A Methodology to Compare the Effects of Demand-Side Management Strategies in the Planning of Islanded/Isolated Microgrids

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Abbreviations

ANN	Artificial Neural Networks
APSO	Accelerated Particle Swarm Optimization
BBO	Bio-geography-Based Optimization
BESS	Battery Energy Storage System
CAPEX	Capital Expenditures
CDF	Cumulative Distribution Functions
COE	Cost of Energy
CPI	Consumer Prices Index
CPP	Critical Peak Pricing
DPSP	Deficiency of Power Supply
DR	Demand Response
DSM	Demand Side Management
EDP	Extreme Day Pricing
ED-CPP	Extreme Day Critical Peak Pricing
EPSP	Excess of Power Supply Probability
DADP	Day-Ahead Dynamic Pricing
DLCt	Direct Load Curtailment
GA	Genetic Algorithms
GHI	Global Horizontal Radiation

GOA	Grasshopper Optimization Algorithm
IBP	Incentive-Based Pricing
ILP	Integer Linear Programming
IMG	Islanded/Isolated Microgrids
LCOE	Levelized Cost Of Energy
LOLE	Loss of Load Expectation
LP	Linear Programming
LPSP	Loss of Power Supply Probability
MCMG	Multi-Carrier Microgrid
MCS	Monte Carlo Sampling
MG	Microgrids
MIP	Mixed Integer Programming
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
MIQP	Mixed Integer Quadratic Programming
MOSaDE	Multi-Objective Self adaptive Differential Evolution
NOCT	Nominal Operational Cell Temperature
NPV	Net Present Value
OPEX	Operational Expenditures
PDF	Probability Distribution Function
PSO	Particle Swarm Optimization
PV	Photovoltaic System
R	Rate of Return

RF	Random Forest
ROI	Return of Investment
RTP	Real-Time Pricing
ShP	Fixed Shape Pricing
STRONG	Stochastic Trust-Region Response-Surface
ToU	Time of Use
WT	Wind Turbines

Abstract

Title: A Methodology to Compare the Effects of Demand-Side Management Strategies in the Planning of Islanded/Isolated Microgrids *

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Ph.D. in Engineering, Electrical Engineering Area

Keywords: Microgrids, Sizing, Dispatch, Demand-Side Management, Dynamic Tariffs.

Description: The integration of sizing, dispatch, Demand-Side Management (DSM) and tariff setting since the planning of Isolated/Islanded Microgrids (IMGs) can potentially reduce total costs and customer payments or increase renewable energy utilization. Despite these benefits, there is a paucity in literature exploring how the sizing, dispatch, DSM and tariffs affects IMG planning. Even more, the reviewed literature lacks of a methodology capable of integrating the four aspects to measure their impacts over the planning of IMGs. To fill this gap, this thesis proposes a methodology that integrates the four aspects and incorporates it as an open-source framework to measure the effects of different DSM strategies on IMG planning. The open-source framework uses modules as building blocks to represent the models of the energy sources, storage systems, the functions of demand response of the customers, and DSM strategies, amongst others. The modular approach allows planners and policymakers to perform their analysis by merely choosing the building blocks that match with their IMG projects' characteristics. The underlying mathematical formulation of the framework guarantees that each building block follow Disciplined Convex Rules, which, by convex analysis rules, will preserve the convexity of the resulting formulation. Therefore, the proposed methodology and framework can guarantee the solution's uniqueness and optimality, regardless of the architecture of the IMG or the building blocks planners or policymakers choose.

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* Ph.D. Tesis

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Resumen

Título: A Methodology to Compare the Effects of Demand-Side Management Strategies in the Planning of Islanded/Isolated Microgrids *

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Palabras clave: Microrredes, Dimensionamiento, Despacho, Gestión de la Demanda, Tarifas Dinámicas.

Descripción: La integración del dimensionamiento, el despacho, la gestión de la demanda gestión de la demanda y la fijación de tarifas desde la planificación de las microrredes aisladas puede reducir potencialmente los costos totales y los pagos de los clientes o aumentar la utilización de energías renovables. A pesar de estos beneficios, hay una escasez en la literatura que explore cómo estas características afectan a la planificación de las microrredes aisladas. Más aún, la literatura revisada carece de una metodología capaz de integrar los cuatro aspectos para medir sus impactos sobre la planificación de microrredes aisladas. Para llenar este vacío, esta tesis propone una metodología que integra los cuatro aspectos y la incorpora como un programa de software libre. La metodología utiliza módulos como bloques de construcción para representar los modelos de las fuentes de energía, los sistemas de almacenamiento, las funciones de respuesta de la demanda de los clientes y las estrategias de gestión de la demanda, entre otros. El enfoque modular permite a los planificadores de microrredes llevar a cabo sus análisis simplemente eligiendo los bloques de construcción que se ajustan a las características de sus proyectos de microrredes aisladas. La formulación matemática garantiza que cada bloque de construcción siga las Reglas Convexas Disciplinadas, lo cual garantiza la convexidad de la formulación resultante. Por lo tanto, la metodología propuesta puede garantizar la unicidad y la optimalizad de la solución, independientemente de la arquitectura de la microrred o de los bloques de construcción que elijan los planificadores.

* Tesis de Doctorado

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Introduction

Isolated/Islanded Microgrids (IMGs) are generally considered as a good solution for rural electrification when the extension of the bulk grid is not feasible. However, such solution faces several challenges before reaching most of the population. This chapter presents the general context of rural electrification around the world, the main challenges that IMG projects need to address, and the contributions of the thesis to alleviate those challenges. Additionally, the introduction will present the objectives and hypothesis of the work, and the associated publications to the development of the thesis.

General context of IMGs and motivation

Access to affordable and high-quality electricity is considered one of the barriers to overcome in order to achieve sustainable economic and social development in rural areas (Soniia et al., 2013). Despite the efforts made by governments to increase the coverage of the service, about 1 billion people, mainly located in sub-Saharan Africa, and South Asia, continue having the largest access-deficit to electricity (International Energy Agency, 2017). The tracking of the Seventh Sustainable Development Goal proposed by the United Nations shows that, with the current policies and speed of advance, 674 million people will still lack access to electricity in 2030 (WorldBank, 2018). In Colombia, 495.988 houses do not have connection to any service of electric energy. According to the Colombian government, 44.638 houses will be connected to the power system, 238.074 houses will use microgrids, and 213.276 houses will use home solar systems to access to the electric energy services. Around COP 7.41 billions (USD 1.95 billions) will be required to provide universal access to electric energy in Colombia (UPME, 2019).

National grids usually provide cheaper energy to the customers than IMGs. However, its extension to remote areas is not always the best approach. Local governments must face capital scarcity and challenges in the construction of the grids due to the geographical conditions in remote areas. Additionally, if the current grids cannot increase power generation or the connection of new loads can compromise its reliability, the extension of the grid becomes unfeasible. In those scenarios, the installation of IMGs to provide energy to isolated communities represents a better alternative (Mekonnen & Sarwat, 2017; Xu et al., 2016).

Hybridization of different energy sources can complement the strengths and weaknesses of different energy resources (Mekonnen & Sarwat, 2017; Xu et al., 2016). Hybridization of energy sources can bring several benefits to IMGs projects, compared to IMGs run by single type generation facilities (Bajpai & Dash, 2012). Among the benefits of hybridization of energy sources it is possible to highlight:

- Manage better fuel scarcity

- Reduce harmful emissions
- Increase flexibility
- Increase efficiency
- Increase reliability
- Reduce energy costs for customers
- Improve the well-being of the community

Nonetheless, the benefits of combining different energy sources in IMGs projects are directly related to its planning and operation. On one side, the partially unpredictable nature of the renewable energy sources and the uncertainties introduced by the electric demand of a community creates challenges for the technical aspects of IMGs (Hafez & Bhattacharya, 2012; W. Zhou et al., 2010). On the other side, tariff setting and public subsidies offered to rural electrification creates challenges and opportunities to the financial aspects of IMGs. Finally, the regulations of a country must be well defined for IMGs in order to succeed (Williams et al., 2015).

Technical challenges

The technical challenges in the implementation of IMGs are usually related to their planning and operation. Planning of IMGs refers to the set of decisions that the planner must make to design an IMG project. Such decisions include: Setting the energy mix, computing the sizing of the energy sources, defining the sources of money to fund the project, and how these sources of money will affect the tariffs for the customers, amongst others (Clairand et al., 2019). The operation of IMGs refers to the set of decisions that the planner must make to operate an IMG project. Such decisions include: defining the energy dispatch strategy, defining economic incentives for customers, setting energy tariffs and its means to be collected, defining Demand-Side Management (DSM) strategies, amongst others (Gamarra & Guerrero, 2015; Khodaei et al., 2015). This set of decisions has significant consequences on the performance and success of IMG projects (Wang et al., 2019).

References (Bernal-Agustín & Dufo-López, 2009; Notton et al., 2006) define the sizing of IMGs as the process of determining the capacity of the energy sources to supply the demand with a predefined desired reliability. The sizing generally aims to minimize investment costs, output energy costs, fuel consumption, or harmful environmental emissions, amongst others. The sizing is partially responsible for unmet loads or excess of energy, which can directly affect the satisfaction of the customers or the investors. An under-sizing affects the comfort of the customers, not providing enough energy when the customers expect to receive it. An over-sizing of non-dispatchable energy sources can cause over-generation. The over generation can lead to a waste of energy, an extra investment cost, and a lack of economic return for the investors of the project due to the non-sold energy (Williams et al., 2015). The final cost and the reliability of the energy supply rely on the selection and application of a proper sizing methodology. In this context, the sizing methodology of IMGs plays a vital role in the success of the project.

The sizing of IMGs relies on the knowledge of the technical specifications, weather conditions, and the characteristics of the load profiles (Zahraee et al., 2016). In this regard, IMG projects can not use a one-size-fits-all approach to system design. By doing a careful resource evaluation and understanding the behavior of the demand profiles, planners can optimize projects to fit local conditions (Domenech et al., 2014). A common mistake is to base IMG projects only on diesel generation. Diesel generators have low capital expenditures, ubiquitous suppliers, and service networks. However, diesel generation presents drawbacks like long term volatility of fuel costs, difficulties in accessing remote areas with constant fuel supply, and the need to reduce environmentally harmful emissions. These drawbacks of diesel generation create the need for cost-efficient means to reduce fossil fuel consumption in IMG projects.

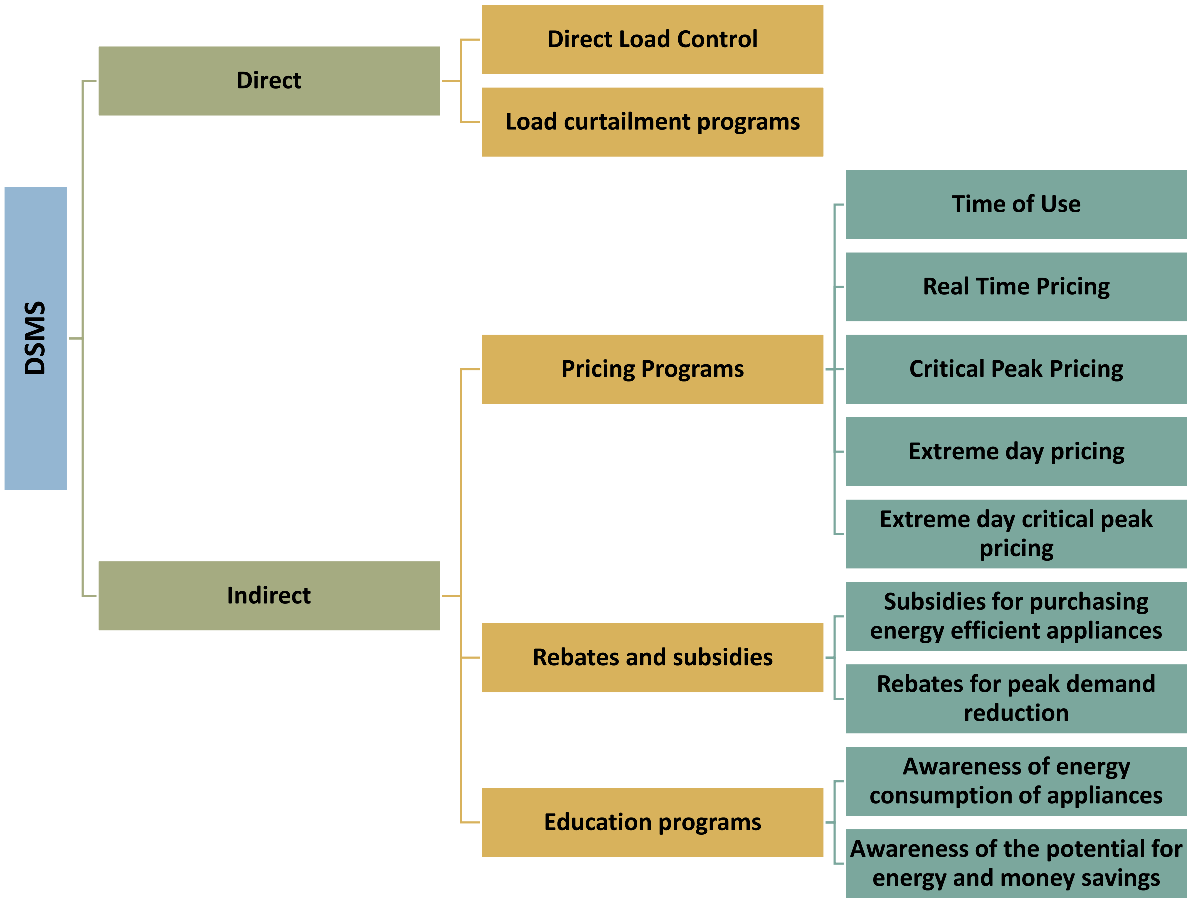
IMG projects that incorporate renewable energy sources, often as an add-on to diesel generator based systems, show great potential to diversify generation and lower operating costs (Hirsch et al., 2018; Nema et al., 2009). Moreover, the consideration of adequate DSM strategies can significantly reduce the costs of energy service provision in IMG (Casillas & Kammen, 2011). The introduction of different sources of energy and DSM in IMG projects creates the need for designing proper dispatch strategies. The dispatch strategy of an IMG usually aims to satisfy load demand at minimum operational cost while satisfying reliability constraints. Other objectives as well seek to enhance the power quality and ensure that the critical loads receive service priority (Hawkes & Leach, 2009; Katiraei et al., 2008). Additionally, a dispatch strategy that correctly implements DSM strategies can reduce curtailment of renewable energy resources and incentive their consumption (Casillas & Kammen, 2011; C. Li et al., 2015).

DSM aims to affect the patterns of consumption of the customers using direct or indirect strategies (Kostkova et al., 2013). Direct strategies are composed of direct load control and Interruptible/Curtailable Programs. In direct load control strategies, there is a remote controller sending signals to customers' appliances like air conditioners, heating systems, water heaters, or public lighting on short notice. The signals can turn on/off the appliances, switch tariffs, or inform about current electricity prices. Customers that sign for an Interruptible/Curtailable Program receive upfront incentive payments or rate discounts to reduce their load to predefined values. Participants who do not respond can face penalties, depending on the program terms and conditions. Interruptible/Curtailable Programs offer alternatives as bidding programs, Emergency Demand Response (DR) programs, Capacity Market programs, and ancillary services.

Indirect DSM are composed of pricing programs, rebates/subsidies, and education programs. Pricing programs charge dynamic tariffs for energy, which can be power-based, energy-based, or a combination of both (Franz et al., 2014; Reber et al., 2018). Energy-based tariffs incentive energy conservation, and therefore, are desired when the energy generation is limited (Casillas & Kammen, 2011). Instead of having a fixed flat rate, dynamic fares vary in time to reveal the actual costs of producing energy. These rates include the Time of Use (ToU) rate, Critical Peak Pricing (CPP), Extreme Day Pricing (EDP), Extreme Day CPP (ED-CPP), Day-Ahead Dynamic Pricing (DADP), and Real-Time Pricing (RTP). Properly designed tariffs motivate the customers to shift their demand to off-peak periods, when the electricity price is lower, and when it is more convenient to produce electricity (Jin et al., 2017). In Price rebates and subsidies, customers receive special discounts or incentives from purchasing energy-efficient appliances or by

Figure 1

Classification of Demand-Side Management Strategies (Kostkova et al., 2013)



making peak demand reductions. Finally, educational programs aim to teach the customers about the energy consumption and expenses of the owned devices. One of the advantages of indirect DSM is that they allow the customers to choose either to participate or not in the program. In contrast, direct DSM forces the customer to participate. Figure 1 shows the classification of DSM proposed by (Albadi & El-Saadany, 2008; Kostkova et al., 2013).

Financial challenges

Financial challenges refer to the scarce resources of capital from public and donor sources to install and operate IMG projects. The scarcity of capital from public and donor sources leads to the need for private capital. Nevertheless, private capital will not invest in IMG projects unless an appropriate level of profit is guaranteed. To attract private investors' interest, IMG planners must find the money streams to make IMG projects economically viable and financially sustainable over time (Schmidt et al., 2013). IMG private investors need to recover their capital and the expected Rate of Return (*R*) through the revenues of the IMG project (Franz et al., 2014). The revenues for microgrids come from different sources (Oueid, 2019; Stadler et al., 2016). However, the isolated condition of IMG projects reduces the number of revenue streams only to the tariffs income or carbon bonuses (Oji & Weber, 2017).

IMG can receive different sources of funding. Private investors can fund the IMG project to build a business model for profit. Public capital can fund the IMG to create a project fully subsidized. Finally, the government and private investors can co-fund the IMG to create a partially subsidized project. On one side, projects for profit generally charge a higher rate than the nationally interconnected utility, which limits access to energy only for those who can pay for it. On the other side, fully subsidized projects usually charge below cost-recovery tariffs to cover part of maintenance, operation, and administration expenses. However, the lack of proper tariffs collection reduces the money stream to operate the project. Lack of proper operation reduces the reliability of the service. If the customers do not receive the energy when they expect to receive it, dissatisfaction will rise, the payments will decrease even more, and the project starts to deteriorate (Daniel Schnitzer, Deepa Shinde Lounsbury, Juan Pablo Carvallo, Ranjit Deshmukh and Jay Apt and Kammen, Daniel M, 2014). On the last side, partially subsidized projects aim to combine the benefits of projects for profit, and fully subsidized projects (Glemarec, 2012; Glemarec et al., 2012; REN 21, 2019; Schäfer et al., 2011; UNEP Finance Initiative, 2012; Zerriffi, 2011). The government benefits of the mixture of capital, reducing the initial investment in the project and reducing the payments of subsidies for its operation. The private investors benefit of a secure business model.

The IMG project benefits with proper maintenance and sustainability due to the investor needs to recover its investments. Finally, customers benefit from a partially subsidized project having lower tariffs than the ones they will have in a project for profit. Additionally, customers also benefit with a more reliable electric energy service than a fully subsidized project (Schnitzer et al., 2014).

Regulatory Challenges

Regulatory challenges refer to the work of policymakers and governments to integrate technical, financial, and social aspects of IMG planning. Technical policies must incentive the participation of renewable energy sources in IMGs and must define the tax benefits for those kinds of energy sources. Additionally, technical policies must define conditions as continuity and quality of the electric energy service offered for IMGs (Andrew Harrison Hubble, 2016).

Financial policies must define clear rules for the sources of money to fund IMG projects to ensure sustainability over time. The way of charging customers for electric energy is probably the most crucial factor to reduce the risk and ensure project sustainability (IRENA, 2016). Sustainable IMG tariffs must at least cover the system's running and replacement costs, and the expected R of the investors. If the investors are allowed to define their tariffs, policymakers must guarantee that the tariff is fair enough not to overpass the consumers' ability and willingness to pay. The presence of public and international aid funds can potentially reduce the cost of the energy for the customers in IMGs. However, policymakers must define clear policies to guarantee that these reductions in the tariffs are directed as a saving to the customers and not as an over-profit for private investors.

Motivation of the research

The planning of IMGs faces technical, financial, and regulatory challenges. Despite this, there is a paucity of literature exploring how technical challenges are related to financial and regulatory challenges in the planning of IMGs. Even more, there is a paucity of literature exploring how DSM, energy tariffs and public subsidies for rural electrification are related to the optimal operation and system design. The author could not find a holistic methodology to study how DSM, energy tariffs or public subsidies affect the financial feasibility of IMGs projects. Such a study will provide insights on how to design fair regulations that include the points of view of the private investor, the government, and customers. However, such a methodology does not exist yet in the reviewed literature.

Objectives and scope of the thesis

The present thesis aims to fulfill the gaps found in the literature review by proposing a holistic methodology to compute the effects of public subsidies and DSM strategies in the planning of IMGs. The work implements seven different DSM strategies based on dynamic pricing and one DSM based on Direct Load Curtailment (DLCt). Even more, the present work aims to provide a framework to evaluate and compare the effects of the proposed DSM strategies on the planning of IMGs. In this regard, the present work has the following objectives.

General objective

To design a methodology to implement and evaluate the effects of different Demand Side Management Strategies based on dynamic tariffs and direct load curtailment over the capital and operational costs and the Levelized Cost of Energy of Islanded/Isolated Microgrids.

Specific objectives

1. To design a framework to evaluate the impact of applying the proposed Demand Side Management Strategies over the planning of Islanded/Isolated Microgrids.

2. To implement the dynamic tariff schemes and the Direct Load Curtailment Demand Side Management Strategies and evaluate the impacts over the total planning costs and Levelized Cost of Energy of Islanded/Isolated Microgrids Projects using the proposed evaluation framework.

3. To compare the performance of the Demand Side Management Strategies using the proposed evaluation framework and to perform a sensitivity analysis to evaluate the effects of varying the main decision parameters.

Hypothesis

The present thesis aims to evaluate the impact of DSM in the planning of IMGs. The study hypothesizes that by influencing the patterns of consumption of electrical energy of the customers, the Levelized Cost of Energy will decrease compared to the base case where no DSM is applied. The study also expects that by influencing the patterns of consumption of electrical energy of the customers other variables as the payments for the energy, diesel consumption, and total costs of the project, amongst others, will have a better performance. The study will validate if the expected results are valid or not in the IMGs context by using the designed methodology in a case study.

Contributions of the thesis

The present thesis aims to evaluate the impact of different DSM strategies in IMGs planning. The thesis required a methodology capable of integrating sizing and dispatch of the energy sources, the proposed DSM strategies, and the effects of public and private funding to evaluate these effects. However, the reviewed literature showed that a methodology with those characteristics does not exist. The thesis proposed its methodology to overcome this drawback. However, the thesis faced and solved different challenges to propose the methodology. A description of the faced challenges and their respective solutions proceeds in this section.

Integrating DSM into IMGs planning

The study assumes that in the IMGs of interest, there is a lack of smart or controllable loads. This forces the study to consider alternative DSM strategies that do not rely on scheduling loads to reduce demand peaks or increase renewable energy consumption. The study alternative to smart loads is the use of price-based signals to incentivize customers to modify their consumption patterns. The thesis integrates the price-based signals into the IMG design as tariff schemes. In this regard, the study requires a methodology capable of proposing energy tariffs that use price signals to modify the customers' patterns of consumption. However, in the reviewed literature, it was not possible to find a methodology with that capability.

The methodology integrated a technical analysis of the energy sources and demand behavior with a financial analysis to overcome this challenge. The methodology captured as well the possibility that IMG projects can have different funding sources. By considering that some of these investors will want to recover their investments, the methodology allows them to do it by receiving the energy tariffs' payments. By integrating the financial analysis and the tariffs, it is possible to formulate the tariffs as optimization formulation's decision variables. This approach allows imposing restrictions over the tariffs to benefit the customers or limit the investors' profit levels that want to recover their investments using the tariffs. The capability to impose restrictions over the tariffs allows the methodology to control the investors' expected levels of profit, which makes the methodology a worth analyzing tool for regulatory proposes.

Risk of combinatorial explosion

The use of nested optimization methodologies for the planning of IMGs requires to solve two different problems, one problem for the dispatch of the energy sources and another problem for sizing. The dispatching problem usually simulates the operation of the IMG for a representative year using optimal or non-optimal strategies. Non-optimal strategies usually rely on the simulation of the dynamics of the system. Optimal strategies require the mathematical characterization of each energy source. The superior level computes the sizing of the IMG using the results of the sub-level problem, the dispatch. However, nested optimization methodologies face the risk of combinatorial explosion. For the dispatch methodologies that follow optimization approaches each new variable/constraint for each interval of time δ_t adds T/δ_t new variables/constraints to the problem (8760 if $T = 1$ year and $\delta_t = 1$ hour). If the dispatch methodology wants to consider a multiyear analysis that single variable/constraint will scale linearly with the number of years YT/δ_t ($219,000$ if if $T = 1$ year and $\delta_t = 1$ hour and $y = 25$ years). Moreover, a stochastic analysis that considers randomly sampled scenarios will increase that single variable/constraint linearly as well with the number of scenarios SYT/δ_t ($219,000,000$ if if $T = 1$ year, $\delta_t = 1$ hour, $y = 25$ years and $S = 1,000$ samples).

The previous shows that each new variable/constraint grows linearly with the number of years and scenarios. However, that numbers are for one new variable/constraint, each new source will add several variables and constraints. However, each iteration of the sizing problem will require recomputing all the dispatch problem again, which leads to the risk of a combinatorial explosion. The methodology proposes to follow the Disciplined Convex Programming rules to formulate one single formulation capable of solving the two problems simultaneously to overcome the combinatorial explosion challenge. By following the DCP rules, it is possible to guarantee a fast convergence to the optimal solution. Additionally, it is also possible to guarantee that the problem will always find an optimal solution if the solution space is not an empty set.

Integrating uncertainties

The planning of IMGs relies on the forecasts of the energy sources' prices, the forecasts of the availability of primary generation resources (renewable and non-renewable), and the forecasts of interest rates. However, these forecasts naturally come with uncertainties. The literature has widely demonstrated that the consideration of the uncertainties in the planning process is highly desirable. The proposed methodology uses the Disciplined Convex Stochastic Programming (DCSP) approach to consider the effects of uncertainties in the planning of IMGs. The DCSP approach relies on the forecasted uncertainties to build a Monte Carlo Sampling (MCS) approach (see appendix 4.4).

Building a modular approach

The proposed methodology relies on an optimization formulation that follows a DCSP approach. However, to use the methodology, the potential user will require considerable knowledge in convex analysis and stochastic optimization. The study proposed a modular approach to reduce the knowledge barrier and allow a more comfortable utilization of the methodology. The modular approach makes the methodology user-friendly, enables easier reproducibility of the study, and allows effortless scalability to different analysis types.

The methodology needs to consider three aspects: consistent modular building, communication between modules, and the interoperability of modules to address this challenge. The methodology relies on the DCP rules to build each of the modules to address the first aspect. Suppose each of the modules follows the DCP rules. In that case, the resulting formulation will follow the DCP rules, which guarantees the convexity of the resulting formulation. The second aspect is the communication of the modules. The methodology designed the modules with predefined inputs and outputs, which enables the modules' communication. Moreover, because each of the modules has predefined inputs and outputs, the modules' interoperability becomes a natural characteristic of the modular approach. By following the modular approach, the methodology guarantees that future users can design different IMG architectures by choosing the modules that meet their requirements.

Publications associated to the thesis

The challenges faced and solved during the development of this thesis served as an opportunity to publish different articles. Table 1 shows the resulting publications of the work developed in the thesis. Additionally, the thesis discussed its partial results in four different conferences (Bastidas et al., 2017; Oviedo-Cepeda et al., n.d.; Oviedo-Cepeda et al., 2017; Oviedo-Cepeda et al., 2018). Appendix 4.4 presents a further description of each of the publications.

Finally, as a summary of the contributions it is possible to state that the thesis provide planners, governments, and policymakers a methodology for planning IMGs addressing their inherent technical and financial challenges. The application of the methodology provides the optimal size and optimal dispatch of each of the energy sources, the optimal energy tariffs, the amount of money required from private investors, and the needed amount of public subsidies from the government to make all kinds of IMG projects financially feasible for the private investors. Additionally, the methodology is proposed as a framework that follows a modular approach capable of integrating and evaluating the impacts of eighth different DSM strategies in the planning of IMGs. The capabilities of the methodology and framework to evaluate different combinations of energy tariffs, private and public capital mixtures, and different DSM strategies make it a worth looking tool for IMG planners or for governments or policymakers to design proper regulations for IMG projects.

Table 1
Contributions of the thesis.

Title	Journal	Reference
Design of Tariff Schemes as Demand Response Mechanisms for Stand-Alone Microgrids Planning	Energy - Elsevier	(Oviedo-Cepeda, Serna-Suárez, et al., 2020)
Sizing of Hybrid Islanded Microgrids using a Heuristic approximation of the Gradient Descent Method for discrete functions	International Journal of Renewable Energy Research	(Oviedo-Cepeda, Largo, et al., 2020)
Design of an Incentive-based Demand Side Management Strategy for Stand-Alone Microgrids Planning	International Journal of Renewable Energy Research	(Oviedo-Cepeda, Khalatbarisoltani, et al., 2020)
Design of a Methodology to Evaluate the Impact of Demand-Side Management in the Planning of Isolated/Islanded Microgrids	Energies - MDPI	(Oviedo-Cepeda, Roche, et al., 2020)
Design of an Incentive-based Demand Side Management Strategy using ILP for Stand-Alone Microgrids Planning	International journal of Sustainable Energy Planning and Management	(Oviedo-Cepeda, Duarte, et al., 2020)

Description of the contents of the thesis

The present thesis divides the problem's presentation, the proposed methodology, and the evaluation of the DSM impacts over IMGs planning into five chapters. The first chapter had presented the introduction and motivation to the problem. The second chapter presents the literature review of the state of the art of sizing methodologies for IMGs planning. The third chapter presents the mathematical formulation of the methodology and the proposed open-source framework. The fourth chapter presents some of the methodology's capabilities by designing and applying the proposed methodology and framework to a case study. Finally, chapter five presents the conclusions of the work.

1. Review of state of the literature on IMG planning

The literature review focuses on the sizing of microgrids. However, due to the broad spectrum of sizing methodologies found in literature, the review will focus only on the sizing methodologies that integrate dispatch strategies and DSM strategies. From the review, sizing methodologies can be classified into two major groups: the multilevel approach and the single level approach. Additionally, the literature review explores some works in tariff design. Section 1.1 explores sizing methodologies with optimal and non-optimal dispatch strategies. Section 1.2 explores sizing methodologies that integrate DSM strategies. Finally, section 1.3 explores tariffs design.

1.1. Sizing strategies that include dispatch of the energy sources

The sizing of IMGs is the process of determining the size of each of the generators and storage systems to supply the demand with a predefined desired reliability (Bernal-Agustín & Dufo-López, 2009). Typical objectives are to minimize investment costs, output energy costs, fuel consumption, or harmful environmental emissions, among others. Sizing of IMG projects is a complicated task since the accuracy of the results relies on the knowledge of the technical specifications of the facilities, weather and climate conditions, and the characteristics of the load profiles (Maheri, 2014). Not only the reliability of the energy supply relies on proper sizing, but also the final cost of the energy. The dispatch aims to generate the control references for the energy sources in order to supply the electrical demand of an IMG (Hatziargyriou, 2014). Typical objectives are to minimize operational costs, fuel consumption, or harmful environmental emissions while satisfying system and reliability constraints.

1.1.1. Single level sizing methodologies

In the single level methodologies, the planner tackles the sizing and dispatch with a single optimization formulation. Single optimization formulations use iterative, numerical, analytical, probabilistic, and graphical methods. These techniques utilize differential calculus to derive the optimum solution (Al-falahi et al., 2017; Siddaiah & Saini, 2016; Sinha & Chandel, 2015). Authors commonly use Linear Programming (LP) (Huneke et al., 2012) and Mixed Integer Linear Programming (MILP) (Ferrer-Martí et al., 2013; Malheiro et al., 2015). Software as DER-CAM or REopt uses Mixed Integer Programming to obtain the optimal size and dispatch strategies of electrical and thermal loads in IMGs (Berkeley Lab, 2018).

Chang and Lin (2015) propose a Stochastic Mixed Integer Programming (MIP) formulation to compute the sizing of multiple IMGs. The work uses an adapted version of the stochastic trust-region response-surface (STRONG) method (Chang et al., 2013). Sanajaoba Singh and Fernandez (2018) propose to use a Cuckoo Search for the sizing of IMGs. The work uses a probabilistic approach and a sensitivity analysis to measure the effects of variations of the wind speed, solar radiation, and capital cost of the energy sources over the Cost of Energy (COE). Balderrama et al. (2019) aim to compare the results of minimizing the Net Present Value (NPV) of an IMG using three different formulations, LP, Integer Linear Programming (ILP), and MILP; and two approaches, deterministic and stochastic. For the stochastic approach, the work considers the uncertainties in the demand and the renewable generation with a two-stage optimization formulation. Ranaboldo et al. (2015) propose a meta-heuristic algorithm named AVEREMS to support the design of IMGs. The AVEREMS algorithm computes the sizing, the best location for the energy sources, and the IMG configuration. Additionally, the AVEREMS method proofs to be efficient for the design of IMGs using low computational resources.

Gupta et al. (2015) use a Biogeography-based optimization (BBO) to minimize the total costs of IMGs. The work uses Artificial Neural Networks (ANN) to forecast renewable energy resources and a deterministic approach to compute the optimal size of the energy sources. Paliwal et al. (2014) use a modified Particle Swarm Optimization (PSO) to minimize the Levelized Cost of Energy (LCOE) of IMGs. The work computes a deterministic optimal sizing of the energy sources considering a reliability constrained formulation. El Alimi et al. (2014) minimize the total costs of IMG projects using an enumerative technique to solve the optimization formulation. Arabali et al. (2014) compare the results of a Pattern search algorithm with Genetic Algorithms (GA) to minimize the total cost of IMGs. The work uses a stochastic approach for the formulation of the problem. However, even though these works find the optimal size and dispatch for the energy sources in one single formulation, none of them consider the effects of the application of DSM strategies in their formulation. Table 2 summarizes the works presented in this section.

1.1.2. Multilevel sizing methodologies

The multilevel approach refers to a sizing process of an IMG that combines two or more levels. In the two levels approach, the lower level simulates the operation of the IMG. The upper level proposes the capacities of the energy sources to the lower level. Sometimes, a third level performs a sensitivity analysis over the main variables. Figure 2 describes the multilevel sizing approach of three levels and a brief description of the purpose of each of the levels in a multilevel sizing

Table 2

Summary of single level sizing methodologies

Ref.	Objective	Sensitivity analysis	Deterministic	Stochastic	Method	Horizon
(Balderrama et al., 2019)	Minimize NPV	Yes	Yes	Yes	LP, ILP, MILP	One year
(Sanajaoba Singh & Fernandez, 2018)	Minimize total costs	Yes	No	Yes	Cuckoo Search	One year
(Chang & Lin, 2015)	Minimize total expected cost	Yes	No	Yes	A-STRONG	Not specified
(Ranaboldo et al., 2015)	Minimize total costs	No	Yes	No	AVEREMS	Not specified
(Gupta et al., 2015)	Minimize total costs	No	Yes	No	BBO	One year
(Paliwal et al., 2014)	Minimize LCOE	No	Yes	No	Modified PSO	One year
(El Alimi et al., 2014)	Minimize total costs	No	Yes	No	Enumerative	Twenty years
(Arabali et al., 2014)	Minimize total costs	Yes	No	Yes	Pattern search, GA	One year

approach proceeds in the following paragraphs.

The purpose of the lower level is to simulate the operation of the IMG, compute the operational costs and check if the reliability parameters are satisfied. The simulation of the operation of the IMG can use either an optimal dispatch strategy or not. Rule-based (Almada et al., 2016; Kanchev et al., 2011) or fuzzy logic (Arcos-Aviles et al., 2017; Kyriakarakos et al., 2012) based dispatch strategies are practical to design, but they do not guarantee optimal dispatch. Heuristic approaches that use GA (C. Chen et al., 2011; Elsied et al., 2016), PSO (M. Chen et al., 2018; Elsayed et al., 2018; Moghaddam et al., 2012), or Artificial Bee Colony (Marzband et al., 2017) can tackle nonlinearities of the formulation and can guarantee near-optimal results for the dispatch under certain assumptions. Despite that Linear Programming (LP) (Luna et al., 2018), Mixed Integer Linear Programming (MILP) (Anglani et al., 2017) or Mixed Integer Quadratic Programming (MIQP) (Chalise et al., 2016) dispatch strategies require a formal mathematical approach to the formulation; they guarantee optimal dispatch results for the dispatch of the energy sources.

