

École polytechnique de Louvain

Reducing the variability of renewable energies

Consistency in integrating a solar system in two different regions both from an economic and environmental point of view

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Abstract

Climate change is a growing concern since the 20th century. Our energy consumption is one of the major reasons of the steady increase in green house gases emissions and the demand in energy has been continuously increasing with, especially, a steep increase for developing countries. Thus, to cope with the rising demand in electricity and to attempt mitigating the climate change, the integration of intermittent renewable energy sources, such as solar and wind, accelerates worldwide. To match these energy sources with energy demand, storage systems are deployed. Stationary batteries are considered as one the key flexibility options for future energy storage systems. However, their production is cost and green house gas intensive and studies are required to verify the consistency in integrating these technologies. This paper focuses on photovoltaic stand-alone systems with three different batteries: lead-acid, NMC lithium-ion and vanadium redox flow battery. A typical dwelling in Stockholm, capital of Sweden, as well as a specific dwelling type in Kigali, capital of Rwanda, are chosen as they are two very different geographical locations linked with a specific energy context. The interests reside in the differences in solar potential and carbon footprint of a dwelling relying solely on the grid as well as its cost. Besides, to determine the optimal capacity of batteries, simulations are performed in literature assuming fixed input values which are inherently uncertain in reality, leading thus to a drastic mismatch between predicted performances and performances in real world. Thus, to avoid this issue, parameters were assigned with some stochasticity and were propagated through a Python-based hybrid renewable energy system model. Minimizing cost and green house gases impact were the driving objectives of the system model and designs with optimal average performance were compared to designs with robust performance. In the case of Rwanda, the self-sufficiency ratio was also considered as Sub-Saharan Africa faces important duration of power outages throughout the year. The results illustrate that, in Stockholm, from any point of view, the use of battery is not interesting. The economically preferable solution is a PV exclusive system but fails to lower overall green house gases emissions compared to a dwelling entirely relying on the grid. In Kigali, small PV system combined with an important grid contribution is the most interesting choice on an economic point of view. Conversely, a self-sufficient energy system composed of an important battery deployment is environmentally optimal, but it is costly. As the deployment of batteries increases the dwelling's self-sufficiency ratio, it may be interesting for the owner as power outages are frequent. Trade-off between an optimized solution from an economic point of view and a system with a higher self-sufficiency ratio but a slightly higher price can then be made depending on the owner's priorities.

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Nomenclature

Acronyms

BOP Balance Of Plant

CAPEX Specific capital expense, €/kWh or €/kW

CAPEX_a Annual capital expense, €

CDF Cumulative Density Function

COP Conference Of Parties

DOD Depth Of Discharge, %

ESS Energy Storage System

GHG Green House Gases

GWP Global Warming Potential

GWP_a Annual global warming potential, $kg_{CO_2,eq}/year$

HRES Hybrid Renewable Energy System

LA Lead-acid

LCA Life-Cycle Assessment

LCOE Levelized Cost Of Electricity, €/MWh

LOO Leave-One-Out

NaS Sodium-sulfur

NMC Nickel Manganese Cobalt

NSGA – II Non-Dominated Sorting Algorithm

OECD Organisation for Economic Cooperation and Development

OPEX Specific operational expense, €/kWh or €/kW

OPEX_a Annual operational expense, €

PCE Polynomial Chaos Expansion

PDF Probability Density Function

PV PhotoVoltaic

PVSC PhotoVoltaic Self-Consumption

SOC State Of Charge, %

SSA Sub-Saharan Africa

SSR Self Sufficiency Ratio, %

TMY Typical Meteorological Year

UQ Uncertainty Quantification

VRF Vanadium Redox Flow

VRFB Vanadium Redox Flow Battery

Symbols

E_{grid} Hourly grid energy consumed, kWh

E_{load} Hourly energy consumed, kWh

$G_{c,a}$ Annual grid cost, €/year

P_{load} Hourly load demand, kW

$R_{c,a}$ Annual replacement costs, €

Chapter 1

Introduction

Electricity production has been steadily increasing in order to comply with the demand for a couple of decades [1]. In fact, the consumption in electricity for countries that are not part of the Organization for Economic Co-operation and Development (OECD) has taken a bigger rise since the beginning of the 21st century while the increase in the consumption of electricity for OECD countries took a lower pace since 2010 [2]. It is not to forget that this total gross electricity production comes along with several environmental impacts. Currently, the most popular one is the climate change due to Green House Gases (GHG) mainly composed of carbon dioxide, CO₂ [3]. Indeed, the emissions of GHG have grown at a faster rate from 2000 to 2010 than they had in the previous three decades. Facing the increasing curve of GHG emissions with the world energy consumption, there is a critical need to switch from the important use of fossil fuels to a majority of renewable energies in order to lower the emissions [1]. One of the priority objectives for the upcoming years is the abatement of global climate impacts as it has been recently discussed during the Conference of Parties (COP). Therefore, in order to cope with the rising demand in electricity and attempting to mitigate climate change to comply with the Paris agreement in 2015, many governments started deploying renewable power generation units [4].

To comply with the Paris agreement, the total share of renewable energies must rise from around 18% of total final energy consumption, in 2015, to around two-thirds by 2050 in which the main part will be from solar and wind resources [5]. Besides, solar PhotoVoltaic (PV) panel is at the moment the fastest growing distributed energy production unit and could potentially reach 22% of global electricity production in 2050. In 2018, installed and grid-connected solar PV power reached 480 GW which was, already, a 20% increase compared to year 2017 (386 GW). In the next ten years, solar PV power installations are expected to reach 2,840 GW globally, which represents an increase of factor six, and even 8,519 GW by 2050 [6]. However, it is not to forget the stochastic and intermittent nature of the solar resource due to daily and seasonal fluctuations. Being a main contributor in the upcoming big share of renewable energy units in the years to come, major challenges for the energy system are expected. A non-exhaustive list of technical and economic challenges will be load supply despite intermittences, power quality due to distributed power units, cost of these technologies, and much more.

Storage technologies are solutions to compensate this intermittent behavior of solar energy since it allows to store excess of electrical energy converted from solar energy and to redistribute this energy at needed time. One of the key flexibility options for future energy storage systems are stationary batteries due to their high efficiency and quick response [7]. If the share of renewable in the energy framework wants to be doubled by 2030 to comply with

Paris' Agreement on climate change, stationary batteries could increase from an estimate of 11 GWh in 2017 to between 100 and 167 GWh in 2030 [8]. Batteries being, through their production phase, green house gases intensive, it is thus important to evaluate their environmental impact to study their renewable consistency in different applications. The focused application in this study is stand-alone PV-battery system with an additional look at a PV-battery community-scaled system in Stockholm. Three different battery storage technologies to be coupled with PV array are considered in the stand-alone case: lead-acid, NMC lithium-ion, vanadium redox flow battery. When evaluating community-scaled designs for Stockholm, sodium-sulfur battery will be added to the list. Each of these batteries are either mature and well-established technologies in the energy storage field or promising batteries in development. When used in an energy system, batteries have to fulfil multiple requirements at the same time. This can be, for example, low cost, long lifetime, high energy density and much more [7]. However, no battery presenting optimal results in each of these requirements exists. Compromises are necessarily made when one battery is chosen rather than another one. There is, therefore, an interest in testing different battery storage technologies in different contexts to ensure that the best one is used.

Lots of studies focus on economic aspects of renewable technologies without taking into consideration their environmental consequences. Also, most of these studies assess fixed values. However, performances of Hybrid Renewable Energy System (HRES) are mainly driven by parameters presenting stochastic behavior (e.g., stochasticity of solar irradiance, absence of uniformity on the production chain of PV panels or batteries that causes differences in climate impact, and much more). Simulated performances compared to real world performances then differ much with deterministic values and optimal designs from deterministic optimizations are highly sensible to the uncertainty of the input parameters in the real-world. Thus, in order to get designs with predicted behaviors that are close to reality and designs that are less sensible to real world uncertainties, robust design optimizations need to be conducted. Stochastic parameters are characterized based on an extensive list of literatures.

This paper, therefore, proposes a study that looks on the integration of PV-battery stand-alone systems in two different geographical contexts that are Stockholm, capital of Sweden, and in Kigali, capital of Rwanda, linked with their specific energy context (grid electricity price and grid carbon footprint). Minimizing cost and GHG emissions through robust optimizations are the driving objectives with an additional look upon SSR in the case of Rwanda in order to deal with frequent power outages.

Chapter 2

State of the art

Solar systems are intended for massive deployment, as it was outlined in the previous section, and they will, inevitably, need to rely on storage technologies. This section presents the actual state of the technologies in terms of solar system and more precisely in this work, small-scale solar systems. A focus on storage technologies state-of-the-art is also conducted in order to identify the best suited ones. Afterwards, state-of-the-art of the method to evaluate the environmental impact of such system design, namely Life Cycle Assessment (LCA), is introduced. Finally, a brief description of the actual way to proceed in term of robust design optimization is presented.

2.1 Small-scale PV systems

As it was previously said in the introduction, the fast-growing potential of PV panels combined with the urgent need to switch from fossil fuels to renewable energies benefits the emergence of PV-based system. Solar PV for electrification offers different possibilities of use that are grouped between two categories: grid-connected and off-grid appliances. Off-grid systems, as indicated by the name, do not have access to the grid and are thus fully self-sufficient. For both categories, distinction between the systems sizes can be made. This is mainly, the community scale mini-grid system and the stand-alone system [9].

2.1.1 Mini-grid system

Such installations are intended to provide energy, mainly electricity, to a number of consumers through an independent distribution grid which evolves apart from the national grid. Clean energy mini-grids quickly gained in importance recently. These types of mini-grids can be either combined to energy storage technologies that will store the excess of produced energy to return it later if necessary or they can also rely on diesel, as an example, to fulfil the potential gaps between production and demand when the system is deployed in off-grid configuration. Typical installed power of solar energy for this kind of installations lies in between 10 kWp to few MWp [10].

2.1.2 Stand-alone system

Stand-alone systems are small electricity production units connected to individuals, mainly households, to fulfil the electricity demand. As it is the case for mini-grid system, when relying on renewable energy sources, energy storage is of common use to compensate the gaps between production and consumption. Three main types of stand-alone can be differentiated.

These are pico systems for which the main goal is to power some electrical appliances, home systems to provide electricity to a whole household and productive systems to supply electricity to clinics, hotels, factories or others [10]. Typical installed power lies under 10 kWp of solar power for the PV array.

2.2 Energy storage systems

To solve this issue of intermittency, energy storage technologies are promising due to their ability to decouple production and consumption. A non-exhaustive list of typical energy storage systems is [3], [11]:

- Mechanical storage: compressed air, heat storage, flywheel energy storage and pumped-storage hydroelectricity.
- Electrical-electromagnetic storage: capacitor and super-capacitor.
- Electrochemical battery energy storage: Flow battery, Li-ion, lead-acid and sodium-sulfur.
- Thermal Storage: Pumped-heat electricity storage.
- Chemical storage: Hydrogen, synthetic natural gas and other chemical compounds.

TECHNOLOGY MATURITY CURVE

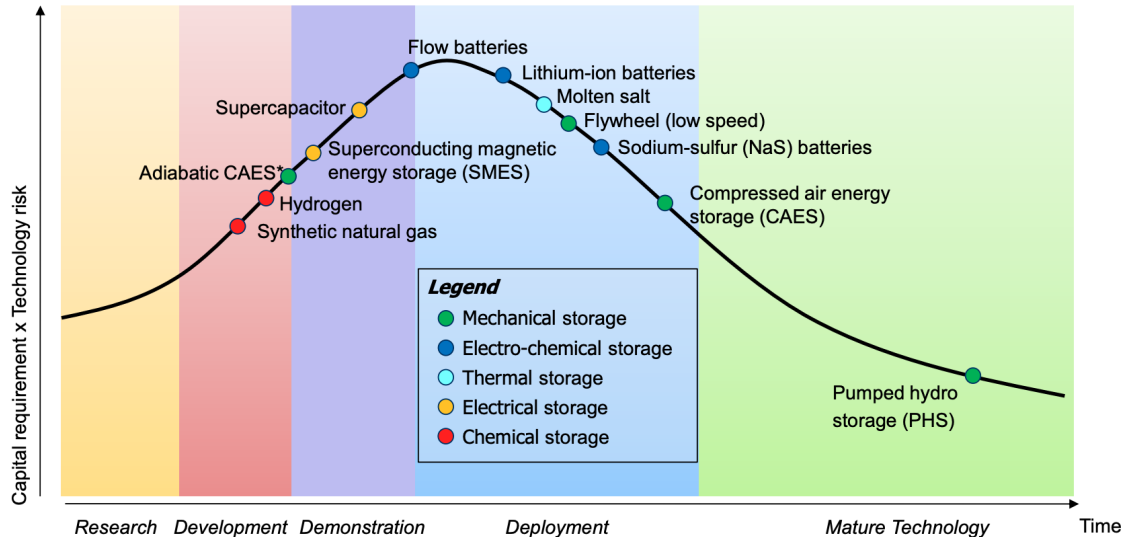


Figure 2.1: Maturity curve for representative Energy Storage Technologies [11]

These technologies are either mature or being freshly commercially available. Depending on their position on the maturity curve presented above in Figure 2.1, they exhibit different costs of deployment and environmental issues. The environmental issues can be multiple and include three major sub-categories [3]. These are the atmosphere, the water, and the land impact. The atmosphere includes the well-known climate change and air quality while the water quality is impacted by the discharge of contaminants, particularly from the mining of energy resources. The land impact category is impacted by energy transformation processes that usually produce solid waste. Therefore, there are multiple measures to quantify these

different types of pollution: $kg_{CO_2,eq}$, $kg_{SO_2,eq}$ or even kg_{PO_4P} . However, as already said in the introduction, only the carbon footprint will be of main interest in this study.

There is no optimal storage system valid in every situation. On contrary, for a specific situation, an energy storage system can be the optimal one but becomes no more optimal when looking at another specific situation [12]. The deployment of a specific kind of storage technology will depend on a multitude of criteria. These criteria are primarily based on technical requirements. Some of them are the required storage capacity, the available power production capacity, the depth of required discharge or power transmission rate, the discharge time, the efficiency, the durability (cycling capacity), and the level of autonomy. On the right-hand side, Figure 2.2 represents the limits of different storage technologies taking into account just two of the previously mentioned criteria: discharge time and power rating. Furthermore, economic, feasibility, and environmental impacts associated to these energy storage capacities should also be taken into account.

