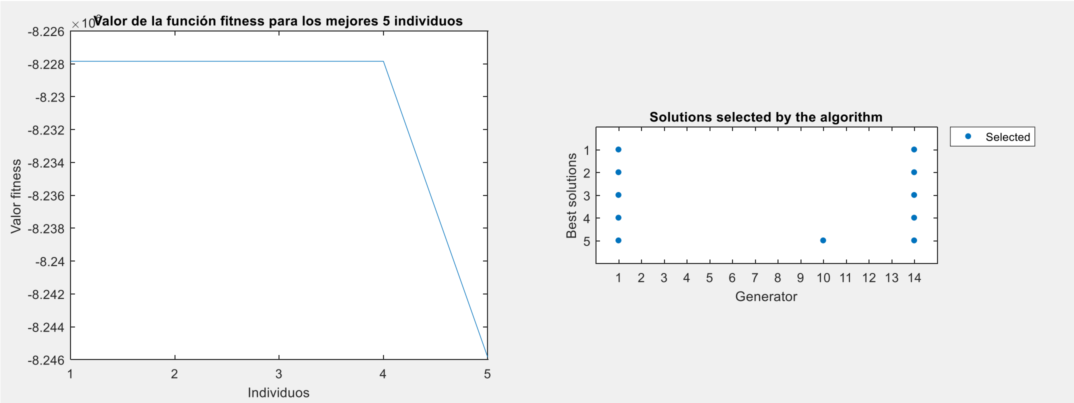


Figure 64 AP. Fitness Functions and Generators. No Additional Resilience. No Constraints Solutions

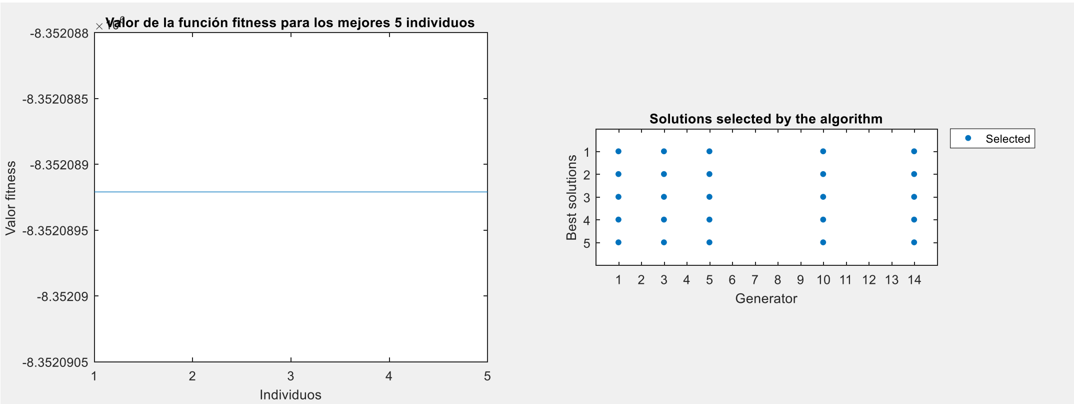


Figure 65 AP. Fitness Functions and Generators. No Additional Resilience .At Least One CHP System Constraint

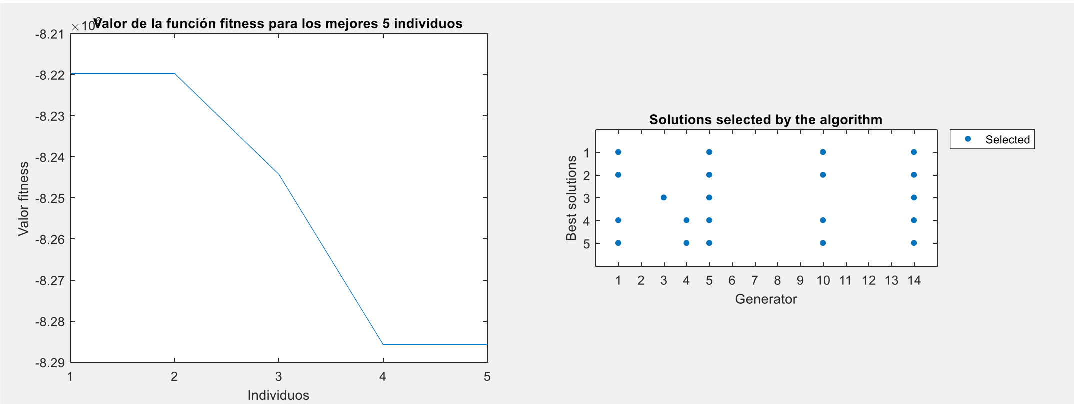


Figure 66 AP. Fitness Functions and Generators No Additional Resilience. PV + Grid Constraint

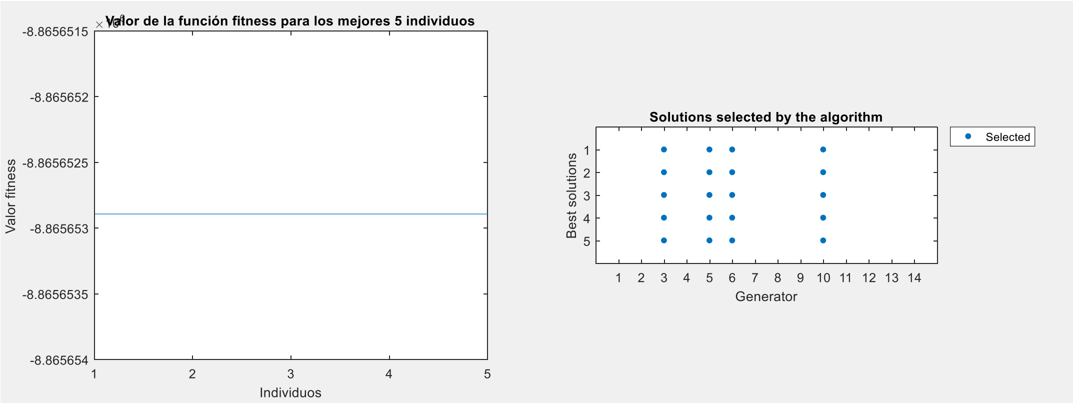


Figure 67 AP. Fitness Functions and Generators No Additional Resilience. Isolated MG Constraint

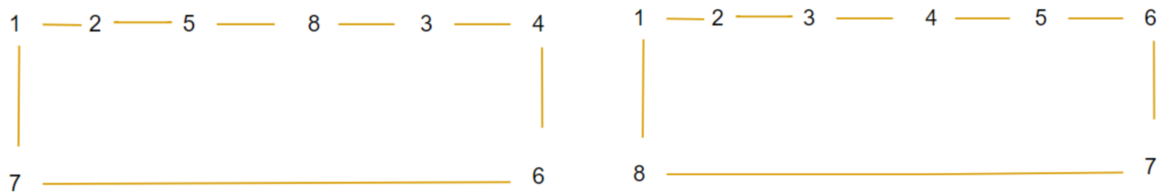


Figure AP68. Customized Power Grid Layouts: Shortest (Left) and Ring (Right)

Table 44 AP. Optimal Solutions per Constraint and Customized Solutions: No Additional Resilience

Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Technology	PV PLANT	PV PLANT	PV PLANT	Diesel Gen.	Diesel Gen.	Diesel Gen.	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Pow. Grid
Size	150 KW	300 KW	450 KW	400 KW	630 KW	1000 KW	400 KW	630 KW	1000 KW	299 KW	635 KW	847 kW	1067 KW	2000 KW
No Constraint	X													X
1 CHP System	X		X		X					X				X
PV+Grid	X				X					X				X
Isolated MG			X		X	X				X				
Customized 1	X	X	X											X
Customized 2	X		X							X				X

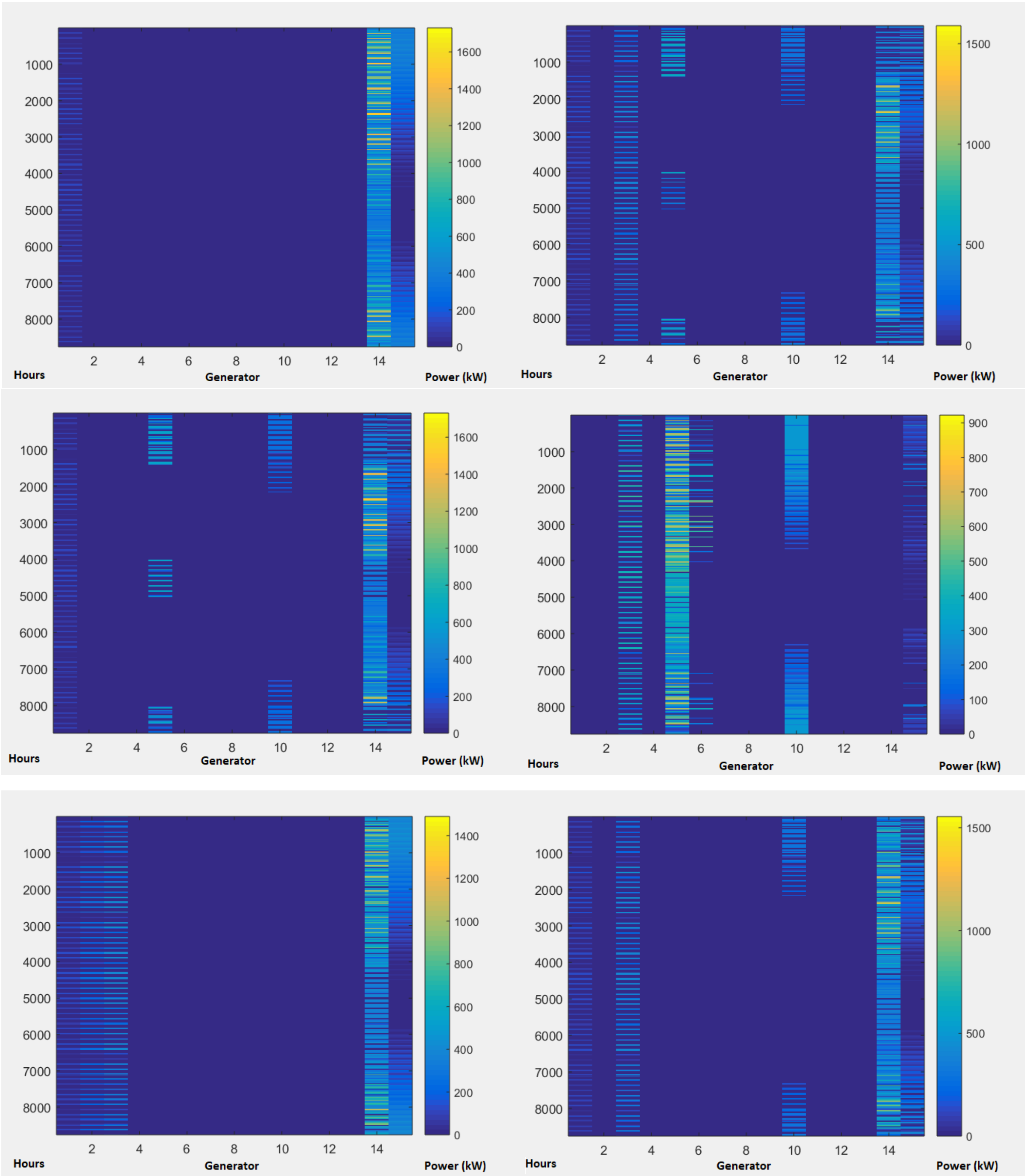


Figure 69 AP. Annual Hourly Schedule Per Generator .No Additional Resilience Solutions, in KW