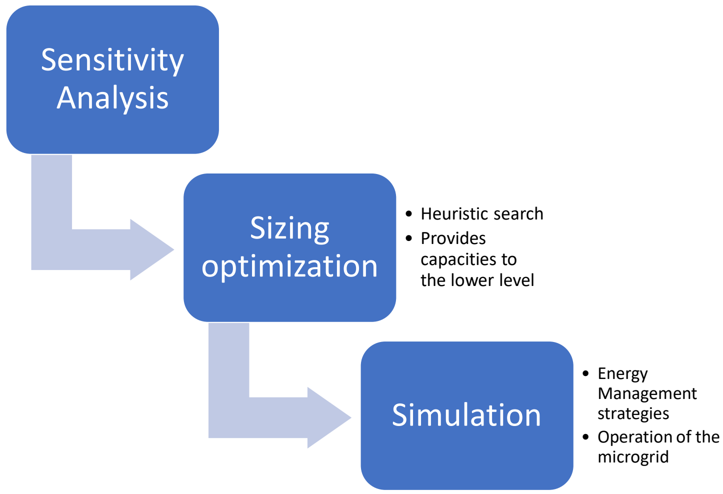
The purpose of the intermediate level is to find the capacities of the energy sources that fulfill the planner objectives. The intermediate level proposes the capacities of the energy sources to the lower level. The lower level simulates the performance of the IMG using those capacities and finds the operational costs. This level can use classical, heuristic, or software approaches. Classical methods combine the simulation of the operation of the IMG with a traditional optimization technique as LP (Nogueira et al., 2014) or MILP (Balderrama et al., 2019) for the sizing. Heuristic techniques use artificial intelligence-based methods to determine the set of optimal solutions (Mahesh & Sandhu, 2015; Ranaboldo et al., 2015; Upadhyay & Sharma, 2014). Software as HOMER, H_2RES, TRNSYS16, or RETScreen use a three levels approach. These software perform energy balances in the lower level using non-optimization-based dispatch strategies. Only the sizing level uses an optimization approach based on heuristic search (Amutha & Rajini, 2016; Connolly et al., 2010; Feng et al., 2018; Hafez & Bhattacharya, 2012; Mathur et al., 2017; "Microgrid Design Toolkit," n.d.). Additionally, the sizing level chooses the horizon of the simulation of the lower level (horizons vary from one critical day to multi-year analysis).

Finally, the higher level performs sensitivity analysis for critical variables. The higher level aims to evaluate how the size of the energy sources or the energy dispatch varies when the main variables change. Husein and Chung (2018) use a sensitivity analysis to measure the impact of inflation, discount, taxes, and loan rates over the NPV. Additionally, the authors use the sensitivity analysis to evaluate the impact of energy sources costs and interest debt over the NPV. Sanajaoba Singh and Fernandez (2018) use a sensitivity analysis to measure the impacts of wind speed, global horizontal radiation, and energy sources price variation over the LCOE. Some works use sensitivity analysis to measure the effect of the uncertainties in the electrical demand or the renewable generation over the system design. However, sometimes this approach can lead to erroneous results (Higle, 2005; Powell, 2016).

Several works in literature use the approach of three levels for the sizing of IMGs. Bukar et al. (2019) use a rule-based controller for the dispatch and a Grasshopper Optimization Algo-

Figure 2

Three levels approach for the sizing of IMG



rithm (GOA) to compute the optimal sizing of an IMG. The work aims to minimize the COE and the Deficiency of Power Supply (DPSP). Ramli et al. (2018) aim to minimize the LCOE and the Loss of Power Supply Probability (LPSP). The work uses a Multi-Objective Self adaptive Differential Evolution (MOSaDE) algorithm for the sizing and a rule-based controller for the dispatch. Askarzadeh and dos Santos Coelho (2015) use PSO to compute the sizing of the energy sources and a rule-based controller for the energy dispatch. Ma et al. (2014) use HOMER to evaluate hundreds of possible combinations to supply the electrical demand of an Island. Maheri (2014) propose a Monte Carlo simulation to tackle the uncertainties in renewable generation and the load in the planning of IMG. The work uses a GA to compute the sizing of the energy sources and a rule-based controller for the dispatch.

Multilevel sizing methodologies that simulate the operation of the microgrid are powerful tools to evaluate the performance of complex systems with almost no simplifying assumptions. However, the lack of an optimization formulation for the dispatch strategy can lead to sub-optimal sizing results, which represents a considerable drawback (Castañeda et al., 2013; Sharafi & ELMekkawy, 2014; Syed, 2017). To improve this drawback, B. Li et al. (2017) create a MILP formulation to obtain the optimal dispatch strategy of an IMG that supplies electric, cooling/heating, and hydrogen loads. The work considers the aging of the energy sources in the analysis and implements a GA to compute the sizing. Fadaeenejad et al. (2014) use iHOGA to evaluate the sizing of an IMG in Malaysia. iHoga software differs from HOMER, giving the option to the user to implement optimal dispatch strategies. iHOGA uses a GA that computes the dispatch strategies and the sizing of the energy sources. Husein and Chung (2018) implement a MILP formulation to obtain the optimal energy dispatch and an enumerative approach to obtain the sizing. The enumerative approach uses different combinations of capacities of energy sources to compute the Life Cycle Costs (LCC) of the IMG project. However, the works that use a search algorithm to compute the sizing, and an optimization algorithm for the operation of the IMG, require to solve several times the dispatch strategy for each combination of energy sources. The need for solving several times the dispatch problem for each possible combination of energy sources can lead to a combinatorial explosion, which represents a considerable drawback. Table 3 summarizes the works presented in this section.

1.2. Sizing and Demand-Side Management

Despite the potential benefits of applying DSM strategies in the planning of IMGs, there is a paucity of literature integrating the optimal planning of IMGs with the design of DSM strategies. This section presents the works found in the literature that explores the integration of sizing and DSM strategies in MGs in 1.2.1. Additionally, this section presents the integration of sizing and DSM strategies in IMGs in section 1.2.2.

1.2.1. Sizing and Demand-Side Management in microgrids

Literature has studied the effects of DSM over the sizing of microgrids. As an example of this, Kahrobaee et al. (2013) design a sizing approach to determine the capacity of a Wind Turbine (WT) and a Battery Energy Storage System (BESS) for a smart household considering price variations in the tariffs. The authors design a three steps process combining a rule-based controller, a Monte Carlo approach, and a PSO to perform the sizing of the components. However, the combination of multiple steps of different types and the lack of an optimization formulation for the dispatch can

Table 3
Summary of multilevel sizing methodologies

Ref.	Objective	Sensitivity Analysis	Sizing (Intermediate level)		Simulation (Lower level)		
			Optimization	Method	Optimization	Method	Horizon
(Bukar et al., 2019)	Minimize COE and DPSP	Yes	Yes	GOA	No	Rule-based	One year
(Ramli et al., 2018)	Minimize LCOE and LPSP	Yes	Yes	MOSaDE	No	Rule-based	One year
(Husein & Chung, 2018)	Minimize LCC	Yes	Yes	Enumera-tive	Yes	MILP	One year
(B. Li et al., 2017)	Minimize LCC considering aging of the ES	Yes	Yes	GA	Yes	MILP	One year
(Amutha & Rajini, 2016)	Minimize NPV	Yes	Yes	HOMER	No	Rule-based	One year
(Askarzadeh & dos Santos Coelho, 2015)	Minimize LCC	No	Yes	PSO	No	Rule-based	One year
(Fadaeenejad et al., 2014)	Minimize NPV	Yes	Yes	iHOGA	Yes	GA	One year
(Nogueira et al., 2014)	Minimize total costs	Yes	Yes	LP	No	Rule-based	Critical period
(Ma et al., 2014)	Minimize NPV	Yes	Yes	HOMER	No	Rule-based	One year
(Maheri, 2014)	Minimize total costs	Yes	Yes	GA	No	Rule-based	One year
(Hafez & Bhattacharya, 2012)	Minimize NPV	Yes	Yes	HOMER	No	Rule-based	One year

lead to sub-optimal results. Erdinc et al. (2015) aim to improve these drawbacks by providing an MILP formulation to design the optimal dispatch strategy. The work considers the seasonal and weekly variations in the load profiles in the presence of a Real-Time Pricing tariff. However, this work did not consider how to design the DSM strategy itself and how different DSM strategies will impact the sizing of the energy sources.

Kerdphol et al. (2016) propose a sizing approach for BESS using PSO to improve the frequency stability of an MG. The work integrates a dynamic DSM strategy considering shedding of non-critical loads to rapidly restore the system frequency and reduce the BESS capacity. A rule-based controller used for the load shedding and a PSO formulation used for the sizing of the BESS proofs to be adequate to regulate the frequency of the MG. However, the rule-based controller and the lack of forecast models to anticipate the critical events can lead to sub-optimal results. Nojavan et al. (2017) propose a bi-objective Mixed-Integer Non-Linear Programming (MINLP) formulation to optimally site and size a BESS in an MG considering DSM strategies. The authors design the two optimization objectives to reduce total costs and the Loss of Load Expectation (LOLE). The work uses a ε-constraint method to draw the Pareto optimal curve and a fuzzy satisfying technique to find the best solution. Despite the high quality of the work, the authors assume that 20% of the load reacts to a ToU tariff ignoring the effects of the self elasticity of the demand. Majidi et al. (2017) use a Monte Carlo Scenario reduction technique to determine the size of a BESS in an MG. The work considers the effects of uncertainties in the forecasted renewable generated power and forecasted consumption. However, similarly to Nojavan et al. (2017), the authors did not consider how the customers react to the DSM strategy; they assume that 20% of the load will react to a ToU tariff.

Amir et al. (2018) propose a combined algorithm to find the size and dispatch strategy of a Multi-Carrier Microgrid (MCMG). The work uses GA to obtain the capacities of the energy sources and an MINLP formulation to obtain the optimum dispatch strategy. The work measures the variations in the patterns of consumption of the customers changing the prices of the different forms of energy. The planning of the MCMG considers demand and price growth over a five years optimization horizon. Despite the high sophistication of the proposed mathematical model, the work does not design the DSM strategy; the work only limits to consider the effects of the prices of the energy providers to the MCMG.

J. Kumar et al. (2019) use HOMER to analyze the techno-economic viability of a rural grid-connected microgrid considering a demand response strategy. The study shows that the integration of the demand response strategy reduces the LCOE. However, the study does not use an optimal energy dispatch strategy, neither an optimal tariff for the demand response strategy, which can lead to sub-optimal solutions. N. Zhou et al. (2016) propose an optimal sizing for a BESS to reduce the uncertainties of the Photovoltaic (PV) system operation. The work use self elasticity and cross elasticity to estimate the response of the customers to a peak-valley ToU tariff scheme. The objective function aims to size the capacity of the BESS, define its optimal location, maximize PV consumption, and increase annual net profits. Bhamidi and Sivasubramani (2020) uses the time shiftable and power shiftable appliances of 1000 smart homes as a DSM resource in a residential microgrid. The microgrid is tied to the power system. The microgrid consider different levels of response of the users to compute the sizing of the energy resources. When have of the homes participate in the DSM program, the PV capacity increased 49%, the capacity of the WT increased 58%, the capacity of the Micro Turbine decreased 64%, the capacity of the diesel generator decreased 50%, and the capacity of the BESS was keep it constant.

1.2.2. Sizing and Demand-Side Management in IMGs

Literature has explored the effects of DSM in the planning of IMGs. As an example of this, Chauhan and Saini (2017) proposes a methodology to integrate a DSM strategy that reschedule shiftable loads depending on the season (winter/summer) with the sizing of IMGs. The work uses an ILP formulation to find the optimal rescheduling of shiftable loads and a Discrete Harmony Search algorithm to compute the sizing. A considerable drawback of the work is that the DSM only focuses on reducing the peak demand while ignoring maximizing exploitation of renewable energy.

Amrollahi and Bathaee (2017) combine a MILP formulation and the capabilities of the HOMER software to compute the sizing of an IMG composed only of renewable energy sources. Due to the lack of dispatchable energy sources, the authors propose to use DSM to reschedule shiftable loads. The rescheduling helps to balance the mismatch between electric energy generation and consumption.

Mehra et al. (2018) propose a work to measure the economic value of applying DSM in the sizing of a nanogrid. The work considers the disaggregation of the electrical demand in critical and non-critical appliances. Besides, the work takes advantage of low-cost computation intelligent devices such as the “utility-in-a-box” solution to implement direct DSM strategies (Harper, 2013). The authors use an exhaustive search algorithm to determine the capacities of the PV system and the BESS. Nevertheless, the work considers the effects of only one kind of DSM strategy and over a small size grid.

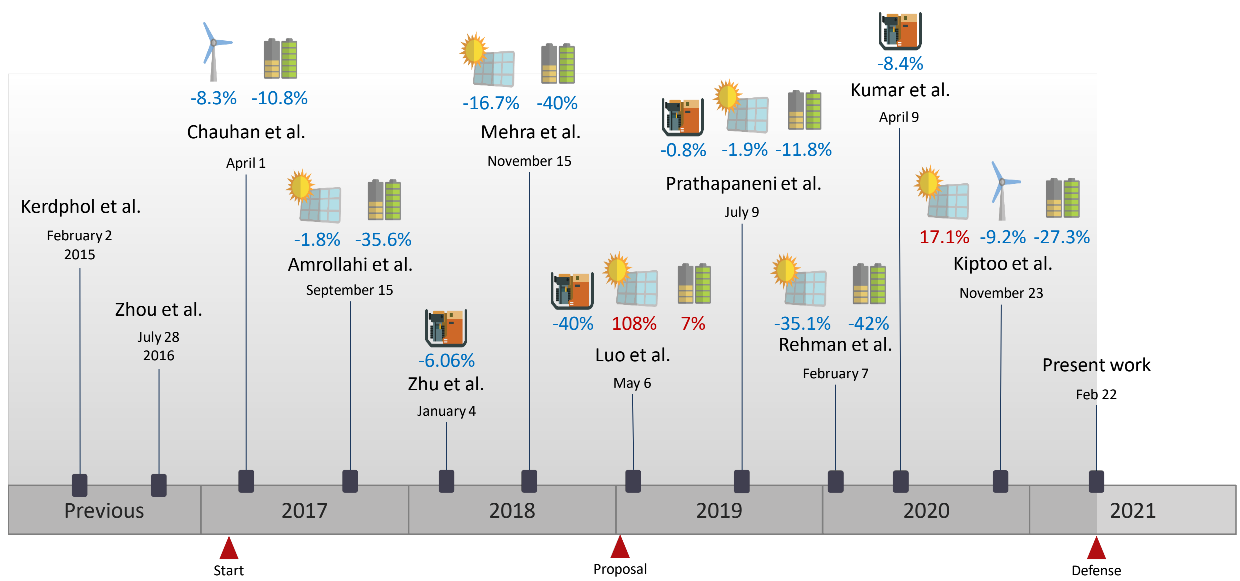
Prathapaneni and Detroja (2019) propose a multiobjective stochastic sizing algorithm that aims to minimize lifetime costs and degradation of the energy sources. The work considers the effects of a DSM strategy that uses shiftable loads like electric vehicles or pumped hydro storage in an IMG. The work uses an Accelerated Particle Swarm Optimization (APSO) to compute the sizing of the energy sources. Despite the consideration of the lifetime costs of the IMG and the degradation of the energy sources, the work considers a basic DSM strategy over a reduced amount of loads that are not always present in IMG applications. Luo et al. (2019) propose a sizing methodology for an IMG using a bilevel optimization algorithm. The first level computes the capacities of the energy sources, considering the effects of different combinations of public subsidies for the installation of the energy sources. The second level performs the dispatch strategy for the energy sources of the IMG using a MINLP formulation. The authors implement in the second level of optimization a rescheduling mechanism of shiftable loads. A study case shows that DSM reduces the installed capacities of the energy sources for the IMG.

Kiptoo et al. (2020) similarly to Amrollahi and Bathaee (2017), aims to implement a DSM strategy to balance generation and electricity demand in an IMG composed only for renewable energy sources . The DSM strategy consider rescheduling shiftable loads. However, the authors aim to improve the work of Amrollahi and Bathaee (2017) by adding a Random forest (RF) regression forecasting approach to forecast the demand. The work shows that the proposed methodology is capable of reducing 12.41% the total costs of the IMG project. Rehman et al. (2020) use HOMER software to find the capacities of the energy sources of an IMG. The work considers a DSM capable of rescheduling shiftable loads and uses Simulink to evaluate the operation of the IMG. The use of Simulink allows the authors to design and test a model predictive control. The model predictive control regulates output power during grid-connected operation and load voltage in the islanding operation of the MG. M. Kumar and Tyagi (2020) used direct load control as a DSM strategy to improve the reliability of a small community microgrid. The work computes the sizing of the IMG using a heuristic approach. The proposed methodology for the work achieves a reduction of 5.32% in the costs of the project.

Table 4 presents a quantitative analysis of the works that combine sizing and DSM in IMGs. Figure 3 presents the timeline of the principal works considered in this section. Table 5 presents a summary of the works that this section presents.

Figure 3

Timeline of the publications that integrate sizing and DSM for IMGs.



1.3. Tariff design

The tariffs of public services affect the welfare of communities as well as the financial performance of the service provider (Gunatilake et al., 2008). A common objective for tariff design is cost recovery, an objective designed to guarantee the financial sustainability of the service provider company. However, there is not a clear consensus on which costs the tariffs should recover (Dole & Bartlett, 2004). The World Water Council defends that cost recovery means that tariffs should

Table 4

Quantitative analysis of the literature review for IMGs.

Chauhan and Saini (2017)

	Strategy	Hydro	Biogas	Biomass	WT	BESS
No DSM		50	50	40	48	133.2
DSM	DLC	50	50	40	44	118.8
% of variation		0	0	0	-8.3	-10.8

Amrollahi and Bathaee (2017)

	Strategy	PV	WT	BESS
No DSM		17	9	90
DSM	DLC	16.7	9	58
% of variation		-1.8	0	-35.6

Zhu et al. (2018)

	Strategy	PV	WT	BESS	DG
No DSM		100	33	100	198
DSM	DLC	100	33	100	186
% of variation		0	0	0	6.06

Mehra (2017) and Mehra et al. (2018)

	Strategy	PV	BESS
No DSM		1.2	0.5
DSM	DLC	2	0.3
% of variation		-16.7	-40

Prathapaneni and Detroja (2019)

	Strategy	PV	DG	BESS
No DSM		31.1	11.8	96.7
DSM	DLC	30.5	11.7	85.3
% of variation		-1.9	-0.8	-11.8

Luo et al. (2019)

	Strategy	DG	PV Th.	PV	BESS	Chiller
No DSM		5	1078	414	57	16
DSM	DLC	3	948	865	61	15
% of variation		-40	-12.1	108.9	7	-6.3

Kiptoo et al. (2020)

	Strategy	PV	WT	BESS
No DSM		1196	2054	7150
DSM	DLC	1401	1866	5200
% of variation		17.1	-9.2	-27.3

Rehman et al. (2020)

	Strategy	PV	WT	BESS	DG
No DSM		21.1	5	90	0
DSM	DLC	13.7	5	52	8.4
% of variation		-35.1	0	-42	New

M. Kumar and Tyagi (2020)

	Strategy	Biogas	BESS
No DSM		56.74	10
DSM	DLC	51.99	10
% of variation		-8.4	0

fund the public service. The revenues of those tariffs should be enough to cover recurring costs, but ensuring that the service is affordable for all the population (Winpenny, 2004). The Asian Development Bank defends that cost recovery should include the following (Asian Development Bank, 2002):

- Collecting enough revenues to fund current operations and future investments.
- Income redistribution among the population.
- Minimization of waste of the production of the services.
- Efficient management of the enterprise.

However, recovering costs is not sufficient; tariff setting must go beyond.

Tariffs are a powerful tool for public policy. Public policies can use tariffs for a variety of social, economic, and financial purposes. These purposes must consider distributive financial justice, economic efficiency, and fair pricing according to the social and economic conditions of the population (Dole, 2003). Dole and Bartlett (2004) affirm that for customers, tariffs must be simple, transparent, and predictable. For owners of service provider companies, tariffs must recover the costs of the creation and operation of the company. For governments, tariffs must be affordable for low-income people for meeting basic needs, promote efficient use of resources, and avoid cross-subsidies (Dole & Bartlett, 2004). Achieving these objectives when designing a tariff will guarantee the application of a fair and efficient tariff. However, some of these objectives have conflicts between each other, which makes the process of setting tariffs a complicated task.

Another aspect to consider in the tariff setting is the conflict between economic efficiency, financial sustainability, and affordability issues. On one side, economic efficiency refers to the maximization of the welfare of society. Maximizing the welfare of the society leads to price the goods at the short-run marginal cost. However, setting the tariffs to recover only marginal costs of production will demotivate private investors to participate in the economic activity. On the other side, the affordability issues set the upper limits of the tariffs. The upper bound must be at least higher than the financial sustainability costs. The ideal tariff must be above the financial sustainability costs and below the limit of the affordability of the population. Additionally, the ideal tariff must provide sufficient revenue to private investors to motivate them to participate in providing the service. Figure 4 shows a graphical representation of the conflicting goals of tariff setting.

Figure 4

Description of an ideal tariff for the pricing of a good

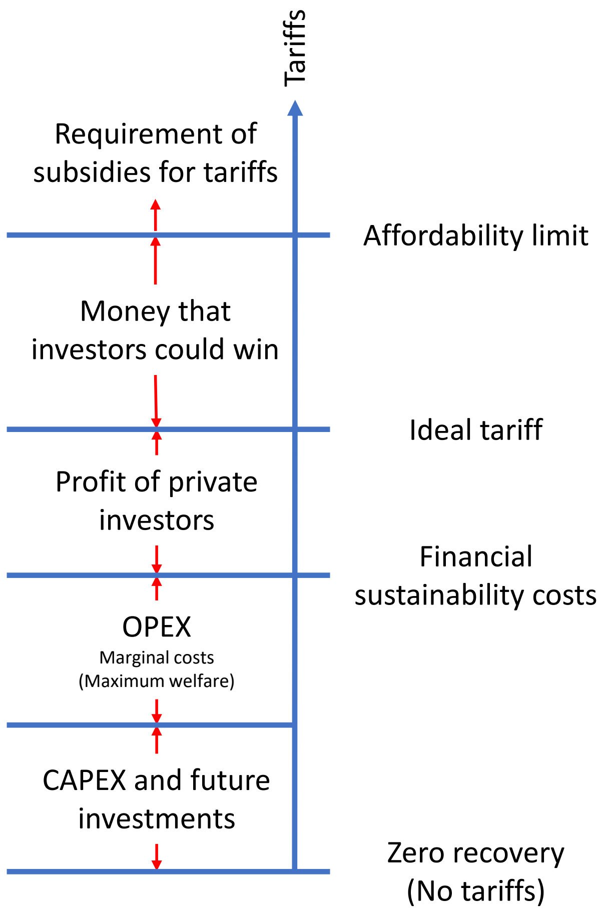


Figure 4 describes the condition of ideal tariffs. The socio-economic conditions of each community set the affordability limit. The affordability limit of the customers defines if the government must partially subsidize an IMG project or not. On one side, if the affordability limit of the customers is below the financial sustainability limit, the government must partially fund the IMG project. Public funding will reduce the amount of money that investors need to recover, which will reduce the required cash-flow income to guarantee financial sustainability. The subsidies of the government must be enough to push the marginal costs and the financial sustainability limits below the affordability bound. If this is not possible to achieve by subsidizing only the capital expenditures, the government will need to partially subsidize the final tariffs as well. On the other side, if the financial sustainability limit is below the affordability limit, the IMG project does not require public funding. In any case, due to the natural monopoly conditions of IMG projects, the government must set proper regulations to prevent excessive profits for private investors (revenue cap regulations).

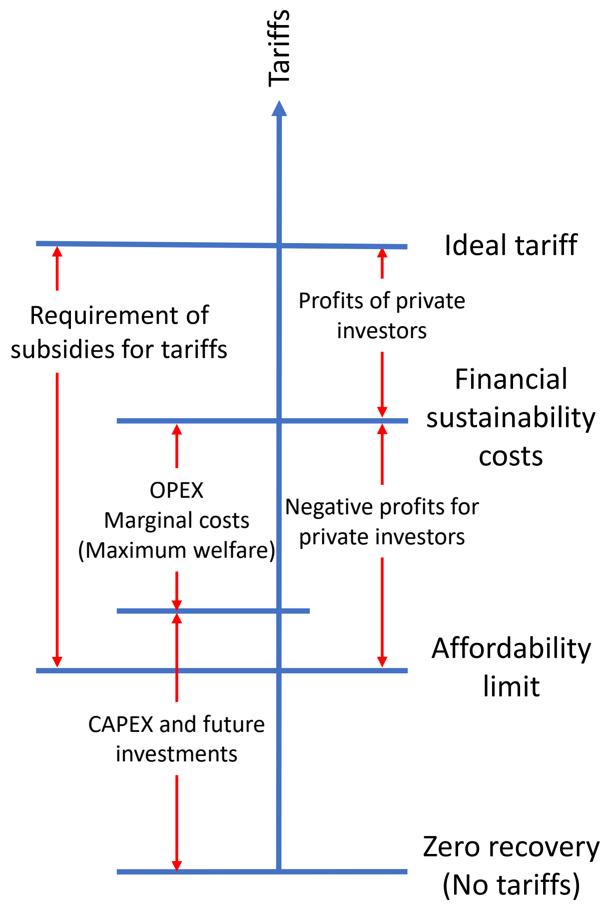
1.3.1. Tariff design for IMGs

Setting proper tariffs for IMG projects requires careful consideration of the local policies and the willingness to pay of the customers (affordability limit) (Meister Consultants Group, 2017). Figure 5 shows that the affordability limit of the customers in isolated/islanded microgrids can be below of the financial sustainability costs. If this is the case, subsidies from the government will be required to make financially feasible the IMG project.

The capacity of the government on subsidizing IMG projects and the affordability limit of the customers intrinsically limits private investment (Meister consultants Group, 2018). In this regard, the government needs careful design of the subsidies meant for IMG projects. If the subsidies offered to IMG projects are too high, private investors will have excessive profits, even charging the regulated tariff. If the subsidies offered to IMG projects are too low, private investors will not recover their investments by charging the regulated tariffs. A possible solution will be to raise the tariffs. Nevertheless, tariffs naturally will have an upper bound determined by the energy price regulations of the country, which also will limit the share of private investment in IMG projects (IRENA, 2016). The tariffs for IMGs can be power-based, energy-based, or a combination of both (Franz et al., 2014; Reber et al., 2018). On one side, power-based tariffs limit the total peak consumption. On the other side, energy-based tariffs depend on metered energy consumption and can, therefore, encourage energy conservation (Casillas & Kammen, 2011). It is possible to define energy-based tariffs according to the consumer group, e.g., residential, institutional, industrial,

Figure 5

Description of ideal tariffs for IMG projects.



commercial, amongst others. Additionally, they can consider block metering, which charges customers differently according to energy consumption. Energy-based tariffs can be constant over time as flat tariffs, but also can consider variations in time, as ToU or RTP tariffs.

Time variations of the tariffs allow the planner to use them as indirect DSM strategies (Parhizi et al., 2015; Yan et al., 2018). Tariffs based on dynamic variations provide the reliability benefits of peak load reductions while improving the allocation of electricity procurement costs among residential customers with diverse demands (Borenstein, 2002; Hirst, 2002). Previous analysis showed that high-use customers respond significantly more, in kW reduction, than low-use customers. However, low-use customers save significantly more in percentage reduction of annual electricity bills(kWh reductions), than do high-use customers (Herter, 2007).

1.4. Analysis of the literature review

Although few works in the literature explore how DSM affects optimal IMG planning, most of them focus on evaluating the impacts of shiftable loads. These works demonstrate that IMG projects obtain economic and environmental benefits by applying DSM strategies in the planning of IMGs. However, none of the works compares the benefits of applying different DSM strategies in the planning of IMGs. Furthermore, only a few studies in the literature focus on the design of tariff schemes and their use as DSM strategies to influence customer consumption patterns. The lack of focus on designing appropriate pricing schemes eliminates the day-to-day aspect of IMG planning, which can lead to real-life project failures.

Due to the conditions of natural monopolies in IMGs and to the consideration of the day-to-day operation of the projects, tariff design should attract considerable interest. On one side, the tariff setting must guarantee the affordability of the service to the customers. On the other side, tariffs must guarantee financial sustainability for the business models of private investors. Finally, governments must establish revenue cap regulations to guarantee that private investors do not have excessive profits. To fulfill these constraints satisfactory, governments should pay attention to the effects of public subsidies in IMG projects. Luo et al. (2019) is the first study known by the authors that correlates subsidy policies for remote areas with the capacity and scheduling of

IMGs. However, the work does not consider the effects of public subsidies over tariff schemes. Moreover, the work does not consider the utilization of tariff schemes as DSM strategies in IMG projects. Table 6 shows the gaps found in the literature review and the expected results of the present dissertation.

2. Methodology formulation

The present thesis aims to study the effects of DSM over the planning of IMGs. This requires a methodology able to:

- Integrate different energy sources for the IMG.
- Compute the sizing of the energy sources.
- Compute the energy dispatch of the energy sources.
- Consider the effects of the DSM over the lifetime of the project.
- Consider business models to recreate the actual conditions of the development of IMG projects.
- Set the tariffs of the energy for the customers.
- Evaluate the impact of the DSM strategies over the planning of IMGs.

A methodology with the above characteristics does not exist in the reviewed literature. In this regard, the study requires designing the above-described methodology. Moreover, the present thesis aims to integrate the proposed methodology in a framework. A framework capable of evaluating different DSM strategies using any energy source and any renewable energy resource over any community, considering any possible business model. The thesis proposes this methodology in Section 2.1 and the evaluation framework in Section 2.2.

Many computer software available in the market can compute the sizing of IMGs. Nevertheless, most of this software does not consider DSM, and indeed, does not design optimal tariff schemes (Oviedo-Cepeda et al., 2018). The impossibility of integrating DSM and tariff design in the commercially available software force the study to use nested optimization models of two levels. In the nested optimization models, the first level computes the sizing and the second level the energy sources dispatch. Nested optimization models allow the formulation to easily integrate heuristic search for the sizing and rule-based controllers or optimization formulations to dispatch the energy sources (Oviedo-Cepeda, Duarte, et al., 2020; Oviedo-Cepeda, Khalatbarisoltani, et al., 2020; Oviedo-Cepeda, Largo, et al., 2020). However, nested optimization models face a combinatorial problem since each iteration of the sizing optimization must completely solve the dispatch problem. To tackle this challenge and avoid the combinatorial problem, the study proposed to use single convex optimization formulations. A single optimization formulation capable of solving the sizing, the dispatch of the energy sources, and defining the optimal tariffs (Oviedo-Cepeda, Serna-Suárez, et al., 2020). Despite its benefits, single optimization formulations do not consider the impacts of uncertainties. To solve this drawback, the study proposed to use Disciplined Convex Stochastic Programming (DCSP) (Oviedo-Cepeda, Roche, et al., 2020). DCSP guarantees the uniqueness and optimality of the solution. Nevertheless, DCSP does not follow a modular approach naturally that the study can implement as a framework. To solve this challenge, the study proposed to build independent optimization modules. Each of the modules follows Disciplined Convex Programming (DCP) rules. By following the DCP rules, the IMG planner can use the modules as building blocks to configure any IMG architecture and perform different analyses. Section 2.2 presents a further explanation about the characteristics and capabilities of the modular approach.

2.1. Proposed methodology

Considering the works of professor Stephen P. Boyd, a mathematical optimization problem generally has the form (Boyd & Vandenberghe, 2004):

$$\begin{aligned} \text{minimize} \quad & f_0(x) \\ \text{subject to} \quad & f_i(x) \leq 0, \quad i = 1, \ldots, m, \\ & h_i(x) = 0, \quad i = 1, \ldots, p \end{aligned} \tag{1}$$

to describe the problem of finding an x that minimizes $f_0(x)$ among all x that satisfy the conditions $f_i(x) \leq 0$, $i = 1, \ldots, m$, and $h_i(x) = 0$, $i = 1, \ldots, p$. We call $x \in \mathbf{R}^n$ the optimization variable and the function $f_0 : \mathbf{R}^n \to \mathbf{R}$ the objective function or cost function. The inequalities $f_i(x) \leq 0$ are called inequality constraints, and the corresponding functions $f_i : \mathbf{R}^n \to \mathbf{R}$ are called the inequality constraint functions. The equations $h_i(x) = 0$ are called the equality constraints, and the functions $h_i : \mathbf{R}^n \to \mathbf{R}$ are the equality constraint functions. If there are no constraints (i.e., $m = p = 0$), the problem 1 is unconstrained.

The set of points for which the objective and all constraint functions are defined,

$$\mathscr{D} = \bigcap_{i=0}^{m} \mathbf{dom} f_i \cap \bigcap_{i=0}^{p} \mathbf{dom} h_i, \tag{2}$$

is called the domain of the optimization problem 1. A point $x \in \mathscr{D}$ is feasible if it satisfies the constraints $f_i(x) \leq 0$, $i = 1, \ldots, m$, and $h_i(x) = 0$, $i = 1, \ldots, p$. The problem 1 is said to be feasible if there exists at least one feasible point, and infeasible otherwise. The set of all feasible points is called the feasible set or the constraint set. The optimal value p^* of the problem 1 is defined as

$$p^* = inf\{f_0(x) \,|\, f_i(x) \leq 0,\ i = 1, \ldots, m,\ h_i(x) = 0,\ i = 1, \ldots, p\}, \tag{3}$$

where inf is the infimum function as defined by (Boyd & Vandenberghe, 2004).

The optimal point x^* is an optimal point, or solves the problem 1, if x^* is feasible and

$f_0(x^*) = p^*$. The set of all optimal points is the optimal set, denoted

$$X_{opt} = \{x \mid f_i(x) \leq 0,\ i = 1,\ldots,m,\ h_i(x) = 0,\ i = 1,\ldots,p,\ f_0(x) = p^*\}. \tag{4}$$

If there exists an optimal point for the problem 1, the optimal value is achieved, and the problem is solvable. If X_{opt} is empty, the optimal value is not achieved, and the problem is not solvable.

2.1.1. Convex optimization

A convex optimization problem is one of the form

$$\begin{aligned} \text{minimize} \quad & f_0(x) \\ \text{subject to} \quad & f_i(x) \leq 0, \quad i = 1,\ldots,m, \\ & a_i^T x = b_i, \quad i = 1,\ldots,p \end{aligned} \tag{5}$$

where, by definition, the functions $f_0,\ldots,f_m$ must be convex. Thus, they satisfy

$$f_i(\alpha x + \beta y) \leq \alpha f_i(x) + \beta f_i(y) \tag{6}$$

for all x, $y \in \mathbf{R}^n$ and all $\alpha, \beta \in \mathbf{R}$ with $\alpha + \beta = 1$, $\alpha \geq 0$ and $\beta \geq 0$.

Comparing 5 with the general standard form problem 1, the convex problem has three additional requirements:

- The objective function must be convex.
- The inequality constraint functions must be convex.
- The equality constraint functions $h_i(x) = a_i^T x - b_i$ must be affine.

Additionally, the feasible set of a convex optimization problem is convex, since it is the intersection of the domain of the problem

$$\mathscr{D} = \bigcap_{i=0}^{m} \mathbf{dom} f_i, \tag{7}$$

which is a convex set, with m (convex) sublevel sets $\{x \mid f_i(x) \leq 0\}$ and p hyperplanes $\{x \mid a_i^T x = b_i\}$. Thus, a convex optimization problem, minimizes a convex objective function over a convex set.

2.1.2. Disciplined Convex Programming

Disciplined Convex Programming (DCP) analysis is a system for constructing mathematical expressions with known curvature from a given library of base functions. The curvature and sign of all the base functions of the library is known in advance. Thus, it is possible to predict the convexity of the results of applying different operators or transformations to the functions of the library. Because the base functions of the library and the operators and transformations are known, it is possible to automatize the process of determining if a mathematical expression is convex or no. The automatization of the DCP analysis gives birth to convex optimization modeling languages as CVX, CVXPY, Convex.jl, and CVXR. Each of these software can ensure that the specified optimization problems formulated on them are convex.

2.1.3. Disciplined Convex Stochastic Programming

The proposed methodology implements a multiyear-stochastic analysis using Disciplined Convex Stochastic Programming (DCSP). DCSP builds on principles from stochastic optimization and convex analysis, representing a considerable advantage to build the desired methodology. (Ali et al., 2015). Equation (8) presents the general formulation of a convex stochastic problem:

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & E(a_1(x,\xi)) \\ \text{subject to} \quad & E(b_i(x,\xi)) = 0, \quad i = 1,\ldots,B, \\ & c_i(x,\xi) \geq 0, \quad i = 1,\ldots,C \end{aligned} \tag{8}$$

where $b_i : \mathbf{R}^n \times \mathbf{R}^q \to \mathbf{R}$, $i = 1,\ldots,B$ are convex functions in x for each value of the random variable $\xi \in \mathbf{R}^q$, and $c_i : \mathbf{R}^n \to \mathbf{R}$, $i = 1,\ldots,C$ are (deterministic) affine functions; since expectations preserve convexity, the objective and inequality constraint functions in (8) are (also) convex in x, making (8) a convex optimization problem (Ali et al., 2015), Liberti and Maculan, 2008, Chapter 7.