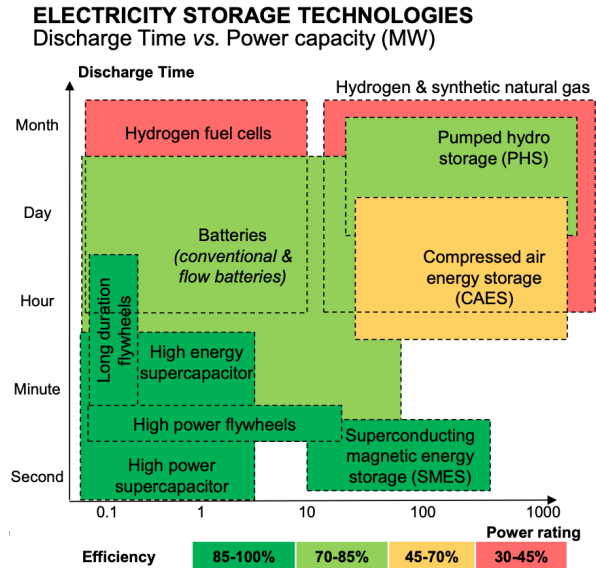


Figure 2.2: Requirements of various storage technologies depending on discharge time and power capacity with the specified range of efficiency. [11]

Having the previous information in mind, the type of application in which the Energy Storage System (ESS) needs to be used will give deciding guidelines to determine the adapted ESS. Some of the main applications are [7], [13], [14], [15]:

- Electric time shift (ETS): Energy is stored when electric prices are low and discharged when electric prices are high.
- Photovoltaics self-consumption (PVSC): End-consumers have their PV installation coupled with a battery to reduce their electricity bill.
- Primary regulation (PR): Energy is stored and released within seconds to respond to sudden peaks in order to avoid changes in grid frequency.
- Renewable support (RS): Energy is stored by RES operators in times of electricity production excess and released during high demands times.
- Energy management (community scale): A number of households share a common battery. This application centralizes the storage of excess energy production from households' own PV installation.
- Transmission and distribution investment deferral (T&D): Storage systems are used to extend the life of the existing T&D equipment by supporting peak demand times that would otherwise require system upgrades. In this way, investments can be avoided or deferred by a couple of years.

- Support of voltage regulation (SVR): Batteries are used to support the voltage of the grid to limit sudden oscillations (flicker). Balanced and smooth voltage in the grid is necessary for proper operation of equipment and prevents damages.

PVSC being one of the most promising technology in terms of carbon footprint and leveled cost of energy, as it has been observed from previous studies, is going to be the guideline of this thesis [7], [14].

Focusing on electrochemical batteries, it is important to mention the important role that they will have within the field of energy storage in a near future made of a high share of renewable power units generation electrical systems. They present several advantages which are their fast response time, high efficiency, large power bandwidth and can then serve to a wide range of applications, can be centralized or decentralized in on- or off-grid applications, low maintenance and much more. However, some drawbacks also exist, among which their relatively low service life, the limited capacity to resist to extreme temperatures that can be reached, leading to a degradation of the battery's performances, and charge time. It must also not be forgotten that their self-discharge rate as well as their relatively low energy density make them particularly not suitable for long-term energy storage. Other disadvantages in their production are their relatively high cost and GHG emissions, which is why there are emerging studies focusing on their environmental footprints. These advantages and drawbacks come differently depending on the battery type. Indeed, each variety of battery comes with its specific advantages and drawbacks. Besides, these factors should be taken into account in a life cycle analysis as a battery lifetime varies depending on the application [13].

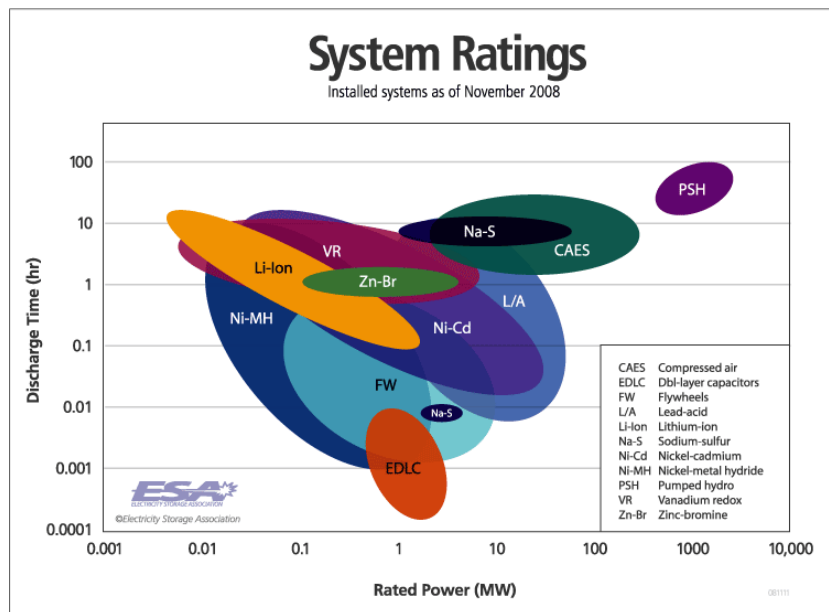


Figure 2.3: Requirements of the different batteries depending on discharge time and rated power from Electricity Storage Association

Zoom in of Figure 2.2 in the battery's area is shown in Figure 2.3. In the objective to create a better match between the variable solar electricity supply and the demand on a few hours to day timescale, batteries having moderate discharge time are needed. Concerning rated power, going for stand-alone system, there is no need to reach high values but, conversely, on a community scale this would be of much importance. Three different battery

types have been chosen for this thesis. These are lead-acid (LA), a specific Li-ion (made of nickel, manganese and cadmium, named thus NMC) and vanadium redox flow (VRF) battery. An additional sodium-sulfur (NaS) battery had been added for a community-scale study. This choice has not been made randomly. Lithium-ion batteries have been recently developed and are currently holding the biggest share of battery stationary storage (1.3 GW and 1.27 GWh) worldwide. Secondly, comes high temperature batteries, including NaS battery, with 171 GW installed power and 1.01 GWh. Thirdly, comes one of the oldest battery types which is lead-acid with 196 MW and 173 MWh. Finally, vanadium redox flow battery is relatively new as seen in Figure 2.1 and have an installed power of 114 MW and 412 MWh.

Note: All the techno-economical parameters characterizing the battery types can be found in Table A.3. The values are presented in ranges as the world is filled with uncertainties. However, it will be seen later that some of these stochastic parameters will be set as deterministic. Thus, mean values of the ranges are attributed to the latter.

A brief description of the four chosen batteries follows to highlight the main characteristics of each of them as well as to make the comparison between the different technologies possible.

2.2.1 Lead-acid battery

Lead-acid battery is of common usage for mini- or micro-grids as well as for stand-alone system. The principal reason comes from its main advantage that lies in being the cheapest battery. Furthermore, being the oldest battery storage technology and thus the most mature one, the uncertainties on the different parameters characterizing this battery are relatively small, leading thus to a better representation of reality. Other advantages are its low self-discharge as well as its low cradle-to-gate carbon footprint. However, the issues with LA batteries remain in their low lifetime expressed in number of cycles and more importantly in their low energy density. One could here notice the trade-offs that might already be interesting for further study. Indeed, compared to the NMC battery type, the LA one has low lifetime but is cheaper and has a lower cradle-to-gate footprint. The idea would be to evaluate the PV-battery system in a lifetime of 20 years to have a more consistent view on the differences that lies between the battery types for the different objectives of interest. The LA's cycle to failure has been designed looking at Figure 2.4.

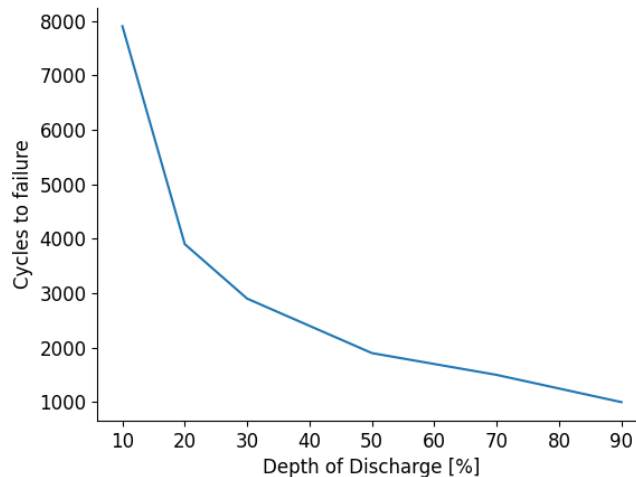


Figure 2.4: Depth of discharge vs lifetime in cycles [16]

2.2.2 Lithium-ion battery

Lithium-ion batteries are currently holding the biggest share in battery stationary storage. In 2016, 200 MW of Li-battery were used in grid-connected installations and this number is fastly increasing. Furthermore, lithium-ion battery presents a high scalability which makes them, consequently, viable for a stand-alone household scaled system as well as for a community-scaled system [17]. This can be verified looking at Figure 2.3.

More specifically, due to the large variety of possible lithium-ion batteries, the Nickel Manganese Cobalt (NMC) oxides battery has been chosen. This choice has been made for two reasons. First of all, it seemed more consistent in working with a particular lithium-ion battery as technical and economical parameters vary widely among the different lithium-ion batteries. Secondly, due to focusing on a particular battery, uncertainties are significantly lowered leading thus to a more robust uncertainty quantification. NMC batteries have the advantage of achieving very high efficiency, relatively high cycle lives, low self-discharge or even high value of energy density reached that is responsible for his widespread use in battery electric vehicle (energy density could reach values more than three times bigger than for lead-acid battery). It is however more expensive than the LA battery and has a relatively high cradle-to-gate carbon footprint (in terms of GHG emissions per kg of battery). The NMC's cycle to failure has been designed thanks to Figure 2.5.

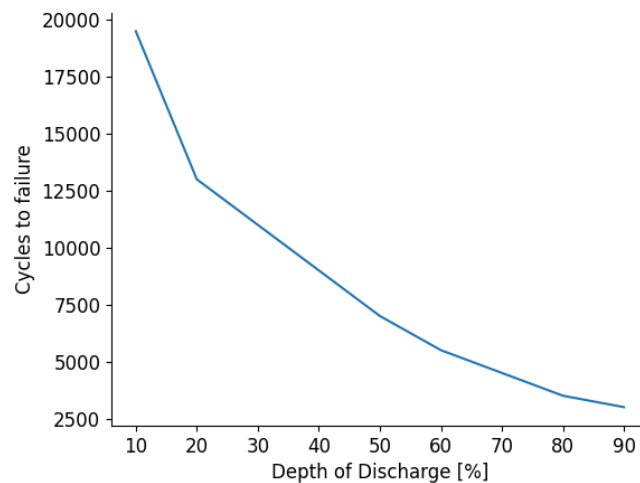


Figure 2.5: Depth of discharge vs lifetime in cycles [18]

2.2.3 VRF battery

A redox flow battery is a new emerging and promising type of battery. Its operating principle, strongly different from the other batteries previously presented, is illustrated in Figure 2.6. One can observe that a flow battery is designed in a way that it contains two electrolyte solutions separated by two distinctive tanks circulated through two independent loops [11],[19]. This more complex design allows the dissociation between power and energy.

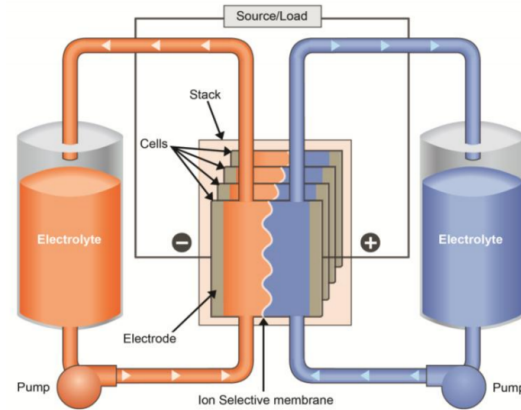


Figure 2.6: Operation principle of flow battery energy storage system [11]

As shown in Figure 2.3, this type of battery is highly scalable simply by variation of the storage tanks' size [20]. Thus, their use will be convenient for small stand-alone system as well as for community-scaled system [21]. This battery type has the advantage of having low cradle-to-gate carbon footprint when considered in $\text{kg}_{CO_2,eq}/\text{kg}$ but has, however, a very low energy density. It has an efficiency that lies between 70% and 80%. However, being a recent technology, its price is highly uncertain and quite high due to the recent breakthrough of the technology (see Figure 2.1). This battery also has the particularity of having a constant life cycle for different depth of discharge as seen in Figure 2.7. Therefore, VRF battery can sustain depth energy discharge without significant degradation of the performances [12], which is a considerable advantage compare to the other batteries.

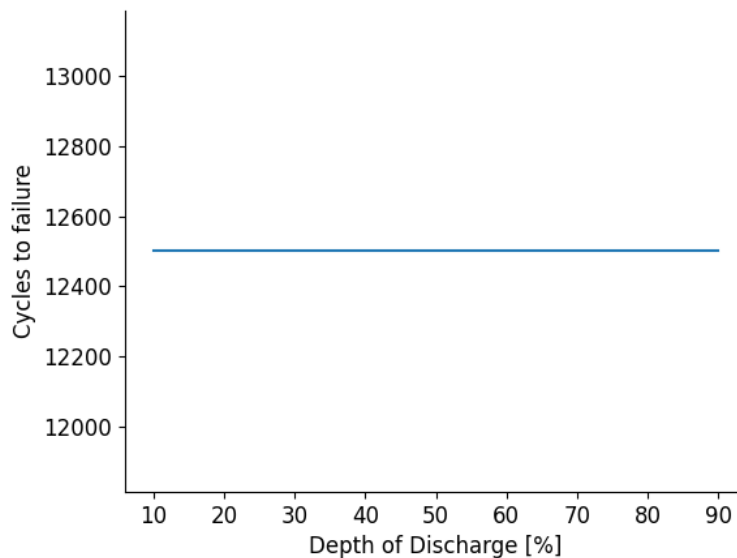


Figure 2.7: Depth of discharge vs lifetime in cycles [22]

2.2.4 NaS battery

High temperature batteries use the improved conductivity of the elements (i.e., sodium and sulfur in this case) when they are in molten state [20]. As it is shown in Figure 2.3, NaS batteries are most likely to be used in larger scale applications. In fact, actually, they are very often used in power applications such as peak shaving, power quality grid support system and much more [17], [21], [23]. Main advantages of this battery lie in its efficiency, its relatively long cycle life and energy density compare to LA battery. These last two are within values of the same order of magnitude as NMC battery. However, NaS batteries suffer from an issue, well expressed by the name of the battery group they belong to, which is the need to keep high temperature in order that the elements stay in molten state. Thus, there is a need for extra insulation as well as active heating [17]. The NaS' cycle to failure has been designed based on Figure 2.8.