Table 45 AP. Key Economic Indicators of the No Additional Resilience Solutions

	No Constraint	One CHP System	PV+GRID	ISOLATED GRID	CUSTOMIZED 1	CUSTOMIZED 2
Initial Invest.	€ (1,185,224)	€ (2,870,338)	€ (2,129,473)	€ (2,875,449)	€ (2,387,418)	€ (2,694,473)
Loan	€ -	€ -	€ -	€ -	€ -	€ -
Annual Savings	€ 215,666	€ 320,048	€ 266,720	€ 242,767	€ 272,240	€ 299,190
NPV	€ 1,620,403	€ 1,314,323	€ 1,429,930	€ 238,671	€ 1,048,052	€ 1,203,209
IRR	17.93%	10.25%	11.98%	6.75%	10.24%	10.17%
DPP	7.89	14.43	12.34	21.66	14.02	14.48
Equiv. Annuity	€ 236,962	€ 353,435	€ 300,626	€ 263,018	€ 290,159	€ 329,197

Table 46 AP. Summary of Key Technical Indicators Per Optimal Solution: No Additional Resilience

		No Constraint	At least 1 CHP	PV+Grid	Isolated MG	Customized 1	Customized 2
Demand	kWh	5,397,863	5,397,863	5,397,863	5,397,863	5,397,863	5,397,863
Generated ON site	kWh	258,907	1,789,994	1,147,472	5,397,863	1,553,443	1,520,387
From the Utility	kWh	5,138,956	3,607,869	4,250,391	-	3,844,420	3,877,477
Renewable Fraction	%	4.8	19.2	4.8	14.4	28.8	19.2
Environ. Emmissions	TnCo2	1,233	1,624.0	1,877	3,761	923	931
Onsite Fuel to Power Eff	kWhe/kWh Fuel (%)	Inf	89%	48%	43%	Inf	424%
Energy to Fuel Ratio	Kwhe+th/kWH Fuel	Inf	2.95	2.50	0.54	Inf	4.68
LCOE	$ per kWh	0.103	0.081	0.091	0.087	0.086	0.082
Breakeven Point	kWh	5,972,218	7,615,200	6,780,066	7,087,687	7,205,333	7,528,911

Table 47 AP. Key Technical Performance Indicators per Generator: No Additional Resilience

NO CONSTRAINTS	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	2,000
Max. Capacity (kW)	150	-	-	-	-	-	-	-	-	-	-	-	-	1,731
Ave. Capacity (kW)	58	-	-	-	-	-	-	-	-	-	-	-	-	587
Annual Operating hours	4,484	-	-	-	-	-	-	-	-	-	-	-	-	8,760
Lifespam Based on Operating Hours (Years)	39	-	-	-	-	-	-	-	-	-	-	-	-	34
Starts	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Energy generated (kWh per year)	258,907	-	-	-	-	-	-	-	-	-	-	-	-	5,138,956
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Fuel (kWh per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	
Efficiency (%)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	1,233

COMBINED HEAT AND POWER	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	2,000
Max. Capacity (kW)	150	-	450	-	630	-	-	-	-	299	-	-	-	1,589
Ave. Capacity (kW)	58	-	173	-	384	-	-	-	-	262	-	-	-	461
Annual Operating hours	4,484	-	4,484	-	798	-	-	-	-	1,795	-	-	-	7,823
Lifespan Based on Operating Hours (Years)	39	-	39	-	165	-	-	-	-	98	-	-	-	38
Starts	-	-	-	-	448	-	-	-	-	313	-	-	-	506
Energy generated (kWh per year)	258,907	-	776,721	-	283,477	-	-	-	-	470,889	-	-	-	3,607,869
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	538,608	-	-	-	-
Fuel (kWh per year)	-	-	-	-	778,482	-	-	-	-	1,236,280	-	-	-	-
Efficiency (%)	-	-	-	-	36.4%	-	-	-	-	81.7%	-	-	-	-
Env. Emmisions (Tons of CO2 per year)	-	-	-	-	195	-	-	-	-	563	-	-	-	866

PV + GRID	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	2,000
Max. Capacity (kW)	150	-	-	-	630	-	-	-	-	299	-	-	-	1,731
Ave. Capacity (kW)	58	-	-	-	446	-	-	-	-	269	-	-	-	517
Annual Operating hours	4,484	-	-	-	905	-	-	-	-	1,806	-	-	-	8,222
Lifespam Based on Operating Hours (Years)	39	-	-	-	145	-	-	-	-	97	-	-	-	36
Starts	-	-	-	-	450	-	-	-	-	301	-	-	-	312
Energy generated (kWh per year)	258,907	-	-	-	403,409	-	-	-	-	485,156	-	-	-	4,250,391
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	554,927	-	-	-	-
Fuel (kWh per year)	-	-	-	-	1,107,840	-	-	-	-	1,273,736	-	-	-	-
Overall kWH to Fuel Ratio (%)	-	-	-	-	36.4%	-	-	-	-	81.7%	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	277	-	-	-	-	580	-	-	-	1,020

ISLANDED MICROGRID	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	2,000
Max. Capacity (kW)	-	-	450	-	630	922	-	-	-	299	-	-	-	-
Ave. Capacity (kW)	-	-	173	-	361	124	-	-	-	213	-	-	-	-
Annual Operating hours	-	-	4,484	-	8,561	3,021	-	-	-	5,419	-	-	-	-
Lifespam Based on Operating Hours (Years)	-	-	39	-	15	43	-	-	-	32	-	-	-	-
Starts	-	-	-	-	138	846	-	-	-	174	-	-	-	-
Energy generated (kWh per year)	-	-	776,721	-	3,093,642	372,078	-	-	-	1,155,421	-	-	-	-
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	1,321,585	-	-	-	-
Fuel (kWh per year)	-	-	-	-	8,495,750	1,018,444	-	-	-	3,033,464		-	-	-
Efficiency (%)	-	-	-	-	36.4%	36.5%	-	-	-	81.7%	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	2,124	255	-	-	-	1,382	-	-	-	-

CUSTOMIZED 1	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	2,000
Max. Capacity (kW)	150	300	450	-	-	-	-	-	-	-	-	-	-	1,490
Ave. Capacity (kW)	58	115	173	-	-	-	-	-	-	-	-	-	-	486
Annual Operating hours	4,484	4,484	4,484	-	-	-	-	-	-	-	-	-	-	8,054
Lifespam Based on Operating Hours (Years)	39	39	39	-	-	-	-	-	-	-	-	-	-	37
Starts	-	-	-	-	-	-	-	-	-	-	-	-	-	336
Energy generated (kWh per year)	258,907	517,814	776,721	-	-	-	-	-	-	-	-	-	-	3,844,420
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Fuel (kWh per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Efficiency (%)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	923

CUSTOMIZED 2	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	2,000
Max. Capacity (kW)	150	-	450	-	-	-	-	-	-	299	-	-	-	1,554
Ave. Capacity (kW)	58	-	173	-	-	-	-	-	-	270	-	-	-	460
Annual Operating hours	4,484	-	4,484	-	-	-	-	-	-	1,795	-	-	-	8,359
Lifespam Based on Operating Hours (Years)	39	-	39	-	-	-	-	-	-	98	-	-	-	36
Starts	-	-	-	-	-	-	-	-	-	313	-	-	-	250
Energy generated (kWh per year)	258,907	-	776,721	-	-	-	-	-	-	484,758	-	-	-	3,877,477
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	554,472	-	-	-	-
Fuel (kWh per year)	-	-	-	-	-	-	-	-	-	1,272,693	-	-	-	
Efficiency (%)	-	-	-	-	-	-	-	-	-	81.7%	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	-	-	-	-	-	580	-	-	-	931

3.3. Optimal Solutions: Additional Resilience

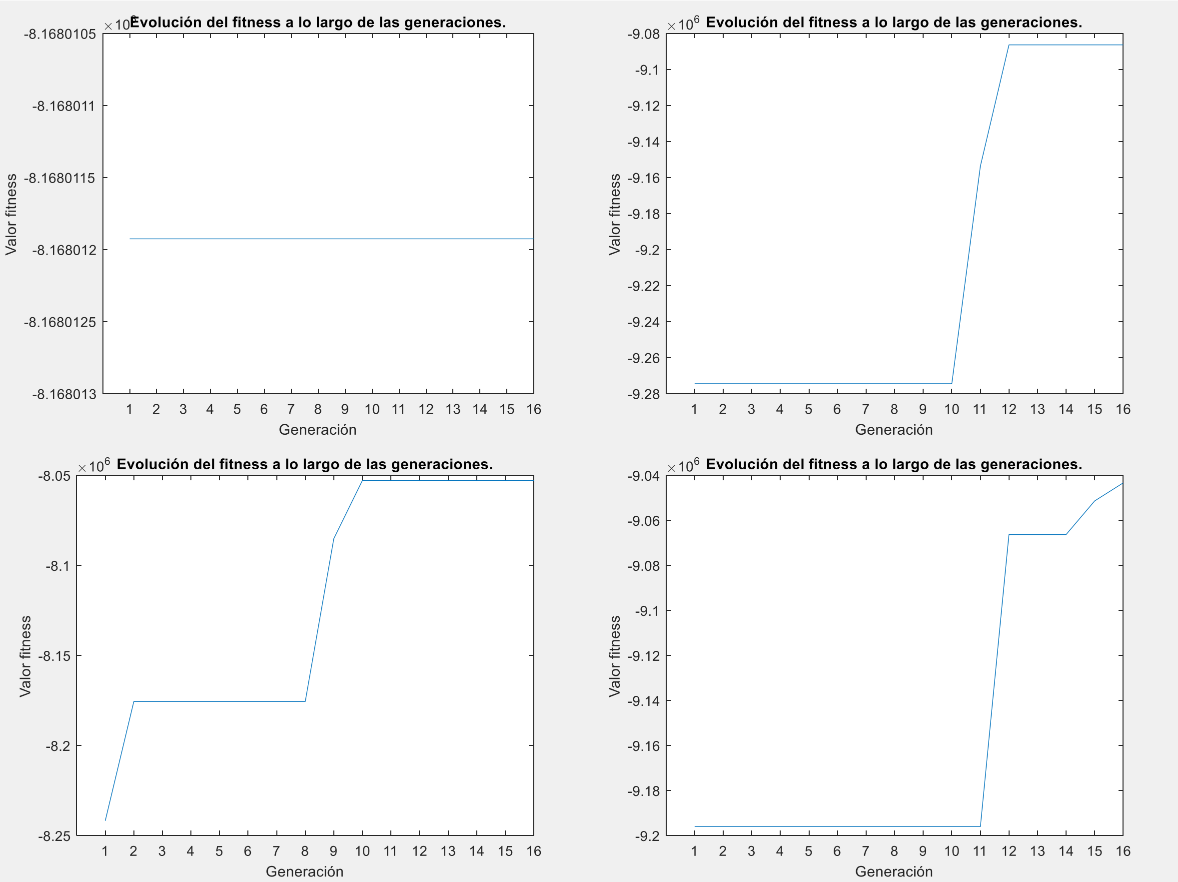


Figure 70 AP. Fitness Function Values Evolution for Additional Resiliency Alternatives