2.1.4. Main assumptions

The formulation of the methodology assumes that the planner can have at least one year of historical data of weather variables and electrical demand. The formulation use this historical data to build the multiyear, and multiyear-stochastic analysis of the methodology by using a scenario construction technique. Section 2.1.5.2 and Appendix 4.4 presents the information about the scenario building technique.

The methodology assumes that there is no presence of smart or controllable loads in the IMGs. Therefore, it is impossible to apply DSM strategies based on controlling or rescheduling loads. Due to this limitation, the present study proposes to use price-based DSM strategies and one DSM strategy based on Direct Load Curtailment (DLCt). Price-based and DLCt DSM strategies are suitable for IMGs that do not have smart or controllable loads.

The formulation requires the price elasticity of the demand to compute the customers' response to the price variations. In this regard, the formulation assumes that the planner can know the price elasticity of the demand of the customers. The integration of the price elasticity of the demand in the formulation intrinsically implies that the customers do not have any incentive to modify their consumption patterns without any external stimulus. This assumption means that customers will not alter their consumption patterns if the IMG uses a flat tariff.

2.1.5. Mathematical formulation

The formulation of the problem aims to minimize the total costs of the IMG project. The total costs of the project are Capital Expenditures (ζ), Operational Expenditures (ϑ), Maintenance Expenditures (μ) and Carbon Taxes Expenditures (Φ):

$$\zeta = \sum_{u=1}^{U} C_u I_u \tag{9}$$

$$\vartheta = \sum_{t=1}^{T} \sum_{u=1}^{U} \lambda_{u,t} E_{u,t} \tag{10}$$

$$\mu = \sum_{t=1}^{T} \sum_{u=1}^{U} \Lambda_{u,t} E_{u,t} \tag{11}$$

$$\Phi = \sum_{t=1}^{T} \sum_{u=1}^{U} B_u F_{u,t} \tag{12}$$

and C_u, I_u, $\lambda_{u,t}$, $\Lambda_{u,t}$, $E_{u,t}$, B_u and $F_{u,t}$ represent the installed capacity, unitary investment cost, unitary dispatch costs, unitary maintenance costs, dispatched energy, carbon dioxide production by liter, and fuel consumption of the u energy source at time t, respectively. T represents the horizon of the optimization and U represents the number of energy sources in the IMG.

The mathematical formulation allows the planner to build all kinds of business models by considering that $i \in I$ number of different investors (φ) can fund the IMG project. These $i \in I$ investors can contribute to pay capital ($\varphi_{i,\zeta}$), operational ($\varphi_{i,\vartheta}$), maintenance ($\varphi_{i,\mu}$) or taxes ($\varphi_{i,\Phi}$) expenditures. The objective function captures the different sources of money to fund the project:

$$X_1 = \underset{C_u, E_{u,t}}{\arg\min} \sum_{i=1}^{I} \varphi_{i,\zeta}\zeta + \varphi_{i,\vartheta}\vartheta + \varphi_{i,\mu}\mu + \varphi_{i,\Phi}\Phi \tag{13}$$

Where C_u and $E_{u,t}$ are the decision variables.

The formulation considers the energy prices as the only revenue stream for the investors that aim to recover their investment and have profits. If the business model has private investors, φ^{priv}, the formulation allows to guarantee an expected Rate of Return, R, using the following constraint:

$$(1+R)\sum_{y=1}^{Y} (\varphi^{priv,\zeta}\zeta_y + \varphi^{priv,\vartheta}\vartheta_y + \varphi^{priv,\mu}\mu_y + \varphi^{priv,\Phi}\Phi_y) \geq \sum_{t=1}^{YT} \pi_{x,t} D_t^{dr} \tag{14}$$

where $\pi_{x,t}$ is a decision variable that represents the price of the energy at time t using the x DSM strategy. D_t^{dr} is the electrical demand after the x DSM strategy is applied. However, it is crucial to highlight that the horizon of this constraint is the life time of the project. The life time of the project is measured in years (Y) for the sum in the left, and in hours for the sum in the right (Y

multiplied by T).

The formulation allows to control the percentage of the demand that is sensible to the price variations of the DSM strategies. To do so, the methodology first define the total demand as the sum of the fix demand, and the price sensible demand in Equation 15. The price sensible demand receives the name of elastic demand.

$$D_t^{flat} = D_t^{fix} + D_t^e \tag{15}$$

where the fix and elastic demand can be represented using η_t as a percentage of the flat electrical demand:

$$D_t^{fix} = (1 - \eta_t) D_t^{flat} \tag{16}$$

$$D_t^e = \eta_t D_t^{flat} \tag{17}$$

Equation 18 presents the relation between the demand with flat tariff (D_t^{flat}), the flat tariff (π^{flat}), the price ($\pi_{x,t}$) of the x DSM strategy, the price-elasticity (e_t) of the customers, and the response of the elastic demand D_t^{edr}.

$$e_t = \frac{\pi^{flat}(D_t^{edr} - D_t^e)}{D_t^e(\pi_{x,t} - \pi^{flat})} \tag{18}$$

By simplifying equation 18 it is possible to obtain the response of the elastic demand to the price variations of the DSM strategies.

$$D_t^{edr} = e_t \frac{D_t^e(\pi_{x,t} - \pi^{flat})}{\pi^{flat}} + D_t^e \tag{19}$$

Consequently, the demand response to the DSM strategies will be the fix demand plus the response of the elastic demand to the price variations. Equation 20 presents the total demand response:

$$D_t^{dr} = D_t^{fix} + D_t^{edr} \tag{20}$$

The formulation allows defining the changes in the total electrical demand after the introduction of the DSM using factor Ψ^c in Equation (21). Factor Ψ^c is an input parameter that the planner choose according to the conditions of the IMG project. Values $\Psi^c \leq 1$ decreases the total energy consumption, while values $\Psi^c \geq 1$ increases the total energy consumption over the optimization horizon. A value $\Psi^c = 1$ indicates that the total energy consumption over the optimization horizon remains constant after the introduction of DSM.

$$\sum_{t=1}^{T} D_t^{dr} - \Psi^c \sum_{t=1}^{T} D_t^{flat} = 0 \tag{21}$$

The formulation naturally includes the balance Equation:

$$\sum_{t=1}^{T} \sum_{u=1}^{U} E_{u,t} - EE_t + LE_t - D_t^{dr} = 0 \tag{22}$$

where EE_t and LE_t are the excess and lack of energy. According to (Chauhan & Saini, 2014; Diaf et al., 2008), the Loss of Power Supply Probability (LPSP) is:

$$LPSP = \frac{\sum_{t=1}^{T} LE_t}{\sum_{t=1}^{T} D_t^{dr}} \tag{23}$$

Similarly, Equation (24) defines the Excess of Power Supply Probability (EPSP) as:

$$EPSP = \frac{\sum_{t=1}^{T} EE_t}{\sum_{t=1}^{T} D_t^{dr}} \tag{24}$$

By using Equations (23) and (24) it is possible to create two constraints to control LPSP (25) and EPSP (26) over the optimization horizon:

$$\sum_{t=1}^{T} LE_t \leq LPSP \sum_{t=1}^{T} D_t^{dr} \tag{25}$$

$$\sum_{t=1}^{T} EE_t \leq EPSP \sum_{t=1}^{T} D_t^{dr} \tag{26}$$

2.1.5.1. DSM integration into the sizing. The methodology integrates ToU, CPP, DADP, Incentive-Based Pricing (IBP), Fixed Shape Pricing (ShP) and DLCt as DSM strategies into the sizing of the IMG. The baseline case for comparisons does not use a DSM strategy, it only uses a flat tariff. The description of the baseline case and each of the DSM strategies proceeds in the following subsections (Celik et al., 2017).

2.1.5.1.1. Flat tariff (Baseline case). In general terms, the value of a flat tariff is the sum of all the costs of producing the energy divided by the total amount of energy produced (Inversin, 2000). Equation (27) describes the yearly payments using a regular flat tariff.

$$\Gamma_n^{flat} = \frac{\zeta_y + \vartheta_y + \mu_y + \Phi_y}{\sum_{t=1}^{T} D_t^{dr}} (1+R) \sum_{t=1}^{T} D_{n,t}^{dr} \tag{27}$$

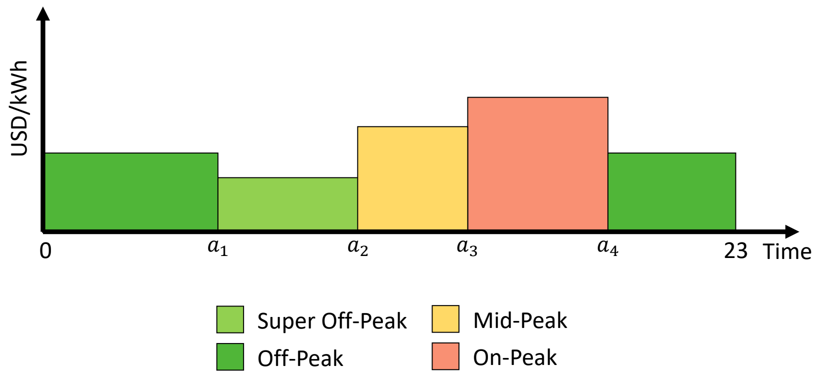
However, this traditional approach does not set an optimal tariff to recover investments while minimizing energy costs. Here we propose to introduce a decision variable π^{flat} into the formulation to find the optimum price for the tariff.

$$\Gamma_n^{flat} = \pi^{flat} \sum_{t=1}^{T} D_{n,t}^{dr} \tag{28}$$

2.1.5.1.2. Time of use tariff. ToU tariffs vary daily or seasonally on a fixed schedule, using two or more constant prices (Baatz, 2017). One of the main benefits of this type of fare is its stability over long periods, which gives the customer a better ability to adapt to it (Glick et al., 2014; Kostkova et al., 2013). To create a ToU tariff, the planner must define the number of Z blocks, and the starting and ending hours of each z block (Glick et al., 2014). The optimization problem considers the prices π_z of the Z number of blocks as decision variables. Figure 6 shows the main components of a ToU tariff, and equation (29) presents the yearly payments using Z different block hours of prices.

Figure 6

Time of use tariff description



$$\Gamma_n^{ToU} = \sum_{t=1}^{T} \sum_{z=1}^{Z} \pi_z D_{z,n,t}^{dr} \tag{29}$$

2.1.5.1.3. Critical peak pricing. CPP tariff can be 3 to 5 times higher than the usual tariff but is allowed only a few days per year (Kostkova et al., 2013). In Equation (30), π^{base} is a scalar variable, that is chosen to be equal to the flat tariff π^{flat}. π_t^{peak} is a decision variable of dimension T. Equation (30) defines the day-ahead forecasted payments using a CPP tariff, and Equation (31) defines the day-ahead hourly critical peak price.

$$\Gamma_n^{CPP} = \sum_{t=1}^{T} (\pi^{base} + \pi_t^{peak}) D_{n,t}^{dr} \tag{30}$$

$$\pi_t^{CPP} = \pi^{base} + \pi_t^{peak} \tag{31}$$

A critical forecasted event as high demand or low generation capacity triggers the critical peak price in a CPP tariff. In this regard, the CPP tariff must include a predictor of the critical event and a decision mechanism to set the value of the critical price. The methodology optimize over one year of synthetic data, which allows the formulation to state constraint (32). Constraint

(32) limits the apparition of the critical price only to a few hours in the year. This constraint uses variable φ^{peak} to control the number of hours with critical price allowed and δ^{peak} to define how many times the base price π^{base} is scaled up. The planner defines φ^{peak} and δ^{peak}. π^{base} and π_{peak} are decision variables that the optimization formulation needs to compute.

$$\sum_{t=1}^{T} \pi_t^{peak} \leq \varphi^{peak} T \delta^{peak} \pi^{base} \tag{32}$$

2.1.5.1.4. Day ahead dynamic pricing. DADP refers to a tariff that is announced one day in advance to customers and has hourly variations. This scheme offers less uncertainty to customers than "hour- ahead pricing" or "real-time pricing," thus allowing them to plan their activities (Borenstein et al., 2002; Joe-Wong et al., 2012). Equation (33) introduces the payments under DADP tariff, using π_t as a decision variable vector of dimension T.

$$\Gamma_n^{DADP} = \sum_{t=1}^{T} \pi_t D_{n,t}^{dr} \tag{33}$$

2.1.5.1.5. Incentive-based pricing. The IBP tariff provides discounts on the tariff to the customers to increase the electric energy consumption or an extra fare to penalize it. The planner can decide the IBP base price to be equal to the flat tariff π^{flat} to guarantee a constant value each day. Variable $\pi_{inc,t}$ computes the hourly incentives and can take positive or negative values. Equation (34) defines the payments using the IBP tariff.

$$\Gamma_n^{IBP} = \sum_{t=1}^{T} D_{n,t}^{dr} (\pi^{base} + \pi_t^{inc}) \tag{34}$$

$$\pi_t^{IBP} = \pi^{base} + \pi_t^{inc} \tag{35}$$

2.1.5.1.6. Fixed Shape Pricing. As mentioned in section 1.3, Dole and Bartlett (2004) affirm that tariffs must be simple, transparent, and predictable for the customers. By following these recommendations, it is possible to design a pricing scheme that combines the benefits of DADP with the predictability of the ToU tariff. This pricing scheme receives the name of Fixed Shape Pricing (ShP). ShP tariffs can provide more stimulus than the ToU tariff. However, the ShP tariff has the same predictability of the ToU tariff. Although the ShP tariff will not be as simple as the ToU, it will be simpler for the customers than DADP tariffs.

The ShP tariff fixes one price for each hour over all the days of the year. ShP tariff does not reflect the real costs of producing electricity in the IMG, which is a drawback. However, in the long run, the ShP tariff might offer better results than the ToU pricing. Additionally, it might be easier to accept by the IMG customers than the DADP tariff.

To build the ShP tariff the methodology assigns one variable for each hour of the day. All these variables are one-dimensional. By using these variables the methodology builds a vector of 24 positions, and repeat it till reaching the optimization horizon. The resulting vector is the price of the tariff. Equation (36) shows the payments of the n customer when the planner choose to use the ShP tariff as DSM strategy.

$$\Gamma_n^{ShP} = \sum_{d=1}^{D} \sum_{h=1}^{24} \pi_{d,h}^{ShP} D_{n,d,h}^{dr} \tag{36}$$

All the tariffs must have restrictions to avoid null or excessive pricing. Governments, policymakers, or IMG owners can guarantee fair fares to the customers with the following constraint:

$$\pi^{min} \leq \pi_x \leq \pi^{max} \tag{37}$$

2.1.5.1.7. Direct Load Curtailment Strategy. The DLCt strategy curtails a portion ε_t out of the demand if required. The planner of the IMG decides the percentage of max curtailed hourly demand θ, and the percentage of the total energy curtailed in the optimization period κ. The final demand and payments are defined as follows:

$$D_t^{dr} = D_t^{flat} - \varepsilon_t \tag{38}$$

$$\Gamma_{n}^{DLCt} = \sum_{t=1}^{T} D_{n,t}^{dr} \pi^{flat} \tag{39}$$

The general restrictions for the DLCt strategy are defined as follows:

$$\varepsilon_t \leq \theta D_t^{dr} \tag{40}$$

$$\sum_{t=1}^{T} \varepsilon_t \leq \kappa \sum_{t=1}^{T} D_t^{dr} \tag{41}$$

It is important to notice that Equation (21) establish a constraint to guarantee that the sum of the demand with flat tariff (base case) is equal to the sum of the demand after the application of any of the DSM strategies. However, the DLCt strategy need to violate this constraint, otherwise the only way to guarantee that the base case demand is equal to the demand with DSM is by making the variable ε_t equal to zero. In order to avoid making ε_t equal to zero the methodology removes constraint (21) for the DLCt DSM strategy.

2.1.5.2. Multiyear analysis. Most of the methodologies found in literature to compute the sizing of IMGs consider one single year for the analysis (refer to Tables 2 and 3). However, by considering this, these methodologies are implicitly assuming that the capital, operational, and maintenance expenditures will remain constant during the lifetime of the projects (20 to 25 years). These kind of methodologies only consider the interest rate to compute future capital, operational, and maintenance costs. Nevertheless, this is not a straightforward justifiable assumption, especially considering that renewable energy sources' costs are decreasing fast in the last years and they are expected to reduce even more its costs in the future (Administration, 2020; Laboratory, 2019). Moreover, new policies taxing carbon emissions can significantly benefit renewable energy projects in the future (government, 2018). By using a multiyear analysis, it is possible to capture those trends in the prices. However, a methodology that uses one single year approach can not incorporate these trends. That is why this study uses a multiyear analysis instead of a single year approach.

Reference (Pecenak et al., 2019) classifies multiyear methodologies in two main categories: the forward-looking model and the adaptive model. On one side, the forward-looking model deals with an optimization formulation that has as a horizon the lifetime of the IMG project (20 to 25 years). This approach has the advantage of being able to integrate future information. However, the enormous size of the optimization formulation can make the problem difficult to solve. Additionally, the formulation will require binary variables to integrate the technologies' replacement, which adds even more complexity to the problem. On the other side, the adaptive model uses a rolling horizon of smaller windows of time (usually one year). This approach does not require binary variables, which represents an advantage. The model easily integrates growth of demand, price forecasts, and energy resources. Additionally, this approach does not require to modify the optimization formulation. Instead, it solves a single year optimization until it reaches the project's lifetime.

The present study adopts the adaptive method. However, despite its advantages, the implementation of the model requires careful attention to previous years' input parameters. The investment decisions of previous years should be known for the model in each window of time. Algorithm 1 shows a simplified step by step guide for the multiyear analysis. The following lines provide a brief description of each line of the algorithm.

```
input  : Weather, forecasted acquisition prices of energy sources and forecasted fuel
         prices over the lifetime of the IMG project.
output: Tariffs of energy for the customers, yearly acquisition and yearly dispatch of
         energy sources over the life time of the IMG project.

prob_info = Set problem information;
historic_data = Save historic weather and demand data;
synthetic_data = create_synthetic_data(historic_data);
for year = 0 to lifetime do
    prev_data = Read results of previous years;
    act_param = Update solver parameters;
    resul = yearly_solver(prob_info, synthetic_data[year], prev_data, act_param);
    summary[year] = resul;
end
```

Algoritmo 1: Multiyear analysis algorithm.

2.1.5.2.1. Set problem information. This line saves the configuration of the analysis in the variable prob_info. This variable contains a list of the energy sources that the optimization includes, the technical and economic characteristics of those energy sources, the lifetime of the project, and interest rate. This variable contains all the information about the multiyear analysis.

2.1.5.2.2. Save historic weather and demand data. This line reads the historic weather and electrical demand data. Afterwards the data is stored in the variable historic_data.

2.1.5.2.3. create_synthetic_data(historic_data). This line creates the synthetic data for the multiyear optimization formulation. A single year approach can use the historical data (of one year). However, to build the multiyear optimization formulation, synthetic data is required for the project lifetime. The function create_synthetic_data takes as inputs the historical data of weather and electrical demand profiles (one year) and returns as output the synthetic data over the lifetime of the project (20 or 25 years). The function follows a four-step process to create synthetic data for the optimization formulation:

1. Divide the historical data by months.
2. Take the data of each month and group it by hours.
3. Fit each hour group to the probability distributions recommended by the literature to each kind of data (Weibull for wind, Beta for Global Horizontal Radiation, log-normal for the demand, amongst others).
4. Build the synthetic new profiles by random sampling the fitted probability distributions at each hour and month.

The above-described process is similar to a Gaussian process without a covariance matrix. Two main reasons force to adopt the above-described process and not the well know Gaussian process. The first reason is that the Gaussian process can model only processes that follow a Gaussian distribution. This limitation forces the study to assume that the wind and Global Horizontal Radiation (GHI) follow a Gaussian distribution, which is not accurate. The second reason is that fitting and sampling a Gaussian process consume more computational power and requires more time to build synthetic data than the above-described process. Equation (42) describes the sampling process to create the synthetic data.

$$SD_t \mid m,h \sim \psi_{m,h} \tag{42}$$

where SD_t represents the Synthetic Data at time t. This variable represents the electrical demand, wind speed, global horizontal radiation, temperature, and others. $\psi_{m,h}$ represents the monthly and hourly fitted distributions using the historical data. A detailed explanation of the process is presented in Appendix 4.4.

2.1.5.2.4. Read results of previous years. This line read the results of the previous years and store the values in variable prev_data. This variable contains the capacities of the energy sources acquired in the past. Additionally, this variable contains a detailed register of the costs paid for buying those energy sources in previous years.

2.1.5.2.5. Update solver parameters. This part of the algorithm updates the cost parameters of the solver. These parameters include the acquisition costs of the energy sources and the fuel costs of that year in particular.

2.1.5.2.6. yearly_solver(prob_info, synthetic_data[year], prev_data, act_param). The function *yearly_solver* contains the formulation described at the beginning of this section (Equations 9–41). This function find the optimal values of the optimization variables C_u, $E_{u,t}$ and $\pi_{x,t}$ over one year. By doing so, the function returns the capacities of the energy sources to install in that year, the dispatch of the energy sources and the energy tariffs for the customers. Additionally, this function returns the payments of each one of the stakeholders of the project.

2.1.5.2.7. summary[year] = resul. This line save the results of *yearly_solver*. Summary is a list that contains the results of each year.

2.1.5.3. Stochastic multiyear analysis. The study proposes a stochastic analysis to deal with the uncertainties of electric demand, weather variables, and future prices. The stochastic approach uses a Montecarlo Sampling (MCS) approach (see appendix 4.4). The MCS approach creates random samples of the probability distribution functions using Equation (42) to build the scenarios. Algorithm 2 describes the multiyear stochastic analysis.

```
input  : Weather, forecasted acquisition prices of energy sources and forecasted fuel
         prices over the lifetime of the IMG project.
output: Tariffs of energy for the customers, average yearly acquisition and yearly
         dispatch of energy sources over the life time of the IMG project.
prob_info = Set problem information;
historic_data = Save historic weather and demand data;
synthetic_data = create_synthetic_data(historic_data);
for scenario = 0 to scenarios do
    for year = 0 to lifetime do
        prev_data = Read results of previous years;
        act_param = Update solver parameters;
        resul = yearly_solver(prob_info, synthetic_data[year], prev_data, act_param);
        summary[year] = resul;
    end
    total_summary[scenario] = summary;
end
```

Algoritmo 2: Multiyear stochastic analysis algorithm.

Algorithm 2 uses the multiyear analysis in its core. The only difference with the multiyear analysis is an additional loop. The stochastic multiyear solves one multiyear problem for each scenario that the MCS approach builds. Variable *summary* stores the results of installing and operating the IMG each year of the simulations. Variable *total_summary* stores the results of installing and operating each of the scenarios of the stochastic analysis. In the end, the results are the average of all the simulations, as Equation (8) describes.

2.2. Proposed evaluation framework: CVXMG

The proposed evaluation framework integrates the mathematical formulation described in Section 2.1 in a Python-embedded modeling package. The evaluation framework follows the recommendations of (Berendes et al., 2018; Morrison, 2018; Wiese et al., 2018) and implements an open-source code. The evaluation framework receives the name of CVXMG. The information to install

CVXMG can be found in GitHub and PyPi. The guide of use of CVXMG is available online at ReadtheDocs.

Figure 7 shows the flow chart diagram of CVXMG. The user inputs, represented by the config.csv file, include the primary energy resources, and the parameters that Table 7 shows. The sources.csv file represent all the characteristics of the energy sources that Table 8 shows. The selection of the energy sources, the analysis type, and the selection of the DSM strategy are explained below.

2.2.1. CVXMG capabilities

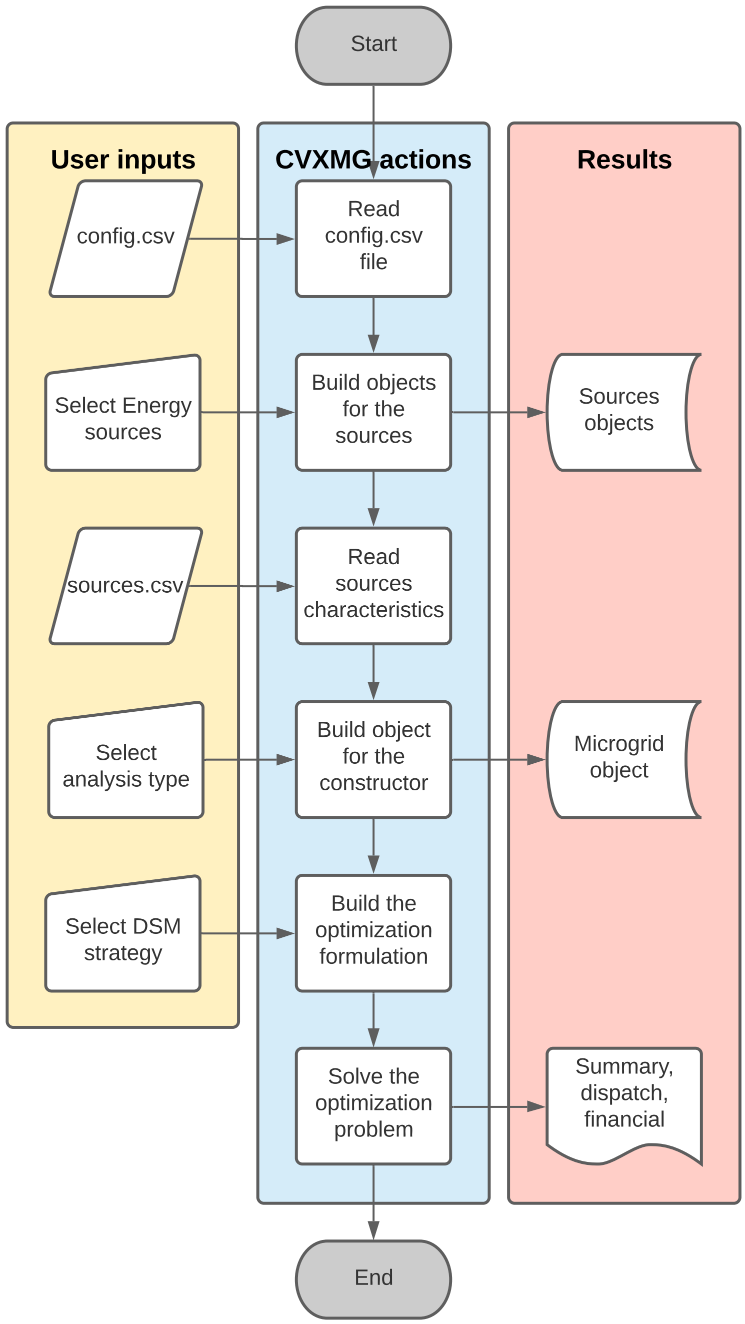
CVXMG is a Python-embedded modeling language designed for the planning of IMGs. CVXMG computes the optimal sizing, the optimal energy dispatch, and the optimal tariffs for the energy. Moreover, CVXMG integrates different DSM strategies in the planning of the IMGs. The package uses a modular approach, allowing its users to choose energy sources, DSM strategies, and analysis types (deterministic, stochastic, multiyear, and stochastic multiyear).

2.2.2. Selection of the energy sources

CVXMG allows choosing different combinations of the most commonly used energy sources for IMG projects: PV, WTs, BESS, and backup Gen-sets. CVXMG allows planners to customize the characteristics of the PV modules, WTs, and BESS. Parameters as the lifetime, initial costs, maintenance costs, efficiencies, amongst others, can be easily specified. CVXMG allows as well to choose the type of gen-set, the type of fuel, and a linear or quadratic power conversion curve. Each of the energy sources' models follows the Disciplined Convex Programming (DCP) rules, which allows a seamless integration into the mathematical formulation. Additionally, due to the modular approach of CVXMG, any energy source with a mathematical model that follows the DCP rules can be further added to the package.

Figure 7

CVXMG flow chart diagram.



2.2.3. Selection of the analysis type

Finally, CVXMG allows planners to choose between different types of analysis to compute the sizing of the IMG. A one-year deterministic approach is the first option. A multiyear deterministic approach is possible, as well. Both types of analysis consider just one scenario for the analysis. The second option is a one-year stochastic approach or a multiyear stochastic approach. The stochastic approaches have the advantage that considers several scenarios for the analysis. The stochastic analysis uses a MCS approach. The MCS approach can use different options for the fitting and posterior sampling of the historical data:

- Adding Gaussian noise to the original data.
- Using Gaussian distributions to represent all the stochastic variables.
- Using Gaussian distributions for electrical demand and temperature, a beta distribution for global horizontal irradiation and a Weibull distribution for wind speed.
- Fitting each distribution individually using maximum likelihood and the Chi-squared test.

2.2.4. Selection of the DSM strategies

The user of CVXMG can choose seven different DSM strategies based on the dynamic pricing of the energy: ToU, ToU with Sun Incentive (ToUSun), ToU with Three Levels of pricing (ToUTL), CPP, DADP, ShP, and IBP. This characteristic allows CVXMG to provide the optimal tariffs for the energy sold to the customers in the IMG. Additionally, CVXMG can use one DSM strategy based on the curtailment of the electric loads (DLCt). The implementation of DSM in the sizing of IMGs makes CVXMG a worth looking tool for different analyses for IMG planners and policymakers.

2.3. Analysis of the proposed methodology and framework

The present chapter introduced the proposed methodology and framework for the analysis of the impacts of DSM in the planning of IMGs. The work design the methodology following the DCP rules to guarantee the convexity of the formulation. Additionally, the study implements the methodology as a framework using object-oriented programming in python 3.7. The framework follows a modular approach to increase its capabilities. The modular approach builds the models of the energy sources, storage systems, demand response functions, or DSM strategies as construction blocks that follow DCP rules. The modular approach allows planners or policymakers to perform their analysis by merely choosing their IMG projects' characteristics. Because the building blocks follow the DCP rules, the solution's uniqueness and optimality will be guaranteed. Furthermore, the proposed framework integrates new energy sources, storage systems, demand response functions, or DSM strategies as long as they follow the DCP rules. These characteristics make the framework a compelling tool with high flexibility and capacity to be extended for the further analysis required by planners, policymakers, or any stakeholder involved in planning IMGs.

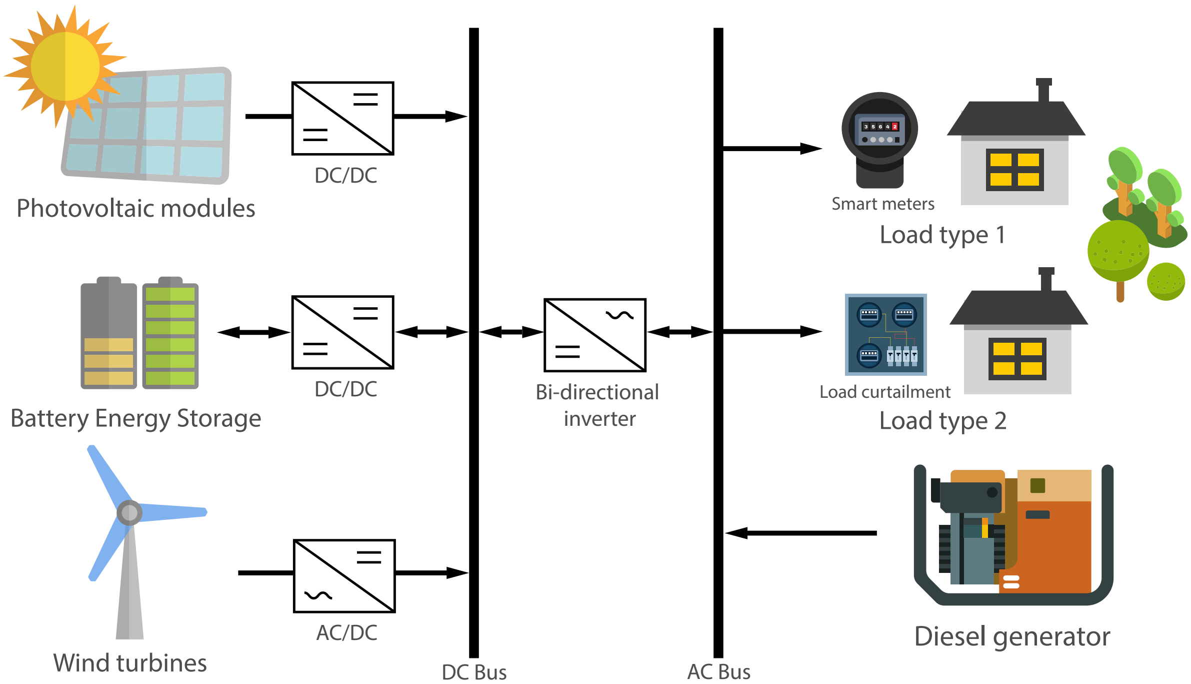
3. Case study and discussion

The case study aims to illustrate the capabilities and performance of the proposed methodology and framework by evaluating the effects of eighth DSM strategies in the planning of a case study IMG. The IMG is composed of PV, BESS, WTs, a Diesel Generator (DG) system, and two different types of load as Figure 8 shows.

This chapter presents a description of the models of the energy sources of the case study in section 3.1. Section 3.2 presents a description of the characteristics of the case study and the parameters for the simulations. Due to the flexibility of the proposed methodology, it is possible to perform different kinds of analysis. The first analysis aims to evaluate the impacts of DSM in the planning of the case study IMG. Section 3.3 presents the characteristics and results of the first analysis. The second analysis aims to compare the performance of the DSM strategies when the government wants to guarantee the same ROI for private investors for all the DSM strategies. While the first analysis selects the percentage of participation of the private investors in one fixed value for all the DSM strategies, the second analysis considers the participation of private investor as a variable that can be tuned to guarantee the same ROI for private investors for all the DSM strategies. Section 3.4 presents the results of the second analysis. The third analysis aims to

Figure 8

Architecture of the IMG case study.



evaluate the performance of the DSM strategies when considering a sensitivity analysis for the energy sources, interest rate, diesel and carbon taxes prices. Section 3.5 presents the results of the third analysis. The final analysis aims to compare the impacts of DSM when considering the planning of two types of IMGs: diesel-based and hybrid-based. Section 3.6 presents the results of the final analysis.

3.1. Energy sources models

3.1.1. Photovoltaic system

References (Lasnier, 1990; B. Li et al., 2017; J. Zhang et al., 2016) describe the output power $E_{PV,t}$ of an N_{PV} number of photovoltaic panels as:

$$E_{PV,t} = N_{PV} \rho_{PV} P_{STC} \frac{G_{A,t}}{G_{STC}} (1 + C_T (T_{C,t} - T_{STC})) \tag{43}$$

where ρ_{PV}, P_{STC} , $G_{A,t}$, G_{STC}, and C_T are the derating factor (unitless), output power of the PV module (kW), GHI (kW/m^2), GHI at standard conditions (kW/m^2), and temperature coefficient of the PV module (%/$^\circ C$), respectively. $T_{C,t}$ is the working temperature of the PV cell at hour t ($^\circ C$), and T_{STC} is the temperature at standard conditions ($^\circ C$). Reference (Skoplaki & Palyvos, 2009) describes $T_{C,t}$ as a function of the ambient temperature and incident solar radiation over the PV module.

$$T_{C,t} = T_{A,t} + \frac{G_{A,t}}{G_{NOCT}} (T_{NOCT} - T_{a,t,NOCT}) \tag{44}$$

where G_{NOCT}, T_{NOCT} and $T_{a,t,NOCT}$ are the solar radiation (kW/m^2), working temperature ($^\circ C$) and ambient temperature ($^\circ C$) at Nominal Operational Cell Temperature (NOCT) conditions (A. Duffie & A. Beckman, 2013; Markvart, 2000).

3.1.2. Battery energy storage system

The lack or excess of energy to supply the demand in one hour can be demanded or stored in the battery. To guarantee that the battery is not charged and discharged simultaneously, the BESS model can integrate binary variables. However, the proposed methodology tries to avoid using binary variables. The methodology proposes to model the BESS as an accumulator to avoid using binary variables.