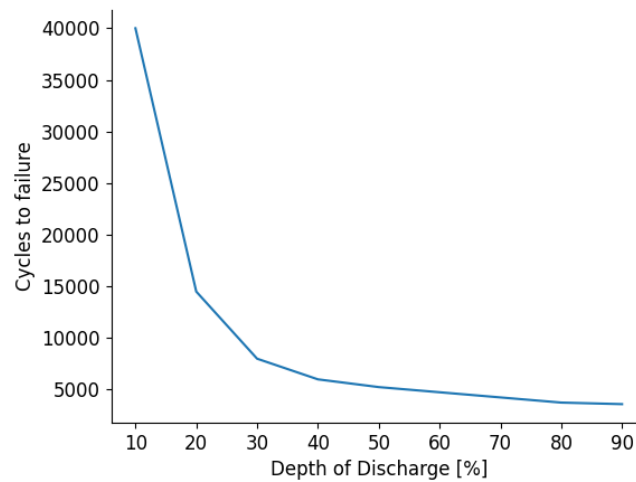


Figure 2.8: Depth of discharge vs lifetime in cycle [24]

2.3 Life Cycle Assessment - LCA

The goal of this thesis is to assess the life cycle climate change impacts of end-user scaled and community-scaled PV-Battery renewable systems in order to raise awareness of such systems taking into consideration two different contexts. Therefore, a first approach to LCA is needed. LCA is defined as the systematic analysis of the potential environmental impacts of a product or service and also analysis of the gross energy consumed by the evaluated components as well as the eventual depletion of raw materials during their entire lifetime [25], [26]. The word entire is important as it includes different stages. A complete LCA includes raw material extraction, transportation, refining and manufacturing, use phase and its decommissioning (followed by any possible recycling). Thus, it goes from the production stage through the use stage. Studies found that the use phase of PV panels as well as batteries are responsible of negligible climate impact while the other phases, especially extraction and manufacturing, are the very important climate impacting ones [27].

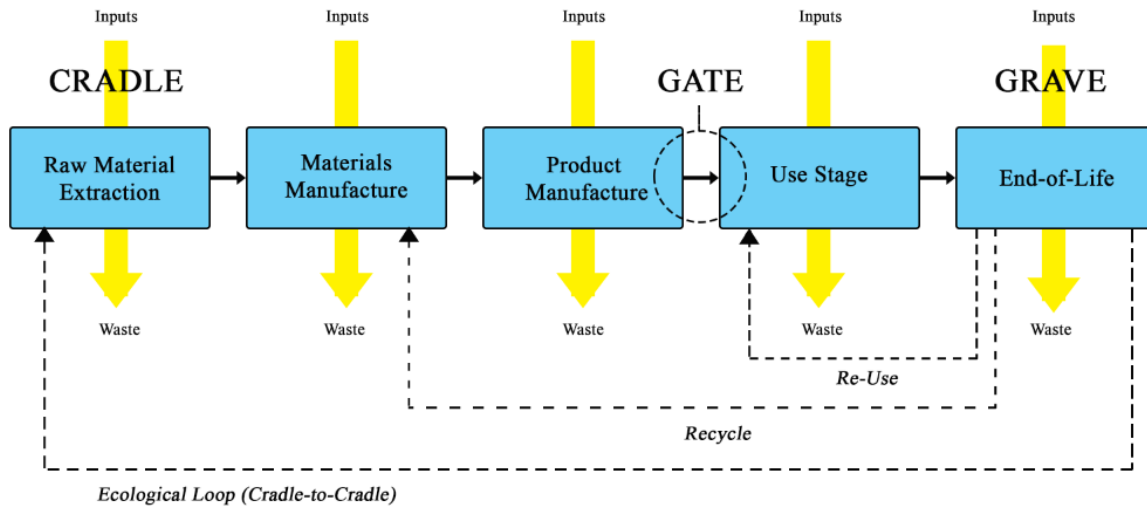


Figure 2.9: Life cycle assessment [28]

LCA follows the guidelines from the ISO standards 14,040 and 14,044 [29], [30]. From these standards, LCA includes four different stages [26],[27], [31]:

1. Goal and scope definition

The boundaries of the study are fixed. This includes, among others, the components of the evaluated system (PV panels, storage technologies and much more), the environmental issues that will be evaluated. More importantly, the steps of the system life that was mentioned above. Figure 2.9 presents the different possible steps that can be taken into account to perform the LCA.

2. Life cycle inventory

Information about the production process of the different technologies assessed are gathered and inventory data about the steps are collected. This stage includes the bulk of the data collection.

3. Life cycle impact assessment

The study can output different results that are the calculation of the gross energy consumed by the technologies to be produced, the greenhouse effect or the global warming potential (GWP) and, finally, the depletion of raw materials. The impact to be chosen needs to be set in this step. To characterize these, different sorts of environmental impacts exist such as particulate matters formation, acidification, eutrophication, ozone depletion, human toxicity and many others. The environmental impact of interest in this work is the GWP and its unit of measure is expressed in $\text{kg}_{\text{CO}_2,eq}$ as CO_2 covers 80% of GHG [3]. This stage can be further divided into three parts that are the classification, the characterization and the valuation. The interested reader is referred to [26] for further information on this subject.

4. Results interpretation and improvements assessment

As the stage's name mentions, the results are analyzed. Based on these results, eventual improvements can be identified and also implemented.

Therefore, more practically with regards to this work, to assess a PV-Battery system with environmental impact, long searches have been made in order to dress a life cycle inventory.

The great majority of these studies did not include recycling as few information are available online on these processes and their quantified environmental benefits. Thus, cradle-to-gate (see Figure 2.9), except for LA batteries since it is a very mature technology and, thus, industrial processes exist to recycle them compared to other batteries, values were taken from which the particular use-phase applied. As these values differ from studies, uncertainty ranges were applied which can be found in the tables in Appendix A.

2.4 Uncertainty quantification (UQ)

Proceeding to robust design optimizations, methods that propagate the uncertainty of the input parameters through the output are of primary interest. Actual state-of-the-art method for the UQ is Monte Carlo Simulation [32]. It is a robust and easy-to-implement technique, but it has the disadvantage to require important amount of model evaluations (10^4 - 10^5) to reach satisfying level of convergence [33]. There exist alternatives to reduce the computational costs that are, for example, Gaussian Process Regression [34] or Polynomial Chaos Expansion [35] which will be of use in this work. Polynomial Chaos Expansion is further described in section 3.5.

Chapter 3

Methodology

In this section, an introduction on the HRES, is made followed by a further development of the context in which the system is used in addition to what has already been explained previously. The performance indicators on which the optimizations are based are also described and, finally, followed by a part about the uncertainty characterization and the eventual reduction that could be made on the first draft of these ranges.

3.1 PV-Battery energy system

The HRES is represented in Figure 3.1. It is a PV system that is eventually composed of a battery storage system with a connection to the grid to fulfil the demand. Solar energy is converted through a PV array into electricity.² This electricity is converted to a DC bus bar via a DC-DC converter. At this stage, two possibilities exist: either the PV array produces enough electricity to respond to the load demand or there is a gap between the load demand and the electricity produced from solar energy.

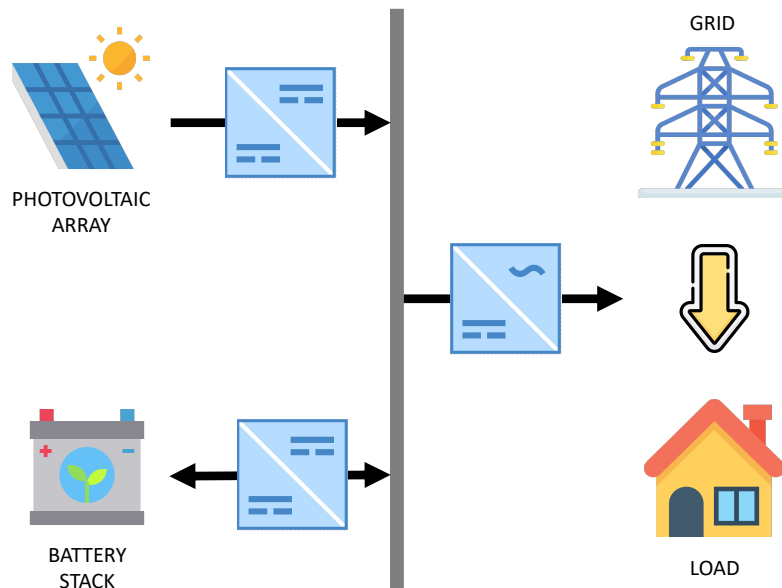


Figure 3.1: Hybrid renewable energy system representation

²The considered PV panel for the Python-based model is the Sunpower SPR-X19-240-BLK (240W) Solar Panel [36].

In the first case, description of the system operation when the electricity produced by the PV array is equal or larger than the load demand. There are three possible choices when using the electricity depending on the situation. Firstly, the electricity is consumed by the household after conversion through a DC-AC converter to make the energy usable by electrical devices in order to fulfil the load demand. After that, if the load demand is fulfilled and there is still electricity from the PV panels left, electricity on the DC bus bar (electricity from the PV array that, already, went through the first DC-DC converter) can be converted via a second DC-DC converter to be stored in a battery stack. Finally, the last possibility enters into account when there is a surplus of energy (i.e., load demand met, and battery stack fully filled). This surplus of electricity is, in this case, lost.

In the second case, when the production of the PV array is not sufficient, the electricity produced by the PV array is fully used by the household. The missing gap of electricity is then, in a first time, filled by the energy stored in the batteries that need to go through a DC-DC converter to reach the DC bus bar and then through a DC-AC converter to be available by the household. If the load demand is still not met, the remaining gap is filled by buying electricity from the grid.

Concerning everything related to the Python-based model of the different system components, the reader is referred to the work of D. Coppiters, W. De Paepe and F. Contino [33].

3.2 Climate and demand data

This section briefly presents the needed data for running the different simulations. A more complete procedure with the uncertainty characterization related to this section is presented in Appendix B. As already mentioned, the two cities in which this paper focuses the study are Stockholm and Kigali. The parameters that need to be evaluated are the yearly solar irradiance, temperature, load demand that are all taken from Typical Meteorological Year (TMY) as well as the parameters linked to the cost of electricity bought on the grid and its carbon footprint.

3.2.1 Stockholm

The hourly solar irradiance and temperature profiles throughout the year are taken in Figure 3.2 and Figure 3.3 respectively.

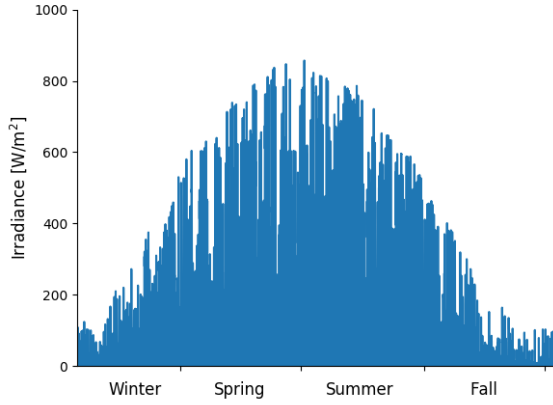


Figure 3.2: Hourly distribution of the global horizontal irradiance along the year in Stockholm

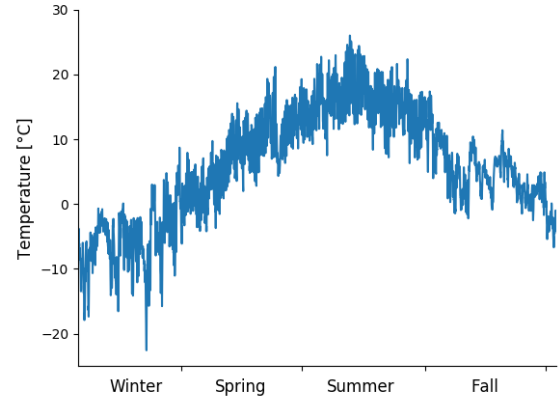


Figure 3.3: Hourly distribution of the temperature along the year in Stockholm

As observed in Figure 3.4 presenting the electricity demand profile throughout the year, the load distribution for a typical dwelling is fluctuating in function of the season. During winter it is logically increasing because of electric heating and lighting. The annual electric consumption for a typical dwelling is around 9,500 kWh which is a relatively high value. The electricity grid's price is around 0.2 €/kWh for the end-user price and around 0.04 €/kWh for the market price with a fluctuating price specified in Appendix B. The grid's carbon footprint is around 30 kg_{CO₂}/MWh [27]. Overall, a 100% grid dependent dwelling has a bill around 1,900 €/year and a carbon footprint of 285 kg_{CO₂}/year.

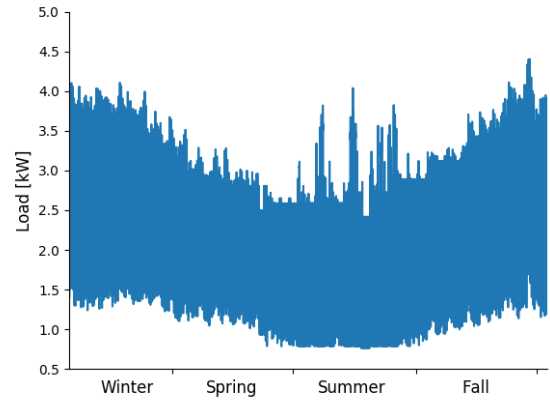


Figure 3.4: Hourly distribution of the load along the year in Stockholm

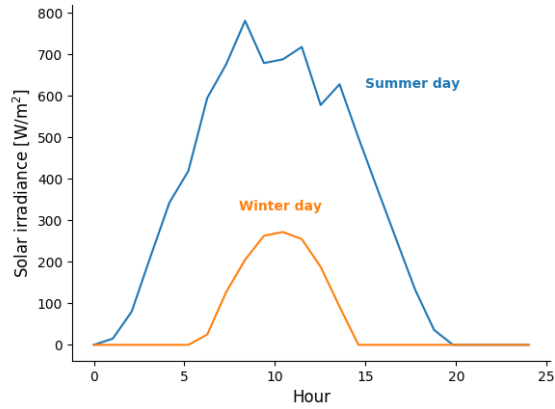


Figure 3.5: Solar irradiance comparison between a typical winter day and a typical summer day.

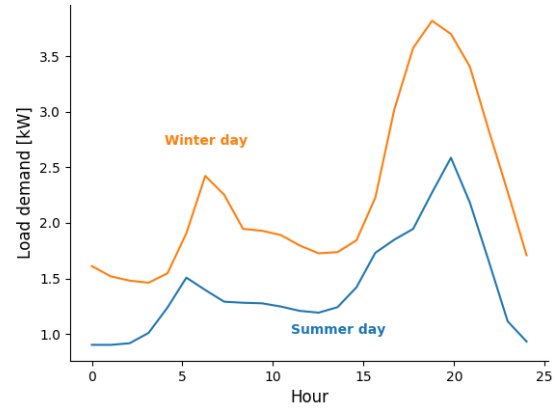


Figure 3.6: Load demand comparison between a typical winter day and a typical summer day

A decorrelation between the load and solar irradiance is thus observed (Figure 3.5 and Figure 3.6). In fact, during times of low solar irradiance, the electricity consumption is at its maximum while, during times of high solar irradiance, the electricity consumption is reduced.

3.2.2 Kigali

The hourly solar irradiance and temperature profiles throughout the year are taken in Figure 3.7 and Figure 3.8 respectively and the load demand profile is presented in Figure 3.9.