Table 48 AP. Optimization Algorithms Performance for the Additional Resilience Alternatives

	ADDITIONAL RESILIENCE					
	Power Dist.	**Pow. Gen. No Constraint**	**Pow. Gen. CHP**	**Pow. Gen. PV + Grid**	**Pow. Gen. Isolated MG**	**TOTAL**
Total Execution Time (secs)	2,631	4,529	6,465	5,583	5,220	24,428
Number of executions	1,304.00	228	278	236	264	
Per Annual Solution (secs)	2.02	19.86	23.26	23.66	19.77	
Per Hourly Interval (secs)	0.00023	0.00227	0.00265	0.00270	0.00226	

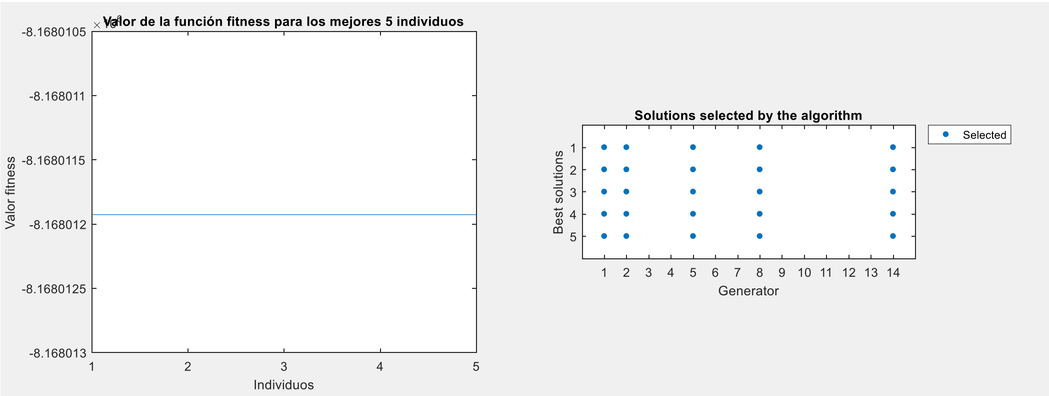


Figure 71 AP. Fitness Functions and Generators. Additional Resilience. No Constraints

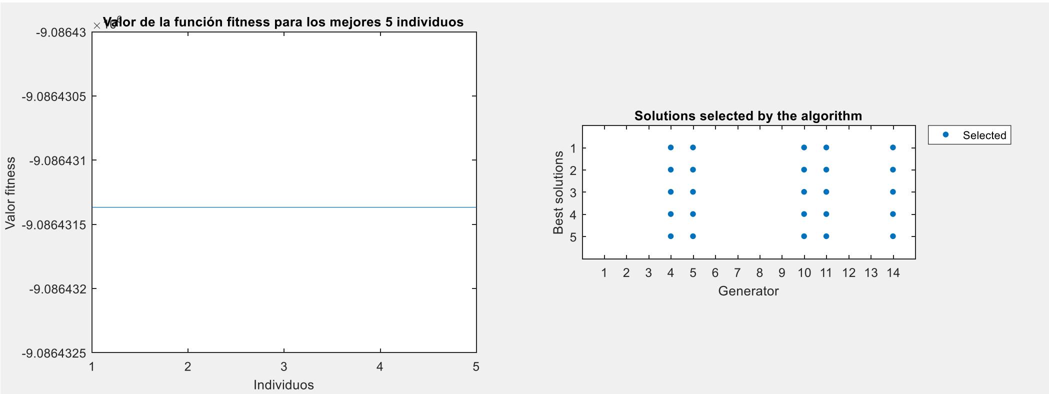


Figure 72 AP. Fitness Functions and Generators. Additional Resilience. At least Two CHP Systems

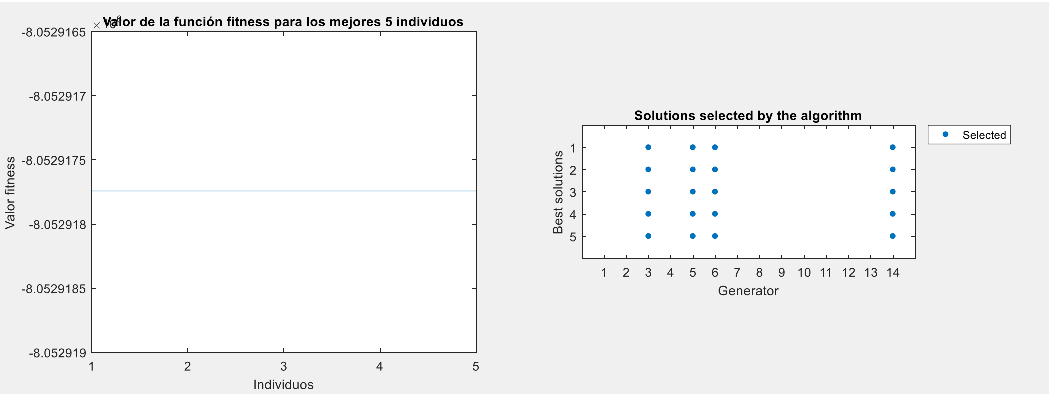


Figure 73 AP. Fitness Functions and Generators. Additional Resilience. PV + Grid Constraint

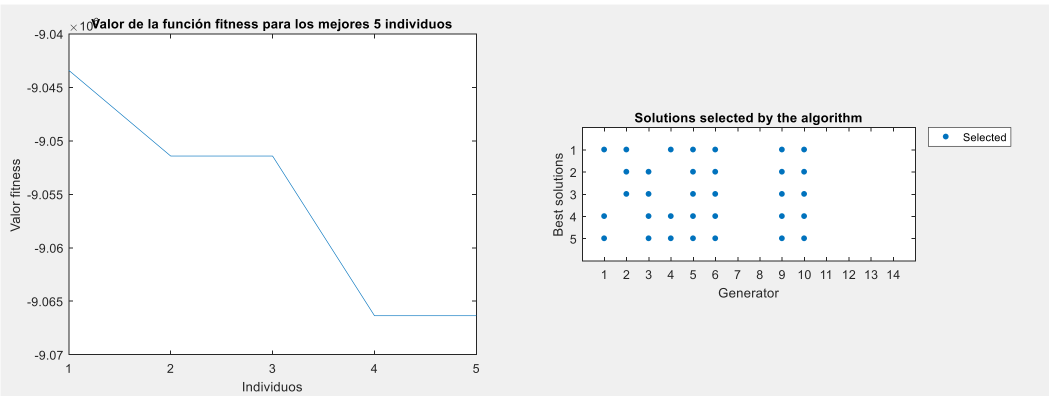


Figure 74 AP. Fitness Functions and Generators. Additional Resilience. Isolated MG Constraint

Table 49 AP. Optimal Solutions per Constraint and Customized Solutions: Additional Resilience.

Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Technology	PV PLANT	PV PLANT	PV PLANT	Diesel Gen.	Diesel Gen.	Diesel Gen.	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Pow. Grid
Size	150 KW	300 KW	450 KW	400 KW	630 KW	1000 KW	400 KW	630 KW	1000 KW	299 KW	635 KW	847 kW	1067 KW	2000 KW
No Constraint	X	X			X			X						X
2 CHP Systems				X	X					X	X			X
PV+Grid			X		X	X								X
Isolated MG	X	X		X	X	X			X	X				
Customized 1	X	X	X		X		X							X
Customized 2	X	X	X		X					X				X