The model of the BESS does not use separate optimization variables for charging and discharging of the BESS. Instead uses one single variable for the dispatch that controls the residual energy of the battery (X. Zhang et al., 2018). Equation (45) presents a simple way of defining the residual energy in a BESS.

$$RE_{B,t} = SOC_t C_B \tag{45}$$

If the following state of the residual energy is superior to the previous, the battery was charged $E_{B,t}$ units during time t. If the following state of the residual energy is inferior to the previous, the battery was discharged $E_{B,t}$ units during time t. Equations (46) and (47) show this.

$$RE_{B,t+1} = RE_{B,t} + E_{B,t} \tag{46}$$

$$RE_{B,t+1} = RE_{B,t} - E_{B,t} \tag{47}$$

Equation (48) describes the initial residual energy of the BESS. The simulations assume that the battery starts half charged (50% of its nominal capacity). Additionally, the simulation assumes that the minimum level of discharge of the battery is 50% and that the maximum level of charge is 100% of its nominal capacity. Equation (49) describes those limits. Moreover, the simulations consider the maximum rate of charge and discharge of the battery. The simulation assumes that the maximum charge and discharge rate in each time slot is 30% of its nominal capacity. For all the simulations, the slot of time is one hour. Equation (50) and (51) describes the limits of charge and discharge of the battery for each time slot, respectively.

$$RE_{B,0} = 0.5C_B \tag{48}$$

$$0.5C_B \leq RE_{B,t} \leq C_B \tag{49}$$

$$E_{B,t+1} \geq E_{B,t} - 0.3C_B \tag{50}$$

$$E_{B,t+1} \leq E_{B,t} + 0.3C_B \tag{51}$$

3.1.3. Diesel generator

The fuel consumption of a DG is a function of its capacity and output power. This function uses linear or quadratic formulations (Arun et al., 2008; Ashok, 2006). Reference (Scioletti et al., 2017) makes a fit to estimate the parameters of a quadratic function using the capacity of the generator and manufacturer-provided fuel consumption data. Bukar et al. (2019) replaces the quadratic fit with a linear approximation to describe the diesel consumption of a DG as a function of its output power and installed capacity. Equation (52) describes the function that Bukar et al. (2019) proposed.

$$F_{DG,t} = 0.246E_{DG,t} + 0.08415C_{DG} \tag{52}$$

where, $E_{DG,t}$, $F_{DG,t}$, and C_{DG} denote the generated power (kW), the fuel consumption (L/hour), and the installed capacity (kW) of the diesel generator. On the other side, the operational costs of the diesel generator can be expressed as:

$$\lambda_{DG} = \alpha^L F_{DG,t} \tag{53}$$

3.1.4. Wind generator

The output power of a wind turbine is a function of the wind speed and its rated capacity. Equation (54) presents a well-accepted model to compute the output power of a wind turbine (Kaabeche et al., 2017; Ramli et al., 2018).

$$E_{WT,t} = \begin{cases} 0, & V_t^w < V^{cut-in}, V_t^w > V^{cut-out} \\ (V_t^w)^3 \left(\frac{E_{WT}^R}{(V^{Rated})^3 - (V^{cut-in})^3}\right) \\ E_{WT}^R \left(\frac{(V^{cut-in})^3}{(V^{Rated})^3 - (V^{cut-in})^3}\right) & , \quad V^{cut-in} \leq V_t^w < V^{Rated} \\ E_{WT}^R, & V^{Rated} \leq V_t^w < V^{cut-out} \end{cases} \tag{54}$$

where V_t^w is the wind speed (m/s), E_{WT}^R is the rated power (kW), V^{cut-in}, V^{Rated}, $V^{cut-out}$ represent the cut-in, nominal and cut-out speed of the wind turbine (m/s), respectively. The proposed methodology for the planning of IMGs uses the model of Equation 54.

3.2. Description of the case study

The case study is located at longitude $77'21'55''$ West and latitude $4'57'16''$ North, Pizarro, Bajo Baudó, Chocó, Colombia. According to the DANE[1] census of 2018 and its projection to 2020, Pizarro has a population of 30,472 inhabitants. Around 6,938 inhabitants live in the municipal seat and 23,534 in rural areas of the municipality (de Estadística (DANE), n.d.). The number of users of the electric energy service is 1,502 (Monthly Telemetry Report, June 2020) ("Centro Nacional de Monitoreo, Informe mensual de Telemetría," n.d.). The study case uses the Meteonorm database of the PvSyst software to obtain the GHI, temperature, and wind speed conditions of the geographical region. The Institute for Planning and Promotion of Energy Solutions for Non-Interconnected Areas (Instituto de Planificación y Promoción de Soluciones Energéticas para las Zonas No Interconectadas - IPSE) provide the electrical energy consumption of the community ("Centro Nacional de Monitoreo, Informe mensual de Telemetría," n.d.). Figure 9 shows the historic yearly standard profile of the electrical demand that Homer Pro provides. Figure 10 shows the yearly GHI. Figure 11 shows the yearly temperature.

The methodology takes as inputs several parameters. Planners or policymakers can decide these values and perform sensitivity analyses over each of them. Table 7 shows the values used for simulations in this work an Table 8 shows the information of the energy sources. The following section uses the MCS approach and the inputs of Table 7 to compute the results for the case study.

As Figure 8 shows, the case study assumes that the microgrid can have two different types of load. The case study uses the load type one when the planner chooses a DSM based on price. The load type one has Smart Meters. The case study uses the second type of load when the planner

[1] Departamento Administrativo Nacional de Estadística (DANE) is a governmental entity of the Colombian Republic that is in charge of producing the official statistics for the country.

Figure 9
Yearly electrical demand.

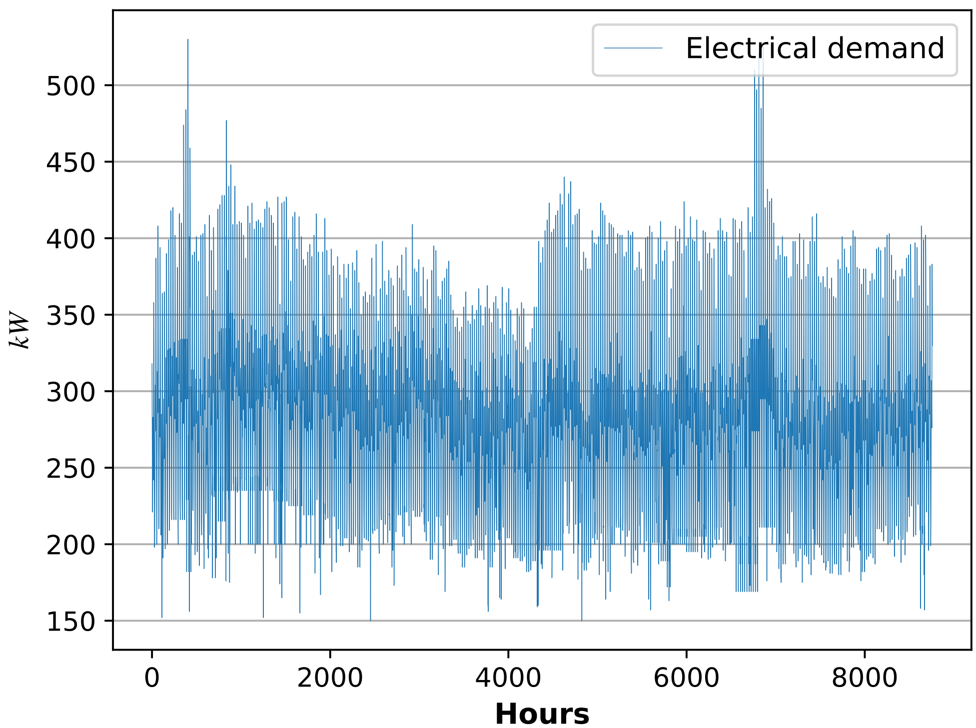


Figure 10
Yearly Global Horizontal Radiation.

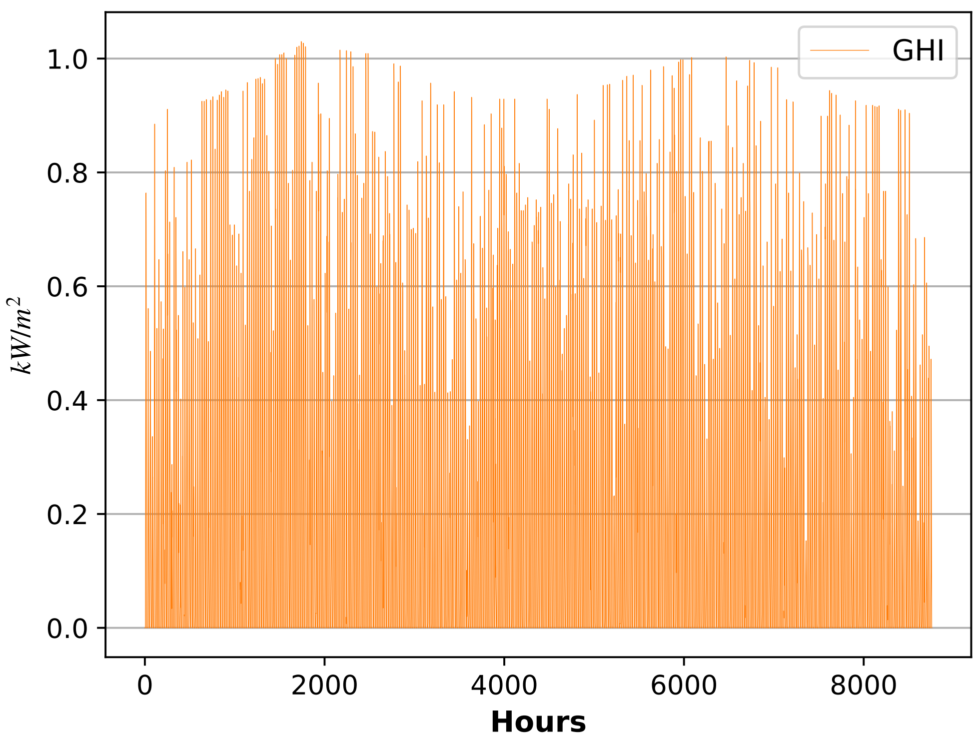


Figure 11
Yearly temperature.

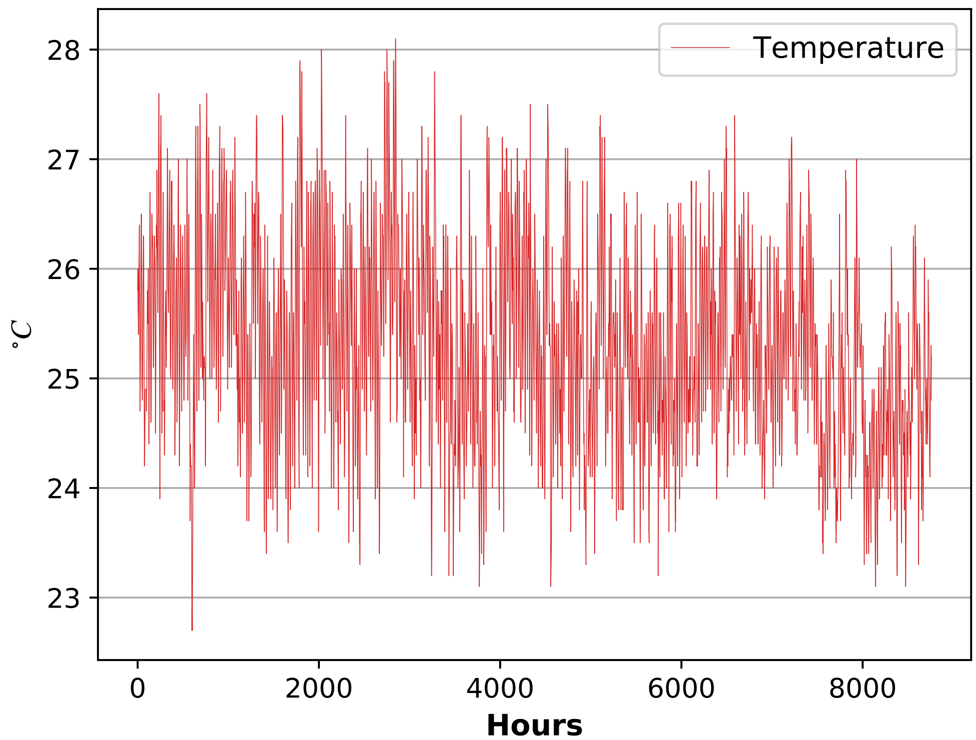
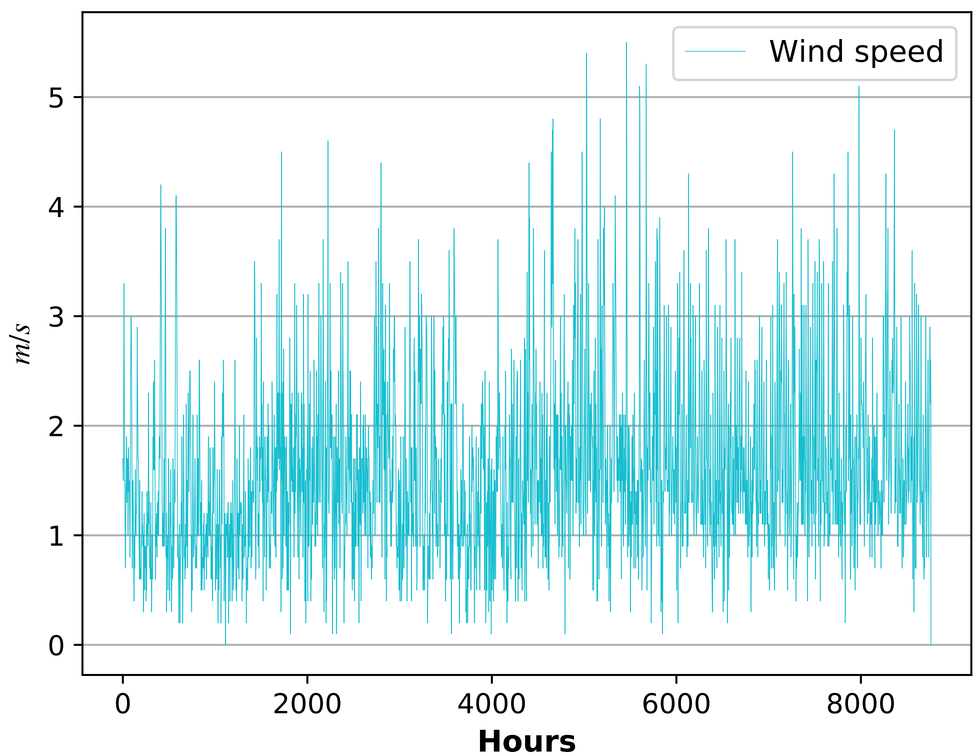


Figure 12

Yearly wind speed.



decides to use the DSM based on DLCt. The second type of load has a device as “GridShare” to perform the curtailment of the electrical demand (Harper, 2013). The case study considers nine IMG designs: Baseline case (flat tariff and no DSM) and one design for each of the proposed DSM strategies (ToU, ToUSun, ToUTL, CPP, DADP, ShP, IBP, DLCt). The case study compares the results of the designs using DSM with the baseline case design. The optimization formulation was written in Python 3.7 using CVXMG. The selected solver is MOSEK, due to its flexibility, speed, and accuracy (E. D. Andersen et al., 2003; E. D. Andersen & Andersen, 2000).

3.2.1. Financial models

The multiyear approach makes it easier to perform financial analysis. The methodology considers capital expenditures, operational expenditures, maintenance expenditures, and carbon taxes as expenditures. On the other side, the only considered income is energy tariffs.

3.2.1.1. Capital Expenditures. The capital expenditures are the expenditures required to achieve commercial operation in a given year. These costs include:

- Equipment installation and substructure supply.
- Site preparation, installation of underground utilities, access roads, and buildings for operations and maintenance.
- Electrical infrastructure, such as transformers, switchgear, power electronics, inverters, and others.
- Project-related indirect costs, including engineering, labor and materials, construction management start up and commissioning, and contractor costs, amongst others.
- Owners’ costs, such as development costs, preliminary feasibility and engineering studies, environmental studies and permitting, legal fees, insurance costs, and property taxes during construction.

Figure 28 shows the capital expenditures projections for the energy sources of the study case. Projections of figure 28 include the above described costs (Laboratory, 2019).

3.2.1.2. Operational Expenditures. Operational expenditures are the expenditures required to maintain commercial operation in a given year. These costs include fuel costs, labor costs, tariff collection costs, amongst others. The case study considers that fuel costs are the only kind of operational costs. Equation (52) computes the operational costs of the diesel generator. Due to the multiyear characteristic of the approach, the case study must consider future fuel cost projections. Figure 28 shows the fuel cost projections. Reference (Administration, 2020) shows the data for the fuel cost projections.

3.2.1.3. Maintenance Expenditures. Maintenance expenditures are the expenditures required to keep the energy sources in proper operation. These expenditures include preventive and corrective maintenance. The case study defines that the private investor entirely pays the maintenance costs. The case study assumes that each energy source's yearly maintenance expenditures are 6% of its capital expenditures.

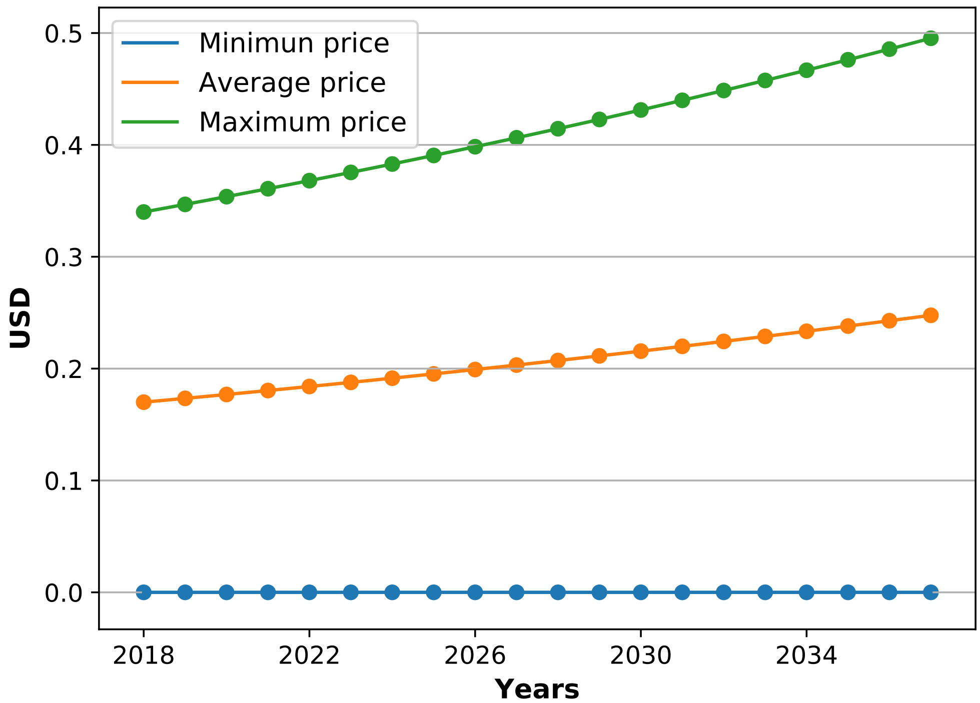
3.2.1.4. Limits for the values of the tariffs. The multiyear analysis must consider the value of the money in time. Therefore, the upper limits of the tariffs must change with time. The case study assumes for the first year that the values for π^{min} and π^{max} in constraint (37) are 0 USD/kWh, and two times the price of the current flat tariff of urban areas in Colombia, 0.34 USD/kWh, respectively (Grupo EPM, 2019). The case study assumes that the average value of the tariffs increases according to the interest rate each year. The case study defines the upper limit of the tariffs π^{max} as two times the value of the average tariff. Figure 13 shows the average, π^{min} and π^{max} values for the case study.

3.2.1.5. Yearly costs and incomes. On one side, yearly costs are the sum of all the required expenditures to maintain commercial operation. These costs include capital expenditures, operational expenditures, maintenance expenditures, and tax payments. On the other side, yearly incomes are the sum of all the incomes of the project. The case study considers that the only source of income to the private investor is the energy tariffs.

3.2.1.6. Return of Investment, Net Present Value, and Cash-flows. The ROI computes the net gain or loss of an investment over a specified period. The return rate expresses the gain or

Figure 13

Yearly tariff limits.



loss of the investment as a percentage of the investment's initial cost. Equation (55) computes the ROI.

$$ROI = \frac{Income - investment}{investment} * 100 \tag{55}$$

The Net Present Value (NPV) specify the net value of the project in dollars of the first year.

$$NPV = \sum_{y=1}^{LT} \frac{Income_y - investment_y}{(1+ir)^y} \tag{56}$$

Finally, the cash-flows refer to the flow of the money in time.

3.2.2. Emissions models and carbon taxes

The methodology registers the fuel consumption of the non-renewable energy generators. The total amount of fuel consumption is used to compute the total CO_2 production (Canada, 2016; Fontaras et al., 2017). Additionally, the case study uses the total fuel consumption to compute the payments for carbon taxes. Due to the lack of a carbon tax policy in Colombia, the case study will use the carbon tax applied by the Canadian government. Figure 28 shows the carbon tax policy implemented by the Canadian government (government, 2018).

3.3. DSM effects evaluation for a Hybrid-based IMG

An interesting analysis from the point of view of the private investor is which DSM strategy is more suitable to its objectives. If the government fix an upper value to its subsidies for IMGs, then the private investor will be interested in knowing which DSM have better performance. This section presents this analysis. The simulations of this section assumes that the government pay the 100% of the CAPEX and a fixed value of 40% for the OPEX. The maintenance and carbon taxes are covered completely by the private investor. Considering this settings, section 3.3.1 describes how the tariffs affect the electrical demand and the sizing of the case study. Section 3.3.2 presents the ROI, net present value and the required subsidies from public funding. Finally, section 3.3.3 presents a comparison of the main results of the case study and the performance evaluation of each of the DSM strategies.

3.3.1. Tariff setting and its effects over the electrical demand and the sizing of the case study

This section evaluates the impacts of the DSM strategies on the consumption patterns of the customers. Additionally, the section evaluates how the changes in the consumption patterns modify the required installed capacities of the energy sources. The case study evaluates three different types of ToU tariffs: Standard (ToU), Sun Incentive (ToUSun), and a ToU tariff with three different levels of prices (ToUTL). The case study also evaluates the DADP tariff, Fixed Shape Pricing (ShP), IBP tariff, and DLCt DSM strategies.

3.3.1.1. Time of Use tariff: Standard case. The ToU Standard tariff uses two levels of prices, off-peak and peak price. The off-peak price is active all day, and the peak price is active between the 17h and the 21h. The optimization formulation computes the peak and off-peak values for each year. Figure 14a shows the average of the ToU tariff for three different years. Figure 14b shows the response of the demand to the tariff. Figure 14c shows the changes in the required capacities of the energy sources due to the ToU tariff.

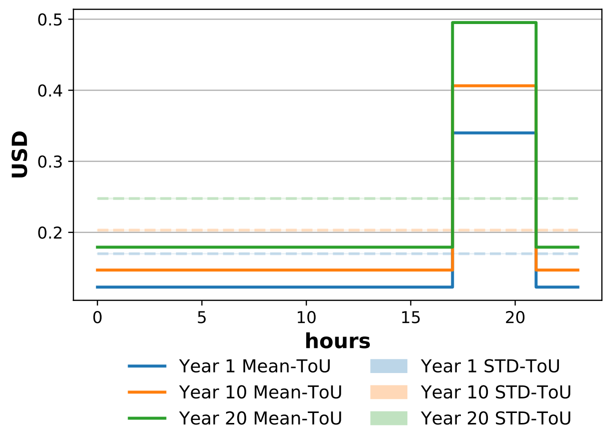
Table 9 summarizes the variations of the required capacities of the energy sources due to the ToU DSM strategy.

3.3.1.2. Time of Use tariff: Solar consumption incentive. The study case evaluates customers' reaction and the impact in the energy sources sizing if the tariff offers a special incentive in the hours with major GHI. The incentive aims to enhance solar energy exploitation. The ToUSun tariff has two different prices: one price for the hours with major GHI (sun price) and one price for the night hours (off-sun price). The optimization formulation computes the sun and off-sun price values for the tariff. The tariff changes the two levels of prices each year. Figure 15a shows the average of the ToUSun tariff for three different years (1, 10 and 20). Figure 15b shows the demand response to the tariff. Figure 15c shows the changes in the required capacities of the energy sources due to the ToUSun tariff.

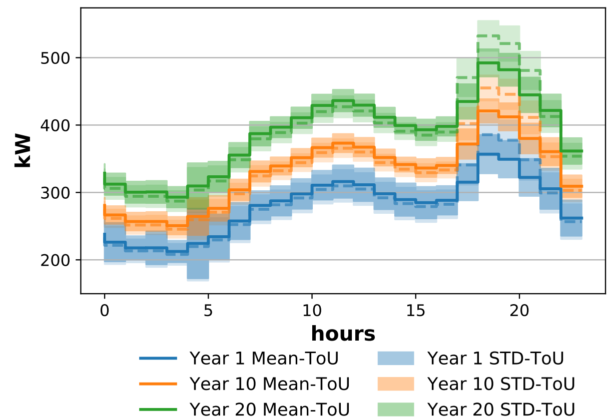
Figure 15 shows that the consumption increases considerably in the hours with more radiation. Additionally, the DSM reduces the consumption in the off-sun hours. Table 10 summarizes

Figure 14

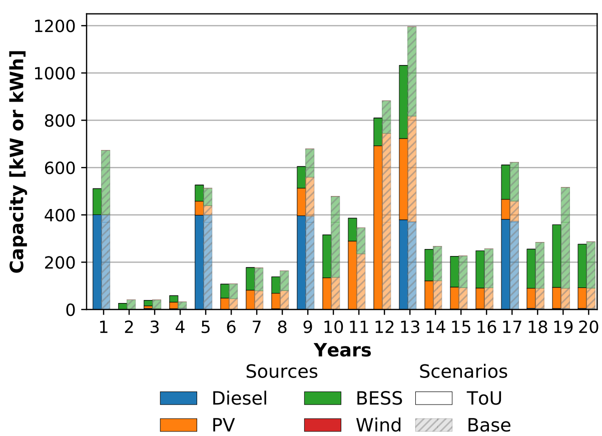
ToU tariff and its effects over the demand and the energy sources capacities.



(a) *Average ToU tariff.*



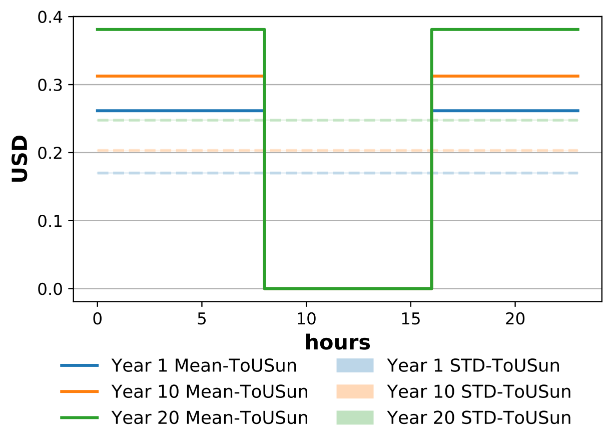
(b) *Average demand response.*



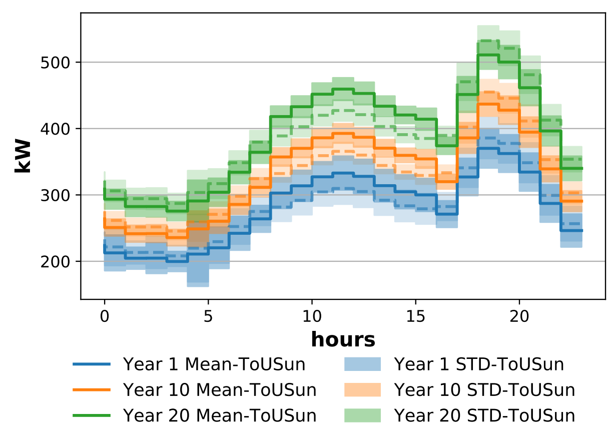
(c) *Yearly installed capacities for the ToU tariff.*

Figure 15

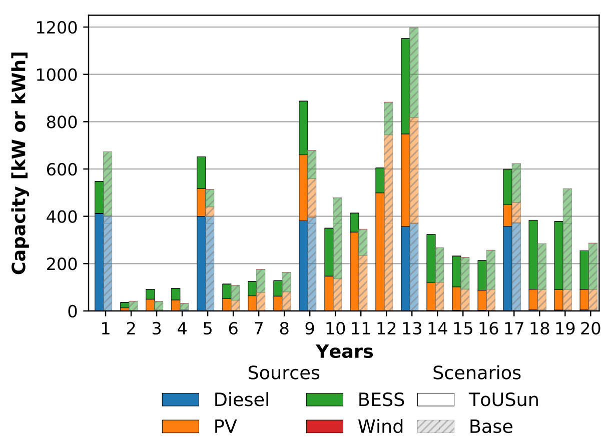
ToUSun tariff and its effects over the demand and the energy sources capacities.



(a) *Average ToUSun tariff.*



(b) *Average demand response.*



(c) *Yearly installed capacities for the ToUSun tariff.*

the variations of the required capacities of the energy sources due to the ToUSun DSM strategy.

3.3.1.3. Time of Use tariff: Three levels case. The study case evaluates a three levels ToU tariff as well. The ToUTL tariff aims to evaluate if a ToU tariff with three different prices provides more advantages than a ToU tariff with two levels of prices. The ToUTL tariff has one level of price for the off-peak hours (off-peak price), one incentive for hours with major GHI(sun price), and one level of price for the peak hours (peak price). The optimization formulation computes the off-peak, sun, and peak prices for each year. Figure 16a shows the average of the ToUTL tariff for three different years. Figure 16b shows the response of the demand to the tariff. Figure 16c shows the changes in the required capacities of the energy sources due to the ToUTL tariff.

Figure 16 shows that the consumption reductions in the peak hours reduce the required BESS capacity. Additionally, the ToUTL DSM strategy increases the PV capacity. Table 11 summarizes the variations of the required capacities of the energy sources due to the ToUTL DSM strategy.

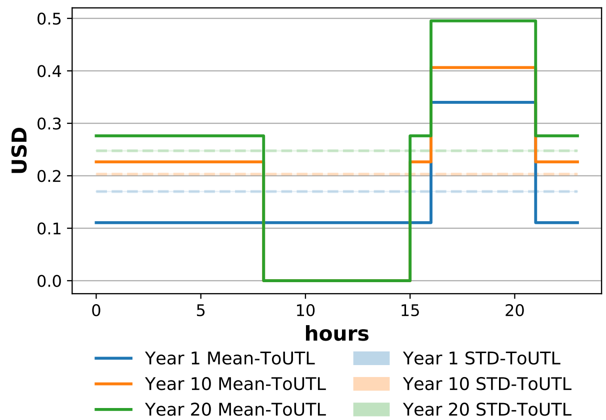
3.3.1.4. Critical Peak Pricing tariff. The Critical Peak Pricing increases the value of the tariffs drastically a few hours in the year. However, the limited amount of hours per year implicitly limits the demand response. Figure 17a shows that despite there is a considerable increase in the prices in the peak hours, the effects over the demand are minimal 17b. Figure 17c shows the changes in the required capacities of the energy sources due to the CPP tariff.

The CPP DSM strategy reduces the required BESS capacity due to its ability to reduce peak consumption. However, CPP DSM does not modify the energy demand's shape, which is a considerable drawback. The lack of ability to influence the consumption patterns leads the CPP DSM strategy to keep almost constant the PV and diesel capacities (respect to the base case). Table 12 summarizes the variations of the required capacities of the energy sources due to the CPP DSM strategy.

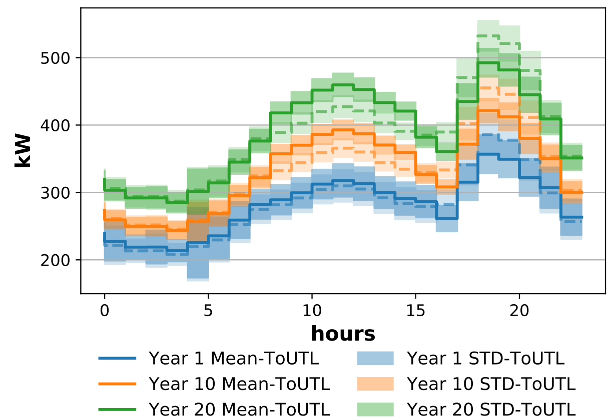
3.3.1.5. Day Ahead Dynamic Pricing tariff. Day Ahead Dynamic Pricing has hourly variations. The hourly variations allow the tariff to reflect the generation costs closely. The case study assumes that the customers can know one day in advance the next day's prices. Figure 18a

Figure 16

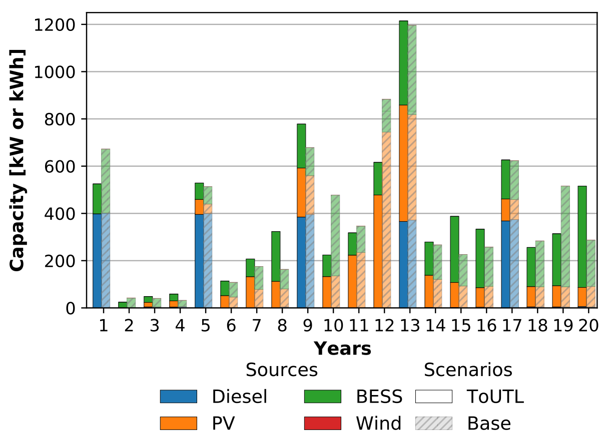
ToUTL tariff and its effects over the demand and the energy sources capacities.



(a) *Average ToUTL tariff.*



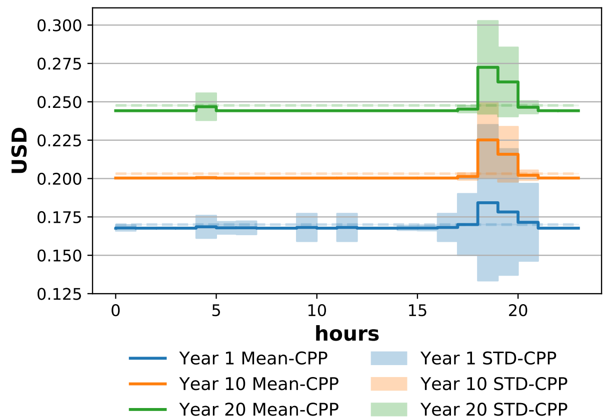
(b) *Average demand response.*



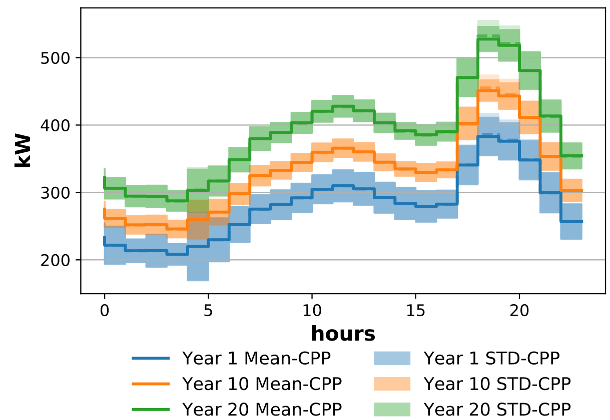
(c) *Yearly installed capacities for the ToUTL tariff.*

Figure 17

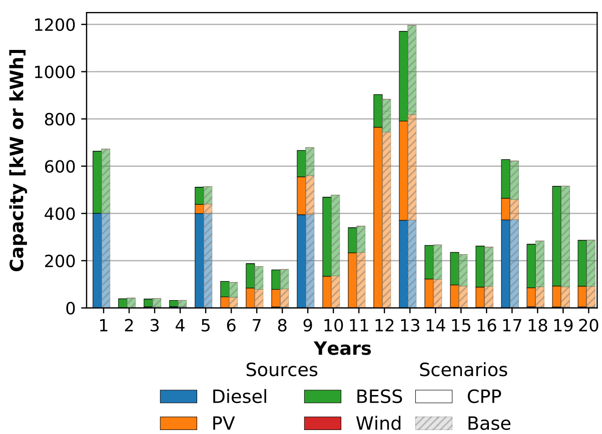
CPP tariff and its effects over the demand and the energy sources capacities.



(a) *Average CPP tariff.*



(b) *Average demand response.*

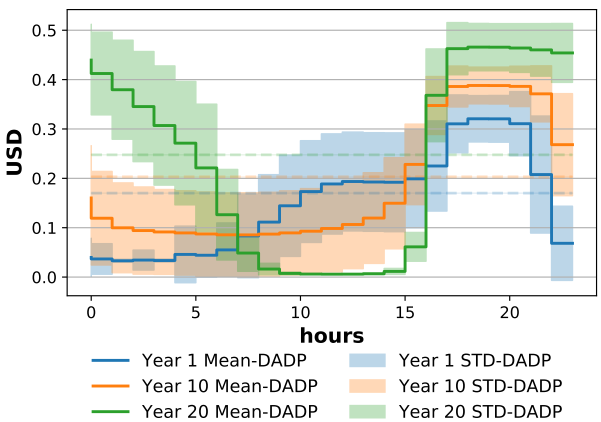


(c) *Yearly installed capacities for the CPP tariff.*

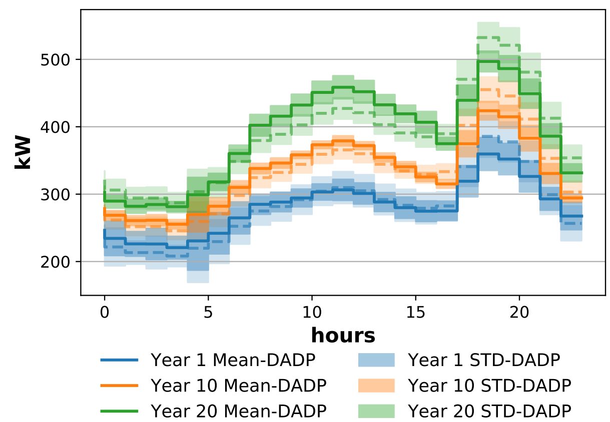
shows the average DADP tariff and Figure 18b shows its average impacts over the demand. Figure 18c show the changes in the required capacities of the energy sources due to the DADP tariff.