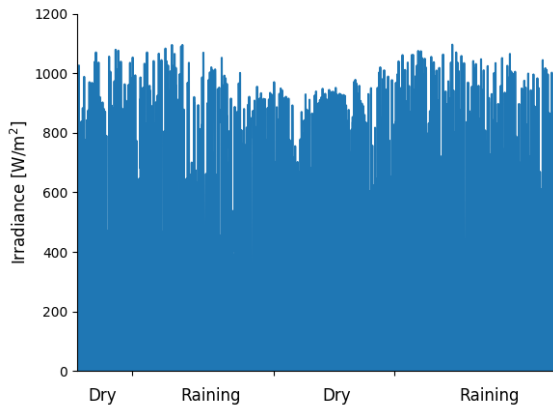


Figure 3.7: Hourly distribution of the global horizontal irradiance along the year in Kigali

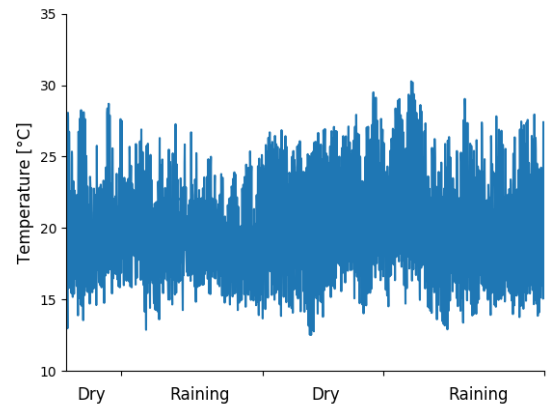


Figure 3.8: Hourly distribution of the temperature along the year in Kigali

Rwanda being a fast growing developing country, strong inequalities in terms of electricity access remain. To understand the hypotheses (the main one being that the considered household must be able to afford a PV-Battery system) taken into account for this thesis, the reader is invited to check Appendix B in order to fully understand the particular situation chosen. As it can be observed from the different figures, the situation is very different from the previous case.¹ Indeed, the irradiance and the temperature are quite constant throughout the year as well as the load consumption. This comes from the fact that it is a country situated near the equator and that no heating is needed since no seasonal changes exist except from raining and dry seasons.

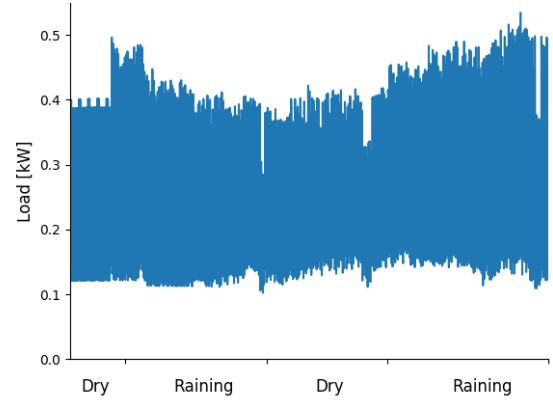


Figure 3.9: Hourly distribution of the load along the year in Kigali

The annual consumption of electricity for the specific dwelling type is around 2,330 kWh. The cost of electricity is around 0.26 €/kWh [37] [38]. Here, the price is set fixed as people pay in advance the amount of kWh they will consume. There is no electricity market in place as it can be found in Europe for example. Overall, a dwelling relying solely on the grid has a bill around 605 €/year and a carbon footprint around 1,100 kg_{CO₂,eq}/year. Besides, Sub-Saharan Africa (SSA) suffered an average of 690 hours of outages in 2015 which was the longest total duration of outages worldwide [39].² The frequency and duration of these outages vary among regions but roughly shows an order of magnitude of these outage durations.

3.3 Performance indicators

In order to give the framework a way to evaluate the output of a simulation, objectives of optimization need to be determined and implemented. Since a techno-eco-environmental analysis of the system performance is realized, three performance indicators, one for each aspect, need to be set: the Levelized Cost Of Electricity (LCOE), the Self-Sufficiency Ratio (SSR) and, finally, the Global Warming Potential (GWP).

3.3.1 Levelized cost of electricity - LCOE

$$LCOE = \frac{CAPEX_a + OPEX_a + R_{c,a} + G_{c,a}}{\sum_{i=0}^{8760} E_{load}} \quad [€/MWh]$$

¹For the sake of reader information, in order to have clear idea of the irradiance, temperature and load distribution throughout the year, the raining and dry seasons spreads as follow: dry season during January, raining season from February until May, dry season from June until August and, finally, raining season from September until December.

²This average excludes Sub-Saharan African economies for which SAIDI/SAIFI data was unavailable. Rwanda is one of them.

The LCOE is expressed in the form of "annualized total system cost" divided by "annual load demand". To obtain the annualized total system cost, the annualized investment costs (i.e., sum of the investments costs of each components divided respectively by the lifetime of the components), the annualized operational and maintenance costs, the annualized replacement costs of the batteries and the cost of the electricity bought on the grid during the year are summed. The annual load demand is directly obtained by the electric profile shown in section 3.2 and better described in Appendix B.

3.3.2 Self-sufficiency ratio - SSR

$$SSR = 1 - \frac{E_{grid}}{E_{load}} \quad [\%]$$

SSR represents the fraction of the load demand covered by the renewable energy system itself. In other words, it is a representation of the time percentage the household relies on the system to respond to its needs. To obtain the ratio, the energy bought on the grid for one year is needed as well as the total energy demand for one year.

Having access to a reliable grid network, this ratio is not of a particular interest in Sweden and therefore will not be one of the objectives of interest. On the opposite, in Rwanda and more generally in SSA, the population is facing important issues related to the quality of the power supply. The power supply is either insufficient or unreliable in many areas where the infrastructure for power supply is present. "In SSA, power is reported to be unavailable for about 540 h per year on average (International Energy Agency 2014)" [40]. An optimization of the SSR could then be of first interest for households.

3.3.3 Global Warming Potential - GWP

$$GWP = GWP_{PV,a} + GWP_{BAT,a} + GWP_{grid,a} \quad [kg_{CO_2,eq}/year]$$

The total GWP of the system is the sum of the different system components' GWP. Let's develop them one by one.

First of all, $GWP_{PV,a}$ is simply obtained multiplying the power of the photovoltaic array in kWp by the parameters gathered from the literature in Table A.1. Then, to annualize this value, it is divided by the system lifetime in years which corresponds in fact to the PV panels lifetime (i.e., 20 years in this case).

$$GWP_{PV,a} = \frac{GWP_{PV} \quad [kg_{CO_2,eq}/kWp] \cdot n_{PV} \quad [kWp]}{SYSTEM \ LIFETIME \quad [years]}$$

Then, $GWP_{BAT,a}$ is obtained using the parameter from the literature, in Table A.3, "GWP". Dividing this parameter by the "energy density", also presented in Table A.3, gives the GWP per unit of storage capacity further multiplied by the capacity of the battery stack which is a design variable and thus a known value in order to get the emissions caused by one battery stack. To consider the replacements of batteries and also to annualize this value, it has to be multiplied by the number of batteries there will be during the system lifetime and divided by the system lifetime in years. This is mathematically expressed by the following equation.

$$GWP_{BAT,a} = \frac{GWP_{BAT} \left[\frac{kg_{CO_2-eq}}{kg_{BAT}} \right]}{E_{density,BAT} \left[\frac{Wh}{kg_{BAT}} \right]} \cdot n_{BAT} \left[kWh \right] \cdot 10^3 \cdot \frac{\#Batteries}{SYSTEM \ LIFETIME \ [years]}$$

Note that the number of batteries will be either 0 (no battery is used) or greater or equal to 1 (any real number). In fact, if we install a battery stack that will not need to be replaced during the system lifetime, we still have to pay completely for it.

Finally, $GWP_{grid,a}$ is obtained by multiplying the amount of electricity taken from the grid during the evaluation along the year multiplied by the grid emissions parameters in Table A.2.

$$GWP_{grid,a} = ELEC_{grid} \left[kWh/year \right] \cdot GWP_{grid} \left[\frac{kg_{CO_2,eq}}{kWh} \right]$$

3.4 Uncertainty characterization

As already mentioned, to avoid mismatch between simulated and real-world performances, parameters were coupled with some stochasticity. Uncertainty regarding the model parameters may have two different origins. These uncertainties may be from randomness due to annual variability (i.e., solar irradiance, temperature and load profile) or may be caused from imprecision due to lack of information (i.e., techno-economical information) and are thus, respectively named aleatory and epistemic uncertainties. Their inherent differences are important to understand as the epistemic uncertainty is reducible whenever more precision are taken into account whereas the aleatory is irreducible [41]. Besides, the uncertainty ranges will be characterized using uniform or gaussian distributions based on literature summarized in Table A.1, Table A.2, Table A.3, Table A.4 and Table A.5. The two stochastic parameters characterized by a gaussian distribution are named "G" (solar irradiance symbol) in Table A.1 "Electricity grid price" in Table A.2

3.5 Surrogate modelling

Considering the number of uncertainties and the computational cost if the model was probed point-by-point, a simplified model can be fitted thanks to surrogate modelling. A computationally efficient sparse Polynomial Chaos Expansion (PCE) is here considered to propagate the uncertainties. PCE takes the advantages of orthogonal polynomials and depending on the parameter distribution, different polynomial bases are used. As an example, uniform distributions use Legendre's polynomials whereas gaussian distributions used Hermite's polynomials.

$$u(\xi) \approx \sum_{i=0}^P y_i \psi_i(\xi) \quad (3.1)$$

where $\xi = (\xi_1, \dots, \xi_d)$ represents a vector of independent random parameters, d is the stochastic dimension and P+1 equals the number of the truncated series determined by the following formula:

$$P + 1 = \frac{(p + d)!}{p!d!} \quad (3.2)$$

with p the degree of the polynomials and d the stochastic dimension. The coefficients of the PCE, y_i , are obtained through least-square minimization. Since the number of coefficients

increases dramatically when $d > 10$, computational cost increases exponentially due to the curse-of-dimensionality. As not all of the polynomials have an important contribution to the output, sparsity is applied which reduces significantly the computational time [42]. Besides, samples are organized through Latin Hypercube.

One important property that has to be checked in order to verify the order that should be chosen accordingly to the precision is the Leave-One-Out (LOO) error. Based on the maximum percentage LOO error from the generated samples, the order can be chosen. In the case of Stockholm and Kigali, 40 samples have been generated based on a rule saying 10 samples per design variables.

Another important property related to PCE is the facility of computing Sobol' indices which allows global sensitivity. Opposite to local sensitivity, global sensitivity provides true impact of each parameter by not excluding synergies and dysergies [43]. A Sobol' index of a parameter quantifies its relative importance to the total variance of the model output. Therefore, stochastic parameters with small Sobol' indices, as they do not participate greatly to the total variance of the model output, can be set as deterministic. The threshold is set at $S_{param} \leq \frac{1}{\#stochastic\ parameters}$. However, a certain tolerance is kept when a parameter's Sobol' index is relatively close to the threshold in case of imprecision due to the generated samples.

3.6 Determining polynomial order

As mentioned just above, the LOO error is here used to verify which order should be used in order to have good accuracy with the PCE surrogate modelling. To save some computational time, some tricks can be used. When determining the polynomial, the simulation runs for a single objective at a time. Therefore, as an example, for a LCOE optimization, GWP_{grid} , the grid's carbon footprint, the ambient temperature and many others non-related to the LCOE can be set as deterministic parameters. LCOE and SSR optimization will have the same parameters set to deterministic. Also, for the LCOE objective, it was assumed that the OPEX and BOP stochasticity were negligible compared to the impact of CAPEX stochasticity on the model output variance. These assumptions can be verified in section C.1 in Appendix C.

All three objectives will each have 10 stochastic parameters. They are expressed in the following tables (Table 3.1 and Table 3.2).

solar irradiance $CAPEX_{PV}$	electricity load $CAPEX_{BAT}$	electricity cost Battery's lifetime	electricity cost ratio $CAPEX_{DCDC}$	$CAPEX_{DCAC}$ discount rate
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Table 3.1: Stochastic uncertainties kept for LCOE and SSR optimization

solar irradiance GWP_{PV}	electricity load Battery's lifetime	electricity cost GWP_{BAT}	electricity cost ratio Battery's energy density	GWP_{grid} discount rate
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Table 3.2: Stochastic uncertainties kept for GWP optimization

3.6.1 First order polynomial

	LCOE	GWP
LA	18.22	3.02
NMC	17.91	3.62
VRFB	14.07	3.08

Table 3.3: Maximum LOO error in the case of Stockholm in [%]

	LCOE	SSR	GWP
LA	13.95	7.69	13.59
NMC	29.26	7.09	10.20
VRFB	8.97	7.08	7.15

Table 3.4: Maximum LOO error in the case of Kigali in [%]

From the results taken in Table 3.3 and Table 3.4, it clearly appears that order 1 is not sufficiently accurate to represent the real model.

3.6.2 Second order polynomial

	LCOE	GWP
LA	0.29	0.09
NMC	0.29	0.01
VRFB	0.26	0.11

Table 3.5: Maximum LOO error in the case of Stockholm in [%]

	LCOE	SSR	GWP
LA	4.72	2.93	1.16
NMC	7.20	2.17	0.63
VRFB	0.2	0.85	0.27

Table 3.6: Maximum LOO error in the case of Kigali in [%]

For Stockholm, the use of a maximum order 2 PCE gives a satisfying model accuracy (Table 3.5). In fact, going for order 3 will not bring much accuracy improvement while it will explode the computational cost. For instance, from (3.2), using order 2 requires 132 model evaluations while using order 3 requires 572 model evaluations (10 uncertainties). The maximum polynomial order for the PCE being determined, the Sobol' indices of the different parameters likely to have impact on the different objectives can be analyzed in order to possibly reduce the stochastic space. This will be conducted in the next section.

Concerning Kigali, the values of maximum LOO obtained for LCOE objective for three of the four batteries with order 2 does not give satisfying values in order to be used as maximum polynomial order if we refer simply to the maximum LOO error returned (Table 3.6). However, having a look inside the design samples leading to such high value of LOO, it appears that they are due to high values taken by the battery stack capacity. In these cases, the battery stack is partially unused either because the joined PV array power is too low and is, thus, not able to provide extra electricity or because the load demand does not imply such amount of battery to be fulfilled. Thus, in such specific cases, non-linearities are present which result in higher LOO. However, as it will be seen later when performing optimizations of LCOE, these kinds of designs are not part of the set of optimal solutions. Concerning the large pool of design samples and those that come into play during optimizations, LOO in the order of magnitude of 0.2% are reached which gives satisfaction for order 2. As explained above, for the case of Stockholm, order 3 will not bring much additional accuracy while it will explode the computational cost.

3.7 Reducing uncertainties

After extensive literature review, 27 parameters were assigned with an uncertainty range. Deep searches have been made in order to have the most realistic and reliable values. The idea was to find as much literature as possible in order to have a high confidence in the given interval. When few literatures were available, the idea was to assign the parameters with wide ranges of values in order to take into account all possibilities. By doing so, if the parameter was considered negligible through Sobol' indices, it could be set deterministic directly. However, the used method is indicative in the sense that it gives an idea of the driving parameters inside the complete stochastic space without focusing exclusively on the designs that will be of interest. Thus, and also in order to keep some real-life variability in the model, it was decided to keep some negligible stochastic parameters among the most impactful ones in the case where there would be less than 10 driving stochastic parameters. As a reminder, the threshold indicating whether a stochastic parameter can be considered as negligible is as defined in section 3.5.