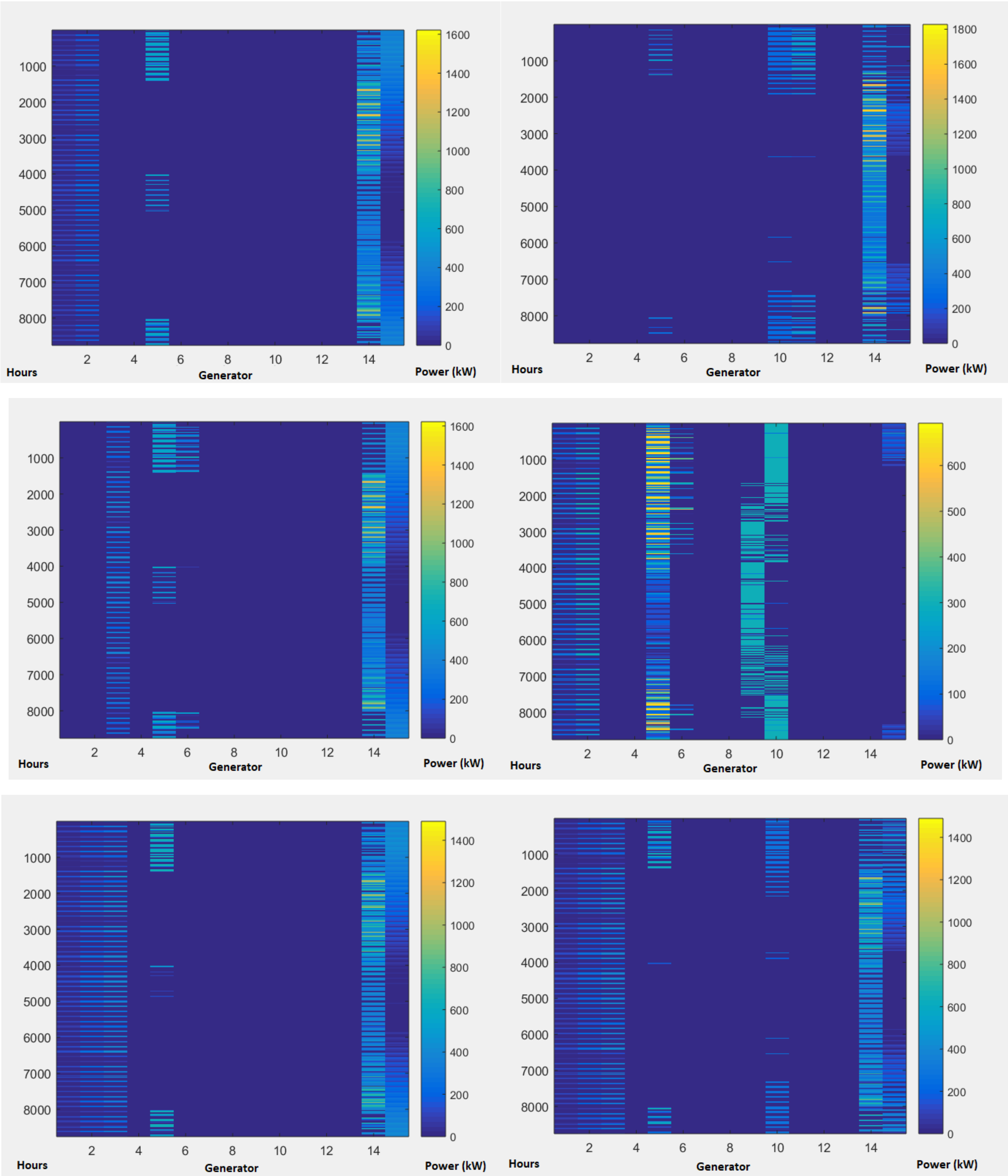


Figure 75 AP. Annual Hourly Schedule Per Generator in KW: Additional Resilience

Table 50 AP. Key Economic Indicators of Additional Resilience Solutions

	No Constraint	Two CHP Systems	PV+GRID	ISOLATED GRID	CUSTOMIZED 1	CUSTOMIZED 2
Initial Invest.	€ (2,080,781)	€ (3,000,000)	€ (2,031,287)	€ (3,000,000)	€ (2,737,700)	€ (3,000,000)
Loan	€ -	€ 928,307	€ -	€ 617,768	€ -	€ 500,457
Annual Savings	€ 255,455	€ 284,903	€ 255,152	€ 229,627	€ 305,003	€ 358,051
NPV	€ 1,216,363	€ 227,597	€ 1,314,134	€ (465,515)	€ 1,137,795	€ 1,238,469
IRR	11.45%	6.62%	11.87%	4.50%	10.00%	9.69%
DPP	12.63	24.27	12.28	24.65	14.52	15.80
Equiv. Annuity	€ 278,476	€ 272,602	€ 282,553	€ 214,062	€ 327,323	€ 357,980

Table 51 AP. Key Technical Indicators Per Solutions: Additional Resilience

		No Constraint	At least 2 CHP	PV+Grid	Isolated MG	Customized 1	Customized 2
Demand	kWh	5,397,863	5,397,863	5,397,863	5,397,863	5,397,863	5,397,863
Generated ON site	kWh	1,188,633	1,066,596	1,309,521	5,400,587	1,877,879	2,289,168
From the Utility	kWh	4,209,229	4,331,266	4,088,340	-	3,519,983	3,108,693
Renewable Fraction	%	14.4	-	14.4	14.4	28.8	28.8
Environ. Emmissions	TnCo2	1,294	2,194	1,347	3,488	1,068	1,524
Onsite Fuel to Power Eff	kWhe/kWh Fuel (%)	107%	39%	90%	45%	211%	117%
Energy to Fuel Ratio	Kwhe+th/kWH Fuel	4.84	2.37	3.69	0.57	6.06	3.07
LCOE	$ per kWh	0.090	0.084	0.090	0.095	0.080	0.070
Breakeven Point	kWh	6,872,581	7,310,463	6,868,724	6,521,285	7,747,716	8,817,025

Table 52 AP. Key Technical Performance Indicators per Generator: Additional Resilience

NO CONSTRAINS	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	1,828
Max. Capacity (kW)	150	300	-	-	630	-	-	-	-	-	-	-	-	1,622
Ave. Capacity (kW)	58	115	-	-	464	-	-	-	-	-	-	-	-	517
Annual Operating hours	4,484	4,484	-	-	888	-	-	-	-	-	-	-	-	8,153
Lifespam Based on Operating Hours (Years)	39	39	-	-	148	-	-	-	-	-	-	-	-	37
Starts	-	-	-	-	462	-	-	-	-	-	-	-	-	290
Energy generated (kWh per year)	258,907	517,814	-	-	411,912	-	-	-	-	-	-	-	-	4,209,229
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Fuel (kWh per year)	-	-	-	-	1,114,862	-	-	-	-	-	-	-	-	
Efficiency (%)	-	-	-	-	36.9%	-	-	-	-	-	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	283	-	-	-	-	-	-	-	-	1,011

TWO CHP SYSTEMS	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	1,828
Max. Capacity (kW)	-	-	-	-	630	-	-	-	-	299	635	-	-	1,828
Ave. Capacity (kW)	-	-	-	-	286	-	-	-		299	432	-	-	559
Annual Operating hours	-	-	-	-	244	-	-	-	-	1,583	1,213	-	-	7,744
Lifespam Based on Operating Hours (Years)	-	-	-	-	539	-	-	-	-	111	144	-	-	39
Starts	-	-	-	-	186	-	-	-	-	585	468	-	-	478
Energy generated (kWh per year)	-	-	-	-	69,693	-	-	-	-	473,073	523,830	-	-	4,331,266
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	541,106	511,456	-	-	-
Fuel (kWh per year)	-	-	-	-	191,392	-	-	-	-	1,242,013	1,285,240	-	-	
Efficiency (%)	-	-	-	-	36.4%	-	-	-	-	81.7%	80.6%	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	48	-	-	-	-	566	541	-	-	1,040

PV+GRID	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	1,828
Max. Capacity (kW)	-	-	450	-	630	896	-	-	-	-	-	-	-	1,622
Ave. Capacity (kW)	-	-	173	-	464	346	-	-	-	-	-	-	-	524
Annual Operating hours	-	-	4,484	-	888	349	-	-	-	-	-	-	-	7,804
Lifespam Based on Operating Hours (Years)	-	-	39	-	148	377	-	-	-	-	-	-	-	38
Starts	-	-	-	-	462	246	-	-	-	-	-	-	-	496
Energy generated (kWh per year)	-	-	776,721	-	411,912	120,888	-	-	-	-	-	-	-	4,088,340
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Fuel (kWh per year)	-	-	-	-	1,131,190	330,893	-	-	-	-	-	-	-	
Efficiency (%)	-	-		-	36.4%	36.5%	-	-	-	-	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	283	83	-	-	-	-	-	-	-	982

ISLANDED MG	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	1,828
Max. Capacity (kW)	150	300	-	-	630	693	-	-	299	299	-	-	-	-
Ave. Capacity (kW)	58	115	-	-	253	180	-	-	280	291	-	-	-	-
Annual Operating hours	4,484	4,484	-	-	7,693	1,078	-	-	4,308	4,382	-	-	-	-
Lifespam Based on Operating Hours (Years)	39	39	-	-	17	122	-	-	37	40	-	-	-	-
Starts	-	-	-	-	388	390	-	-	1,086	1,038	-	-	-	-
Energy generated (kWh per year)	258,907	517,814	-	-	1,943,292	193,600	-	-	1,208,115	1,276,133	-	-	-	-
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	1,459,656	-	-	-	-
Fuel (kWh per year)	-	-	-	-	5,336,662	529,919	-	-	2,745,716	3,350,382	-	-	-	-
Efficiency (%)	-	-	-	-	36.4%	36.5%	-	-	44.0%	81.7%	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	1,334	132	-	-	494	1,527	-	-	-	-

CUSTOMIZED 1	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	1,828
Max. Capacity (kW)	150	300	450	-	630	-	-	-	-	-	-	-	-	1,490
Ave. Capacity (kW)	58	115	173	-	440	-	-	-	-	-	-	-	-	472
Annual Operating hours	4,484	4,484	4,484	-	737	-	-	-	-	-	-	-	-	7,608
Lifespam Based on Operating Hours (Years)	39	39	39	-	178	-	-	-	-	-	-	-	-	39
Starts	-	-	-	-	494	-	-	-	-	-	-	-	-	500
Energy generated (kWh per year)	258,907	517,814	776,721	-	324,436	-	-	-	-	-	-	-	-	3,519,983
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Fuel (kWh per year)	-	-	-	-	890,965	-	-	-	-	-	-	-	-	
Efficiency (%)	-	-	-	-	36.4%	-	-	-	-	-	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	223	-	-	-	-	-	-	-	-	845

CUSTOMIZED 2	Pv solar	Pv solar	Pv solar	Diesel Gen	Diesel Gen	Diesel Gen	NG Genset	NG Genset	NG Genset	CHP	CHP	CHP	CHP	Grid
Rated Capacity (kW)	150	300	450	400	630	1,000	400	630	1,000	299	635	847	1,067	1,828
Max. Capacity (kW)	150	300	450	-	630	-	-	-	-	299	-	-	-	1,490
Ave. Capacity (kW)	58	115	173	-	378	-	-	-	-	285	-	-	-	424
Annual Operating hours	4,484	4,484	4,484	-	529	-	-	-	-	1,882	-	-	-	7,501
Lifespam Based on Operating Hours (Years)	39	39	39	-	248	-	-	-	-	93	-	-	-	40
Starts	-	-	-	-	398	-	-	-	-	549	-	-	-	762
Energy generated (kWh per year)	258,907	517,814	776,721	-	200,084	-	-	-	-	535,641	-	-	-	3,108,693
Thermal Output (kWh per year)	-	-	-	-	-	-	-	-	-	612,673	-	-	-	-
Fuel (kWh per year)	-	-	-	-	549,470	-	-	-	-	1,406,283	-	-	-	
Efficiency (%)	-	-	-	-	36.4%	-	-	-	-	81.7%	-	-	-	-
Env. Emmisions (kg CO2 per year)	-	-	-	-	137	-	-	-	-	641	-	-	-	746