Figure 18

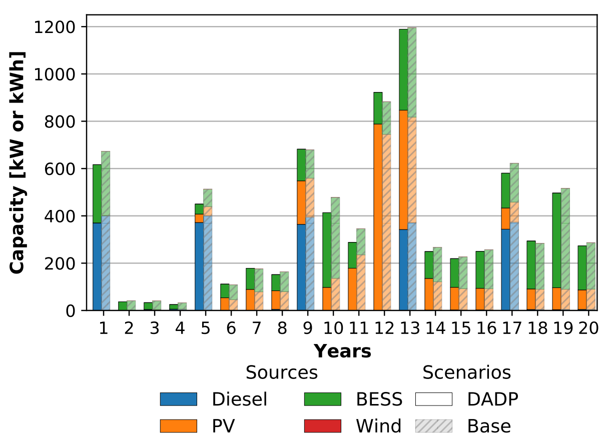
DADP tariff and its effects over the demand and the energy sources capacities.



(a) *Average DADP tariff.*



(b) *Average demand response.*



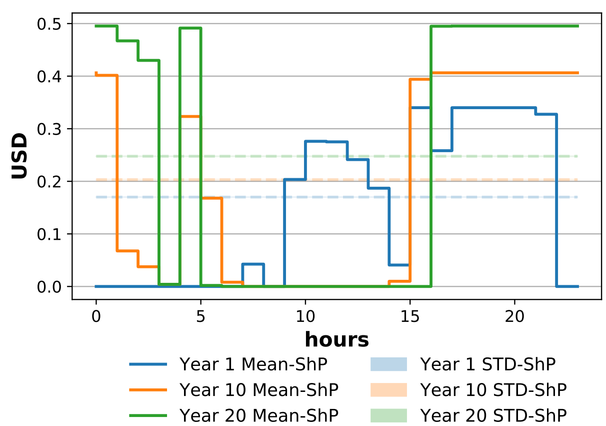
(c) *Yearly installed capacities for the DADP tariff.*

DADP DSM strategy modifies the demand shape significantly, increasing the utilization of renewable energy. These variations lead to significant changes in the required capacities. Table 13 summarizes the variations of the required capacities of the energy sources due to the DADP DSM strategy.

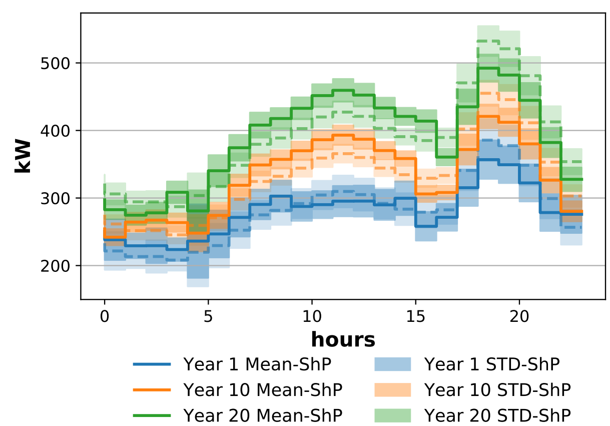
3.3.1.6. Fixed Shape Pricing tariff. The study case considers using a Fixed Shape Pricing scheme. The ShP tariff computes one price level for each hour. The hourly variation of the ShP tariff reflects better the hourly production costs of the electric energy than any of the ToU tariffs. Additionally, the ShP keeps constant the price level of each hour over each year of operation. Figure 19a shows the average of the ShP tariff for three different years. Figure 19b shows the response of the demand to the tariff. Figure 19c shows the changes in the required capacities of the energy sources due to the ShP tariff.

Figure 19

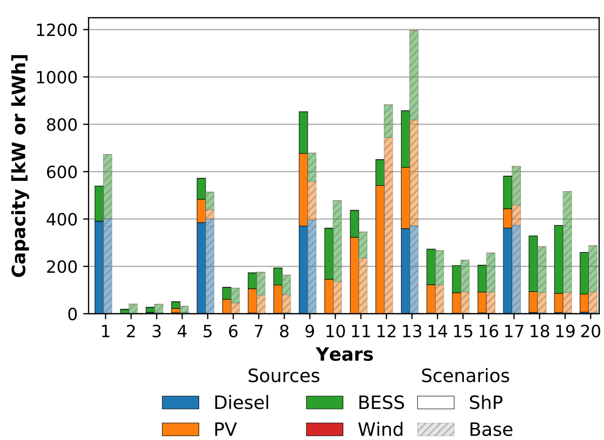
ShP tariff and its effects over the demand and the energy sources capacities.



(a) *Average ShP tariff.*



(b) *Average demand response.*



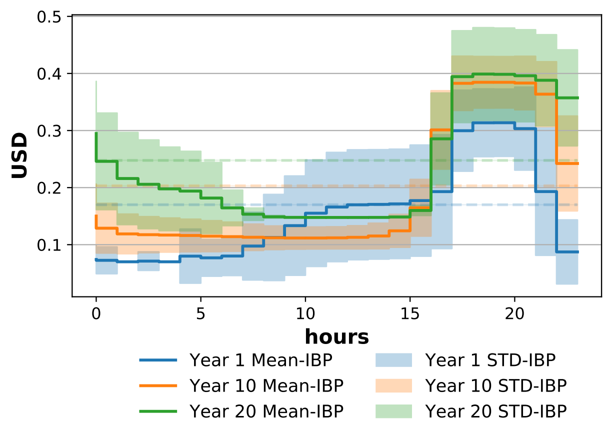
(c) *Yearly installed capacities for the ShP tariff.*

Figure 19 shows that the ShP DSM strategy effectively modifies the shape of the electrical energy demand. Additionally, the ShP tariff reduces the installed capacities of the energy sources. Table 14 summarizes the variations of the required capacities of the energy sources due to the ShP DSM strategy.

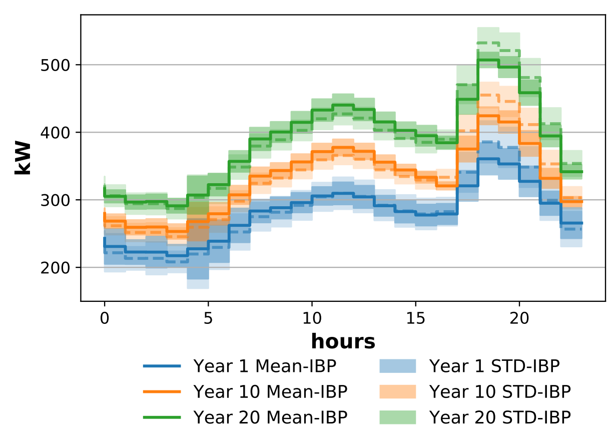
3.3.1.7. Incentive-Based Pricing tariff. As the DADP tariff, the incentive-based tariff has hourly variations. However, the perception of the customers to the tariff might be different. They can receive monetary rewards if they adapt their consumption patterns or monetary penalization if they do not modify their consumption patterns. Figure 20a shows the final tariff offered to the customers. Figure 20b shows the demand response to the IBP pricing scheme. Figure 20c show the changes in the required capacities of the energy sources due to the IBP tariff.

Figure 20

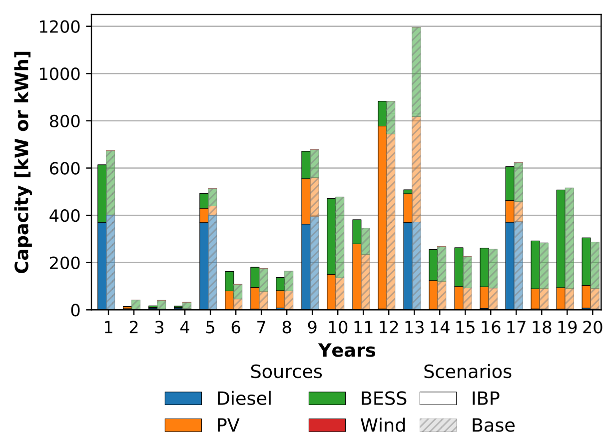
IBP tariff and its effects over the demand and the energy sources capacities.



(a) *Average IBP tariff.*



(b) *Average demand response.*



(c) *Yearly installed capacities for the IBP tariff.*

IBP DSM strategy reduces the PV installed capacity; the DADP DSM strategy increases it. Additionally, the IBP DSM strategy reduces more the BESS required capacity. However, the IBP DSM strategy cannot reduce the diesel capacity as much as the DADP DSM strategy. Table 15 summarizes the variations of the required capacities of the energy sources due to the IBP DSM strategy.

3.3.1.8. Direct Load Curtailment. The Direct Load Curtailment DSM does not use a tariff to incentivize customers to modify their consumption patterns. Instead, the DLCt DSM strategy curtails a portion of the demand when it is more expensive to generate electricity. Figure 21a shows that the tariff that the DLCt DSM strategy applies is the same as the base case. Additionally, Figure 21b shows that the effects of the DLCt DSM strategy are minimal when $\theta = 6\%$ and $\kappa = 3\%$. Figure 21c show the changes in the required capacities of the energy sources due to the DLCt tariff.

The DLCt DSM strategy is the only strategy that increases the BESS installed capacity compared to the base case. However, having a bigger BESS allow the strategy to significantly reduce the diesel capacity (only the DADP DSM has a more significant reduction in the diesel capacity). In the long term, the reductions in diesel consumption pay for the bigger BESS installed capacity. Table 16 summarizes the variations of the required capacities of the energy sources due to the DLCt DSM strategy.

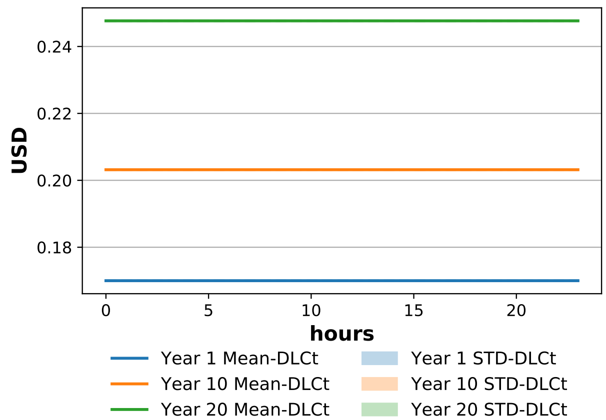
3.3.1.9. Comparison of the variations of the installed capacities. Each of the DSM strategies modifies the electric demand of the customers differently. By modifying the customers' consumption patterns, it is possible to change the required installed capacities of the energy sources. Table 17 summarizes the changes in the installed capacities of the energy sources when considering that only the 30% of the demand reacts to the price variations of the DSM strategies.

3.3.2. Return of Investment, Net present value and required subsidies from public funding

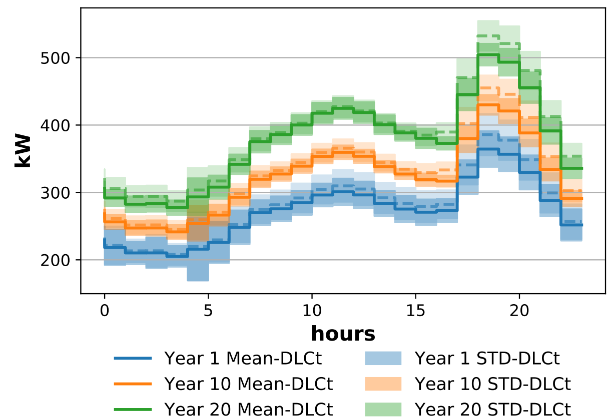
The methodology considers the participation of private investors in IMG projects. Private investors recover their investments and make their profits with the tariffs. However, the charged tariffs have a superior limit, which intrinsically limits the project's private investor's participation. The limits in the tariffs force the government to fund IMG projects partially. Table 18 shows the amount of

Figure 21

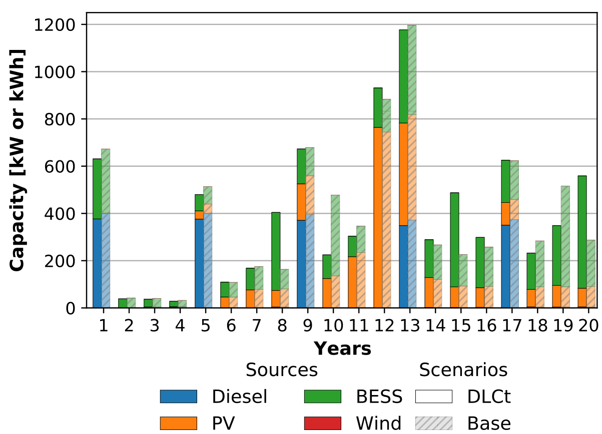
DLCt tariff and its effects over the demand and the energy sources capacities.



(a) *Average DLCt tariff.*



(b) *Average demand response.*



(c) *Yearly installed capacities for the DLCt tariff.*

subsidies required for each type of DSM. Additionally, Table 18 shows the Net Present Value and ROI of the case study.

For better clarity in the variations, Table 19 presents the percentage variations of the subsidies, NPV and ROI compared to the base case.

3.3.3. Comparison of main results

The DSM introduction in the IMG planning modifies total costs, investors' profits, customers' payments, private costs', and LCOE amongst others. Equations (57)–(62) present how to compute these values.

$$\text{Total costs} = \zeta + \vartheta + \mu + taxes \tag{57}$$

$$\text{Private profits} = \sum_{t=1}^{T} \pi_{x,t} D_{f,t} - (\varphi_{ci}\zeta + \varphi_{oi}\vartheta) \tag{58}$$

$$\text{C. payments} = \sum_{t=1}^{T} \pi_{x,t} D_{f,t} \tag{59}$$

$$\text{Private costs} = \varphi_{priv}(\zeta + \vartheta) + \mu + taxes \tag{60}$$

$$\text{Energy} = \sum_{t=1}^{T} D_{f,t} - |EE_{f,t}| - |LE_{f,t}| \tag{61}$$

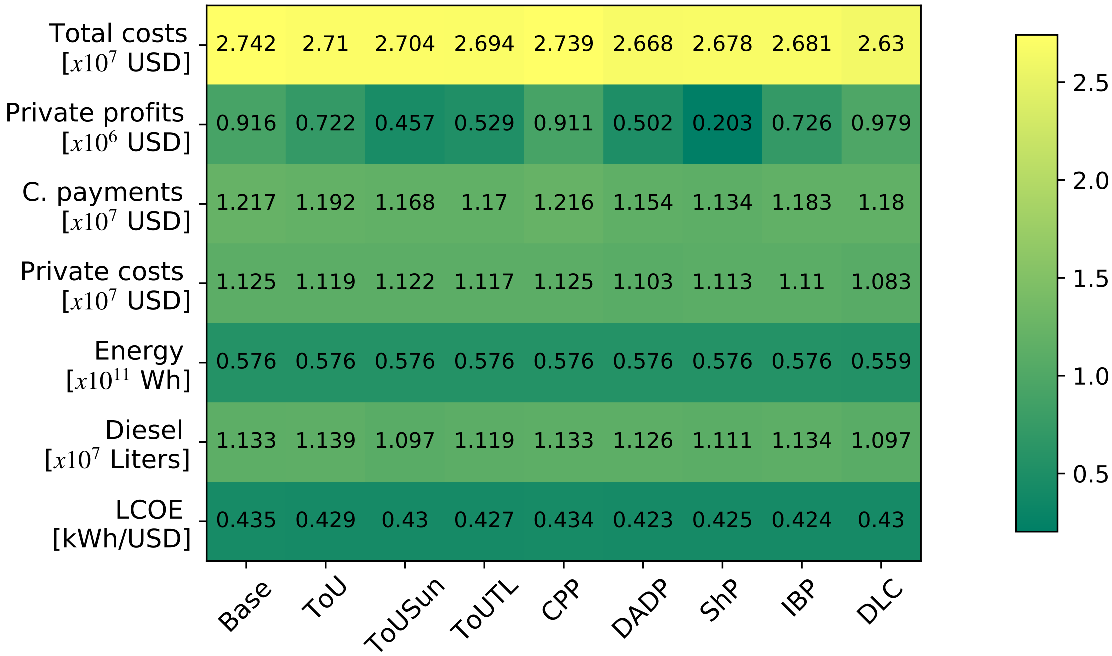
$$\text{LCOE} = \frac{\text{Energy}}{\text{Total costs}} \tag{62}$$

Figure 22 presents a side to side comparison of the main results of the different DSM strategies. Figure 23 presents the same comparison as Figure 22. However, instead of the values, it shows the percentage variations between the DSM strategies and the base case.

The DSM strategies have different performance in different aspects. Equation (63) is

Figure 22

Comparison of main results.



adopted to measure the performance of each of the DSM strategies. Figure 24 presents the performance evaluation of the different DSM strategies.

$$\text{Performance} = \frac{\text{Max value}}{\text{Number of attributes}} \frac{\text{worst} - \text{current}}{\text{worst} - \text{best}} \tag{63}$$

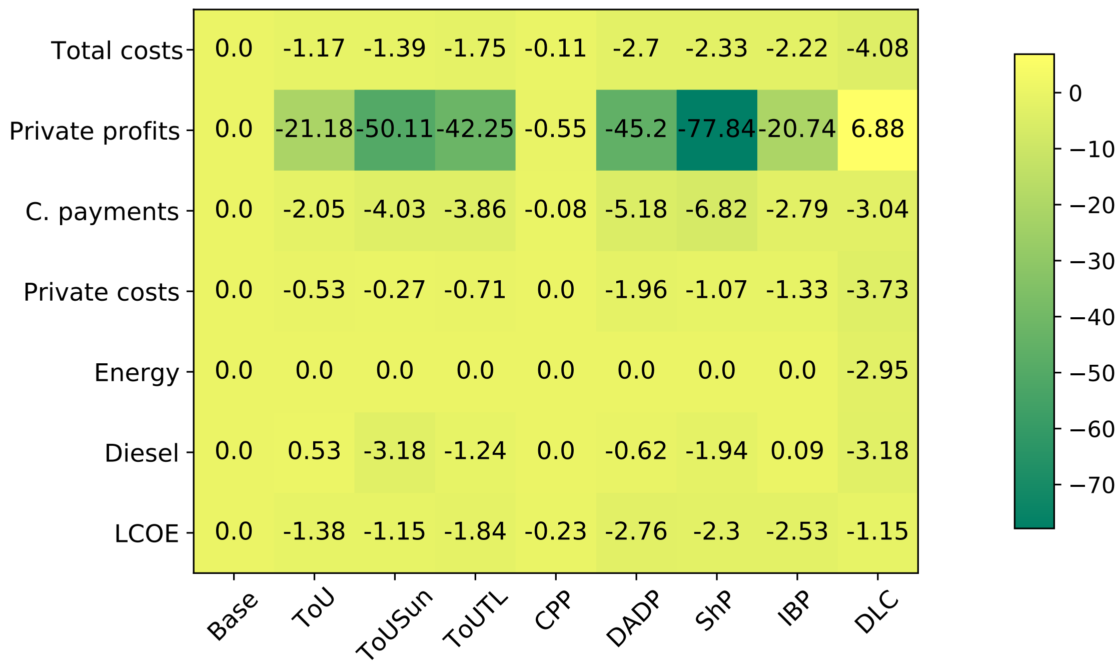
Figure 24 shows that the DLCt DSM strategy performs better than its counterparts. In this regard, it is interesting to notice that the DLCt DSM is the only strategy that can not offer customers an incentive to increase energy consumption. Despite this, the DLCt strategy has a good performance compared to the other strategies.

3.4. DSM strategies comparison when guaranteeing the same ROI for private investors

An interesting analysis from the point of view of the regulator is to know how the payments in the subsidies change when the government wants to guarantee the same ROI for private investors for all the DSM strategies. Additionally, it is interesting to analyze how the payments of the

Figure 23

Percentage variation of the main results compared to the base case.

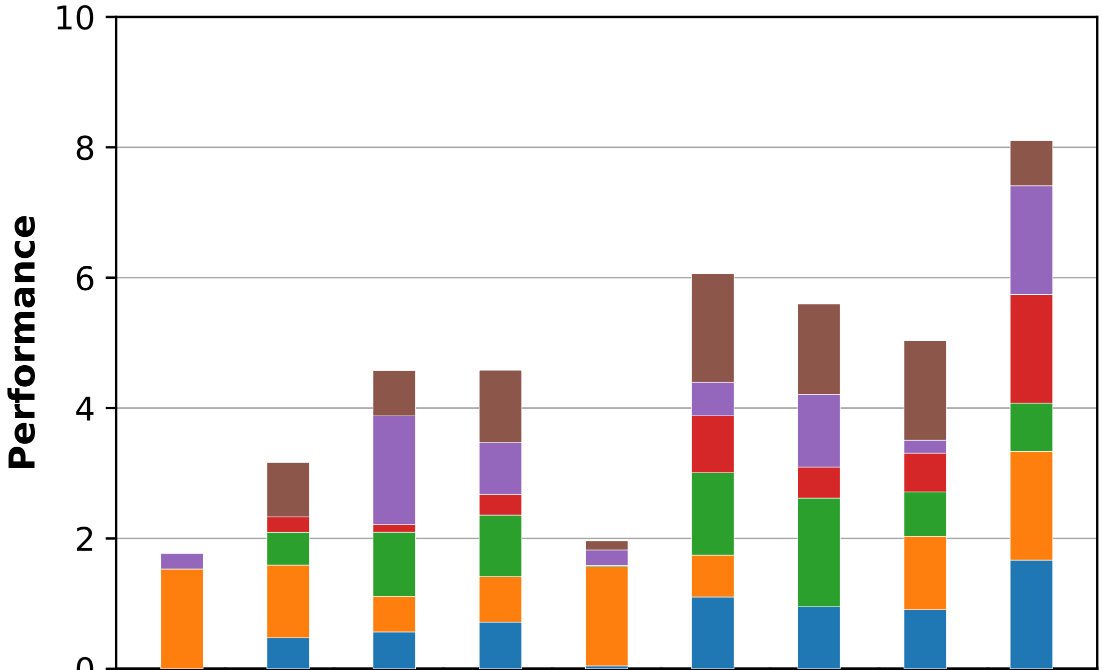


customers change in this scenario. This section presents an evaluation of the main impacts of the DSM strategies for the planning of the case study IMG when the government guarantees the same ROI for the private investors. To guarantee the same ROI for private investors, the regulator or policymaker needs first to find the share of public and private funding for each DSM strategy in which the ROI is equal to a predefined value for all the DSM strategies. To achieve this, the study of this section considers only two investors for the IMG project, the government (public capital) and an independent investor (private capital). This means that $I = 2$ in Equation 13. To find the share of public and private capital, the study applied a simple heuristic search. The values for the CAPEX, maintenance and carbon taxes investments of public and private capital are shown in Table 20. Table 21 shows the share of public and private capital for the OPEX for all the DSM strategies. The values in Table 20 are fix for all the DSM strategies while the values of Table 21 change for each DSM strategy.

This section performs its analysis with the values of Table 20 and 21. Section 3.4.1 presents

Figure 24

Comparison of the performance of the DSM strategies.



	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
LCOE	0.00	0.83	0.69	1.11	0.14	1.67	1.39	1.53	0.69
Diesel	0.24	0.00	1.67	0.79	0.24	0.52	1.11	0.20	1.67
Private costs	0.00	0.24	0.12	0.32	0.00	0.87	0.48	0.60	1.67
C. payments	0.00	0.50	0.98	0.94	0.02	1.27	1.67	0.68	0.74
Private profits	1.53	1.11	0.55	0.70	1.52	0.64	0.00	1.12	1.67
Total costs	0.00	0.48	0.57	0.71	0.04	1.10	0.95	0.91	1.67

the payments of subsidies and NPV of the projects. Section 3.4.2 presents the main results of the analysis. Finally, section 3.4.3 presents the performance of the DSM strategies when the same ROI is guaranteed for private investors.

3.4.1. Subsidies, NPV and ROI

Table 22 presents the subsidies paid by the government and the NPV for all the DSM strategies. To make an easier representation of the results Table 23 presents the percentage variations compared to the base case (flat tariff no DSM).

Table 23 shows that the NPV is not reduced for all the DSM strategies compared to the base case. Despite this, the reductions in the Subsidies can reach up to 2.42% for the DADP DSM strategy and up to 5.02% for the DLCt DSM strategy.

3.4.2. Main results

Figure 25 gives a better idea of how the main results of the planning of the IMG change when the government guarantee the same ROI for private investors for all the DSM strategies. Figure 26 presents the percentage changes of the main variables compared to the base case.

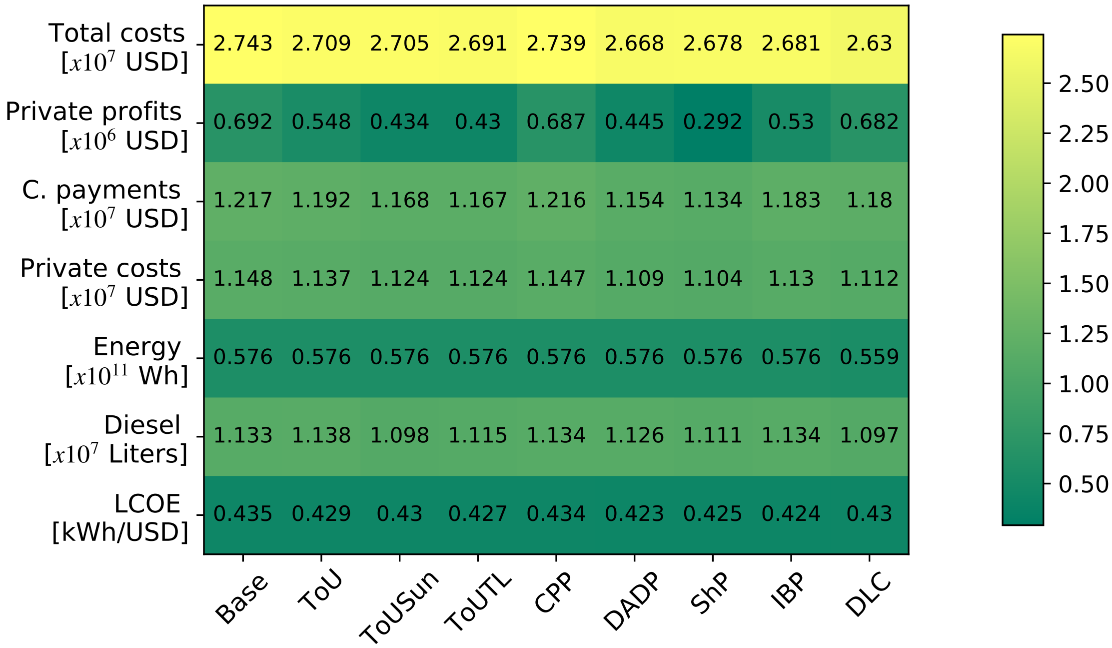
Figure 25 and 26 shows a reduction in the customer payments of 5.18% for the DADP DSM strategy and a reduction of 6.82% for the ShP DSM strategy. The private costs also present the biggest reduction for the DADP and ShP DSM strategies: 3.4% and 3.83%, respectively. However, ToUSun and DLCt are the more environmentally friendly DSM strategies, the reductions in diesel consumption for these two strategies are 3.09% and 3.18%, respectively.

3.4.3. Performance of the DSM strategies when the same ROI is guaranteed for private investors

Figure 27 presents the performance of the DSM strategies when the government wants to guarantee the same ROI for private investors.

Figure 27 shows that the ShP DSM strategy performs better than DADP DSM strategy. However, the DLCt is superior to both. ToUSun and ToUTL DSM strategies perform similarly,

Figure 25
Comparison of main results.



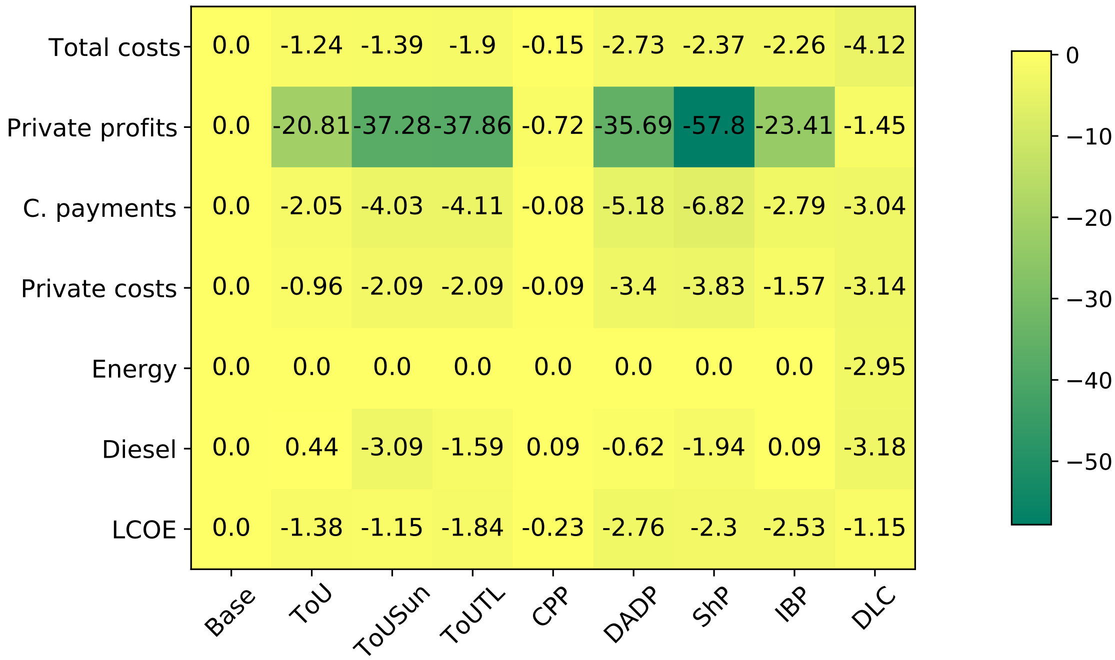
and their performance is not relatively far from DADP and ShP DSM strategies.

3.5. Sensitivity analysis

The sensitivity analysis aims to measure the impacts of the variations in the projection costs of the energy sources and Consumer Prices Index (CPI) over the case study. The analysis use the projection costs of (Administration, 2020) and (Laboratory, 2019) to build two different scenarios: low and high. Due to the lack of data for the gen-set, diesel and CPI, the study assumes a reduction of 20% for the low scenario and a growth of 20% for the high scenario as compared to the base case. The study case assumes as well a reduction of 40% in the tax prices for the low scenario, and a growth of 40% for the high scenario, as compared to the base case. Figure 28 presents the cost projections for the three scenarios. The sensitivity analysis evaluates the impacts over the sizing of the energy sources for the low, standard and high scenarios in Section 3.5.1. Additionally, Section 3.5.2 presents the NPV, ROI and subsidies comparison, and Section 3.5.3 presents a comparison

Figure 26

Percentage variation of the main results compared to the base case.



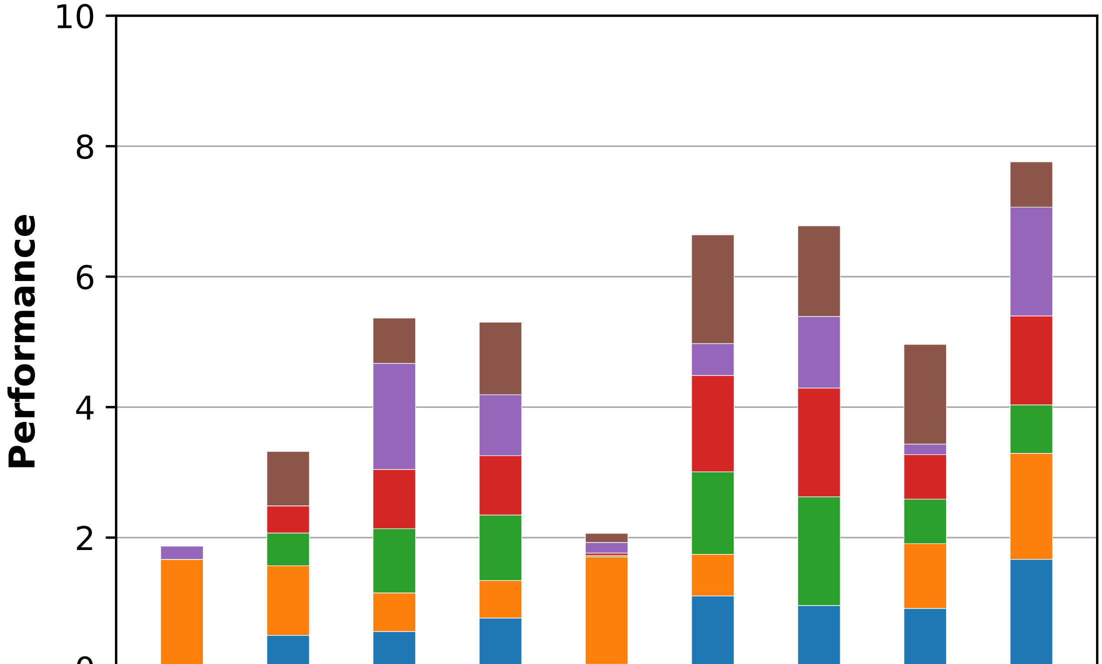
of the variations of the main variables compared to the base case. Finally, Section 3.5.4 presents the performance of the DSM strategies for the the three scenarios.

3.5.1. Variation in the capacities of the energy sources

The variations in the projections of the energy sources, taxes and CPI will modify the yearly optimization results. Figure 30 presents the variations in the installed capacities for the three considered scenarios. Figure 30 shows big differences in the installation of renewable resources, specially the BESS for the low scenario. This behavior is expected due to the reduced price of the renewable energy sources. It is also possible to see in Figure 30 that renewable energy investments reduce compared to the base case, due to the high prices of the renewable energy sources.

Figure 27

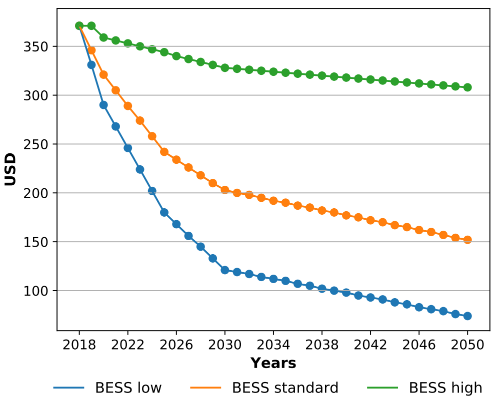
Comparison of the performance of the DSM strategies when the same ROI is guaranteed for private investors.



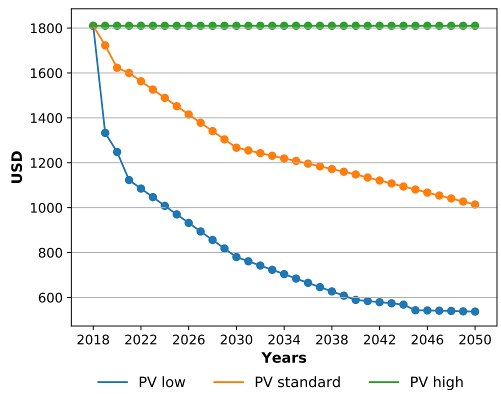
	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
LCOE	0.00	0.83	0.69	1.11	0.14	1.67	1.39	1.53	0.69
Diesel	0.20	0.00	1.63	0.93	0.16	0.49	1.10	0.16	1.67
Private costs	0.00	0.42	0.91	0.91	0.04	1.48	1.67	0.68	1.36
C. payments	0.00	0.50	0.98	1.00	0.02	1.27	1.67	0.68	0.74
Private profits	1.67	1.07	0.59	0.58	1.65	0.64	0.00	0.99	1.63
Total costs	0.00	0.50	0.56	0.77	0.06	1.11	0.96	0.91	1.67

Figure 28

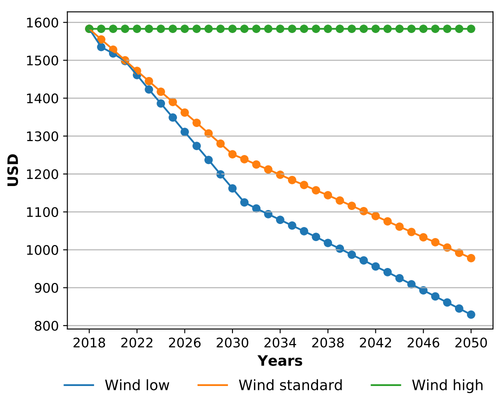
A. BESS capital expenditures (Laboratory, 2019), B. PV capital expenditures (Laboratory, 2019), C. Wind capital expenditures (Laboratory, 2019), D. Diesel generator capital expenditures.