Stockholm

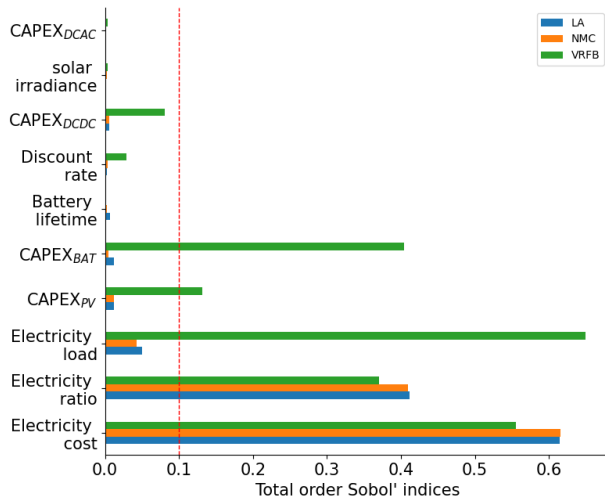


Figure 3.10: Total order Sobol' indices in the case of Stockholm for a LCOE optimization

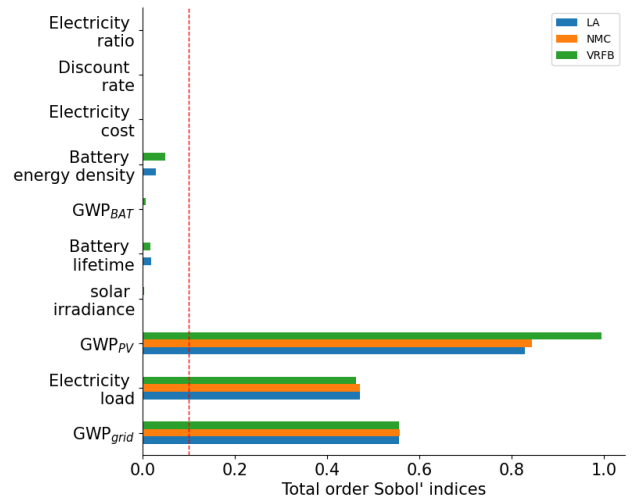


Figure 3.11: Total order Sobol' indices in the case of Stockholm for a GWP optimization

As it is observed from the figure above (i.e., Figure 3.10 and Figure 3.11) representing the total order Sobol' indices from a LCOE and a GWP optimization respectively, there are some common driving stochastic parameters among the different batteries. These driving stochastic parameters do not exceed the number of five, thus five other stochastic parameters are chosen according to their importance to respect the number of ten stochastic parameters as mentioned above. Some of these parameters vary accordingly to the battery type. Table 3.7 sums the different stochastic space that will be used for the robust design optimizations in Stockholm.

Common stochastic parameters	Electricity cost	Electricity ratio	GWP_{grid}	Electricity load
	GWP_{PV}	$CAPEX_{PV}$	$CAPEX_{BAT}$	$CAPEX_{DCDC}$
LA	Battery lifetime	Battery's energy density		
NMC	Battery lifetime	Discount rate		
VRFB	Battery's energy density	Discount rate		

Table 3.7: Common driving stochastic parameters and the additional stochastic parameters according to the battery type in the case of Stockholm

Kigali

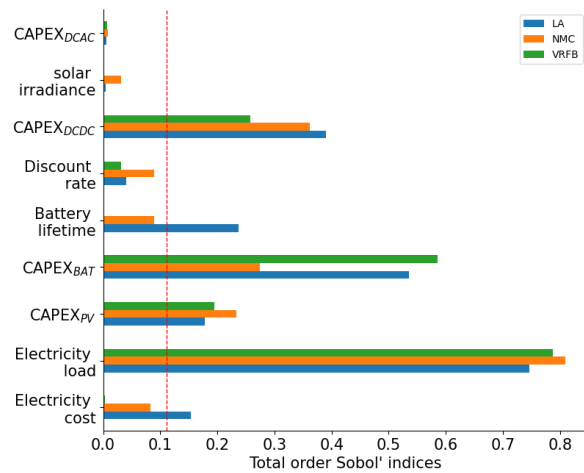


Figure 3.12: Total order Sobol' indices in the case of Kigali for a LCOE optimization

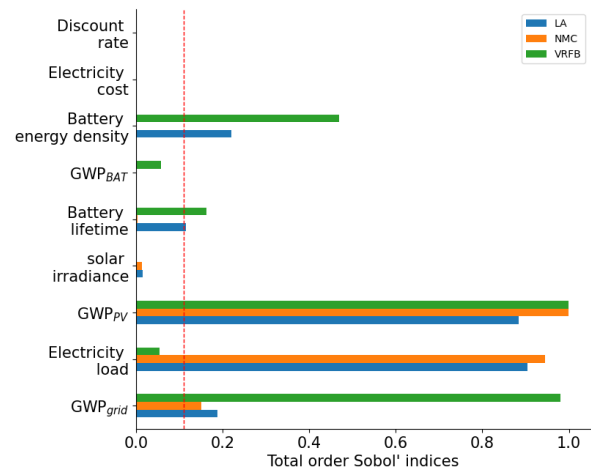


Figure 3.13: Total order Sobol' indices in the case of Kigali for a GWP optimization

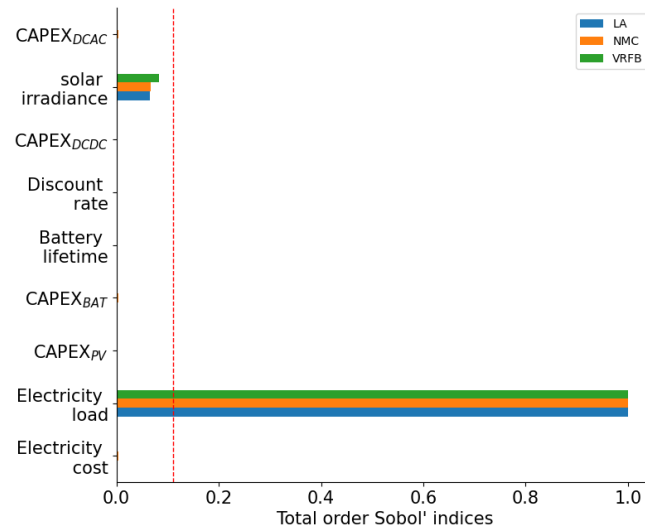


Figure 3.14: Total order Sobol' indices in the case of Kigali for a SSR optimization

In the case of Kigali, it can be seen by comparing the Sobol' indices with the ones in the case of Stockholm that there are some noticeable differences for certain Sobol' indices values. Indeed, it is observed that the Sobol' indices of $\text{CAPEX}_{\text{BAT}}$, $\text{CAPEX}_{\text{DCDC}}$, CAPEX_{PV} in the case of Kigali are distinctively higher than those from the case of Stockholm. Inversely, GWP_{grid} and the electricity cost parameter tend to be much lower than in the case of Stockholm. This results from the fact that the system in Kigali will tend to be self-sufficient, thus installing PV panels and using a battery due to the high cost of electricity as well as its high carbon footprint. Also, there are globally less negligible Sobol' indices regardless of the battery type. Table 3.8 sums the different stochastic space that will be used for the robust design optimizations for Kigali.

Common stochastic parameters	solar irradiance		GWP_{grid}	Electricity load	Battery lifetime
	GWP_{PV}		CAPEX_{PV}	$\text{CAPEX}_{\text{BAT}}$	$\text{CAPEX}_{\text{DCDC}}$
LA	Battery's energy density		Electricity cost		
NMC	Discount rate		Electricity cost		
VRFB	Battery's energy density		GWP_{BAT}		

Table 3.8: Common driving stochastic parameters and the additional stochastic parameters according to the battery type in the case of Kigali

3.8 Surrogate-assisted robust design optimization

The surrogate-assisted robust design optimization aims at optimizing LCOE, GWP and in the specific case of Kigali SSR. By optimizing LCOE and GWP, it is meant that the surrogate-assisted model searches for best designs that minimize the objective of interest's mean (except for SSR, the surrogate-assisted robust design maximizes its mean) as well as its standard deviation. The objective of interest's mean indicates the expected value over the system lifetime and its standard deviation indicates the uncertainty on this last value. The objective in minimizing the standard deviation makes the system more robust to uncertainty related to stochastic input parameters and thus increases the probability in obtaining the expected mean value or, at least, value close to this. The model explores all solutions by varying continuously the four design variables: n_{pv} the installation of PV panels expressed in kWp, n_{bat} the capacity of the battery stack expressed in kWh, pv_dcdc and bat_dcdc which are respectively the DC-DC power electronics related to the PV panels and the battery stack expressed in kW. To sort the different solutions and to select the best ones to get through the optimal set of design, NSGA-II is used. Besides, a population size of 30 was fixed and the optimization algorithm samples thanks to the Latin Hypercube Sampling (LHS) method. Also, it is characterized by a crossover and mutation probability of 0.9 and of 0.1 respectively. More information and details can be found in the work of D. Coppiters and al. [33].

Chapter 4

Results & Discussion

In this chapter, the deterministic design optimizations will be presented first. Thanks to its low computational cost and simplicity, the deterministic design optimizations simply reflect major trends that will be observed when running the robust designs optimizations. Precise solutions of these deterministic solutions are not to be remembered as they will present drastic mismatch between simulated performances and real-world performances. It is important to keep in mind that this thesis will focus on robust design optimizations. The Pareto sets obtained by the robust optimizations will be analyzed and uncertainty quantification on some designs of the Pareto sets will be realized. This will give an idea on how the uncertainties of the input parameters propagate through the model and it will also give the driving uncertainties. The stochastic performances of the different designs will, also, be evaluated. From there, the optimal designs for both locations will be discussed and similarities or differences between economically optimal and environmentally optimal designs will be confronted and investigated.

4.1 Deterministic design optimizations

To perform the deterministic study, the solely use of the LA battery has been used, excluding NMC and VRF battery types. The philosophy behind is simply to express a pattern of result to look at the trends the robust optimizations may follow as already said in the introduction of this chapter. The deterministic optimization is just a tool to understand robust optimization. Conclusions between different batteries can not be done in the absence of uncertainty which is why only optimizations with LA battery will be carried.

Stockholm

Optimizing both LCOE and GWP of the system for Stockholm in the case of LA battery use, the obtained results are presented in Figure 4.1 and Figure 4.2. A first remark can be highlighted concerning the battery use. In fact, since no battery stack is ever used at all (see Figure 4.2), there would be no difference in the results returned for the different batteries.

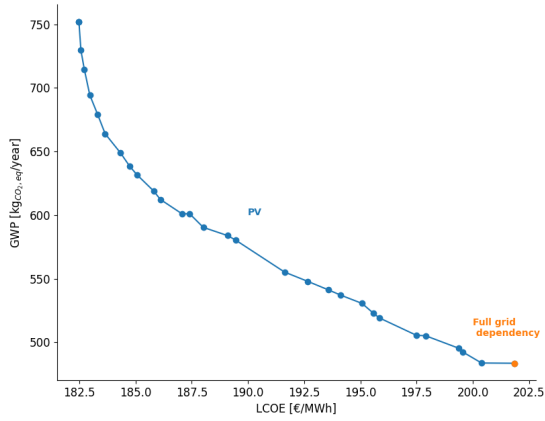


Figure 4.1: Pareto front for the optimization of LCOE and GWP in Stockholm

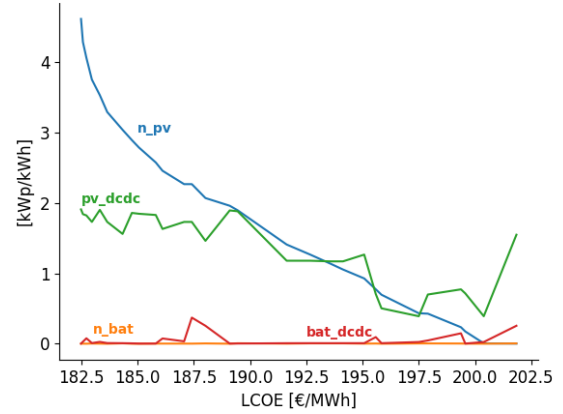


Figure 4.2: Design variables for the optimization of LCOE and GWP in Stockholm

Concerning the results themselves, the reliance on PV panels to produce electricity will reduce the LCOE but, on the other side, will increase the GWP. In fact, in such a reduced scale and with the climate condition encountered in Sweden, there is no possibility to compete the energy production methods, namely, a major part of nuclear power and hydropower. The grid electricity deterministic situation in the region of Stockholm in terms of LCOE and GWP is represented at the bottom right points of Figure 4.1, to know $LCOE = 200$ [€/MWh] and $GWP = 484$ [kg $_{CO_2,eq}$ /year]. The absence of battery use may be understood by the low solar potential available in Sweden. All the energy produced by the PV panels is directly used by households and it is not reasonable to imagine installing more PV panels only to store electricity in a battery stack. It will increase significantly the LCOE and the GWP of the system and result in a non-optimal solution compared to grid electricity. Besides, when decreasing the $CO_{2,eq}$ emissions, it can be observed that the PV and battery DC-DC converters, respectively pv_dcdc and bat_dcdc , start behaving randomly at a certain upper limit. This comes from the fact that they are not attributed with GWP parameter due to lack of information in literature. The optimizer then plays with these values randomly.

Kigali

As it was explained in the previous section, in the case of Kigali, optimizations of the three objectives are realized: LCOE, SSR and GWP. The results for LA battery are presented in Figure 4.3, Figure 4.4 and Figure 4.5. The pareto fronts and then, consequently, the design variables curves are a bit shaking but the characteristic shapes of the results are still well highlighted and can be pointed out.