Figure 76 AP. EPS's Thermal Demand Coverage Per Source: Additional Resilience

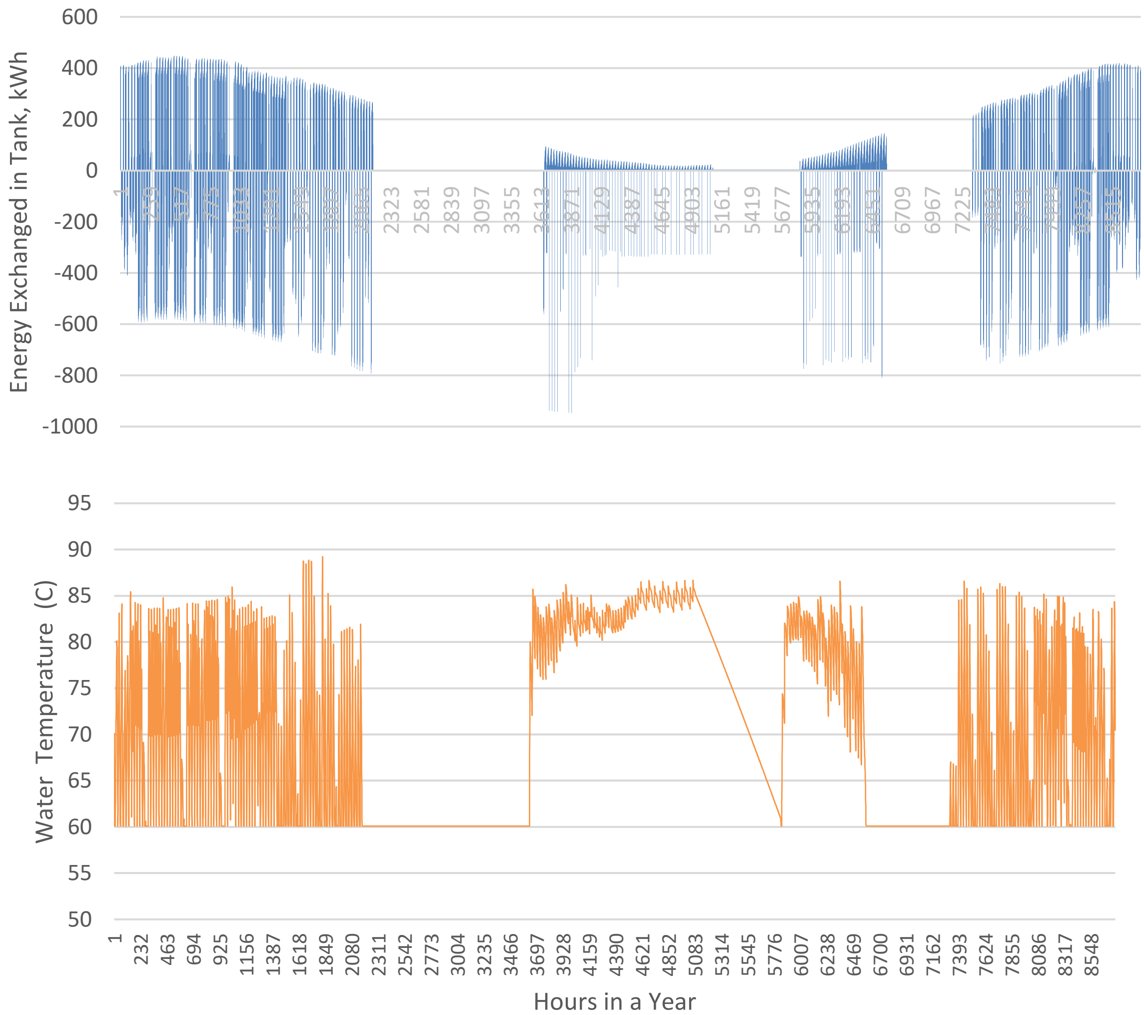


Figure 77 AP. Energy Exchanged in Tank and Water Temperature: Additional Resilience, Two CHP systems

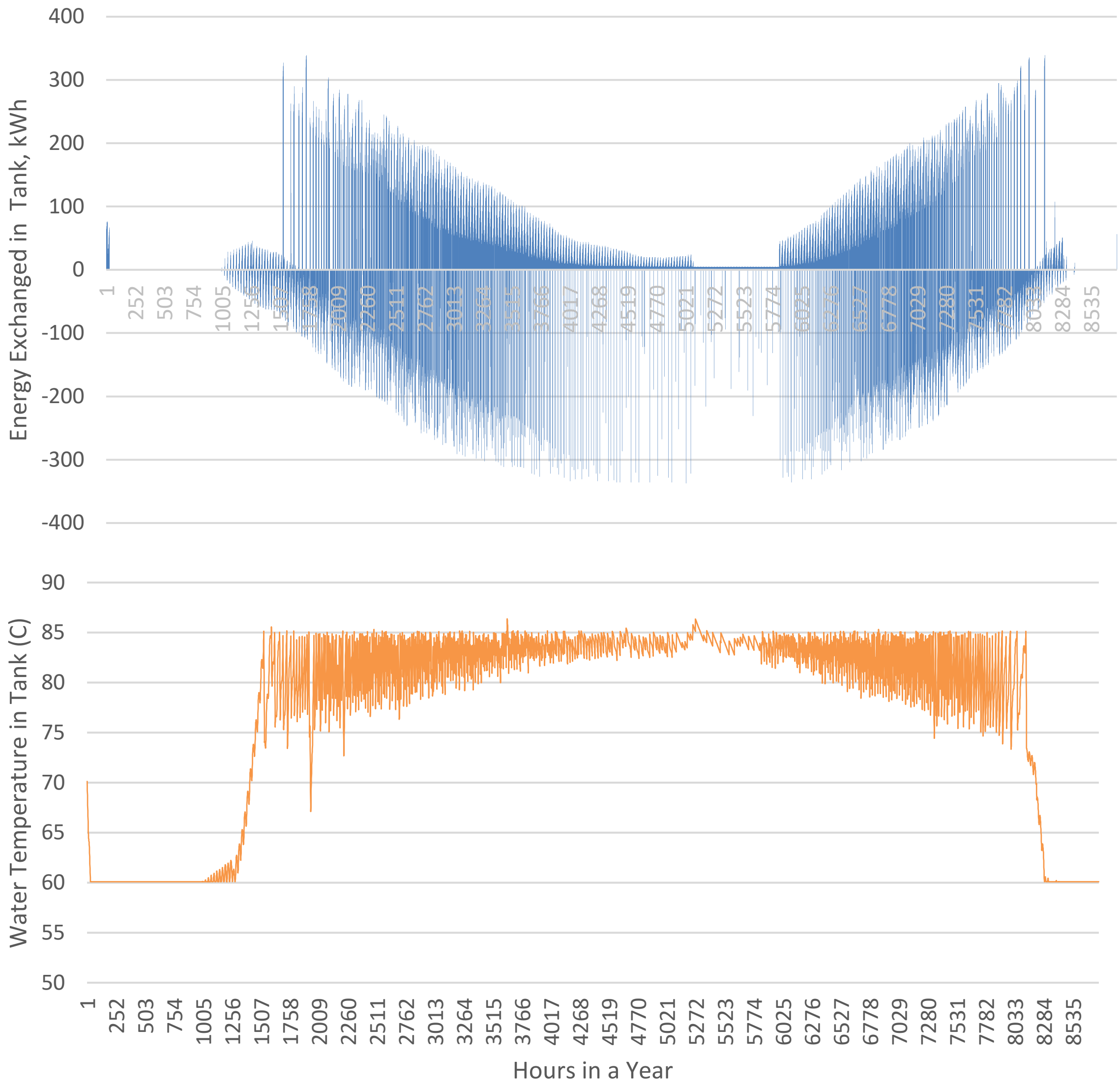


Figure 78 AP. Energy Exchanged in Tank and Water Temperature: Additional Resilience, Isolated Microgrid

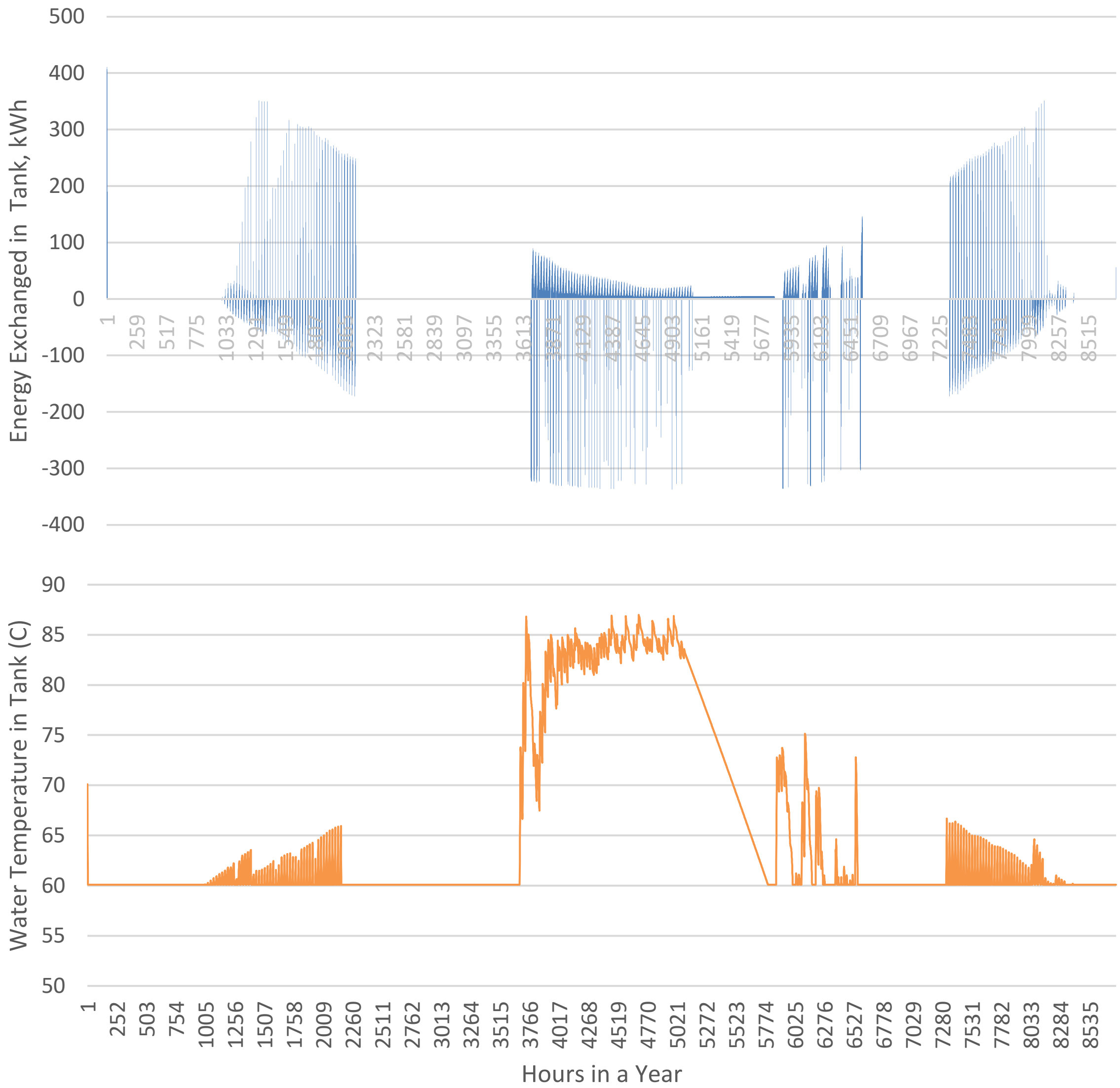


Figure 79 AP. Energy Exchanged in Tank and Water Temperature: Additional Resilience, Customized 2