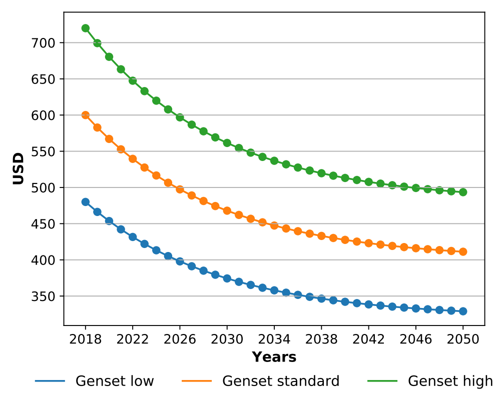
(a) *BESS prices.*



(b) *PV prices*



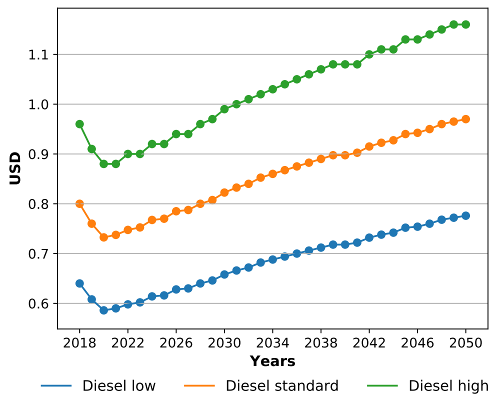
(c) *Wind prices*



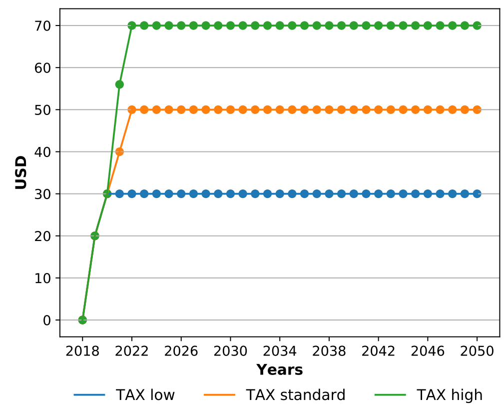
(d) *Diesel generator prices*

Figure 29

A. Diesel price (Administration, 2020), B. Carbon Tax price (government, 2018).



(a) *Diesel prices*



(b) *Tax prices*

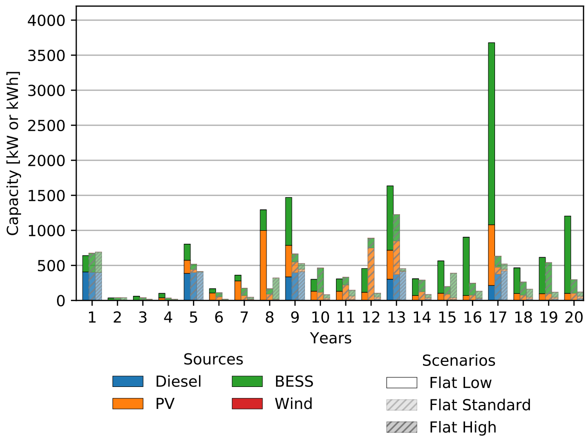
3.5.2. Variation in the NPV, ROI and subsidies paid by the government

The NPV and ROI of a project are hugely affected by the projection costs of the energy sources. Even more, the projection costs of the energy sources significantly affect the total amount of subsidies that the government need to pay for rural electrification projects. In this regard, it is of special interest to know how the NPV, ROI and Subsidies are affected under different assumptions. Table 24 shows the total variations of the NPV, ROI and Subsidies for the three scenarios.

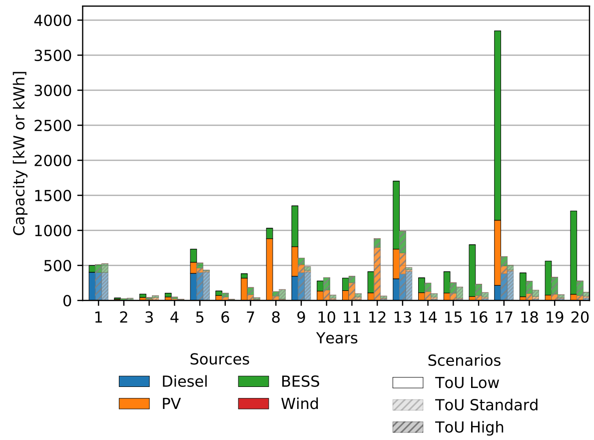
Table 24 shows that the variations in the projection costs of the energy sources, the diesel and CPI significantly affect the NPV of the project. However, the biggest change occurs in the ROI of the project. The sensitivity analysis considers that private investors pay 40% of the OPEX and taxes, and pay 100% of the maintenance of the project for the three scenarios. Despite keeping the same conditions for the three scenarios, private investors get high profits in the low scenario, and high losses for the high scenario. The subsidies that the government pays have significant variations as well. For more clarity in the results Table 25 shows the percentage variations.

Figure 30

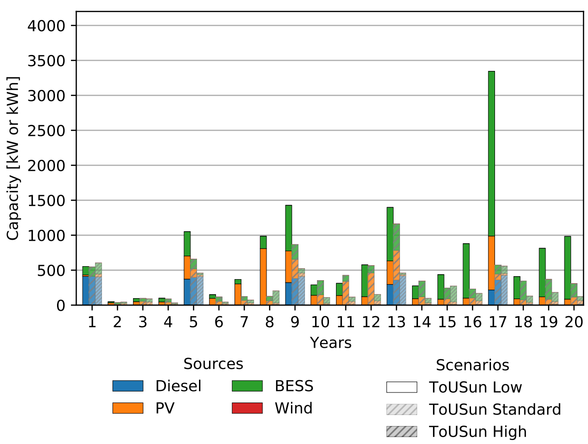
Variations in the capacities (Part A).



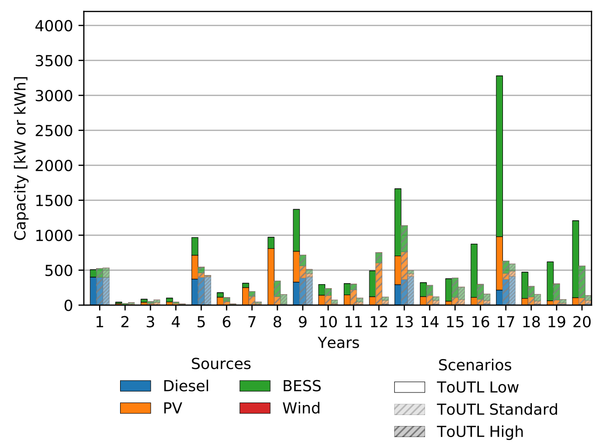
(a) *Capacities with flat DSM.*



(b) *Capacities with ToU DSM.*



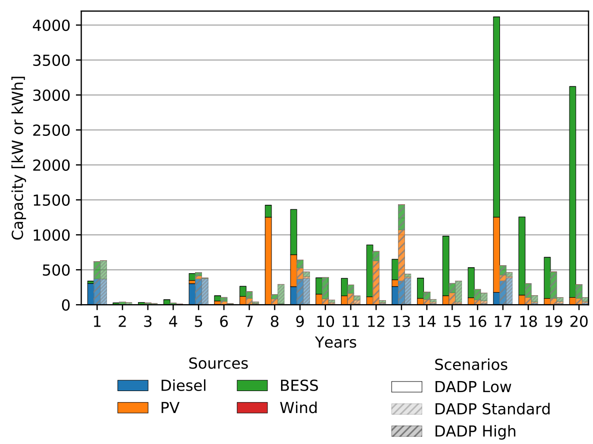
(c) *Capacities with ToUSun DSM.*



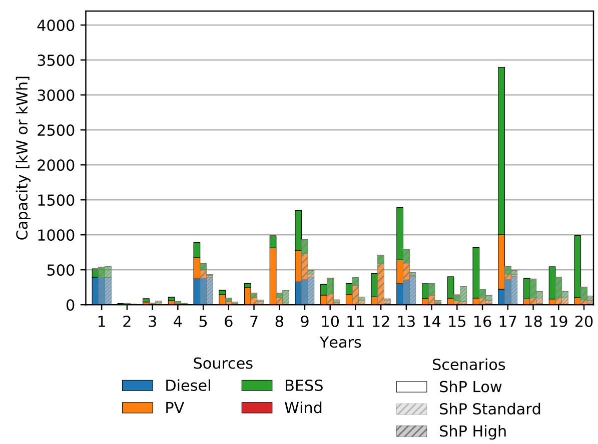
(d) *Capacities with ToUTL DSM.*

Figure 31

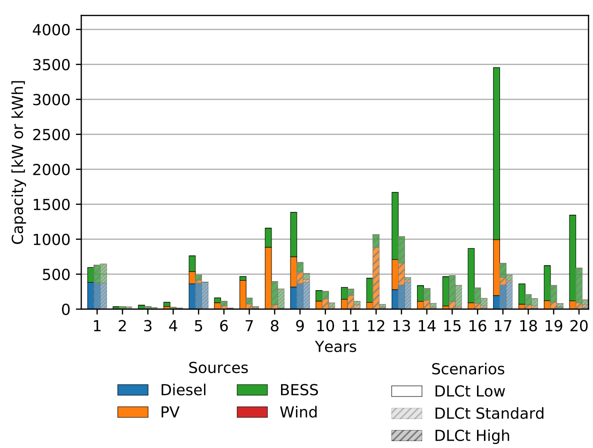
Variations in the capacities (Part B).



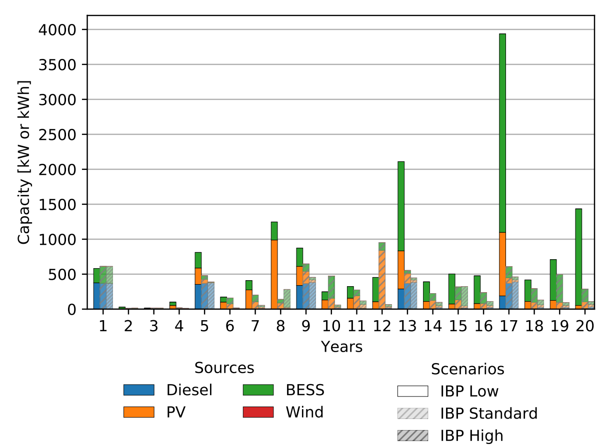
(a) *Capacities with DADP DSM.*



(b) *Capacities with ShP DSM.*



(c) *Capacities with IBP DSM.*



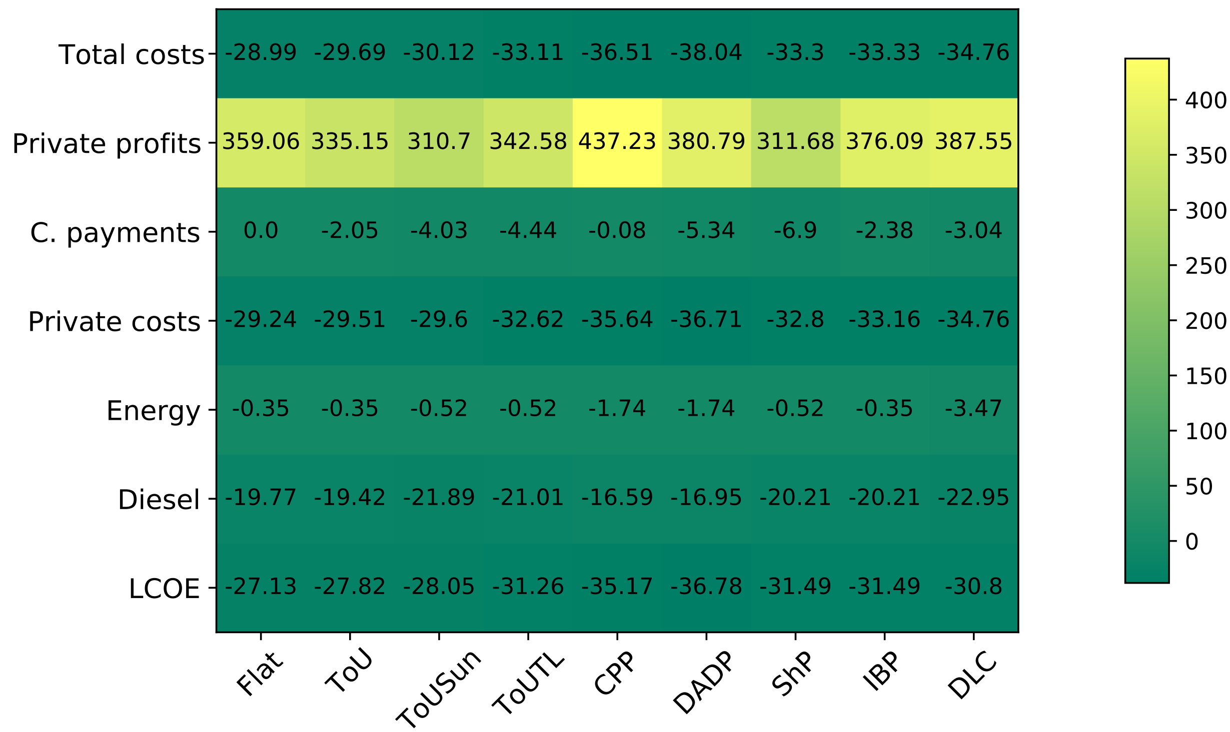
(d) *Capacities with DLCt DSM.*

3.5.3. Comparison of the main variables

The main results of the planning of the IMG change when the projection costs change. Figure 32 shows the percentage variations of the main variables for the low scenario. Figure 33 shows the percentage variations of the main variables for the high scenario.

Figure 32

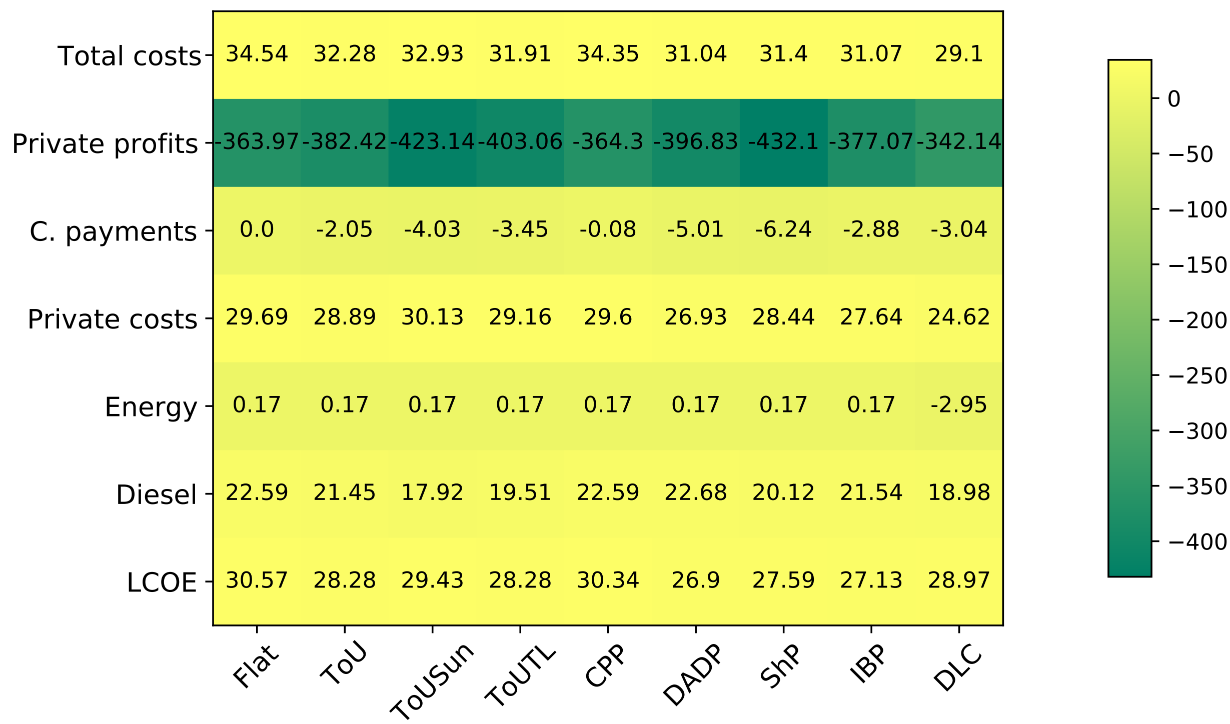
Percentage variations for the Low scenario.



The optimization formulation chooses to install big shares of renewable energy when the prices are low, but when the prices are high chooses to increase the diesel capacity as Figure 30 shows. The differences in the sizing of the IMG leads to changes in the diesel consumption for the low and high scenarios. The variations in the diesel consumption affects directly the operational costs, increasing the payments of private investors. However, the payments of the customers remain almost constant because all the scenarios provide similar amounts of energy. The almost constant

Figure 33

Percentage variations for the High scenario.



payments of the customers and the differences in the payments of private investors lead to massive changes in the private profits. This reinforce the results showed by Table 24, reductions in the prices of renewable energy sources will significantly reduce the amount of subsidies paid by the government for rural electrification projects.

3.5.4. Performance of the DSM strategies

Figure 34 shows the changes in the performance of the DSM strategies for the three scenarios.

Figure 34

Performance of the DSM strategies for the Low, Standard and High scenarios.

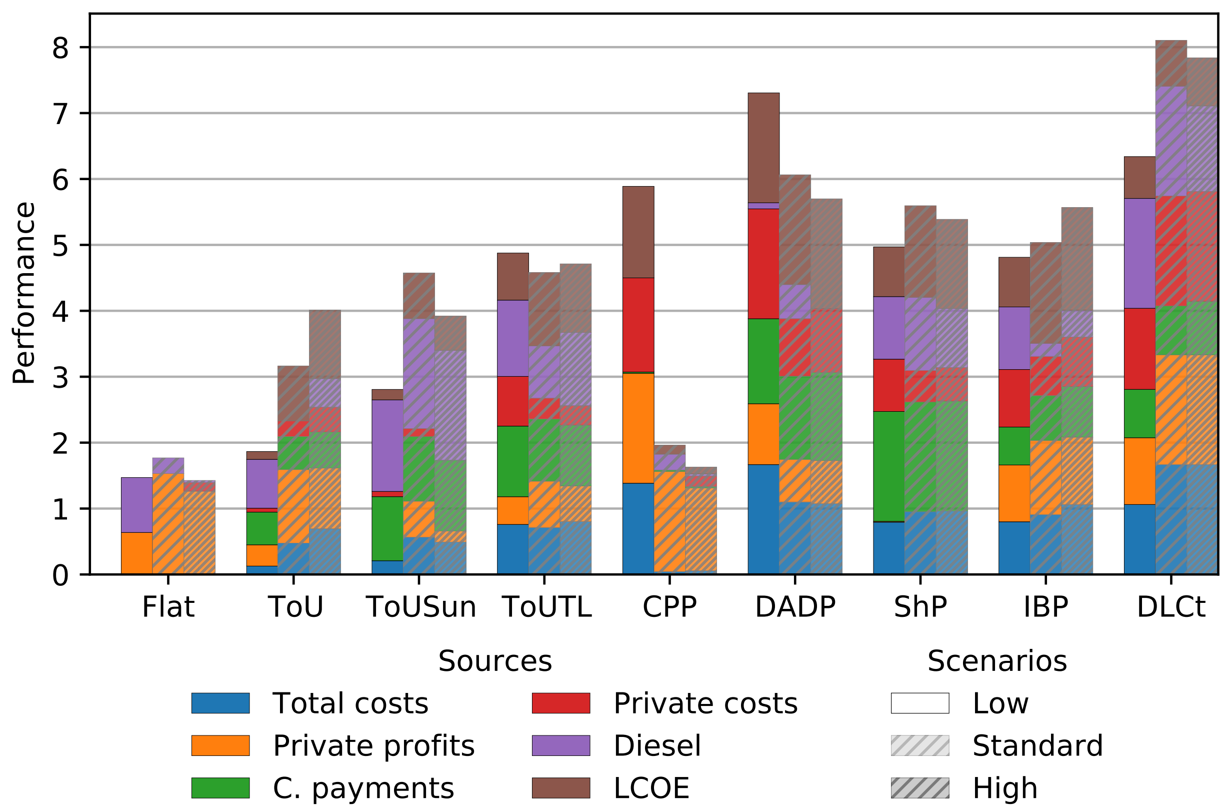


Figure 34 shows that ToUTL, CPP and DADP DSM strategies perform better for the low scenario, while ToU, and IBP DSM strategies perform better for the high scenario. The Flat, ToUSun, ShP and DLCt DSM strategies perform better for the standard scenario.

3.6. Diesel-based IMG vs Hybrid-based IMG.

95.9% of the IMG projects in Colombia's rural areas use only diesel generation (SSPD, 2019). The government prefers this type of generation due to the reduced inversion of diesel-based IMGs compared to hybrid-based IMG projects. However, in the long term, the installation of hybrid-based IMGs instead of diesel-based IMGs could reduce Capital Expenditures (CAPEX), Operational Expenditures (OPEX), and the government's payments in subsidies for IMG projects. In this regard, this section evaluates the financial viability of replacing a diesel-based microgrid for a hybrid microgrid in Section 3.6.1. Additionally, the study evaluates the effects of the DSM strategies over the main variables of the IMG in Section 3.6.2. This analysis compares the study's results to the scenario where the IMG operates only with diesel generation and has a flat tariff (no DSM).

3.6.1. Return of Investment, Net Present Value, and required subsidies from the government

The present section aims to evaluate the financial viability of installing hybrid-based IMGs, considering integrating DSM strategies in their planning. The financial evaluation will show the government and policymakers the potential savings of providing electric energy to the country's islanded/isolated regions using hybrid-based IMGs with DSM.

3.6.1.1. Analysis of the Return of Investment of the hybrid-based vs the diesel-based IMG comparison. The study evaluates the ROI of the IMG project for private investors. The ROI considers the money that private investors pay for operational costs. The evaluation of the ROI includes as well the maintenance and tax costs. The cash-flow income of private investors come from the payments of the tariffs.

Table 27 shows the percentage variations of the ROI of the investors compared to the IMG that works only with diesel and uses a flat tariff (no DSM).

Tables 26 and 27 show that the private investors lose money when they pay 40% of the OPEX for the IMG that works only with diesel. Additionally, Table 27 shows that by changing the diesel-based IMG for an hybrid-based IMG the ROI of the private investors improve considerably.

3.6.1.2. Analysis of the Net Present Value of the hybrid-based vs. the diesel-based IMG comparison. The NPV considers the total value of the project. Table 28 shows the total NPV for the diesel-based and hybrid-based IMGs. Table 29 show the percentage variations of the NPV compared to the diesel-based IMG with flat tariff.

Table 29 shows the percentage variations of the NPV compared to the IMG that works only with diesel and uses a flat tariff (no DSM).

Tables 28 and 29 show that by changing the diesel-based IMG for an hybrid-based IMG the total value of the project is reduced more than 10%. However, this reduction does not consider the application of DSM. When the study considers DSM, the reductions in the total costs can reach up to 12.32% for the IBP DSM strategy and up to 15.06% for the DLCt DSM strategy.

3.6.1.3. Analysis of the required subsidies from the government for the hybrid-based vs. the diesel-based IMG comparison. In Colombia, the access to electric energy is a fundamental right declared in the constitution of the country (Article 334, 365, and 370 (Administrativa, 1991)). In this regard, the government should subsidize access to the electric energy for the users who can not afford it. The payments of subsidies reach considerable amounts for the country. Between 2014 and 2018, the Mines and Energy Ministry (Ministerio de Minas y Energía) reported payments of COP 1.3 Billions (USD 337.96 Millions). Most of these payments go to subsidize the fuel for the diesel-based IMGs in the country's isolated regions. In this regard, the present section aims to evaluate how much the subsidies can be reduced for the case study when changing the diesel-based IMG for hybrid-based IMG. Additionally, the effects of the DSM strategies over the payments of the subsidies are also measured. Table 30 shows the payments of the government for subsidies for the case study using only diesel and a hybrid microgrid.

Table 31 shows the percentage variations compared to the diesel-based IMG with flat tariff for more clarity in the results.

Tables 30 and 31 shows a reduction of 6.52% in the subsidies just by replacing the diesel-based IMG for and hybrid-based IMG. ToUTL and ShP have interesting savings. As expected, DADP and DLCt DSM strategies have better performance, reaching up to 10.66% reductions in the government's required subsidies.

3.6.2. Main results of the Hybrid-based vs Diesel-based IMG

Figure 35 shows the values of installing and operating the IMG only with diesel. This figure provides total profits and payments to private investors and customers, respectively. However, Figure 35 presents only the total values. Figure 36 presents a percentage comparison of the hybrid-based IMG against the diesel-based IMG.

Figure 35

Main results for the diesel-based IMG.

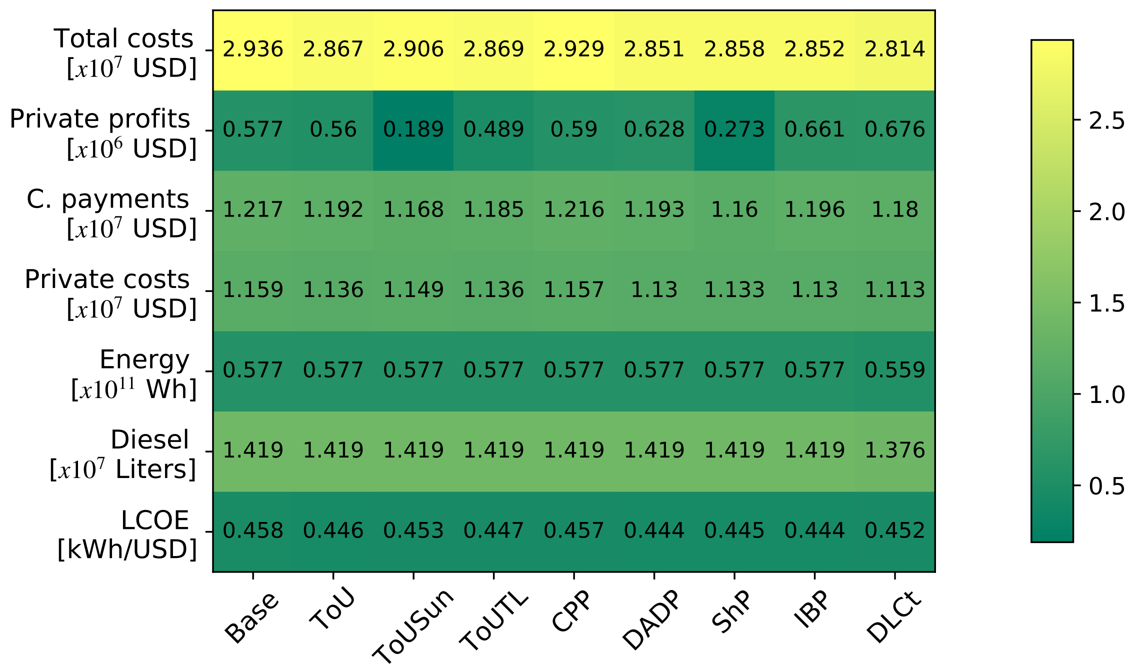
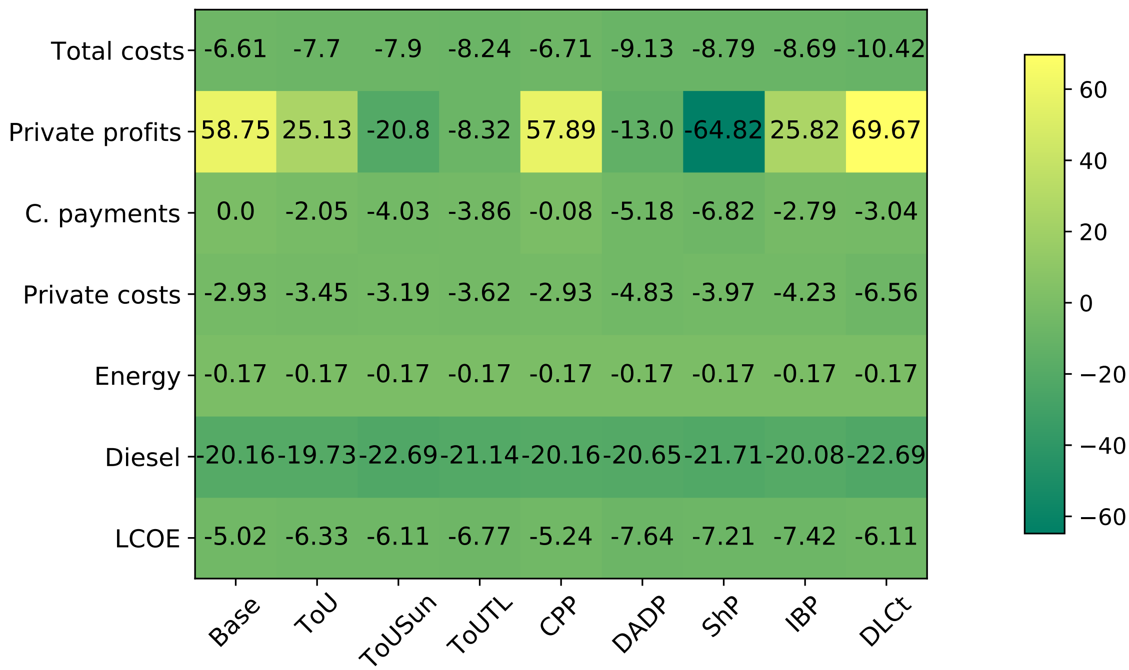


Figure 36 shows that the replacement of a diesel-based IMG for a hybrid-based IMG reduces the total costs for all the DSM strategies. When comparing the flat scenario for both IMGs, total cost reductions reached 6.61%, and diesel consumption decreased 20.16%. Nevertheless, the DADP and DLCt DSM strategies can reduce up to 9.13% and 10.42%, respectively. Additionally, the energy LCOE reached reductions of up to 7.64% for the DADP DSM strategy.

Figure 36

Percentage variation of the hybrid-based IMG compared to the diesel-based IMG.



3.6.3. Performance of the diesel-based IMG

Figure 37 presents the performance of the different DSM strategies when the IMG operates only with diesel generation.

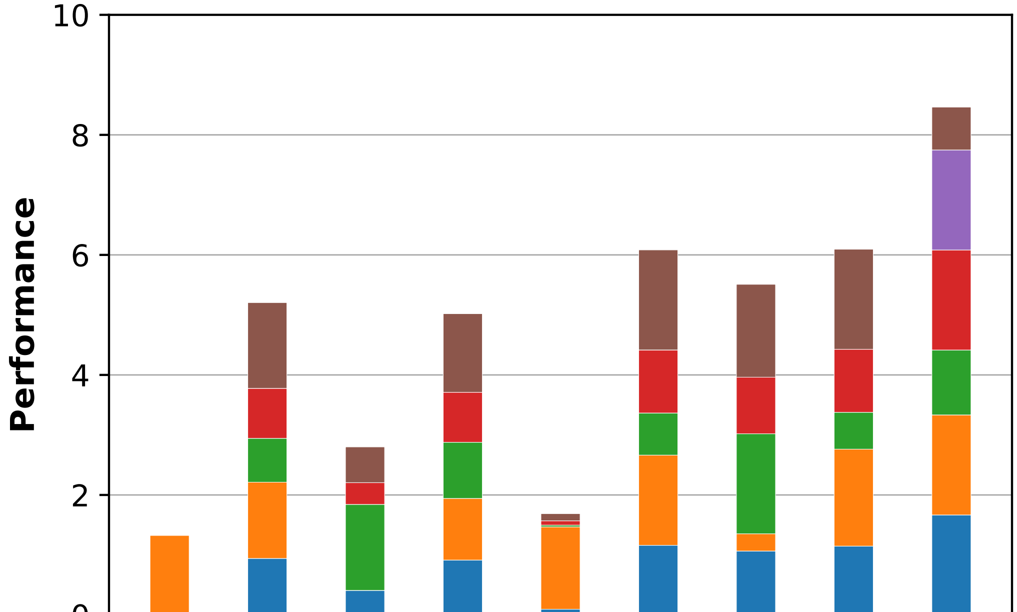
Comparing Figure 37 with Figure 24 it is possible to see that the DSM strategies have more positive effects for hybrid-based IMGs than for diesel-based IMGs. The advantage of hybrid-based microgrids comes from their possibility of exploding renewable generation. The present analysis clarifies that DSM strategies reduce customer payments, private costs, diesel consumption, and LCOE in both types of IMGs.

3.7. Analysis of the case study

This chapter presented the impacts of eighth DSM strategies in the planning of a case study IMG using measured data of the electrical demand provided by the IPSE. The software PVsyst provided the temperature, GHI, and wind speed data to the MCS approach. The MCS approach created

Figure 37

Performance of the diesel-based IMG.



	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
LCOE	0.00	1.43	0.60	1.31	0.12	1.67	1.55	1.67	0.71
Diesel	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.67
Private costs	0.00	0.83	0.36	0.83	0.07	1.05	0.94	1.05	1.67
C. payments	0.00	0.73	1.43	0.94	0.03	0.70	1.67	0.61	1.08
Private profits	1.33	1.27	0.00	1.03	1.37	1.50	0.29	1.62	1.67
Total costs	0.00	0.94	0.41	0.92	0.10	1.16	1.07	1.15	1.67

synthetic data for the stochastic analysis. The data of Table 7 configured the parameters of the simulations.

By using these settings for the proposed framework, the study performed four different types of analysis:

- Impact evaluation of the DSM strategies for the planning of the case study IMG.
- Performance comparison of the DSM strategies when the government guarantees the same ROI for private investors for all the DSM strategies.
- Sensitivity analysis when considering low and high forecast scenarios of the energy sources, interest rate, diesel and carbon taxes prices.
- Comparison of the effects of the DSM strategies when comparing two types of IMGs: diesel-based and hybrid-based.

3.7.1. Analysis of the impacts of DSM over the case study

Section 3.3 presented the DSM impacts over the planning of the case study IMG. The analysis aimed to measure the performance of the DSM strategies when the government fixes its subsidies to a defined percentage of the project's total value. This analysis is of particular interest to private investors. Considering these conditions, the DSM strategies that perform better were DLCt, DADP, and ShP. The DLCt DSM strategy was the one that reduced the most the diesel consumption (-3.18%), the total payments of the private investors (-3.73%), and the total costs of the project (-4.08%). Additionally, the DLCt DSM strategy was the one with better profits for private investors (+6.88%). The DADP DSM strategy was the one that reduced the most the LCOE (-2.76%). However, the ShP DSM strategy had an overall score close to the DADP, 5.6 for ShP vs. 6.07 for DADP.

3.7.2. Analysis of the impacts of DSM when the government guarantees the same ROI for private investors

Section 3.4 presented the DSM impacts over the planning of the case study IMG when the government wants to guarantee the same ROI for private investors. This analysis is of particular interest to the government. Instead of fixing a predefined value of participation in the IMG projects, the government is interested in minimizing its payments in subsidies. So, the government limits its subsidies just to guarantee the ROI expected by private investors. Considering these conditions, the DSM strategies that perform better were DLCt, ShP, and DADP. The DLCt DSM strategy reduced the most the diesel consumption (-3.18%) and the project's total costs (-4.12%). Furthermore, the DLCt DSM strategy had significantly high private profits. The ShP DSM strategy reduced the most the private costs (-3.83%) and the customer payments (-6.82%). The DADP DSM strategy once again reduced the most the LCOE (-2.73%). Additionally, the DADP and ShP DSM strategies again had a similar overall score, 6.67 for DADP vs. 6.79 for ShP.

3.7.3. Analysis of the sensitivity analysis

Section 3.5 presented the sensitivity analysis for the low, standard, and high scenarios of price forecasts of the energy sources. Considering these conditions, DLCt, DADP, and ShP DSM strategies perform better than the others. Surprisingly, the DLCt and ShP DSM strategies perform better for the standard and high scenarios than for the low scenario. The DADP DSM performs better for the low scenarios than for the standard and high scenarios. An exciting outcome of this analysis is that reductions in the interest rate and renewable energy sources lead to a high increase in private investors' profits. This means that in the future IMG projects might not need any subsidies from the government to provide electric energy to the islanded/isolated communities.

3.7.4. Analysis of the DSM impacts for diesel-based IMGs vs. hybrid-based IMGs

Section 3.6 presented another exciting analysis for the government. How the payments in subsidies change when replacing diesel-based IMGs for hybrid-based IMGs. Nearly 96% of the IMGs in Colombia operate wit diesel gen-sets. So, if the replacement of these gen-sets by hybrid-based IMGs can reduce the government's expenses, it seems an idea worth it to investigate. The study tested two different IMGs with the same electrical demand, weather, and configurations for the simulations to perform this analysis. The study tested all the DSM strategies for both IMGs as well. Considering these conditions, the DLCt, IBP, and DADP DSM strategies were the ones that perform better. The DLCt DSM strategy outperforms the others, reducing the most the diesel consumption, the private costs, and the total costs. However, the DLCt strategy was the one that reduces the most private profits. The DADP and IBP DSM strategies reduce the most the LCOE. It is interesting to notice that the ShP DSM strategy was the one that reduces the most customer payments and performed quite well, with a score of 5.52, compared to 6.08 and 6.1 for the DADP and IBP DSM strategies, respectively. Another interesting outcome of this study was to know that by replacing the diesel-based IMGs by hybrid-based IMGs, the government can save 6.61% in the total costs of the project, save 20.16% in the diesel payments, and reduce the LCOE 5.02% without applying any DSM strategy. Even more, the profits of private investors can increase by 58.75% just by making the replacement. However, if the government chooses to make the replacement and apply DSM, these results can reach up to 10.42% reductions in total costs, 22.69% reductions in diesel consumption, and up to 7.64% reduction in the LCOE. Private profits can reach an improvement of up to 69.67%. These results show the replacing diesel-based IMGs by hybrid-based IMGs is an idea worth considering by the government, even more, if the application of DSM accompanies the replacement.