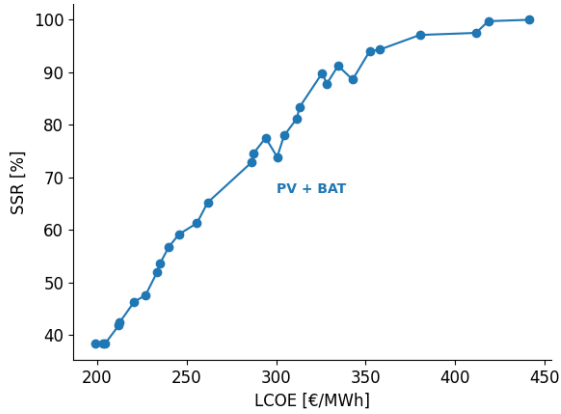


Figure 4.3: Pareto front looking at LCOE and SSR objective in Kigali with lead-acid battery

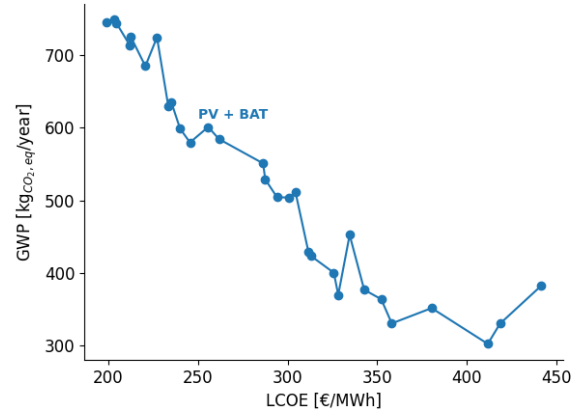


Figure 4.4: Pareto front looking at LCOE and GWP objective in Kigali with lead-acid battery

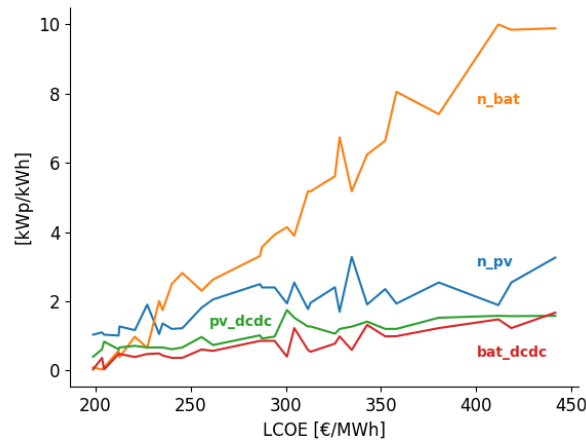


Figure 4.5: Design variables for the optimization of LCOE, SSR and GWP in Kigali with lead-acid battery

In the case of Kigali, the grid electricity deterministic situation is $LCOE = 260$ [€/MWh] with $GWP = 1072.72$ [kg $_{CO_2,eq}$ /year]. There is then an obvious point in going for a PV-Battery system in Kigali since there is the capacity to reach high SSR while decreasing the GWP. The LCOE, on the other hand, is not reduced in any cases. In fact, relying on PV-Battery leads, in many cases, in an increase of LCOE. Besides, importance of LCOE compared to the two other objectives must not be forgotten to consider the final optimal design of the system. Population in developing countries gave much more importance on their costs than on the climate impact they can have.

Concerning the results, in order to reach high SSR and low GWP (they go hand in hand since they are the direct results of an abandonment of electricity from the grid), there is a need for an important battery stack that will be used to restore electricity during times of low solar irradiance. The amount of PV panels does not need to be significantly increased due to the result combination of high solar irradiance throughout the year fulfilled with low

energy demand. If the objective is to reduce LCOE, the maximum SSR that can be reached is 65 [%] and for GWP, the minimum is about 580 [$\text{kg}_{\text{CO}_2,eq}/\text{year}$].

4.2 Robust design optimizations and uncertainty quantification

Optimizations of LCOE and GWP will be applied on the energy system with the different batteries and in the two different locations as well as an optimization of SSR in Kigali for each battery. In both locations, energy system for a single end-user is investigated. In the case of Stockholm, further work on a community scaled energy system will be conducted in order to know to what extent the electrical grid, which is already really well developed and mostly reliant on carbon-free energy sources, may be competed since this will allow to introduce a fourth type of battery, namely NaS battery. This will result in 23 optimizations. From the different Pareto fronts taking the optimal designs, it will be highlighted that, in some cases, a trade-off exists between the minimization of the objective's mean and the minimization of the objective's standard deviation. The results obtained for Stockholm will first be presented followed by the ones obtained for Kigali.

4.2.1 Stockholm

Single end-user scale

Economic evaluation

The performances obtained by robust optimization of a single end-user scale energy system for three different batteries, namely LA, NMC and VRF battery, are presented in Figure 4.6 for the Pareto fronts and in Figure 4.7 for the evolution of the system composition in order to go from the design with the lowest mean to the most robust design.

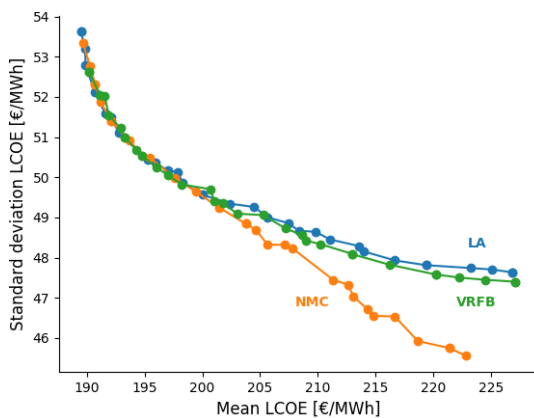


Figure 4.6: Pareto front comparison between the different batteries in Stockholm when optimizing LCOE. Use of NMC battery in the energy system leads to more a robust design.

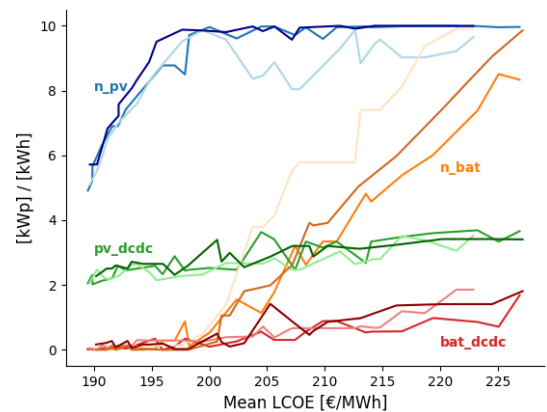


Figure 4.7: Design variables comparison between the different batteries in Stockholm when optimizing LCOE - traditional colors are for LA, light colors are for NMC and dark colors are for VRFB.

Firstly, common similarities to all systems regardless of the battery used will be presented. In Figure 4.6, one can observe that trade-off between the mean and standard deviation of LCOE is, indeed, present. For all batteries, the minimum mean design is achieved by a 5 kWp PV array without battery stack and leads to a mean LCOE of 190 €/MWh with a standard deviation of 53 €/MWh. For this system design, the reliance on the grid electricity being important (SSR of 20% reached), the uncertainties related to the grid electricity price dominates the output variability whatever the battery used. This can be seen in the upper plot from Figure 4.8.

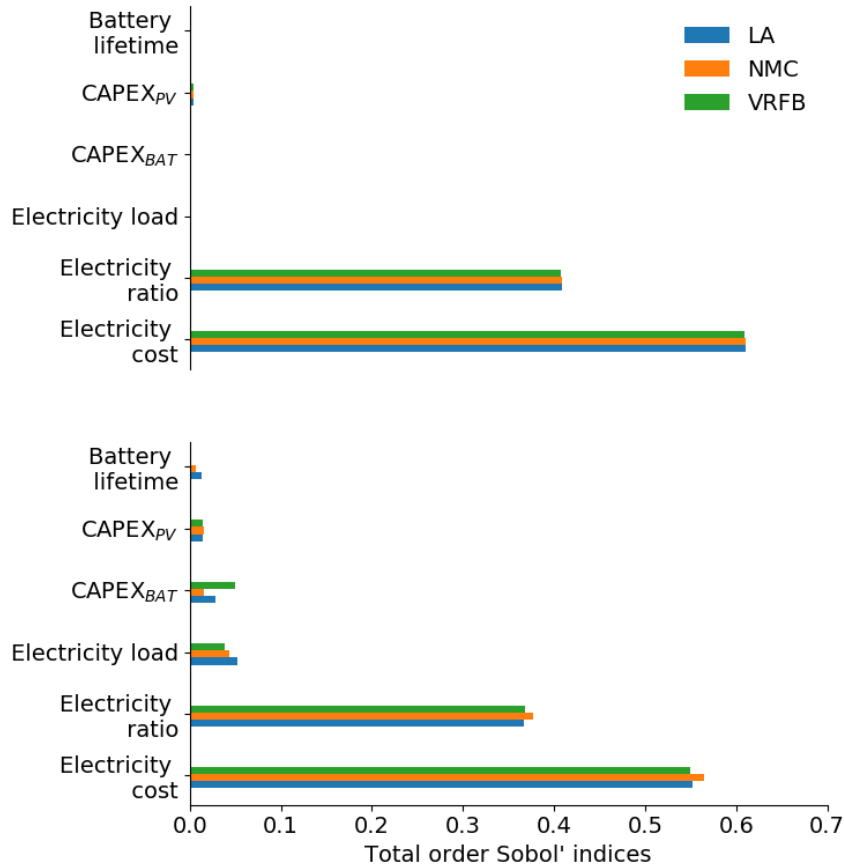


Figure 4.8: Sobol' indices comparison between the minimum mean designs (upper plot) and between the robust designs (lower plot) for the different batteries in Stockholm when optimizing LCOE. The minimum mean design is mainly driven by the uncertainty on the electricity cost and electricity ratio while, contribution of the latter in the robust designs variability has been reduced in favor of parameters that characterize the solar system.

As Figure 4.7 shows and better represented by Figure 4.9 taking the example of the robust optimization using LA battery (figures presenting the Pareto fronts with separation between PV-exclusive optimal designs and PV-battery optimal design and figures presenting the design variables' evolution for all the batteries separately are taken in Appendix D), there is a need to introduce battery stack at a certain point to reach lower values of standard deviation since the decrease in the standard deviation goes hand in hand with a greater reliance on the PV-Battery system (developed later). In fact, a battery stack allows to fulfill the electricity demand even during low solar irradiance period (both during the day and during part of the night).

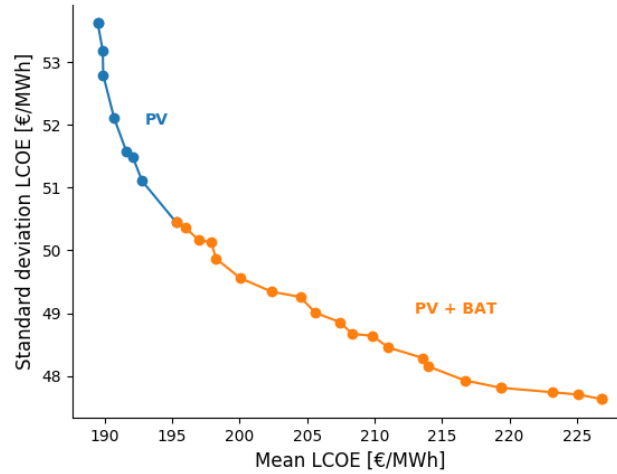


Figure 4.9: Pareto front from the LCOE robust optimization in Stockholm with lead-acid battery presenting separation between PV-exclusive designs and PV-Battery designs. An increase of the PV array power achieves a reduction of the standard deviation, but introduction of a battery stack is needed to further reduce the LCOE standard deviation.

Increasing the PV array power allows to relatively reduce the standard deviation while keeping a mean value of LCOE quite unchanged as it can be seen on the different Pareto fronts presented (Figure 4.9). The standard deviation drops to 50.45 €/MWh while the mean LCOE increases up to 195.30 €/MWh. Relying only on PV panels without battery stack, at a certain point, SSR stagnates and reaches a maximal mean value of 26%. At this point, introduction of battery stack is needed to reach higher values of SSR and, consequently, to reduce the standard deviation at the cost of an increase of the mean LCOE. Putting the PV array power as well as the battery stack capacity to its maximum (fixed to a realistic but already quite high value of 10 kWp for the PV array and 10 kWh for the battery stack) only allows to reach mean value of SSR slightly below 35%. Thus, in any case, the optimal system designs remain primarily dependent on the grid electricity which explains why low values of standard deviation can not be reached. The reason why the mean LCOE of the grid electricity is low compared to what can be reached by a PV-Battery system comes simply by the large scale at which the grid electricity is produced. Concerning the high standard deviation of the grid electricity LCOE, this can be explained by the uncertainty on the grid electricity cost being already significant (Gaussian distribution: $\mathcal{N}(40, 15)$ €/MWh) and it is even more accentuated by the parameters characterizing the ratio of the electricity cost (i.e. the percentage of the end-user electricity bill that is due to the cost of electricity itself) in which the uncertainty is characterized by the following uniform distribution, $\mathcal{U}(0.2, 0.4)$.

System components	Lowest mean design	Robust design		
		LA	NMC	VRFB
PV array power [kWp]	5.11	10	9.65	10
Battery stack capacity [kWh]	0	8.33	9.90	9.85
PV DCDC converter power [kW]	2.08	3.66	3.52	3.41
Battery DCDC converter power [kW]	0	1.68	1.86	1.81
Characteristic values				
μ_{LCOE} [€/MWh]	189.65	226.87	222.86	227.12
σ_{LCOE} [€/MWh]	53.35	47.63	45.55	47.40
μ_{GWP} [kg $_{CO_2,eq}$ /year]	786.94	1,220.47	1,140.15	1,212.21
σ_{GWP} [kg $_{CO_2,eq}$ /year]	156.87	247.84	237.47	246.18
μ_{SSR} [%]	21.26	33.82	34.98	33.75
σ_{SSR} [%]	1.89	3.04	3.42	3.14
$\mu_{lifetime}$ [years]	/	7.44	21.76	41.39

Table 4.1: Comparison of optimal system designs in Stockholm between the different batteries when optimizing LCOE

Already presented above, the minimum mean designs which are the same for all batteries are taken in Table 4.1 as well as the robust designs for the different batteries. This introduces the differences that can be observed from one battery to another. As Figure 4.6 highlights, use of NMC battery leads to a most robust solution (LCOE standard deviation of 45.55 €/MWh) compared to the two other batteries (LCOE standard deviation of 47.50 €/MWh). However, from Figure 4.7, the system composition of optimal designs is approximately the same regardless of the battery used. Thus, the differences that can be observed between the different robust design must come from the uncertainty ranges characterizing the battery parameters combined with their behavior inside the system lifetime. Firstly, on the cost of the batteries. There are two mature battery technologies, namely LA battery and NMC battery, that have, thus, narrower uncertainty ranges (respectively, $\mathcal{U}(102, 354)$ €/kWh and $\mathcal{U}(190, 500)$ €/kWh and one emerging technology which is VRF battery with much more widespread uncertainty range ($\mathcal{U}(110, 809)$) €/kWh for the investment costs (Table A.3 in the appendices). Secondly, on the battery lifetime in years, or equivalent, the number of battery changes required during the system lifetime. Proceeding to a deterministic run, it turns out that the LA battery, in the present system configuration, has a deterministic lifetime of 7.44 years and will, thus, need to be replaced at least twice with chances to be replaced three times. Conversely, NMC and VRF batteries, which have deterministic lifetime of 21.75 years and 41.39 years respectively, have great chance of not having to be replaced. With these two elements in mind, systems using NMC battery, that has a narrow investment cost range with high chances not to be replaced, presents a lower standard deviation compared to the two other battery technologies.

The LCOE standard deviation is, in this case, still characterized mainly by the electricity grid parameters but their contributions have been reduced in favor of the parameters characterizing the system (see Figure 4.8). However, the SSR reached by the system being about 34%, the contribution of the grid electricity parameters to the output variability remains, by far, the most important (Sobol' index for the parameters related to the PV-Battery system does not reach 10% while the parameters related to the grid electricity are within 35% and 55%). Thus, in the case of Stockholm, further work that would be done on improving the stochasticity characterization for the PV parameters as well as for the battery parameters will not bring much improvement in the objective of reducing the LCOE standard deviation.