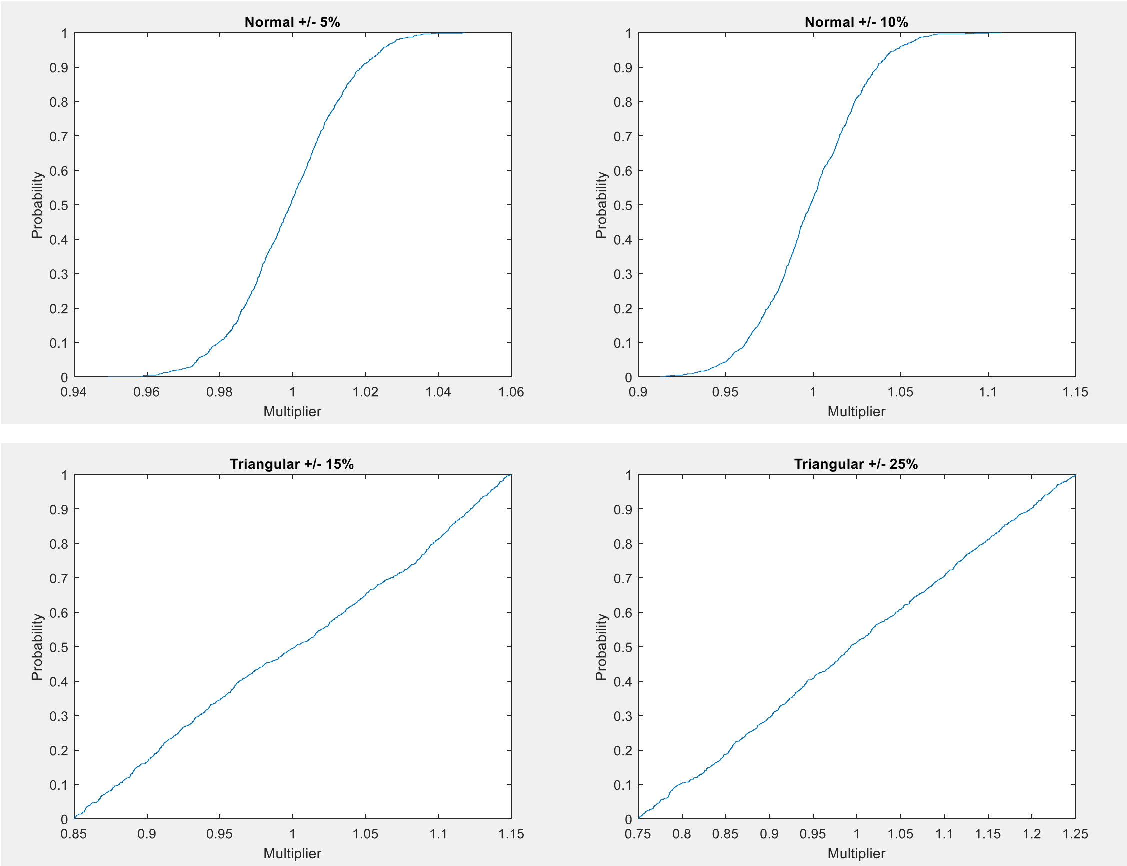
4. Risk Analysis

4.1. Sensitive variables table

Table 53 AP. Probability Distribution Applied per Variable

PROB. DIST.	VARIABLES
Normal 5%	$C^{A}_{O\&M\ gen}$
Normal 10%	$C^{0}_{CAPg}, C^{0}_{CAP\ Tank}, C^{0}_{CAP\ PDS}, C^{0}_{MISC\ MG}$
Triangular 15%	$C^{A}_{REP\ g}, C^{A}_{REP\ PDS}$
Triangular 25%	$C^{A}_{O\&M\ PDS}$
Triangular 50%	$SAV^{N+1}_{g}, SAV^{N+1}_{PDS}$
Triangular Diesel	$PR^{h}_{DIESEL}, C^{A}_{O\&Mgen}$
Normal Electricity	$PR^{h}_{ELEC\ GRID}, C^{A}_{O\&Mgen}$
Normal Natural Gas	$PR^{h}_{NG}, C^{A}_{O\&Mgen}$

4.2. Cumulative Probability Distributions Applied to Sensitive variables



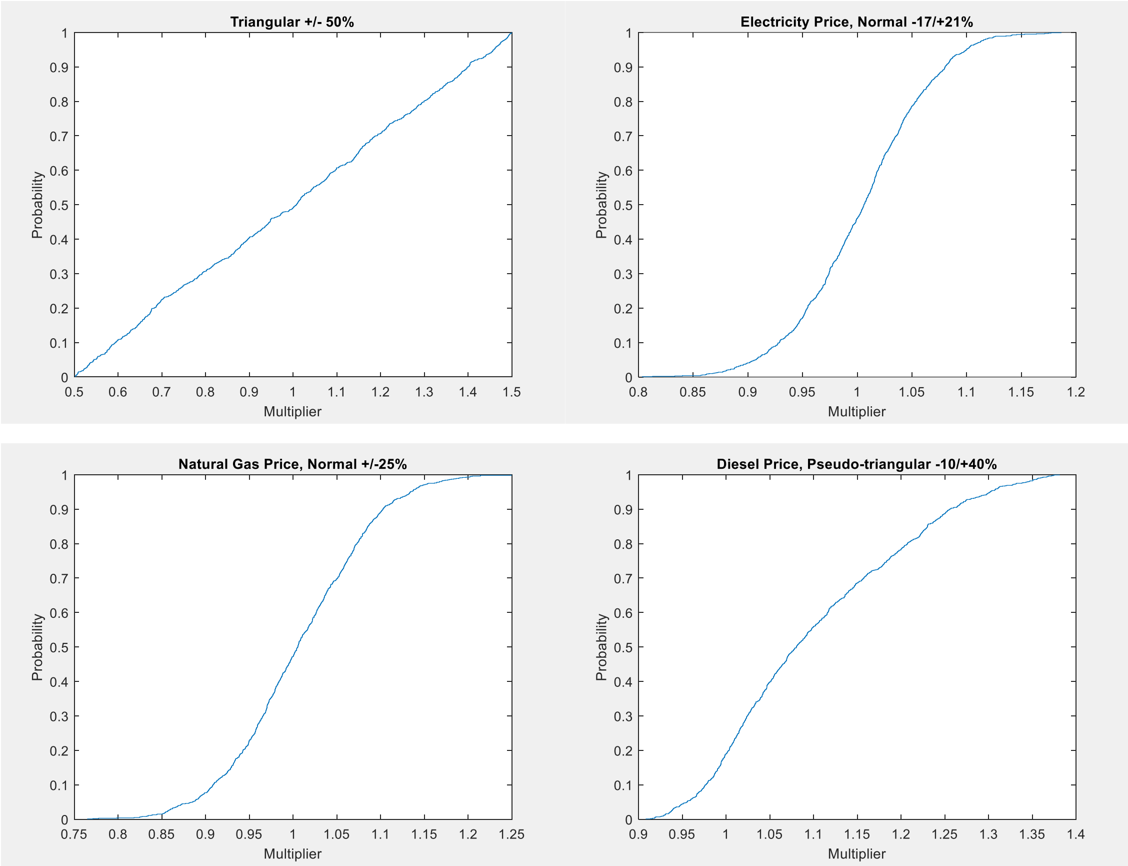


Figure 80 AP. Cumulative Probability Distributions Applied in the Monte Carlo Simulation

4.3. Risk Analysis Results No Additional Resilience

Table 54 AP. Risk Analysis Indicators of the No Additional Resilience Solutions

NO ADD RL, IRR 12% DPP 15 yrs	No Constraints	At least 1 CHP System	PV+GRID	ISOLATED GRID	CUSTOMIZED 1	CUSTOMIZED 2
Value at Risk (Savings) MAXdNPV	€ 2,127,242	€ 2,165,496	€ 2,154,507	€ 1,998,483	€ 1,814,695	€ 2,009,586
Value at Risk (Savings) MEANdNPV	€ 1,618,269	€ 1,317,934	€ 1,429,416	€ 287,725	€ 1,045,311	€ 1,203,658
Value at Risk (Savings) MINdNPV	€ 1,158,446	€ 452,478	€ 702,250	€ (1,936,551)	€ 294,002	€ 446,630
Probbaility of obtaining savings	100.0%	100.0%	100.0%	67.0%	100.0%	100.0%
IRR over X% at 90% probability	16.46%	9.09%	10.75%	3.53%	9.00%	9.06%
DPP under Y years at 90% probability	8.89	16.38	13.94	25.01	15.86	16.54
IRR goal (Over X at 90%)	12%	12%	12%	12%	12%	12%
Incentive for IRR goals	€ -	€ 588,323	€ 199,520	€ 1,514,204	€ 442,711	€ 513,263
Additional Annual Savings for IRR goals	€ -	€ 75,011	€ 25,439	€ 193,061	€ 56,446	€ 65,441
DPP goal (Under Y at 90%)	15	15	15	15	15	15
Incentive for DPP goals	€ -	€ 69,857	€ -	€ 1,269,540	€ 91,466	€ 50,334
Additional Annual Savings for DPP goals	€ -	€ 7,193	€ -	€ 206,468	€ 9,418	€ 5,183
IRR goal (Over X at 90%)	10%	10%	10%	10%	10%	10%
Incentive for IRR goals	€ -	€ 210,149	€ -	€ 1,190,807	€ 113,491	€ 186,734
Additional Annual Savings for IRR goals	€ -	€ 23,152	€ -	€ 131,189	€ 12,503	€ 20,572
DPP goal (Under Y at 90%)	17.5	17.5	17.5	17.5	17.5	17.5
Incentive for DPP goals	€ -	€ -	€ -	€ 665,433	€ -	€ -
Additional Annual Savings for DPP goals	€ -	€ -	€ -	€ 144,955	€ -	€ -
IRR goal (Over X at 90%)	8%	8%	8%	8%	8%	8%
Incentive for IRR goals	€ -	€ -	€ -	€ 967,030	€ -	€ -
Additional Annual Savings for IRR goals	€ -	€ -	€ -	€ 90,590	€ -	€ -
DPP goal (Under Y at 90%)	20	20	20	20	20	20
Incentive for DPP goals	€ -	€ -	€ -	€ 607,180	€ -	€ -
Additional Annual Savings for DPP goals	€ -	€ -	€ -	€ 128,098	€ -	€ -