3.7.5. Final remarks

After performing the study, it is possible to conclude that the proposed methodology and framework effectively generate the DSM signals for the demand, either using price signals as tariffs or the signals to curtail the demand. The study also demonstrated that the signals effectively modify the patterns of consumption of the customers and that the changes in consumption patterns effectively modify the planning results of the IMG. By using the proposed DSM strategies, not only the LCOE was reduced, but the payments for the energy, diesel consumption, and total costs of the project, which represent a considerable advantage for IMGs planning.

4. Conclusions

The present thesis proposed a holistic methodology to compute the effects of public subsidies and Demand Side Management (DSM) in the planning of Islanded/Isolated Microgrids (IMGs). The thesis defines an optimal formulation and proposes it as a framework using a modular approach. The optimization formulation computes the optimal sizing and optimal dispatch of the energy sources. Moreover, the optimization formulation computes the optimal tariffs for energy, adding the possibility of creating different business models. Finally, the thesis used the methodology to evaluate the impact of seven indirect DSM strategies and one direct DSM strategy in planning a case study IMG. Below, there is a brief description of the lessons learned in the process of formulating and testing the methodology.

4.1. Methodology design

Many software available in the market can compute the optimal sizing of IMGs. However, most of these software does not allow the needed flexibility to design DSM strategies and dynamic energy tariffs. The lack of flexibility and tariff design force the thesis to abandon using software and adopt nested optimization models of two optimization levels. However, multilevel optimization formulations face an inherent combinatorial problem. Each iteration of the sizing problem must completely solve the dispatch problem. The thesis formulated a single convex optimization formulation to deal with the combinatorial problem. Even more, IMGs planning needs to address the effects of uncertainties. In this regard, the thesis uses Disciplined Convex Stochastic Programming (DCSP) to design the methodology to consider the effects of the uncertainties in the electrical demand and renewable energy resources. The DCSP formulation guarantees the uniqueness and optimality of the solution. The thesis designed the methodology to integrate the following DSM strategies:

- Time of Use of two pricing levels.

- Time of Use with a solar incentive.
- Time of Use with three pricing levels.
- Critical Peak Pricing.
- Day Ahead Dynamic Pricing.
- Fixed Shape Pricing.
- Incentive-Based pricing.
- Direct Load Curtailment.

4.2. Construction of the framework

The present thesis proposes a framework to evaluate the DSM impacts over the planning of IMGs. The framework uses a modular approach to represent each energy source, storage system, demand response function, or DSM strategy. In this regard, the proposed framework allows planners to easily configure their IMG projects by merely choosing the blocks they need. The following is a list of the available blocks:

- Energy sources (Gensets, Photovoltaic modules and Wind Turbines).
- Energy storage sources.
- Demand Side Management strategies (Eighth different options).
- Demand response models (Linear).
- Load types (Residential, commercial, community and industrial).
- Analysis types (Deterministic, stochastic, multiyear deterministic and multiyear stochastic).
- Time frames of the analysis ($\geq$one year).

- Sensitivity analysis (Low, standard and high scenarios).

Additionally, the framework's modular approach allows future planners to add any additional block (energy sources, storage systems, DSM strategies, demand response functions, amongst others.) as long as the newly added blocks follow the DCP rules. If the new blocks follow the DCP rules, the final optimization formulation will preserve convexity, guaranteeing the uniqueness and optimality of the final solution. However, it is worth mentioning that the use of DCP implicitly restricts the capabilities of the proposed methodology. While DCP offers high speed and uniqueness of the solution, it restricts the models to be convex. The DCP rules restrict energy sources' models, demand response models, and others to be convex. The methodology can not integrate non-convex models, which will lead either to a simplification of the model or the model's exclusion. Nevertheless, due to the extended horizon of the planning of IMGs (20 years or more), the approximation is justifiable.

4.3. DSM evaluation

The proposed formulation allows policymakers to affect the perceived benefits of the stakeholders of the IMG project. In the planning of IMGs, the three main stakeholders are customers, private investors, and governmental institutions. In this regard, the first stakeholder to consider is the customers. Customers want tariffs that reduce their payments. Policymakers can directly reduce customer payments by increasing public funding for IMG projects and limiting the tariffs that private investors can charge for the energy in the proposed formulation. The second stakeholder is private investors. To attract private investors interest in funding IMG projects, the business model must guarantee relatively stable profits. Policymakers can guarantee relatively stable profits by increasing public funding for IMG projects and allowing private investors to increase the energy tariffs in the proposed formulation. The third stakeholder in IMG planning is the government. Policymakers must define the lower and upper bounds of the share of public funding and the upper limits of the energy tariffs that private investors can charge in the proposed formulation. Finally, policymakers must consider the effects of the DSM strategies on the environment as well. Policymakers can achieve this by increasing the value of the carbon tax in the proposed formulation, which will lead to a reduction in the acquisition and utilization of diesel gen-sets. The study proposes four different types of analysis to evaluate the effects of the DSM strategies on the stakeholders of the project:

- Impact evaluation of the DSM strategies for the planning of the case study IMG.
- Performance comparison of the DSM strategies when the government guarantees the same ROI for private investors for all the DSM strategies.
- Sensitivity analysis when considering low and high forecast scenarios of the energy sources, interest rate, diesel and carbon taxes prices.
- Comparison of the effects of the DSM strategies when comparing two types of IMGs: diesel-based and hybrid-based.

The study designs each analysis to share light to policymakers about how the DSM strategies will behave under different assumptions. The first analysis aims to evaluate the benefits of the DSM strategies when the government fixes the share of public and private capital. This scenario considers that private investors have full freedom to choose the DSM strategy that benefits them. Considering this, DLCt, CPP, and IBP DSM strategies present the more significant gains for private investors. However, the CPP DSM strategy only reduced 0.08% customer payments compared to the base case, which can lead the customers not to accept this DSM strategy. In this regard, IBP and DLCt DSM strategies will likely be more accepted by the customers, considering that the customers' reductions can reach up to 3.04%.

The study designs each analysis to share light to policymakers about how the DSM strategies will behave under different assumptions. The first analysis aims to evaluate the benefits of the DSM strategies when the government fixes the share of public and private capital.The study designs the second analysis for evaluating the performance of the DSM strategies when the government wants to attract private investors interested in IMG projects. To do so, the study assumes that the government will guarantee the same return rate to private investors regardless of the selection of the DSM strategy. For this type of analysis, the government is willing to increase its share of public capital in IMG projects to benefit private investors and customers. Considering this, ShP, DADP, and ToUTL DSM strategies benefit the most the customers by reducing their payments. DLCt, IBP, and DADP benefit the most the government by reducing the payments of subsidies.

The study designs the third analysis for evaluating how sensible the performance of the DSM strategies is to price variations in the market. The study considers price variations in capital expenditures, operational expenditures, carbon taxes, and interest rates. The study shows that even for the worst-case scenario, it is still an excellent choice to integrate DSM strategies into IMG planning.

The study designs the fourth analysis for evaluating how DSM strategies will perform in a diesel-based IMG. Additionally, the study evaluates the improvements in system design and operation when a hybrid-based IMG replaces a diesel-based IMG. This analysis is of particular interest for a country like Colombia, where more than 95% of its IMGs are diesel-based. This study shows policymakers that the replacement of current diesel-based IMGs by hybrid-based IMGs leads to a general improvement to all the stakeholders of IMG projects. Even when the project does not consider DSM, the total cost reductions reach up to 6.61%. However, if the hybrid-based IMG considers DSM, the reductions in total costs can reach up to 10.42%.

Finally, after performing the study, it is possible to conclude that all the DSM strategies reduced customer payments, private investments, diesel consumption, and total costs. However, these benefits came at a cost; the profits of private investors were reduced as well. This creates a compelling challenge for regulators and policymakers: how to set energy tariffs that benefit the customers and the environment on one side and guarantee a reasonable return rate for private investors on the other side. However, regulators and policymakers can use the proposed methodology and framework to solve this problem, at least, from a technical point of view.

4.4. Performance of the DSM strategies

The study presented a comparison of the performance of eighth DSM strategies. This performance gives a high qualification to the Direct Load Curtailment strategy. However, this strategy affects the customer's comfort. The second strategy with better qualification is the Day Ahead Dynamic Pricing. Nevertheless, the tariffs' hourly variation might confuse the customers of IMGs.

An interesting outcome of the study was the ShP DSM strategy. The ShP DSM strategy had an overall score close to the DADP DSM. However, the ShP maintains a fixed price over the whole year, leading to a better acceptance of the customers to this kind of tariff. In this regard, further studies sharing the different DSM options with the communities to know the potential acceptance of the tariffs are required.

Finally, it is possible to conclude that after applying the proposed methodology and framework, not only the LCOE is reduced, but the payments of the customers for the energy, the diesel consumption, and the total costs of the project were reduced as well, which supports that the original hypothesis of the present thesis is correct.

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Table 5

Summary of sizing methodologies that consider DSM in the planning of MGs and IMGs

Ref.	Objective	Sizing	EMS	Elasticity	DSM	Deterministic or stochastic	Type
(J. Kumar et al., 2019)	Minimize total costs	HOMER	Rule-based	Not considered	Re-scheduling of non essential load	Deterministic	MG
(Majidi et al., 2017)	Minimize total costs	MIP	MIP	Not considered	DLC of shiftable loads under ToU	Stochastic	MG
(Nojavan et al., 2017)	Minimize LCOE	MINLP	MINLP	Not considered	DLC of shiftable loads under ToU	Stochastic	MG
(Kerdphol et al., 2016)	Minimize NPV	PSO	Rule-based	Not considered	DLC of curtailable loads	Deterministic	MG
(N. Zhou et al., 2016)	Minimize total costs	NSGA-II	Rule-based	Self and cross	DR under ToU tariff	Deterministic	MG
(Erdinc et al., 2015)	Minimize total expected cost	MILP	MILP	Not considered	DLC of shiftable loads under dynamic tariffs	Deterministic	MG
(Kahrobaee et al., 2013)	Minimize total costs	MC and PSO	Rule-based	Not considered	DLC of shiftable loads under RTP	Stochastic	MG
(Chauhan & Saini, 2017)	Minimize total annualized costs	DHS	ILP	Not considered	DLC of shiftable loads	Deterministic	IMG
(Amrollahi & Bathaee, 2017)	Minimize NPV and LCOE	HOMER	MILP	Not considered	DLC of shiftable loads	Deterministic	IMG
(Mehra, 2017; Mehra et al., 2018)	Minimize total costs	Exhaustive search	Rule-based	Not considered	DLC of non-critical loads	Deterministic	IMG
(Luo et al., 2019)	Minimize total annualized costs	MILP	MILP	Not considered	DLC of shiftable loads	Deterministic	IMG
(Kiptoo et al., 2020)	Minimize NPV	MILP	MILP + RF	Not considered	DLC of shiftable loads	Deterministic	IMG
(Rehman et al., 2020)	Minimize NPV, LCOE	HOMER	Simulink	Not considered	DLC of shiftable loads	Deterministic	IMG
(Amir et al., 2018)	Minimize total costs	GA	MINLP	Self and cross	DR + setting dynamic tariffs	Deterministic	MCMG

Table 6

Summary of the Analysis of the literature review

Features	2017	2018	2019	2020	Literature gaps	Proposed work
Integration of sizing and DSM	(Amrollahi & Bathaee, 2017; Chauhan & Saini, 2017)	(Mehra, 2017; Mehra et al., 2018)	(Luo et al., 2019; Prathapa-neni & Detroja, 2019)	(Kiptoo et al., 2020; Rehman et al., 2020)		✓
Stochastic optimization formulation			(Prathapaneni & Detroja, 2019)			✓
Life time evaluation of the project			(Prathapaneni & Detroja, 2019)			✓
Study of subsidies impacts			(Luo et al., 2019)			✓
Forecasting impacts in the operation				(Kiptoo et al., 2020)		✓
Validation of operation				(Rehman et al., 2020)		✓
Design of tariffs for IMGs					✓	✓
Utilization of tariffs as DSM strategies in IMGs					✓	✓
Comparison of different DSM strategies using the same test bench					✓	✓
Influence of public subsidies on tariff setting for IMGs					✓	✓

Table 7
Values of the input parameters for the simulations.

Parameter	Symbol	Value
Curtailment factor	Ψ_c	1
Price elasticity of the demand	e_t	-0.3
Percentage of CAPEX paid by the government	φ_{cg}	1.0
Percentage of CAPEX paid by the private investor	φ_{ci}	0.0
Percentage of OPEX paid by the government	φ_{og}	0.6
Percentage of OPEX paid by the private investor	φ_{oi}	0.4
Electrical demand with flat tariff	D_t^{flat}	See Figure 9
Global Horizontal Radiation	G_t^A	See Figure 10
Temperature	T_t^A	See Figure 11
Wind speed	V_t^w	See Figure 12
Number of scenarios	S	100
Interest rate	ir	2%
Price of the carbon taxes	Φ	See Figure 29b
Flat tariff (Initial value)	π^{flat}	0.17 USD
Yearly growth of the demand	γ^D	2%
Percentage of hourly curtailed demand (DLCt DSM)	θ	6%
Percentage of total curtailed energy (DLCt DSM)	κ	3%
Minimum value for the tariffs	π^{min}	See Figure 13
Maximum value for the tariffs	π^{max}	See Figure 13
Percentage of the demand sensible to the price variations	β	25%

Table 8
Values of the input parameters for the energy sources.

Parameter	Symbol	Value
Initial investment of the BESS	I_{BESS}	See Figure 28a
Initial investment of the PV	I_{PV}	See Figure 28b
Initial investment of the wind turbines	I_{WT}	See Figure 28c
Initial investment of the diesel generator	I_{DG}	See Figure 28d
Operation costs of the BESS	λ_{BESS}	0
Operation costs of the PV	λ_{PV}	0
Operation costs of the wind turbines	λ_{WT}	0
Operation costs of the diesel generator	λ_{DG}	See equation 53
Fuel consumption of the diesel generator	$D_{DG,t}$	See equation 52
Diesel price per liter	α^L	See Figure 29a
Maintenance costs of the BESS	Λ_{BESS}	6% of I_{BESS}
Maintenance costs of the PV	Λ_{PV}	6% of I_{PV}
Maintenance costs of the wind turbines	Λ_{WT}	6% of I_{WT}
Maintenance costs of the diesel generator	Λ_{DG}	6% of I_{DG}
Life time of the project (Years)	L^p	20
Life time of the BESS	L^{BESS}	6
Life time of the PV	L^{PV}	25
Life time of the wind turbines	L^{WT}	15
Life time of the diesel generator	L^{DG}	3

Table 9
Sizing variations due to the ToU DSM strategy.

PV	-3.48%
BESS	-23.43%
Diesel	0.67%

Table 10
Sizing variations due to the ToUSun DSM strategy.

PV	4.06 %
BESS	-8.31%
Diesel	-2.49%

Table 11
Sizing variations due to the ToUTL DSM strategy.

PV	0.4 %
BESS	-2.25%
Diesel	-1.75 %

Table 12
Sizing variations due to the CPP DSM strategy.

PV	0.04%
BESS	-1.14%
Diesel	-0.15%

Table 13
Sizing variations due to the DADP DSM strategy.

PV	2.99%
BESS	-7.98%
Diesel	-7.61%

Table 14
Sizing variations due to the ShP DSM strategy.

PV	-0.31%
BESS	-20.14%
Diesel	-3.49%

Table 15
Sizing variations due to the IBP DSM strategy.

PV	-3.75%
BESS	-18.19%
Diesel	-3.66 %

Table 16
Sizing variations due to the DLCt DSM strategy.

PV	-1.76%
BESS	13.18%
Diesel	-6.13%

Table 17

Comparison of the sizing variations for all the DSM strategies.

Source	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
PV	-3.48%	4.06 %	0.4 %	0.04%	2.99%	-0.31%	-3.75%	-1.76%
BESS	-23.43%	-8.31%	-2.25%	-1.14%	-7.98%	-20.14%	-18.19%	13.18%
Diesel	0.67%	-2.49%	-1.75 %	-0.15%	-7.61%	-3.49%	-3.66 %	-6.13%

Table 18

Required subsidies from the government, Net Present Value and ROI of the case study.

	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
Subsidies [$x10^6$]	11.74	11.5	11.51	11.42	11.71	11.32	11.34	11.35	11.21
NPV [$x10^6$]	-10.94	-10.86	-11.08	-10.93	-10.92	-10.86	-11.12	-10.71	-10.37
ROI [%]	18.84	17.99	15.44	16.44	18.87	16.0	13.41	18.35	20.27

Table 19

Percentage variations compared to the case study.

	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
Subsidies [%]	0	-2.04	-1.96	-2.73	-0.26	-3.58	-3.41	-3.32	-4.51
NPV [%]	0	-0.73	1.28	-0.09	-0.18	-0.73	1.65	-2.1	-5.21
ROI [%]	0	-4.51	-18.05	-12.74	0.16	-15.07	-28.82	-2.6	7.59

Table 20

Share of public and private capital for CAPEX, Maintenance and Carbon taxes to guarantee the same ROI for all DSM strategies.

Investor	CAPEX	Maintenance	Carbon taxes
Public	100%	0%	0%
Private	0%	100%	100%

Table 21
Share of public and private capital for the OPEX to guarantee the same ROI for all DSM strategies.

Investor	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
Public OPEX	0.58679	0.58975	0.59859	0.59595	0.58669	0.59654	0.60549	0.58829	0.58169
Private OPEX	0.41321	0.41025	0.40141	0.40405	0.41331	0.40346	0.39451	0.41171	0.41831

Table 22
Required subsidies from the government, Net Present Value and ROI of the case study.

	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
Subsidies [$x10^6$]	11.55	11.36	11.49	11.36	11.54	11.27	11.41	11.19	10.97
NPV [$x10^6$]	-10.94	-10.86	-11.09	-10.59	-10.93	-10.85	-11.12	-10.71	-10.37
ROI [%]	15.02	15.01	15.0	15.01	15.02	15.04	15.03	15.0	14.96

Table 23
Percentage of variation of the required subsidies from the government, Net Present Value and ROI compared to the base case.

	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
Subsidies [%]	0.	-1.65	-0.52	-1.65	-0.09	-2.42	-1.21	-3.12	-5.02
NPV [%]	0.	-0.73	1.37	-3.2	-0.09	-0.82	1.65	-2.1	-5.21
ROI [%]	0.	-0.07	-0.13	-0.07	0.	0.13	0.07	-0.13	-0.4

Table 24
Total variations of the NPV, ROI and Subsidies.

		Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
NPV	Low	-5.31	-5.36	-5.49	-4.9	-3.64	-3.82	-5.09	4.65	-4.41
	Standard	-10.94	-10.86	-11.08	-10.93	-10.92	-10.86	-11.12	-10.71	-10.37
	High	-17.3	-17.03	-17.45	-17.12	-17.27	-17.01	-17.27	-16.84	-16.47
ROI	Low	62.73	61.06	58.48	64.84	82.73	77.72	61.13	68.82	71.41
	Standard	18.84	17.99	15.44	16.44	18.87	16.0	13.41	18.35	20.27
	High	-8.97	-9.25	-11.83	-10.29	-8.92	-10.92	-12.53	-9.08	-7.85
Subsidies	Low	8.72	8.59	8.53	8.17	7.63	7.39	8.13	8.16	8.01
	Standard	11.74	11.5	11.5	11.42	11.71	11.32	11.34	11.35	11.21
	High	15.44	15.03	15.15	14.98	15.41	14.9	14.91	14.88	14.76

Table 25
Percentage variations of the NPV, ROI and Subsidies.

		Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
NPV	Low	51.46	50.64	50.45	55.17	66.67	64.83	54.23	143.42	57.47
	Standard	0.	0.	0.	0.	0.	0.	0.	0.	0.
	High	-58.14	-56.81	-57.49	-56.63	-58.15	-56.63	-55.31	-57.24	-58.82
ROI	Low	232.96	239.41	278.76	294.4	338.42	385.75	355.85	275.04	252.29
	Standard	0.	0.	0.	0.	0.	0.	0.	0.	0.
	High	-147.61	-151.42	-176.62	-162.59	-147.27	-168.25	-193.44	-149.48	-138.73
Subsidies	Low	-25.72	-25.3	-25.83	-28.46	-34.84	-34.72	-28.31	-28.11	-28.55
	Standard	0.	0.	0.	0.	0.	0.	0.	0.	0.
	High	31.52	30.7	31.74	31.17	31.6	31.63	31.48	31.1	31.67

Table 26
Diesel-based IMG and Hybrid-based IMG ROI comparison.

	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
ROI (only diesel)	12.89	13.43	9.55	12.74	13.08	14.24	10.79	14.56	14.36
ROI (hybrid)	18.83	17.96	15.42	16.42	18.85	16.02	13.45	18.36	20.25

Table 27
Percentage variation of the ROI compared to the diesel-based IMG with flat tariff.

	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
ROI (only diesel) [%]	0.	4.19	-25.91	-1.16	1.47	10.47	-16.29	12.96	11.4
ROI (hybrid) [%]	46.08	39.33	19.63	27.39	46.24	24.28	4.34	42.44	57.1

Table 28
Net Present Value for the hybrid-based vs the diesel-based IMG.

	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
NPV (only diesel) [$x10^6$]	-12.04	-11.68	-12.19	-11.75	-11.98	-11.54	-11.87	-11.52	-11.40
NPV (hybrid) [$x10^6$]	-10.94	-10.86	-11.09	-10.94	-10.92	-10.85	-11.12	-10.71	-10.37

Table 29
Percentage variation of the NPV compared to the diesel-based IMG with flat tariff.

	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
NPV (only diesel) [% variation]	0	-2.99	1.25	-2.41	-0.5	-4.15	-1.41	-4.32	-5.32
NPV (hybrid) [% variation]	-9.14	-9.8	-7.89	-9.14	-9.3	-9.88	-7.64	-11.05	-13.87

Table 30
Required subsidies from the government for the hybrid-based vs the diesel-based IMG.

	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
Subsidies (only diesel) [$x10^6$]	12.56	12.2	12.40	12.20	12.52	12.11	12.15	12.11	12.01
Subsidies (hybrid) [$x10^6$]	11.74	11.5	11.51	11.42	11.72	11.32	11.34	11.35	11.22

Table 31
Percentage of the variation of the payments in subsidies compared to the diesel-based IMG with flat tariff.

	Flat	ToU	ToUSun	ToUTL	CPP	DADP	ShP	IBP	DLCt
Subsidies (only diesel) [%]	0%	-2.86%	-1.27%	-2.86%	-0.31%	-3.58%	-3.26%	-3.58%	-4.37%
Subsidies (hybrid) [%]	-6.52%	-8.43%	-8.35%	-9.08%	-6.68%	-9.87%	-9.71%	-9.63%	-10.66%

Appendices

The appendices of this thesis present the Monte Carlo Sampling approach considered for the stochastic analysis. Additionally, the path that the study followed to proposed the methodology exposed in this thesis. Finally, the appendices present a comparison of the the methodology with relevant literature.

Appendix A. Monte Carlo Sampling Approach

The Monte Carlo Sampling (MCS) approach requires three steps. The first step prepares the data before the fitting. The second step fits the historic data into Probability Distribution Functions (PDFs). Finally, the third step sample the PDFs to generate synthetic data. The present Appendix aims to further explain each of the steps of the process and to present the process of fitting the electrical demand for the month one (January) and the hour one (01:00 am) as an example. Section 4.4 presents the data preparation, Section 4.4 presents the fitting process and Section 4.4 presents the sampling procedure.

Data preparation

The first step is the data preparation. The proposed methodology requires at least one year of historical data of the primary energy sources (global horizontal irradiation, wind, hydro, biomass, etc.) and the electrical demand. For the proposed case study the software PvSyst provides the Global Horizontal Irradiation (GHI), wind speed and temperature. The "Instituto de Planificación y Promoción de Soluciones Energéticas para las Zonas No Interconectadas (IPSE)" provides the historic of the electrical demand for the case study. The IPSE provide the historic data from july of 2019 to june of 2020. The IPSE data required some outlier removal mainly to the lack of generation in some hours of the year (failures of the diesel generation system).

Fragment historic data by months

The first stage in the data preparation is to divide the yearly data into monthly data. A simple fragmentation of the datasets is enough to achieve this goal. After this stage, there is $4 \cdot 12 = 48$ datasets, each one with duration of one month.

Create the daily average of each month of each dataset

The second stage in the data preparation is to create the daily average for each month. However, to create the daily average the second stage must fragment the monthly datasets again. This time the monthly datasets must be fragmented by hours. Each monthly dataset produces 24 datasets (one for each hour of the day). So, a total amount of $48 \cdot 24 = 1152$ datasets are produced at this stage.

Data preparation: Example

Table 32 shows the dataset for January at $01:00h$ and Figure 38 shows its histogram.

Table 32
Electrical demand January 01:00h.

Date	Demand [kW]	Date	Demand [kW]
2020-01-01 01:00:00	299.0	2020-01-17 01:00:00	289.0
2020-01-02 01:00:00	229.0	2020-01-18 01:00:00	289.0
2020-01-03 01:00:00	214.0	2020-01-19 01:00:00	289.0
2020-01-04 01:00:00	231.0	2020-01-20 01:00:00	244.0
2020-01-05 01:00:00	236.0	2020-01-21 01:00:00	204.0
2020-01-06 01:00:00	205.0	2020-01-22 01:00:00	205.0
2020-01-07 01:00:00	219.0	2020-01-23 01:00:00	194.0
2020-01-08 01:00:00	217.0	2020-01-24 01:00:00	230.0
2020-01-09 01:00:00	225.0	2020-01-25 01:00:00	218.0
2020-01-10 01:00:00	240.0	2020-01-26 01:00:00	237.0
2020-01-11 01:00:00	249.0	2020-01-27 01:00:00	206.0
2020-01-12 01:00:00	234.0	2020-01-28 01:00:00	216.0
2020-01-13 01:00:00	247.0	2020-01-29 01:00:00	232.0
2020-01-14 01:00:00	235.0	2020-01-30 01:00:00	231.0
2020-01-15 01:00:00	235.0	2020-01-31 01:00:00	191.0
2020-01-16 01:00:00	235.0		

Data fitting to PDFs

The second step of the MCS approach fits each of the 1152 datasets to PDFs. The methodology creates a python script to fit the datasets to PDFs using the maximum likelihood approach. The script test the Beta, Exponential, Gamma, Normal, Pearson3, Triangular, Uniform and Weibull distributions to see which can fit better the data. The script uses the chi-square test to determine which distribution fits better the data. The results consider the d-value and p-value as well. Table 34 shows the distributions sorted using the chi-square test results. Figure shows the three distributions that fits better the example dataset.

Figure 38
Histogram of the example dataset.

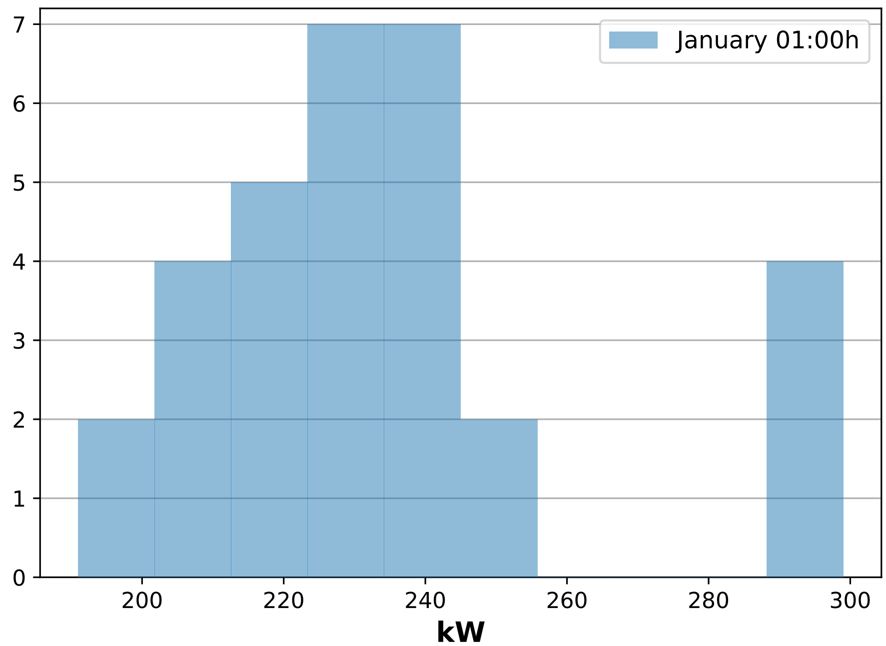


Table 33
Descriptive statistics of the example dataset.

Parameter	Value
count	31.0
mean	233.0
std	27.2
min	191.0
25%	216.5
50%	231.0
75%	238.5
max	299.0

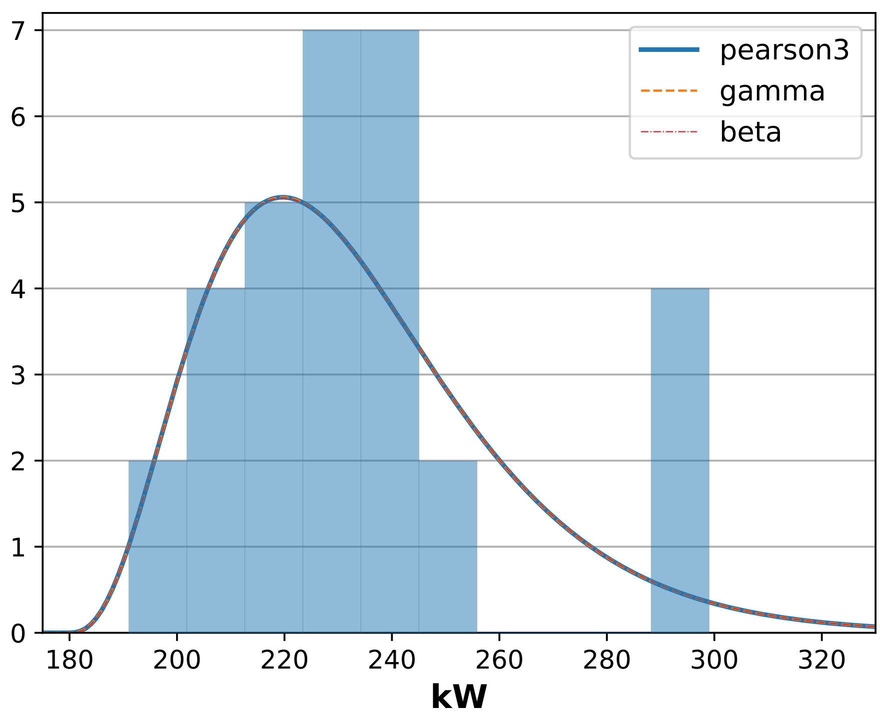
Table 34

Distributions sorted by goodness of fit.

Distribution	chi-square	d-value	p-value
Pearson3	11.681236	0.12015	0.75688
Gamma	11.681779	0.12015	0.75689
Beta	11.707748	0.12051	0.75274
Weibull	13.827697	0.12856	0.66118
Triangular	19.425824	0.19311	0.17355
Normal	30.217017	0.18357	0.21870
Uniform	55.560775	0.33393	0.00139
Exponential	115.471498	0.22764	0.06804

Figure 39

Three distributions that fits better the example dataset.



Q-Q and P-P plots are another useful way to see graphically the goodness of the fitting process. Q-Q plot compares probability distributions by plotting their quantiles against each other. P-P plot compares the Cumulative Distribution Functions (CDFs) of two distributions. Figure 40 shows the Q-Q and P-P plots of the example dataset against the resulting distribution of the fitting.

Sampling of the fitted distributions

The final step in the MCS approach is the sampling of the distributions fitted in the second step. The last step builds the synthetic data. The script save the parameters of the distribution that fits best the data to build the PDF. Table 35 shows the parameters for the distribution that fits better the dataset. Figure 42 shows three different histograms build using random sampling from the PDF.

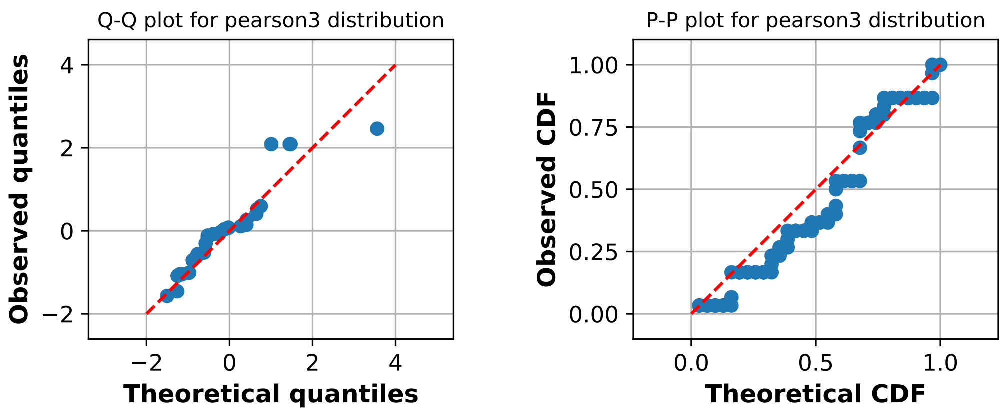
Table 35
Parameters of the distribution that fits better the sample dataset.

Distribution	Pearson3
Skew	1.00069
Loc	233.06451
Scale	26.78549

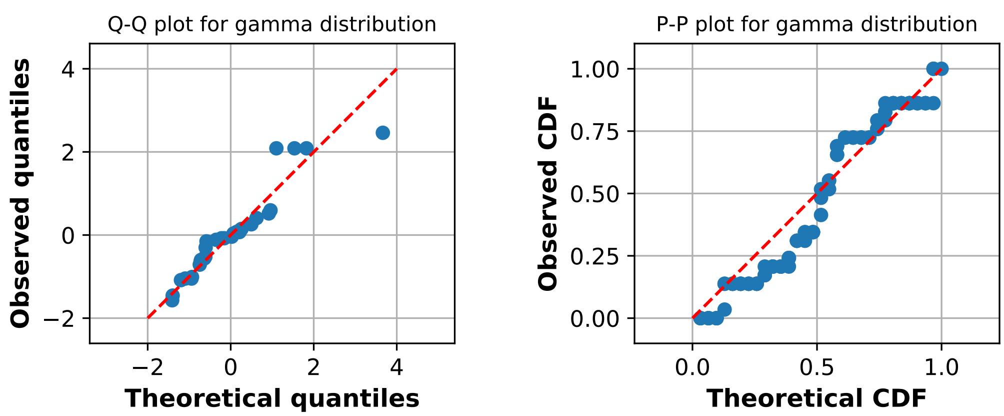
It is important to highlight that the distribution fitting is not new in the state of the art of power systems. Reference (Jordehi, 2018) presents a review of how to deal with uncertainties in electric power systems. The case study presented in this study follows the recommendations of (Jordehi, 2018) and applies a Gaussian distribution for the electrical demand and temperature, a Weibull distribution for the wind speed, and a Beta distribution for the GHI. However, the approach presented above can be easily integrated in the analysis using a different configuration in CVXMG.

Figure 40

Q-Q and P-P plots of the distributions fitting to the example dataset (Part A).



(a) *Q-Q and P-P plots of the Pearson3 distribution fitting.*



(b) *Q-Q and P-P plots of the Gamma distribution fitting.*

Figure 41
Q-Q and P-P plots of the distributions fitting to the example dataset (Part B).