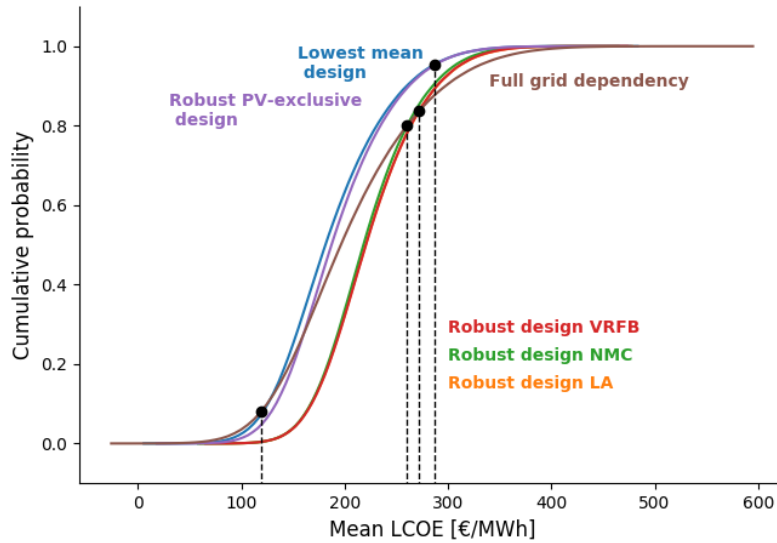


Figure 4.10: CDF comparison between five optimal designs (the minimum mean design, the robust PV-exclusive design and the three robust designs) and the full grid dependency case in Stockholm when optimizing LCOE. Lowest mean designs, and more generally PV-exclusive designs, achieves the best economic performances.

The stochastic performances of the different designs can also be analyzed. In fact, the presence of a trade-off between minimizing the LCOE mean and the LCOE standard deviation means that each design presents advantage either in mean performance or in robustness. In Figure 4.10, the five different designs' CDF are presented when considering the three different batteries:¹

- the minimum mean design that is the same regardless of the battery type considered in the optimization since no battery stack is used
- the most robust designs with LA or VRF battery that are closely the same
- the most robust design with NMC battery
- the robust PV-exclusive design that is also the same regardless of the battery type considered in the optimization

¹PDF comparison between different optimal solutions are, also, available battery by battery in Appendix D to provide the interested reader with a different representation of stochastic performances.

Besides, the full grid dependent design CDF is also represented. It appears that the PV-exclusive design achieves the highest probability of having, in the real life, the LCOE below a fixed threshold. This is true except for a LCOE mean value below 120 €/MWh, where relying solely on the grid gives a higher probability to be below the fixed threshold and a value above 286 €/MWh, where the robust designs using exclusively PV array achieve the highest probability. This can be illustrated by taking an example. If the owner fixes an upper limit for LCOE of 200 €/MWh, the minimum mean design provides a probability of 64% that the LCOE will be below this threshold in reality. Relying one hundred percent on the grid, the probability drops to 52%. Finally, concerning the most robust designs, they all provide a probability around 33% that the LCOE will be below the threshold.

As it was said in the previous paragraph, under 120 €/MWh for LCOE mean, the full grid reliance provides the highest probability to be below a fixed threshold. However, the difference with the minimum mean designs is extremely weak. Concerning the zone above mean LCOE of 286 €/MWh, the robust PV-exclusive designs achieve slightly higher probability than the minimum mean designs of ending-up with a value of LCOE below the fixed threshold. This is explained by the lower standard deviation reached by the latter design that, therefore, steepens the CDF and allows an intersection to occur between the two CDF. However, again, the difference in probabilities is extremely weak.

The previous discussion leads to the conclusion that the minimum mean designs (i.e., PV array without battery stack) is the most interesting one from an economic point of view. Besides, the robust designs seem to be totally uninteresting if SSR is not considered as a preponderant element in the choice to be made. However, PV-exclusive designs achieve rather low SSR (around 20%) while relying on robust PV-Battery designs bring non-negligible improvement on that side (SSR value of around 33%). Therefore, if a larger SSR threshold is required by the owner, the robust designs become interesting. Among these designs, the use of NMC battery leads to the lowest standard deviation (reasons are explained above) while keeping the same LCOE mean as with the two other batteries, what results in a steeper CDF and, thus, in a slightly higher probability to be under any fixed threshold for the LCOE. For example, if the fixed upper limit for LCOE is 250 €/MWh, the use of NMC achieves a probability of 74% to be under this threshold while 72% is achieved when using lead-acid or VRF battery. It is important to mention that the more the threshold fixed for the LCOE is low, the more the differences between the batteries are reduced.

The CDF of the most robust designs do not intersect the CDF of the PV-exclusive designs which means that they are only of interest when a higher SSR threshold is requested by the owner.

Environmental evaluation

Alongside the economic optimizations previously developed, an analysis of the environmental impact of the energy system can be conducted. Nowadays, the carbon footprint of an installation is of particular interest, and it would be interesting to see if the economically optimized system design presents similarities with the environmentally optimized one. However, it must be kept in mind that, for what concerns end-users, typically households, the economic criterion remains of primary importance. The environmental impact of the economically optimized designs is taken in Table 4.1 but these are far from being the optimal choice from an environmental point of view. The environmental optimization results obtained for

the three batteries are presented in Figure 4.11 for the Pareto fronts and in Figure 4.12 for the system composition of the different optimal designs. The Pareto fronts presenting the separation between the different system designs they imply for each battery individually are available in Appendix D. As it can be observed on the different Pareto fronts, no difference is present when using a different battery in the system design. In fact, the set of optimal designs exclusively includes PV array without battery stack (Figure 4.12). Thus, there is no need to distinguish the results of the different battery and, consequently, a general analysis of the common result will be realized.

Note: Converters' evolution along the Pareto front are not taken in Figure 4.12. In fact, converters' design variables have quite chaotic behaviors since it does not enter into the GWP evaluation as it was already mentioned in the deterministic optimization section of this chapter. Then, the algorithm plays with them without having the possibility to find a path through an optimal point. Although it does not have any influence on the climate impact, it has as consequence that, even if it is not an objective of interest, the convertors are not economically optimal. In fact, it has no sense for an owner to pay for useless convertor power. Thus, the power of the different convertors is determined through a deterministic run. The values kept are the minimal ones for which the deterministic results remain the same as the deterministic results obtained when using the system design from the robust optimization. This remark is valid for all the following environmental evaluations that will be presented.

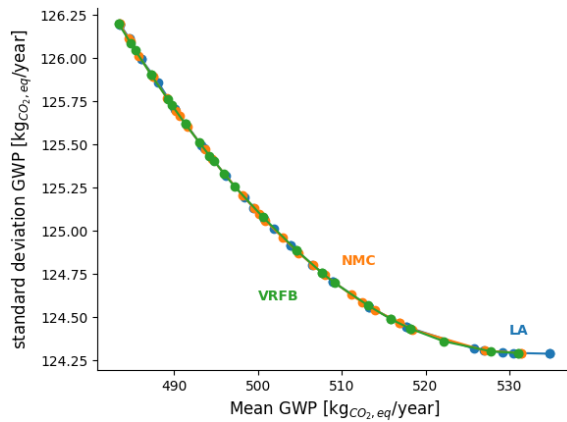


Figure 4.11: Pareto front comparison between the different batteries in Stockholm when optimizing GWP. A reduced trade-off is observed and the achieved performances are the same regardless of the battery technology used.

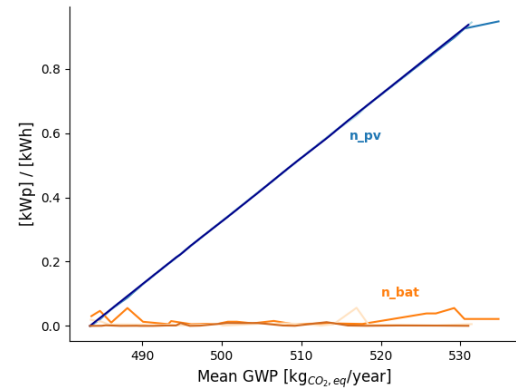


Figure 4.12: Design variables comparison for the different batteries in Stockholm when optimizing GWP - traditional colors are for LA, light colors are for NMC and dark colors are for VRFB. No battery stack is never used.

A trade-off between the minimization of the mean GWP and the standard deviation of GWP is present even if the reduction of the standard deviation remains reduced (1.6 % reduction). Thus, uncertainty quantification will be realized on the minimum mean GWP system design (i.e., 483.61 kg_{CO2}/year with a standard deviation of 126.19 kg_{CO2}/year) which is, in fact, the full grid dependency case, as well as on the robust system design (i.e., 534.80 kg_{CO2}/year with a standard deviation of 124.29 kg_{CO2}/year) that are taken in Table 4.2. In order to achieve a reduction of the GWP standard deviation, the power of the PV array is slightly

increased until it reaches a value around 1 kWp. Besides, it is observed that the range of the standard deviation is pretty much negligible. This simply comes from the fact that all the systems present on the Pareto front are mainly grid dependent. Besides, even if the carbon footprint uncertainty range is small (i.e. uniform distribution : $\mathcal{U}(0.02, 0.04)$ $\text{kg}_{CO_2,eq}/\text{kWh}$, see Table A.2 in Appendix A), GWP standard deviation reach quite high values due, mainly, to the load demand uncertainty which is relatively important.

System components	Lowest mean design / Full grid dependency	Robust design
PV array power [kWp]	0	0.95
Battery stack capacity [kWh]	0	0
PV DCDC converter power [kW]	0	0.85
Battery DCDC converter power [kW]	0	0
Characteristic values		
μ_{LCOE} [€/MWh]	207.79	201.57
σ_{LCOE} [€/MWh]	67.58	63.74
μ_{GWP} [$\text{kg}_{CO_2,eq}/\text{year}$]	483.61	534.80
σ_{GWP} [$\text{kg}_{CO_2,eq}/\text{year}$]	126.19	124.19
μ_{SSR} [%]	/	5.76
σ_{SSR} [%]	/	1.03

Table 4.2: System optimal designs in Stockholm when optimizing GWP

As it is observed from Figure 4.13, the systems are mainly driven by the uncertainty on the load demand as just explained and the electricity grid parameters as the minimum mean GWP is in fact a 100% grid dependent system whereas the robust design is characterized by a small PV system (i.e., PV modules installation less than 1 kWp) expressed in Table 4.2 which achieves around 5.8% SSR. Small values of Sobol' indices for the parameter representing the PV array's carbon footprint in the case of the robust designs are thus observed. Thus, as it is the case for the LCOE optimization, further work in order to improve the uncertainty range on the PV parameters will not bring much improvement in the reduction of the GWP standard deviation.

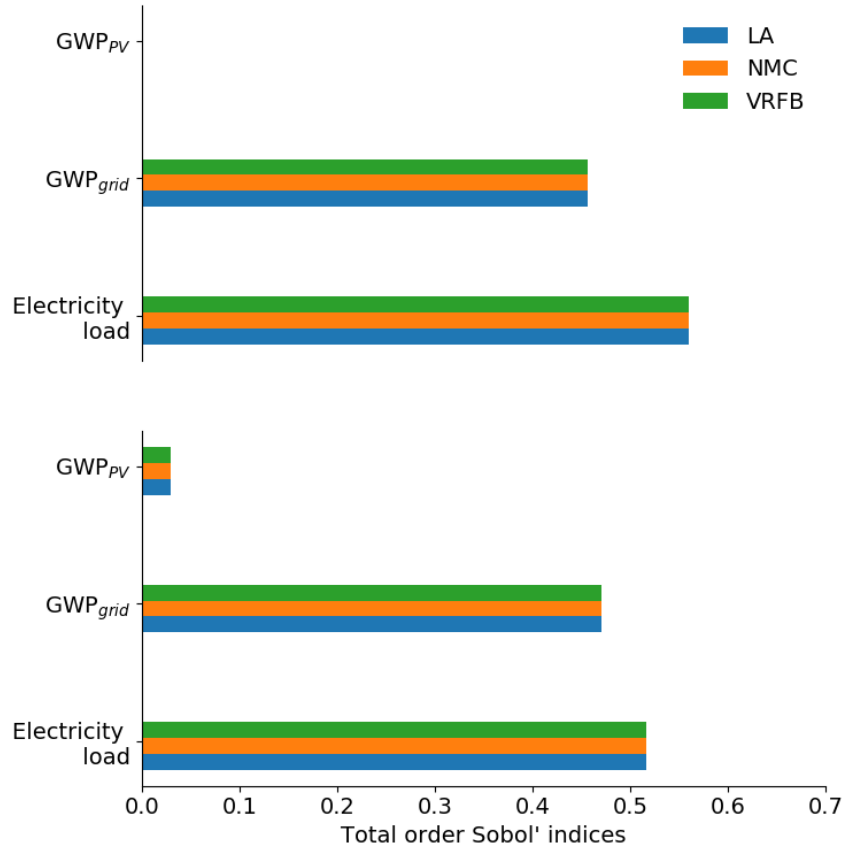


Figure 4.13: Sobol' indices comparison between the minimum mean designs (upper plot) and between the robust designs (lower plot) for the different batteries in Stockholm when optimizing GWP. The parameters characterizing the grid are, in both cases, the main driving ones but the slight increase in reliance on the solar system makes the GWP of PV panels a reduced driving parameter for the robust designs GWP standard deviation.

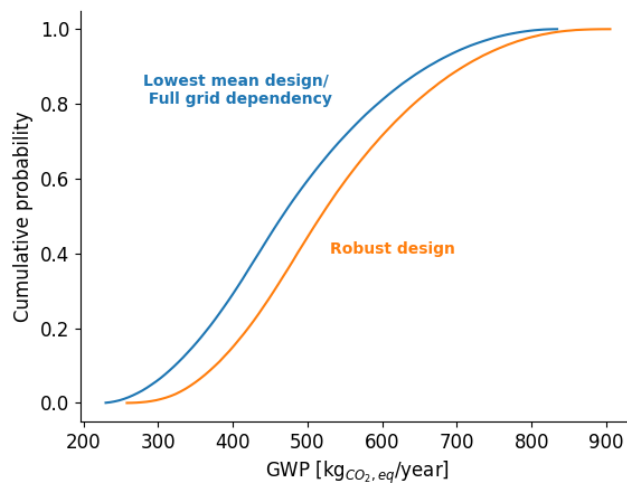


Figure 4.14: CDF comparison between two optimal designs (the minimum mean design which is the full grid dependency and the robust design) in the case of Stockholm when optimizing GWP. Full grid dependency is the best choice from an environmental point of view since no intersection between the CDFs occurs.

Then, with regard to stochastic performances of the two considered optimal designs, it is easily observed from Figure 4.14, which presents a comparison between the two environmentally optimal designs (full grid dependency and small PV-exclusive design), that the lowest mean design, which is in fact a full grid dependent system, completely outdraws the robust design.¹ The probability of the system GWP to be below a fixed threshold in reality is, in any case, greater when relying fully on the grid compared to the robust design. Furthermore, the difference is quite important. If, for instance, a upper limit for GWP is fixed at 500 $\text{kg}_{\text{CO}_2,eq}/\text{year}$, the full grid dependency achieves a probability of 60% to result in a GWP below the threshold in reality while the robust design, only, achieves a probability of 44%.