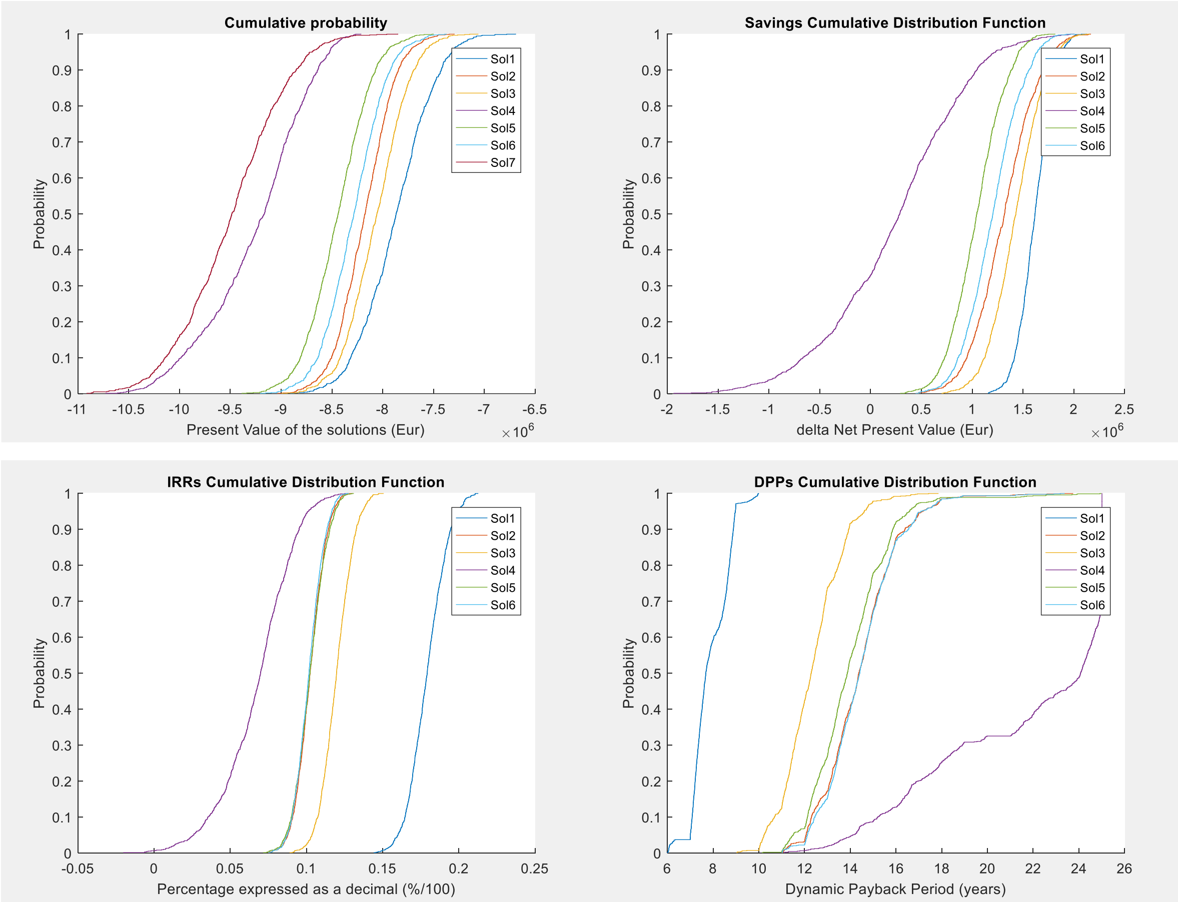


Figure 81 AP. Cumulative Probability Distributions of Risk Analysis Indicators No Additional Resilience Solutions

4.4. Risk Analysis Results Additional Resilience

Table 55 AP. Risk Analysis Indicators of Solutions with Additional Resilience

ADD RL, IRR 12% DPP 15 yrs	No Constraint	Two CHP Systems	PV+GRID	ISOLATED GRID	CUSTOMIZED 1	CUSTOMIZED 2
Value at Risk (Savings) MAXdNPV	€ 1,971,040	€ 1,047,410	€ 2,127,464	€ 1,218,896	€ 2,058,823	€ 2,283,974
Value at Risk (Savings) MEANdNPV	€ 1,211,421	€ 220,157	€ 1,314,794	€ (445,477)	€ 1,133,721	€ 1,234,953
Value at Risk (Savings) MINdNPV	€ 531,548	€ (467,368)	€ 566,552	€ (2,618,692)	€ 354,479	€ 380,894
Probbaility of obtaining savings	100.0%	79.9%	100.0%	20.3%	100.0%	100.0%
IRR over X% at 90% probability	10.1%	5.7%	10.4%	2.0%	8.8%	8.5%
DPP under Y years at 90% probability	14.64	25.00	14.12	25.01	16.66	17.91
IRR goal (Over X at 90%)	12%	12%	12%	12%	12%	12%
Incentive for IRR goals	€ 244,979	€ 1,585,606	€ 233,509	€ 2,290,965	€ 576,515	€ 798,529
Additional Annual Savings for IRR goals	€ 31,235	€ 202,165	€ 29,772	€ 292,098	€ 73,506	€ 101,812
DPP goal (Under Y at 90%)	15	15	15	15	15	15
Incentive for DPP goals	€ -	€ 1,062,211	€ -	€ 1,362,448	€ 37,231	€ 143,772
Additional Annual Savings for DPP goals	€ -	€ 31,119	€ -	€ 85,729	€ 3,833	€ 62,006
IRR goal (Over X at 90%)	10%	10%	10%	10%	10%	10%
Incentive for IRR goals	€ -	€ 1,561,254	€ -	€ 2,224,103	€ 222,509	€ 587,746
Additional Annual Savings for IRR goals	€ -	€ 172,000	€ -	€ 245,025	€ 24,513	€ 64,751
DPP goal (Under Y at 90%)	17.5	17.5	17.5	17.5	17.5	17.5
Incentive for DPP goals	€ -	€ 1,006,455	€ -	€ 1,242,918	€ -	€ 108,157
Additional Annual Savings for DPP goals	€ -	€ 18,907	€ -	€ 58,928	€ -	€ 27,710
IRR goal (Over X at 90%)	8%	8%	8%	8%	8%	8%
Incentive for IRR goals	€ -	€ 1,080,985	€ -	€ 1,779,869	€ -	€ -
Additional Annual Savings for IRR goals	€ -	€ 101,265	€ -	€ 166,736	€ -	€ -
DPP goal (Under Y at 90%)	20	20	20	20	20	20
Incentive for DPP goals	€ -	€ 810,369	€ -	€ 1,116,237	€ -	€ -
Additional Annual Savings for DPP goals	€ -	€ 6,579	€ -	€ 34,332	€ -	€ -

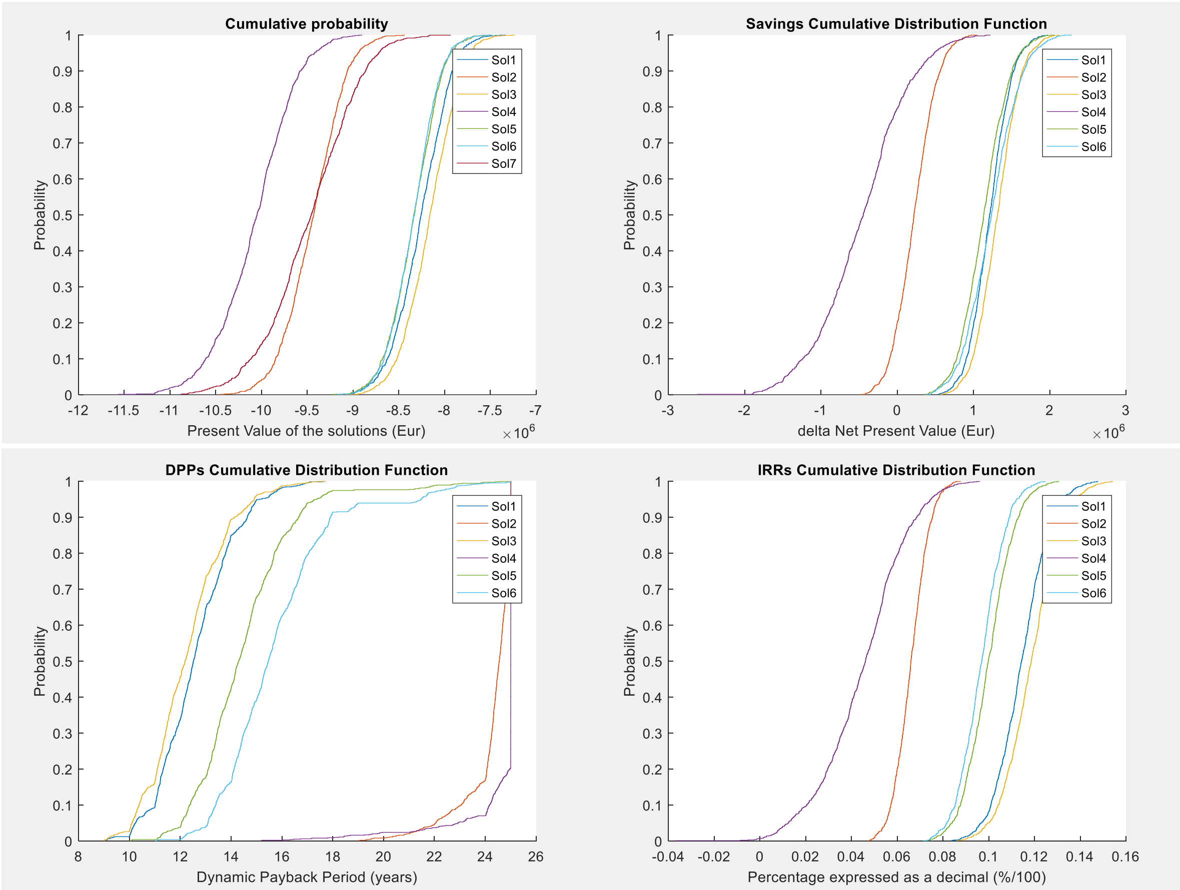


Figure 82 AP. Cumulative Probability Distributions of Risk Analysis Indicators for Additional Resilience Solutions