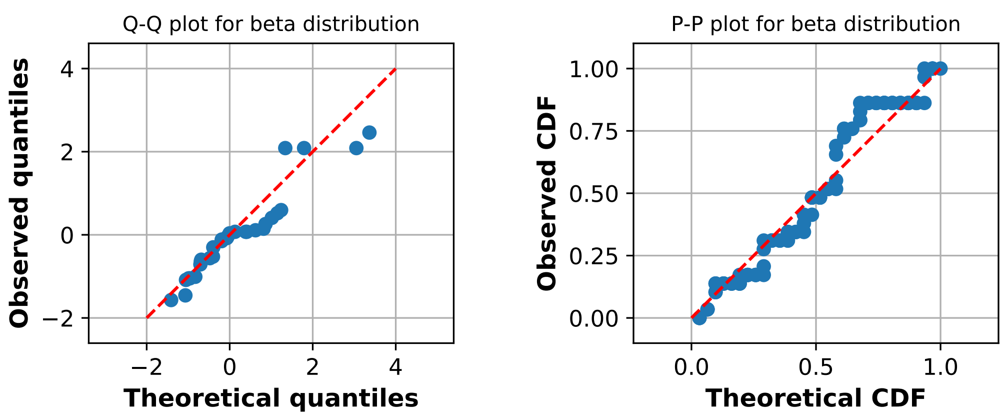
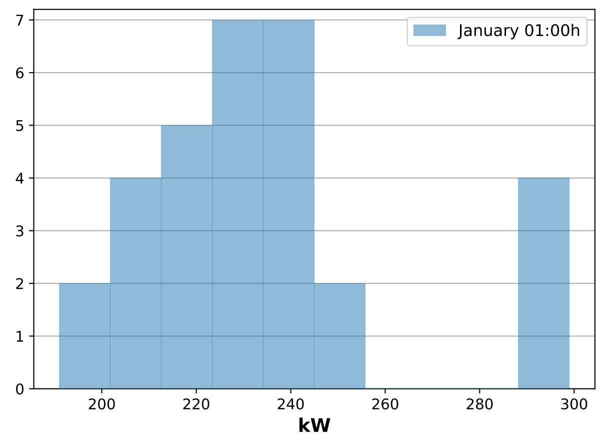
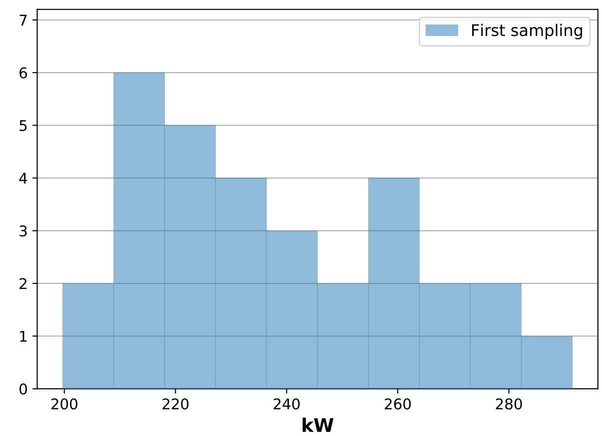


Figure 42

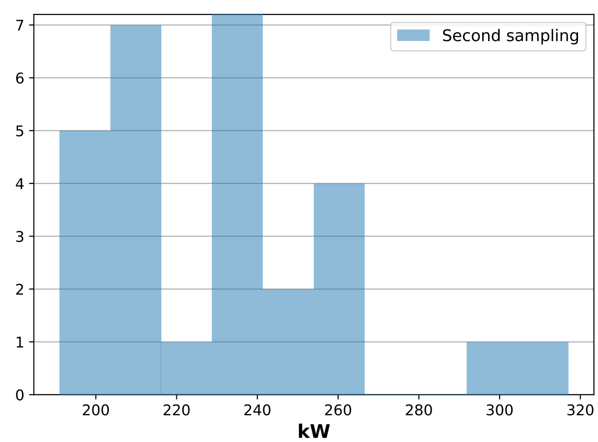
Three different histograms randomly sampled from the fitted PDF.



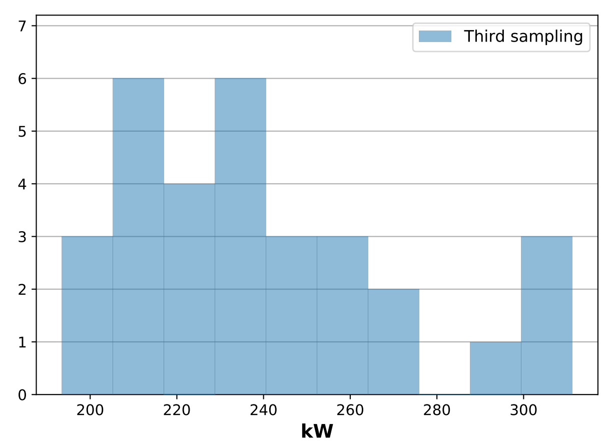
(a) *Histogram of the dataset (original).*



(b) *Histogram of the first sampling.*



(c) *Histogram of the second sampling.*



(d) *Histogram of the third sampling.*

Appendix B. Stages of the thesis and associated products

Designing a methodology with the capabilities described in chapter 2 required to follow an exploratory process. The exploratory process evaluated the suitability of computer software, heuristic, traditional and hybrid formulations to carry on the study of the dissertation. This appendix provides a brief description of the study's path before reaching the final formulation presented in Section 2.1. Additionally, this appendix presents some of the advantages and drawbacks of the methodologies, and the reason why they were discarded. Refer to the cited publications in each section for an extended evaluation of the methodologies.

Literature review

The idea of this stage was to explore different sizing methodologies and different DSM strategies. Additionally, this stage search in the available literature the different ways of integrating DSM in the sizing of IMGs. The literature review stage produces the candidature dissertation and two conferences (Bastidas et al., 2017; Oviedo-Cepeda et al., 2017).

Use of software to perform the sizing

At this stage, the study analyzes the capabilities of different commercial and academic software to perform the sizing of the IMG. The study tried Homer Pro, DER-CAM, and RETScreen. The study published an attempt to model a price-based DSM using Homer Pro in a conference (Oviedo-Cepeda et al., 2018). The work integrates the price-based DSM into the sizing problem with an optimization problem. The work proposes an algorithm to create synthetic load profiles considering customers' home appliances. The optimization formulation inputs the synthetic load profile and returns the modified load profile with the respective price-based DSM. However, due to the software's limited capabilities to model different DSM strategies, the idea of using preexisting software was abandoned.

Integration of dispatch strategies with rule-based controllers

At this stage, the study designed its first sizing algorithm that integrates DSM in the planning of IMGs. The first sizing algorithm incorporates a rule-based dispatch strategy into the optimization formulation. However, this algorithm faces a combinatorial problem. The study proposes to design a heuristic algorithm to avoid performing an exhaustive search. The heuristic algorithm reduces the space search for the sizing of the IMG. The work compares the results of the heuristic algorithm with Genetic Algorithms and an exhaustive search. However, a considerable drawback of this approach is the lack of an optimization formulation for the dispatch of energy sources. Reference (Oviedo-Cepeda, Largo, et al., 2020) shows the results of the work.

Integration of dispatch strategies with optimal criteria

This stage uses Integer Linear Programming (ILP) to dispatch the energy sources to improve the drawbacks of the previous approach. This formulation uses the same heuristic approach to compute the sizing of the IMG designed in the last stage. However, like the previous approach, this formulation faces a combinatorial problem, representing a considerable drawback. Reference (Oviedo-Cepeda, Duarte, et al., 2020) publish the results of this analysis.

Sizing and dispatch using one single formulation

The study proposes to use a single formulation to face the combinatorial problem. One single formulation that does not separate the sizing and the dispatch as separate formulations avoid dealing with combinatorial problems. The study uses Disciplined Convex Programming (DCP) to create the formulation. DCP is a framework to design and solve convex problems (Agrawal et al., 2018). Equation (64) presents the general formulation of a convex problem:

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & a_1(x) \\ \text{subject to} \quad & b_i(x) = 0 \quad i = 1, \ldots, B, \\ & c_i(x) \geq 0 \quad i = 1, \ldots, C \end{aligned} \tag{64}$$

where $x \in \mathbf{R}^n$ is the optimization variable, $a_1 : \mathbf{R}^n \to \mathbf{R}$ is a convex objective function, $b_i : \mathbf{R}^n \to \mathbf{R}$, $i = 1, \ldots, B$ are convex inequality constraint functions, and $c_i : \mathbf{R}^n \to \mathbf{R}$, $i = 1, \ldots, C$ are affine equality constraint functions.

The study designed the incentive-based DSM (Oviedo-Cepeda, Khalatbarisoltani, et al., 2020), and the price-based DSM strategies using DCP formulations (Oviedo-Cepeda, Serna-Suárez, et al., 2020). A study of the effects of a price-based DSM over the sizing of the BESS is presented as well in (Oviedo-Cepeda et al., n.d.). However, the formulation used for these studies is deterministic. Moreover, the formulation do not consider a way to validate the obtained results, representing a drawback for the formulation.

A single stochastic formulation for the sizing and dispatch

The study proposed to design a stochastic methodology to address the drawbacks of the previous formulation. Additionally, the new methodology proposed simulating the IMG operation to validate the sizing results. The study proposed to use Disciplined Convex Stochastic Programming (DCSP) for the design of the methodology. DCSP builds on principles from stochastic optimization and convex analysis, representing a considerable advantage to build the desired methodology (Ali et al., 2015). Using a formulation based on DCSP reference (Oviedo-Cepeda, Roche, et al., 2020) presents a comparison of different DSM strategies. However, the study uses one single representative year for the sizing of the IMG, which can be considered as a drawback.

A multiyear stochastic formulation for the sizing and dispatch

The final methodology of the study uses the principles of DCSP to build the optimization formulation. However, this methodology uses a multiyear approach instead of a single year approach. Single year methodologies implicitly assume that all the years will be the same during the project's lifetime. The multiyear approach allows evaluating the performance of the IMG yearly. Additionally, the multiyear approach allows the study to integrate future cost projections of energy sources easily. Section 2.1 describes the final methodology used for the study.

Appendix C. Comparison of the proposed formulation against other methods in the literature

As discussed in the introduction and the literature review sections, the problem of sizing, energy dispatch, Demand Side Management (DSM), and tariff settings had been previously studied. However, the literature review could not identify a work that combines the four aspects of a unified test bench to evaluate different DSM strategies. In this regard, the present thesis proposed the evaluation framework and a unified test bench to compare the performance of different DSM strategies. Thus, the study can not compare the proposed methodology to another methodology that integrates the same four aspects. Such a methodology is not available in state of the art yet. Nevertheless, the study can compare isolated aspects of the methodology as the optimal sizing or optimal dispatch to the methodologies that do a similar analysis in the state. Additionally, the methodology proposes its way of validation. Section 4.4 presents a comparison of the methodology's optimal sizing with the sizing results of the software HOMER Pro. Section 4.4 presents the quantitative results of other methodologies that perform optimal sizing and DSM in state of the art and evaluates the possibility of comparing the proposed methodology with their results. Finally, section 4.4 presents an alternative way of validating the proposed methodology. The alternative way of validation was proposed during the thesis's development, and the results are published in (Oviedo-Cepeda, Roche, et al., 2020).

Optimal Sizing comparison

As discussed in the introduction and the literature review sections, several studies in the literature perform the optimal sizing of Islanded/Isolated Microgrids (IMGs). These studies integrate an optimization formulation that depends on the types of mathematical models selected to represent the energy sources. For example, suppose a Battery Energy Storage System (BESS) uses a Mixed Integer Programming (MIP) model for the charge and discharge. In that case, the optimization formulation of the sizing will follow the MIP framework. Suppose, on the other side; the energy source models use nonlinear sources. In that case, the optimization formulation will follow a nonlinear approach. If the energy source models are convex, then the sizing formulation will follow a convex approach. However, even if all the above models' inputs are the same, the results will be different because the optimization formulations have different assumptions (in this example, for the energy sources models). Nevertheless, each of the optimization formulations' solutions will be optimal, even if the results are different.

Consider, for example, the HOMER Pro software. As described in the Users Guide, the software can provide optimal results for the sizing on IMGs. The underlying mathematical premise of HOMER is quite simple. HOMER uses a rule-based controller to dispatch the energy sources and a heuristic search over a grid of possible combinations of capacities of energy sources, similar to the thesis work proposed in (Oviedo-Cepeda, Largo, et al., 2020). Due to its simplicity, the HOMER software can compute hundreds of different combinations of energy source capacities and provide the optimal sizing of an IMG. Moreover, due to the simulation of the energy sources' behavior, HOMER Software can integrate sophisticated energy sources' models. These two characteristics make HOMER a world wide recognized software for the sizing of IMGs.

The study compares the study case results with the HOMER Pro software. However, the proposed method integrates the sizing and the optimal energy tariff setting, the optimal dispatch, and the optimal Demand Side Management, everything for multiyear or stochastic approaches. Thus, to perform the comparison, the study should reduce the complexity of the proposed optimization formulation and create a new optimization problem capable of providing only the optimal sizing.

The originally proposed methodology allows choosing the percentage of electrical demand that is sensible to the DSM. So, the deactivate the effects of the DSM, the percentage of demand sensible to the DSM was defined as zero ($D_t^{edr} = 0$ in Equation 69). Additionally, the selected tariff for the comparison was selected to be flat. The original methodology allows to define the percentage of participation of different investors and guarantee that those investors recover their investments. So, those constraints need to be eliminated. Finally, to increase the simplicity, some terms of the original objective were deactivated as well. The final version of the new optimization problem proceeds as follows:

$$\zeta = \sum_{u=1}^{U} C_u I_u \tag{65}$$

$$\vartheta = \sum_{t=1}^{T} \sum_{u=1}^{U} \lambda_{u,t} E_{u,t} \tag{66}$$

$$\mu = \sum_{t=1}^{T} \sum_{u=1}^{U} \Lambda_{u,t} E_{u,t} \tag{67}$$

$$X_1 = \arg\min_{C_u, E_{u,t}} \sum_{i=1}^{I} \varphi_{i,\zeta} \zeta + \varphi_{i,\vartheta} \vartheta + \varphi_{i,\mu} \mu \tag{68}$$

$$D_t^{dr} = D_t^{fix} + D_t^{edr} \tag{69}$$

$$\sum_{t=1}^{T} \sum_{u=1}^{U} E_{u,t} - EE_t + LE_t - D_t^{dr} = 0 \tag{70}$$

$$LPSP = \frac{\sum_{t=1}^{T} LE_t}{\sum_{t=1}^{T} D_t^{dr}} \tag{71}$$

$$EPSP = \frac{\sum_{t=1}^{T} EE_t}{\sum_{t=1}^{T} D_t^{dr}} \tag{72}$$

Once the study defined the new optimization formulation, it is possible to compare the results with the software HOMER Pro.

Additionally, to the GHI, wind and load information, HOMER should receive the information of Table 7 for the project's main configuration and the information of 8 for the energy sources. Moreover, the study should specify the type of dispatch that HOMER should use for the

Figure 43

Global Horizontal Radiation in HOMER Pro software.

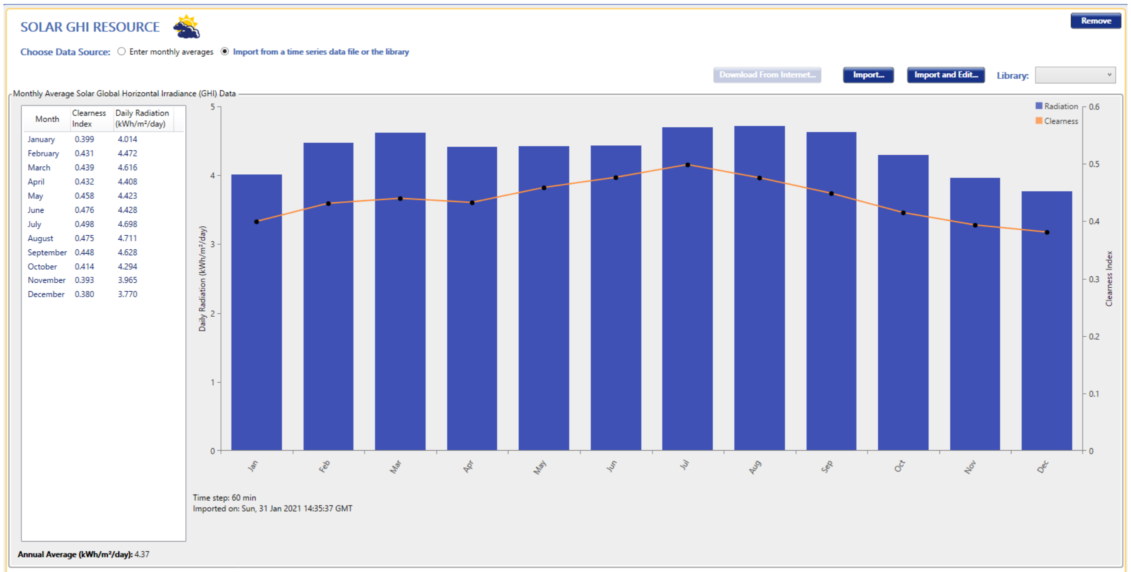


Figure 44

Wind speed in HOMER Pro software.

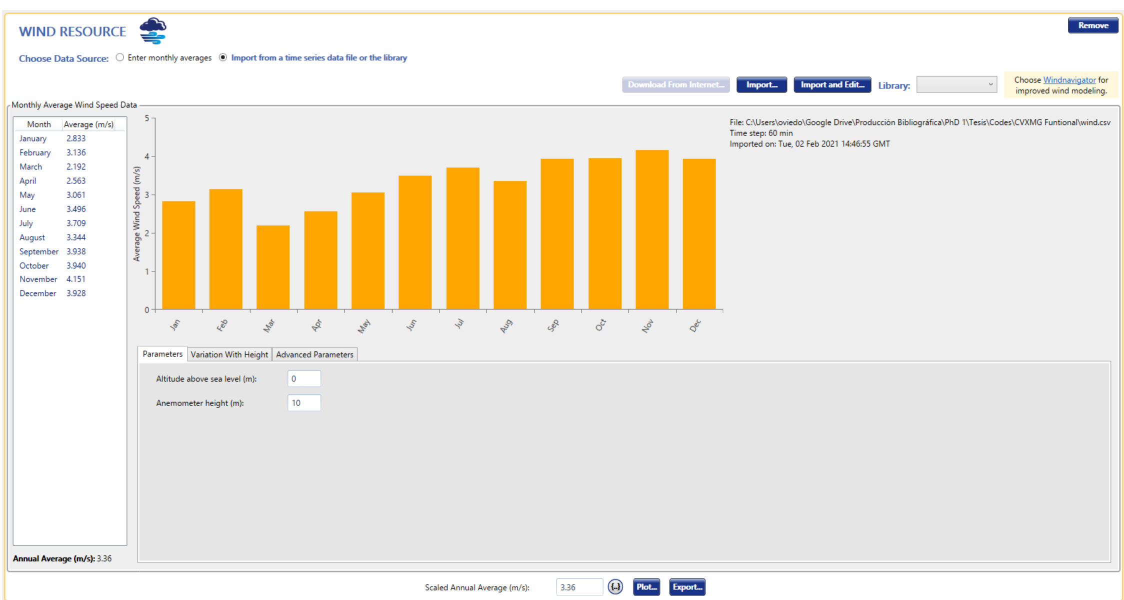
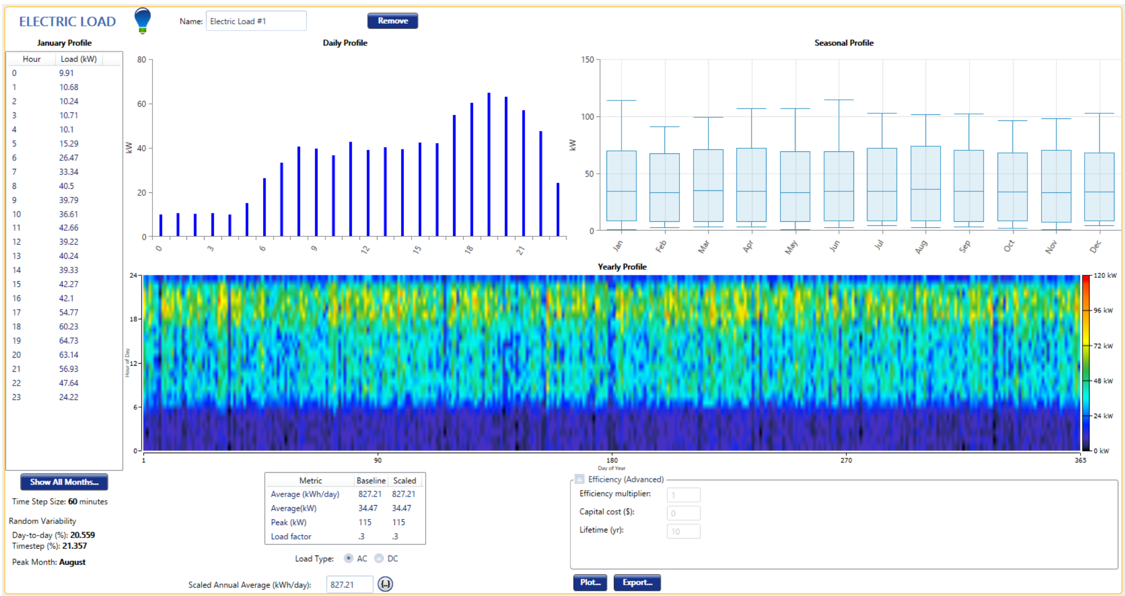


Figure 45

Electrical Demand in HOMER Pro software.



optimization.

HOMER Pro software provides four different types of controllers to perform the sizing of the IMG. The first type of controller is the *Cycle Charging strategy*. According to the HOMER user guide, The cycle charging strategy is a dispatch strategy whereby whenever a generator needs to operate to serve the primary load, it operates at full output power. Surplus electrical production goes toward the lower-priority objectives to prioritize: serving the deferrable load, charging the storage bank, and serving the electrolyzer.

The second type of controller is the *Load Following*. According to the HOMER user guide, the load following strategy whereby whenever a generator operates, it produces only enough power to meet the primary load. Lower-priority objectives such as charging the storage bank or serving the deferrable load are left to the renewable power sources.

The third type of controller is the *Homer Generator Order*. According to the HOMER user guide, the generator order dispatch algorithm follows the order of priority defined by the user in a table. The generator order dispatch will use the first row in the table that meets the required operating capacity. The battery will be used whenever it permits using an earlier row in the generator order.

Finally, the fourth type of controller is the *Combined Dispatch*. According to the HOMER user guide, in every time step, the combined dispatch decides which is the cheapest decision to make: either use Load Following or Cycle Charging strategies.

Once the software HOMER has been completely configured according to the study case, it is possible to start performing the sizing of the IMG. The study evaluated the four types of controllers' sizing results in HOMER Pro software and compared them to the proposed algorithm's obtained results. Table 36 shows the results comparison.

Table 36

Values of the input parameters for the energy sources.

Source	Cycle Charging	Load Following	Generator Order	Combined Dispatch	Proposed model	Units
Diesel Gen.	130	130	130	130	43	kW
PV	145	147	143	176	248	kW
BESS	422	210	192	504	309	kWh
Wind	0	0	0	0	0	kW

Table 36 shows that the proposed sizing methodology reduces the diesel generator capacity by 66%, and increases around 62% the capacity of the PV capacity. In contrast, the BESS capacity relies on the boundaries of the HOMER results. However, it is crucial to notice that HOMER fixes the diesel generator's value to guarantee the stability of the IMG. The consideration of stability modifies the sizing results by reducing the PV capacity. The proposed methodology does not consider the stability effects over the sizing of the IMG.

The study considered the alternative of comparing the results of the proposed formulation with DER-CAM. DER-CAM, different from HOMER, allows integrating an optimal dispatch to the optimal sizing of the IMG. However, DER-CAM does not allow importing the GHI, the wind speed, or the load, as HOMER allows. Not using the same input data for the problem will provide different sizing results, which will not add any value to the comparison study.

Integration of Sizing and Demand Side Management comparison

As discussed in the introduction and the literature review sections, some articles evaluate the impacts of Demand Side Management over the sizing of IMGs. As an example of this, Lan Zhu et al. (2014) uses the Integrated Resources Planning framework to measure the results of applying an optimal direct load control (DLC) strategy in a microgrid. They argue that microgrids' load is less than the load in the power system and is more specific and controllable. Despite that the models of DLC have several years of study in the literature, they introduce a model proposed by Kurucz et al. (1996). The model uses an integer linear programming approach and can use different control periods. The model is selected due to its simplicity and feasibility to be applied in the planning phase of the microgrid. The work presents the models used for the renewable generators, non-renewable generators, and storage systems in the microgrid. Afterward, the algorithm to combine the microgrid planning and DLC is introduced.

An optimization problem is formulated to perform the DLC and the planning of the microgrid. The optimization problem is formulated to minimize the net present value of the microgrid as follows:

$$f = min[f(c_1) + f(c_2) + f(c_3)] \tag{73}$$

Where $f(c_1)$ is the initial investment costs, $f(c_2)$ is the initial investment related to the installation of the needed technologies to perform the DLC, and $f(c_3)$ are the system operational costs. The decision variables are the planning capacity X_k of each generator k, the output power of generator k at time t, the number of directly controllable loads $e(i)$, and the capacity of the controllable load m. The constraints of the problem are presented as follows:

$$\sum_{k=1}^{N_s} P_k(t) \geq P(t) \tag{74}$$

$$X_k \leq X_{kmax} \tag{75}$$

$$P_k(t) \leq X_k \tag{76}$$

$$S_{min} \leq S(t) \leq S_{max} \tag{77}$$

$$P_{SBmin} \leq P_{SB}(t) \leq P_{SBmax} \tag{78}$$

$$-P_{SB}(t) \leq (S_{max} - S(t))\alpha_C \tag{79}$$

$$m \leq m_{max} \tag{80}$$

$$\sum_{i=96(d-1)+25}^{96d} be(i) \leq m \tag{81}$$

Equation 74 is used to guarantee that the generated power is enough to supply the load all the time. Equation 75 is used to guarantee that all the planned Xk generators are not greater than the previously determined capacity. Equation 76 is used to guarantee that all the X_k generators produce less power than the allowed at any time. Equation 77 is used to set the limits of the state of charge for the batteries. Equation 78 is used to set the power limits allowed for the batteries. Equation 79 is used to set the maximum charge rate for the batteries. Equation 80 is used to control the maximum capacity of installed controllable load, and equation 81 is used to regulate the maximum capacity of the desired controllable load in the day.

The study case results show that the proposed model provides an effective approach for the least cost planning in microgrids using DSM in IMG planning. The study evaluated the changes in diesel generator installed capacities, PV, BESS, and Wind. The study considered several configurations for the IMG. Table 37 shows the results of the study.

The results of the study showed that by considering that the diesel generator reduces its

Table 37
Results of the study presented in (Lan Zhu et al., 2014)

Source	No DLC	DLC = 50 kW	DLC = 100 kW	Double cost of DLC	Partial period	Units
Diesel Gen.	200	160	150	160	175	kW
PV	100	100	100	100	100	kW
BESS	100	100	100	100	100	kWh
Wind	0	0	0	0	0	kW

capacity between 12.5% and 25%. The study chooses to maintain the installed capacities of PV and BESS constant.

In 2018 the continuation of the study mentioned above was published. In the second work, Zhu et al. (2018) includes the interruptible loads (IL) and shiftable loads (SL) into the microgrids. The interruptible loads are based on a contract between the customer and the power supply company or an independent system operator (ISO). The customer reduces the electrical consumption for a monetary reward provided by the power supply or the ISO in the contract. The Power supply and the ISO use this agreement to reduce the customers' load when is needed. Different objectives of pure interruptible loads problems could be formulated as the minimum purchase cost of interruptible loads in the power market, minimum cost commitment for frequency response, or minimize the system operational costs. Common algorithms used for the solution of the interruptible loads' optimization problems could be priority heuristic algorithm, sensitivity-based method, dynamic programming, mixed integer programming, binary particle swarm optimization amongst others.

On the other side, the shiftable loads reduce the maximum power demanded from the generators but not the net energy consumption. However, a reduction in the demanded power at the peak time can reduce the needed installed capacity for a project. The studies in shiftable loads are focused on reducing the peak load, reducing the operating system costs, and maximizing the customer's revenue for frequency regulation. Standard algorithms used to solve the shiftable load's optimization problems are integer linear programming, glow-worm swarm particles optimization, and dynamic programming, amongst others (Zhu et al., 2018).

In the Integrated Resources Planning model, the interruptible loads and shiftable loads are considered as optional power sources that can be modeled as negative loads:

$$P'(t) = P(t) - \sum_{i=1}^{M}[S(i,t)C(i)] - P_{SL,out}(t) + P_{SL,in}(t)\forall t = 1,2,\ldots,N \tag{82}$$

Where $P(t)$ is the total forecasted load for time period t; $P'(t)$ is the new load for time period t after interruptible loads and shiftable loads are applied; N is the number of periods per year (1 hour as a unit); M is the number of users that sign an agreement for interruptible loads with the power supplier or the ISO; $S(i,t)$ is one if the user i is selected for providing interruptible loads during the period t and 0 otherwise; $C(i)$ is the interruptible loads capacity of power that user i can disconnect at time t; $P_{SL,out}(t)$ is the curtailed load of shiftable loads on the period t, $P_{SL,in}$ is the increased load of shiftable loads on the period t. The objective of the application of the Integrated Resources Planning model is to minimize the costs of the planning of the microgrid; the functions are described as follows:

$$F1 = min(Z_W + Z_{PV} + Z_{SB} + Z_{DE} + Z_{IL} + Z_{SL} + Z_C) \tag{83}$$

Where Z_W + Z_{PV} + Z_{SB} + Z_{DE} + Z_{IL} and Z_{SL} are the initial investment, operational and maintenance costs of wind turbines, photovoltaic panels, energy storage batteries, diesel generators. IL, SL and Z_C the cost of the carbon trading produced for the reduction in the use of the diesel generators. The decision variables are defined as:

$$X1 = [S_W, S_{PV}, S_{DE}, S_{SB}, P_{DE}(t), P_{SB}(t), P_{SL,out}(t), P_{SL,in(t)}, S(i,t), C(i), T_d(i)] \tag{84}$$

Where S_W, S_{PV}, S_{DE}, S_{SB} denote the capacity of wind turbines, photovoltaic batteries, diesel generators and the energy storage batteries respectively; $P_{DE}(t)$, $P_{SB}(t)$ are the output power of the diesel generators and energy storage batteries; $T_d(i)$ is the duration of the interruption for user i

each time.

The constraints of the problem are related to the power balance, capacity, and output power of each generator, battery operation, load curtailment, interruption duration, maximum number and time interval of interruptions for interruptible load, and power balance for the shiftable load.

The solution of this optimization problem is compared to the solution obtained using a traditional planning model. The comparison problem is formulated in two stages; first, estimate the new load after applying the interruptible loads and shiftable loads. Second, estimate the needed capacity of the Distributed Generators in the microgrid. The decision variables for the second optimization problem are:

$$X2 = [P'_{max}, P_{SL,out}(t), P_{SL,in}(t), S(i,t), C(i), T_d(i)] \tag{85}$$

Where P'_{max} is the maximum load for the microgrid after controlling the interruptible and shiftable loads. The objective function is to minimize P'_{max} and the only constraint is to limit the maximum peak load. Table 38 shows the results of the optimization problem.

Table 38
Results of the study presented in (Zhu et al., 2018)

Source	No DSM	DSM	clipping model	Units
Diesel Gen.	198	186	188	kW
PV	100	100	100	kW
BESS	100	100	100	kWh
Wind	33	33	33	kW

The simulations show that applying Demand Side Management using interruptible and shiftable loads reduces the installed capacity of the diesel generator 6%, while the pure clipping model only reduced 5%. The study chooses to maintain the installed capacities of PV and BESS constant.

An alternative way to evaluate the performance of the proposed methodology

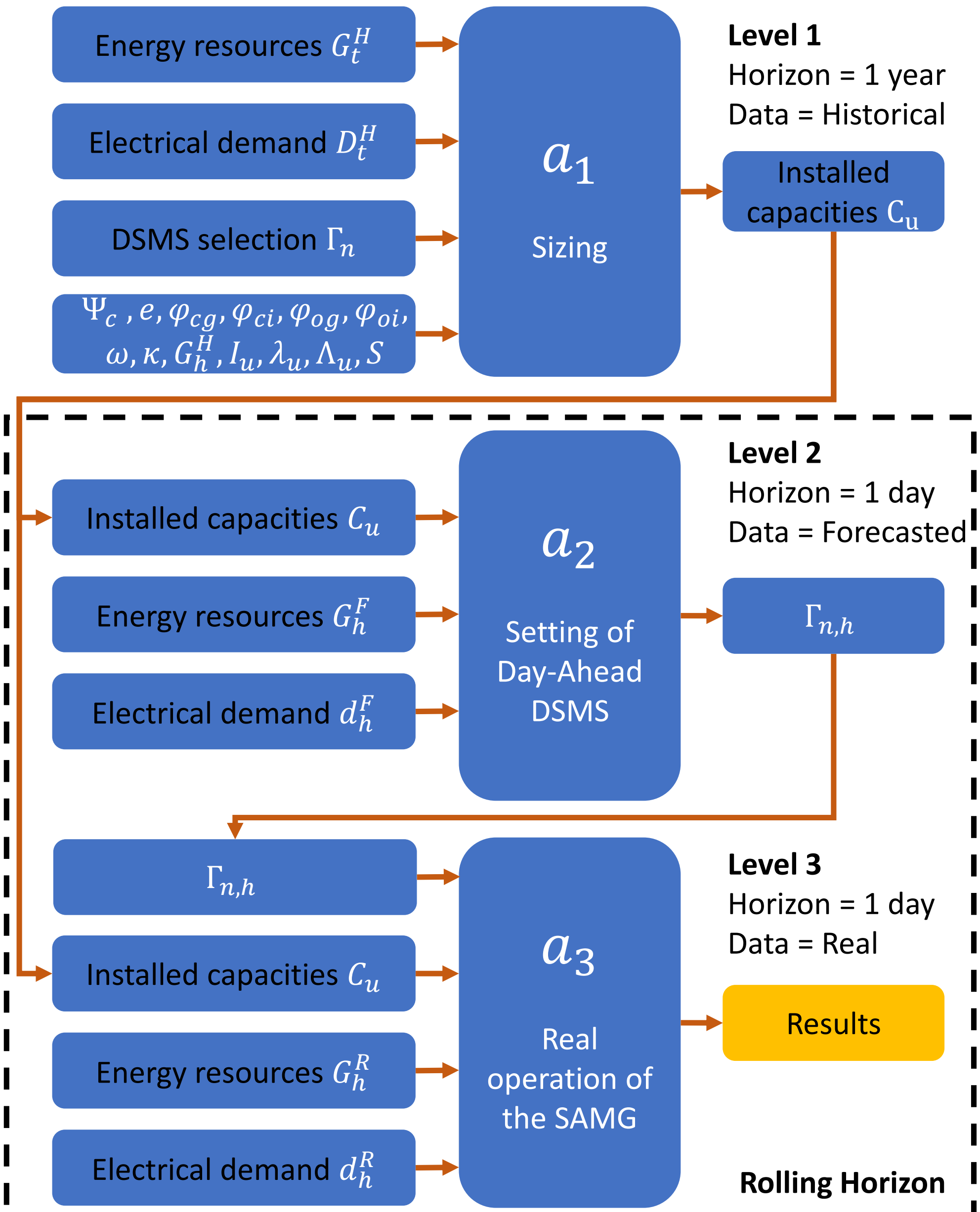
Performing a comparison of the proposed methodology results with other studies in the literature is difficult due to the differences in the optimization methods, the inner assumptions of the methodologies, and the lack of data to perform the comparison (load or primary energy resources). Thus, as proposed in (Oviedo-Cepeda, Roche, et al., 2020), there is an alternative way to validate the proposed methodology's results. In (Oviedo-Cepeda, Roche, et al., 2020), the thesis study proposes performing the IMG sizing to compute the DSM signals and simulate the microgrid behavior in separate stages. This proposition allows the study to consider three different optimization problems that are naturally related to the others. Figure 46 shows the three proposed optimization levels.

The article proposes a method to validate the results of the methodology. However, more than the method itself is the underlying assumption that it is more important. The article considers three optimization problems separately. The first optimization problem is the sizing problem. The methodology assumes that the first optimization problem uses data generated using the Monte Carlo approach described in Appendix 4.4. Therefore, the first optimization problem is an optimization problem with incomplete information (Stochastic approach). The second optimization level computes the DSM signals one day ahead. The second optimization level considers that the capacities were found in the first optimization level. Thus the second level already has fixed the capacities of the energy sources. The second optimization level also integrates uncertainties in the forecasts. Therefore, the second optimization level also is a problem with incomplete information (Stochastic approach). Finally, the third level performs the dispatch of the energy sources once the DSM signals are received and once the uncertainties in the forecasts are revealed. Consequently, the third optimization problem has complete information (Deterministic approach).

By combining three different optimization problems with incomplete and complete information, it is possible to simulate how the microgrid will operate. Moreover, the article's proposed approach allows estimating how the results of the first optimization level are related to the third optimization level. This analysis is of particular interest because it allows the study to compare the results of an optimization problem with incomplete information with the results of an optimization

Figure 46

Graphical description of the proposed methodology.



problem with complete information. In practical terms, this means that it is possible to measure how bad the estimations performed in the sizing were compared to the results of the simulation of the microgrid operation. Even more, the analysis allows defining as an input parameter the percentage error of the forecasts. Thus, it is possible to evaluate the errors of the sizing in any particular location if the forecasts' percentage error is known (electrical demand and weather). Figure 47 shows the impact of the errors in the forecasts over the sizing of the study case considered in the (Oviedo-Cepeda, Roche, et al., 2020).

Figure 47

Percentage differences between the results of the first level and the third level for the five DSMs and the base case.