4.5. Risk Analysis Results No Additional Resilience

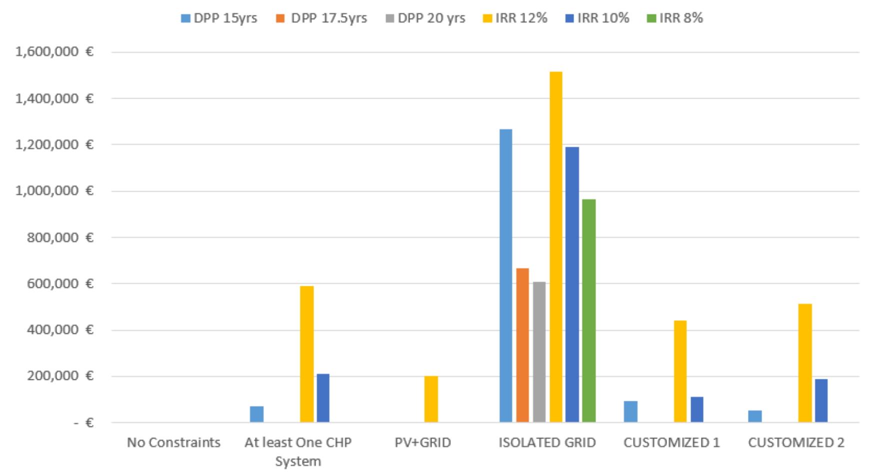


Figure 83 AP. Incentives to Fulfill the Goals for No Additional Resilience Solutions

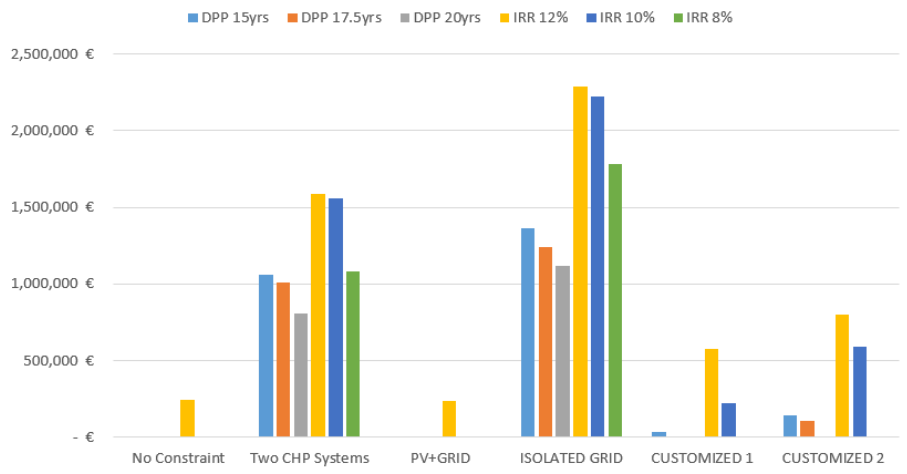


Figure 84 AP. Incentives to Fulfill the Goals for Additional Resilience Solutions

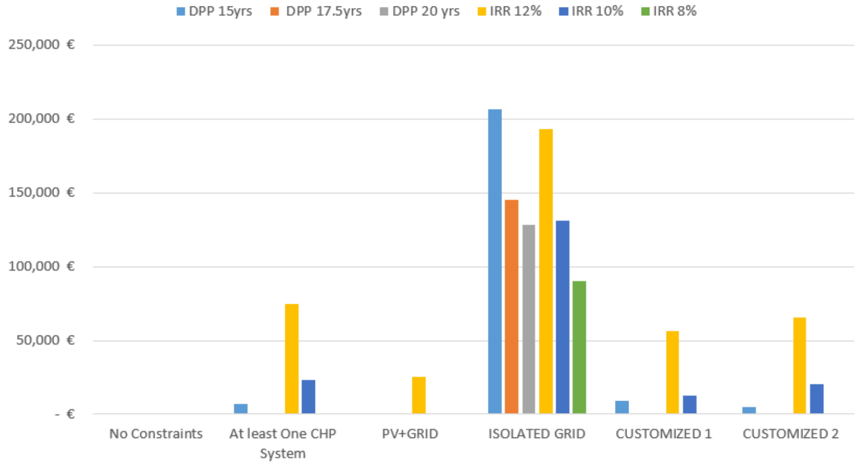


Figure 85 AP. Savings to Fulfill the Goals for No Additional Resilience Solutions

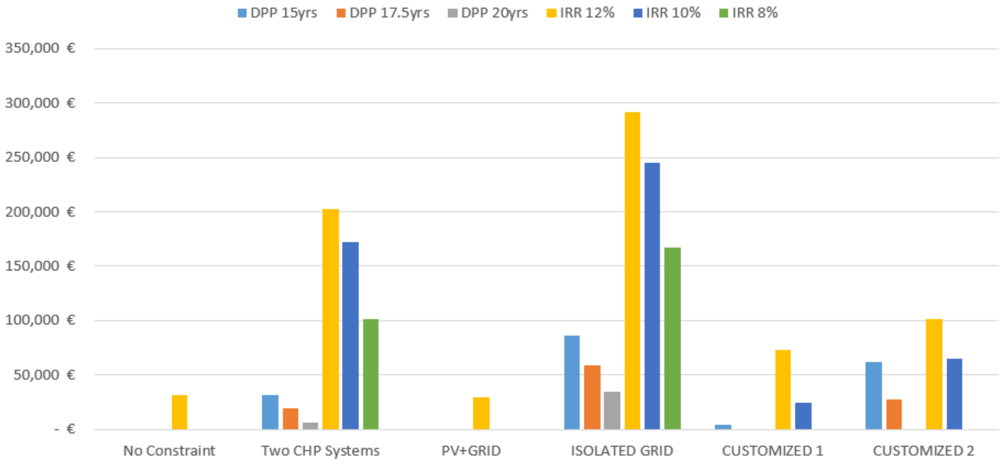


Figure 86 AP. Savings to Fulfill the Goals for Additional Resilience Solutions

Table 56 AP. Total Solutions Requiring Incentives per Goal and Type of Incentive

	One-time Incentives	Annual Cost Savings
IRR 12%	11	11
IRR 10%	8	8
IRR 8%	3	3
DPP 15 years	7	8
DPP 17.5 years	4	4
DPP 20 years	3	3

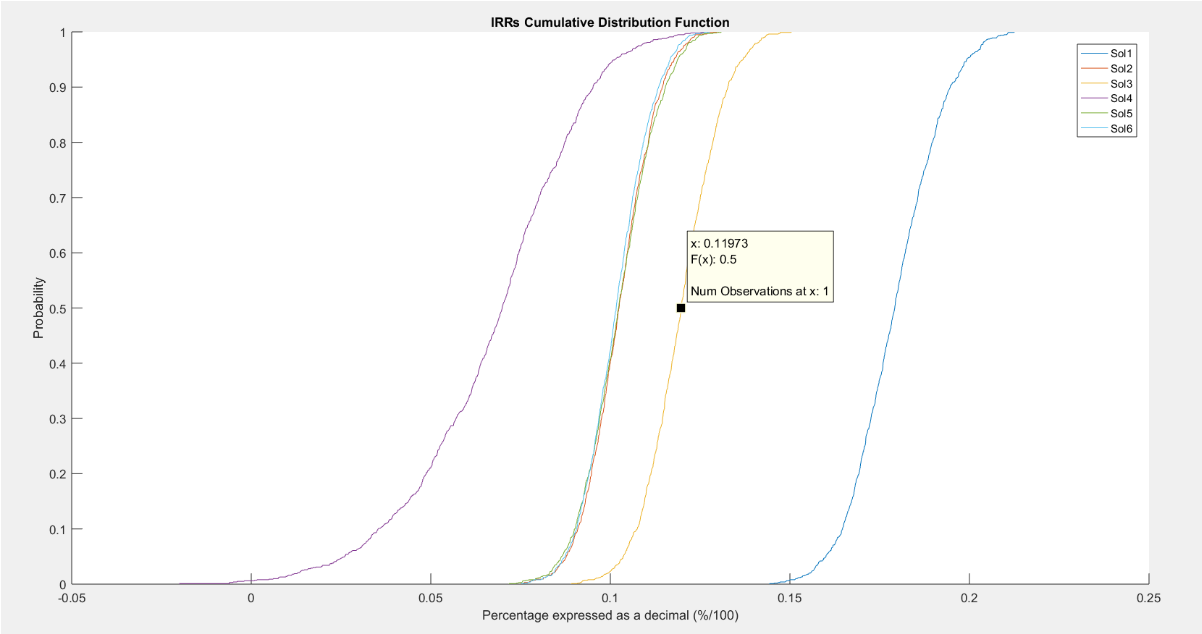


Figure 87 AP. Detail 1 of the Risk Analysis Results for the IRRs. No Additional Resilience Solutions

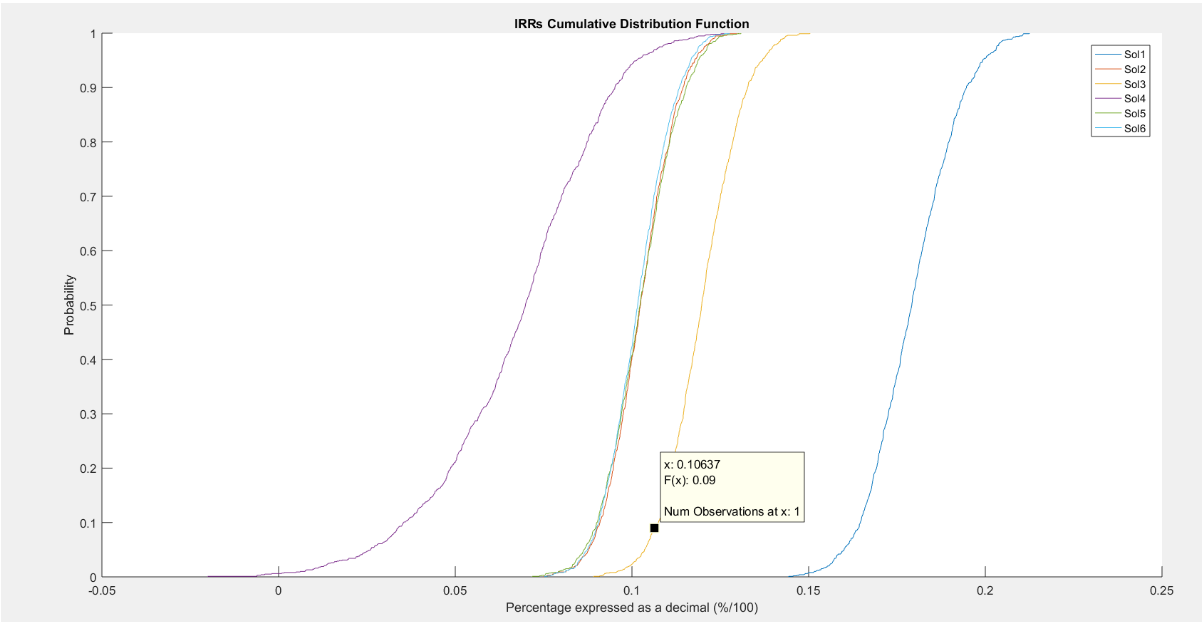


Figure 88 AP. Detail 2 of the Risk Analysis Results for the IRRs. No Additional Resilience Solutions

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