General discussion

Finally, from the two objectives of interest, the LCOE and GWP optimization, it can be concluded that the minimum mean designs are the most interesting from an economic as well as from an environmental point of view. In fact, in both cases, the reduction of standard deviation achieved does not allow to compensate the increase of the objectives of interest's mean. These two systems driven by two different objectives are different and summarized in Table 4.3. Regardless of the objective, the optimization do not favor the installation of battery stack. Only a PV installation enables to lower the electric bill by covering part of the electric load demand in the case of Stockholm for a single dwelling.

System components	Optimum LCOE design	Optimum GWP design
PV array power [kWp]	≈ 5	0
Battery stack capacity [kWh]	0	0
PV DCDC converter power [kW]	≈ 2.07	0
Battery DCDC converter power [kW]	0	0
Characteristic values		
μ_{LCOE} [€/MWh]	189.4	207.79
σ_{LCOE} [€/MWh]	53.5	67.58
μ_{GWP} [$\text{kg}_{\text{CO}_2}/\text{year}$]	779.35	483.61
σ_{GWP} [$\text{kg}_{\text{CO}_2}/\text{year}$]	155.29	126.19
μ_{SSR} [%]	21.03	/
σ_{SSR} [%]	1.89	/

Table 4.3: Comparison of the optimal system designs depending on the optimization

As it can be concluded from the characteristic values presented in Table 4.3, the LCOE optimum design has a mean LCOE of 18.4 €/MWh cheaper as well as a more robust LCOE optimum since it presents a standard deviation of 14.1 €/MWh cheaper. This system is composed solely of a 5 kWp PV panels installation with a 2.07 kW PV DC-DC converter

¹The PDF comparison between the different optimal solutions is presented in Appendix D to provide the interested reader with a different representation of stochastic performances.

power. This installation enables to cover partially the minimum average load needed without having to compensate the production and the demand with storage. However, the installation of such a system increases much the electricity carbon footprint due to relatively high carbon footprint of PV panels (i.e. uniform distribution: $\mathcal{U}(800, 2368)$ $\text{kg}_{\text{CO}_2,eq}/\text{kWp}$). While the full grid dependent dwelling has an average carbon footprint of $483.61 \text{ kg}_{\text{CO}_2,eq}/\text{year}$ with standard variation of $126.19 \text{ kg}_{\text{CO}_2,eq}/\text{year}$, the PV system increases, comparatively, the dwelling's average carbon footprint of $295.74 \text{ kg}_{\text{CO}_2,eq}/\text{year}$ as well as an increase of $29.1 \text{ kg}_{\text{CO}_2,eq}/\text{year}$ for the standard deviation. This represents respectively an increase of 61.15% and 23.06% for the average and standard deviation carbon footprint for the PV system while the average and standard deviation LCOE decreases of 8.9% and 20.83% respectively. The PDF presenting the situation explained are displayed in Figure 4.15 and Figure 4.16 (the corresponding CDF are, also, presented in Appendix D, Figure D.13 and Figure D.14).

Finally, due to these reasons, the full grid dependent design is the best optimal design in terms of social welfare to comply with the 2015 Paris agreement. However, from an individual point of view, as the PV design is the most optimal design in terms of LCOE, one could be tempted to add a PV installation to his dwelling. Taxes and regulations may be applied by the Swedish government if one pollutes more by adding personal PV panels. Besides, SSR values are here presented even though they, most probably, do not interest the dwelling's owner as the Swedish grid is completely reliable on the contrary to Rwanda where there are often power cuts.

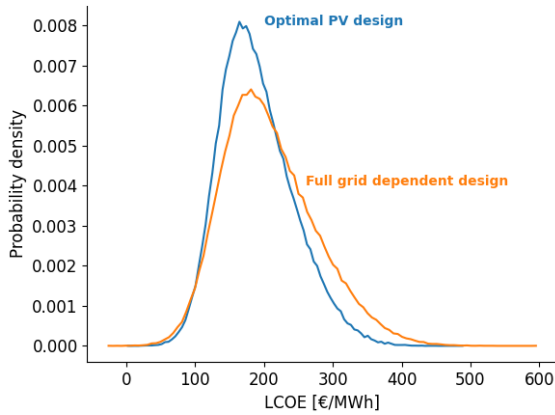


Figure 4.15: PDF comparison between the economically optimum design (PV-exclusive) and the environmentally optimum design (Full grid dependency) on LCOE basis. The optimal PV design PDF is narrower, which means that standard deviation has been reduced, and the mean value is slightly shifted to the left compare to the full grid dependency

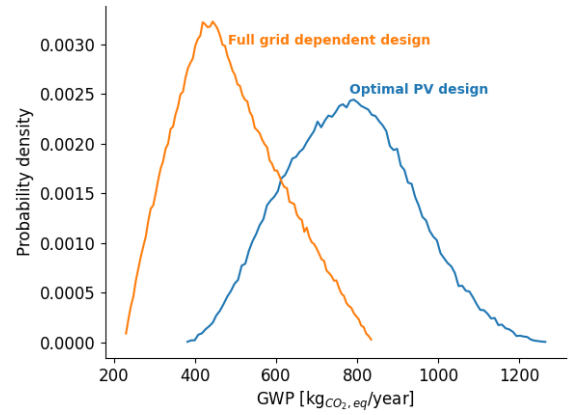


Figure 4.16: PDF comparison between the economically optimum design (PV-exclusive) and the environmentally optimum design (Full grid dependency) on GWP basis. Important shift to the right is made by the optimal PV design PDF added to an enlargement of this PDF which means that an increase of GWP mean and GWP standard deviation are the results of the carbon footprint and uncertainty range of the PV installation in the optimal PV design result.

Besides, one could wonder why the optimal LCOE design does not have a PV DC-DC converter power that equals the nominal power of the PV array installation in order to fully benefit from the production of the PV panels in case of high solar irradiance. In fact, having a look at Figure 4.17, it clearly appears that an important part of the PV electricity production is shortened by the DC-DC converter due to his power. This can be explained by several reasons. Firstly, as there is no battery to buffer the production from the demand, it is unnecessary to produce more than what is needed by the dwelling. Therefore, as the cost of the converters is proportional to their nominal power, increasing it to the nominal power of the PV array would increase the cost of the system. Peaks of electric load demand can reach values around 3 kW during an hour (i.e., hourly averaging assumption explained in section 3.2) but the average hourly consumption during summer is in a window that is half lower than the peak values (Figure 4.17). A DC-DC converter around 2.07 kW is thus chosen by the optimizer as it reduces as much the LCOE. Besides, as we are located in Stockholm, the 5 kWp array is rarely at its nominal power since conditions that are close to the condition that allows to characterize the kWp unit (i.e., 1000 W/m^2 , 25°C and clear sky [44]) are rarely met. However, having a higher solar PV nominal power allows producing more electricity during times of lower solar irradiance such as the early morning or the late afternoon. A balance is found between the PV panels and the DC-DC converter nominal power by the algorithm in order to fulfil the LCOE lowering objective.

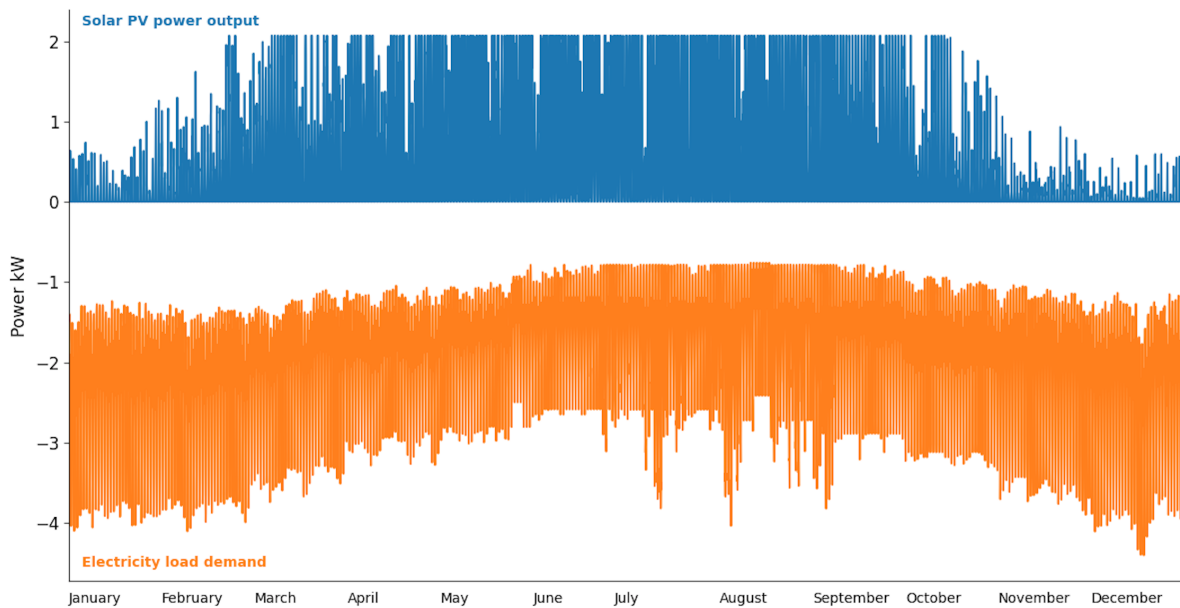


Figure 4.17: Power curves for the optimal LCOE design. PV array electricity production is shortened by the DC-DC converter power and load demand, during summer, is around 2 kWp most of the time without considering the peaks.

4.2.2 Community-scale design

A wide range of end-user scale batteries have been tested. Difficulties for an end-user scaled energy system, regardless of the battery used, to compete the grid has been highlighted in the previous analysis, especially concerning the climate impact for which the total grid dependency remains, by far, the best solution. However, even if economic gains can be made by installing a PV exclusive energy system, these gains are rather small. This is why it would be interesting to investigate the potential benefits, both from an economic and environmental point of view, to introduce a fourth battery which is NaS battery. In order to be in the operating

area of the latter battery, as it has been developed in chapter 2, optimizations of energy systems supplying a community composed of 1000 dwellings are, thus, realized.¹ Finally, it is important to mention that the results obtained in the end-user scale can not be directly compared to the ones obtained when considering end-user scaled design. Therefore, in order to have all the batteries on an equal footing, community scaled energy system with each battery will be evaluated both from an economic and an environmental point of view.

Economic evaluation

The results are presented in Figure 4.18 and in Figure 4.19, respectively for the Pareto fronts comparison and the design variables comparison. As it was already the case for end-user scaled system, minimum mean designs are the same regardless of the battery used (LCOE mean of 189.24 €/MWh and LCOE standard deviation of 53.17 €/MWh) due to the important grid reliance but going for a greater reliance on the energy system, differences appear between batteries. NMC battery as well as NaS battery offer the best performances (LCOE mean around 220 €/MWh and LCOE standard deviation around 44.5 €/MWh). This is explained by the range of their respective characterizing parameters that are close to each other.

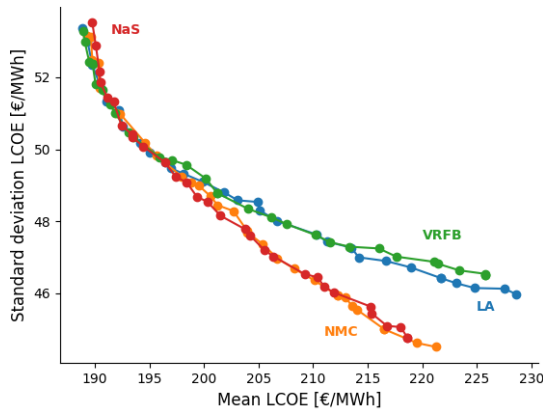


Figure 4.18: Pareto fronts comparison for the different batteries in Stockholm when optimizing LCOE for a community scaled system. NMC battery as well as NaS battery leads to the most robust designs.

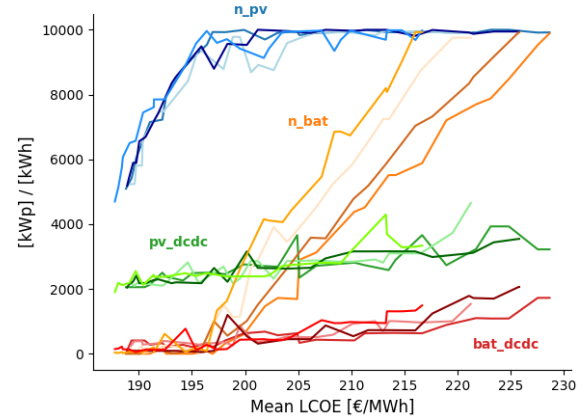


Figure 4.19: Design variables comparison for the different batteries in Stockholm when optimizing LCOE for a community scaled system - traditional colors are for LA, light colors are for NMC, dark colors are for VRFB and flashy colors are for NaS.

Table 4.4 presents characteristic values of the minimum mean design and the two robust designs, one using NMC battery and the other using NaS battery. The two latter, besides achieving similar economic performance, achieve, also, similar environmental performance. GWP mean of 1,158 kg_{CO₂,eq}/year/dwelling with standard deviation of 234 kg_{CO₂,eq}/year/dwelling which is, as a reminder, a performance very far from what the grid achieves.

¹The exact same procedure for NaS battery as for the other batteries concerning the determination of the maximum polynomial order and the reduction of the stochastic space has been conducted. The results are taken in section C.2 in Appendix C.

System components	Lowest mean design	Robust design	
		NMC	NaS
PV array power [kWp]	5,237.29	9,913.02	9,974.60
Battery stack capacity [kWh]	0	9,751.11	9,926.06
PV DCDC converter power [kW]	2,183.18	4,653.60	3,340.56
Battery DCDC converter power [kW]	0	1,541.11	1,494.88
Characteristic values			
μ_{LCOE} [€/MWh]	189.24	221.23	218.68
σ_{LCOE} [€/MWh]	53.17	44.50	44.78
μ_{GWP} [kgCO ₂ /year/dwelling]	794.35	1,158.08	1,157.50
σ_{GWP} [kgCO ₂ /year/dwelling]	139.3	232.57	234.57
μ_{SSR} [%]	21.46	34.89	34.92
σ_{SSR} [%]	2.01	3.36	3.39
$\mu_{lifetime}$ [years]	/	21.4	22.04

Table 4.4: Comparison of optimal system designs in Stockholm between the different batteries when optimizing LCOE considering community scaled energy system

From the Sobol' indices presented in Figure 4.20, it appears that, for the minimum mean designs (that are the same regardless of the battery used) as well as for the robust designs, the parameters characterizing to the grid electricity are, by far, the most driving ones (Sobol' indices around 60% is reached by the cost of electricity parameter and around 40% for the ratio). Contribution of the parameters related to the energy system to the LCOE standard deviation has slightly increased for the robust designs but still remains weak.

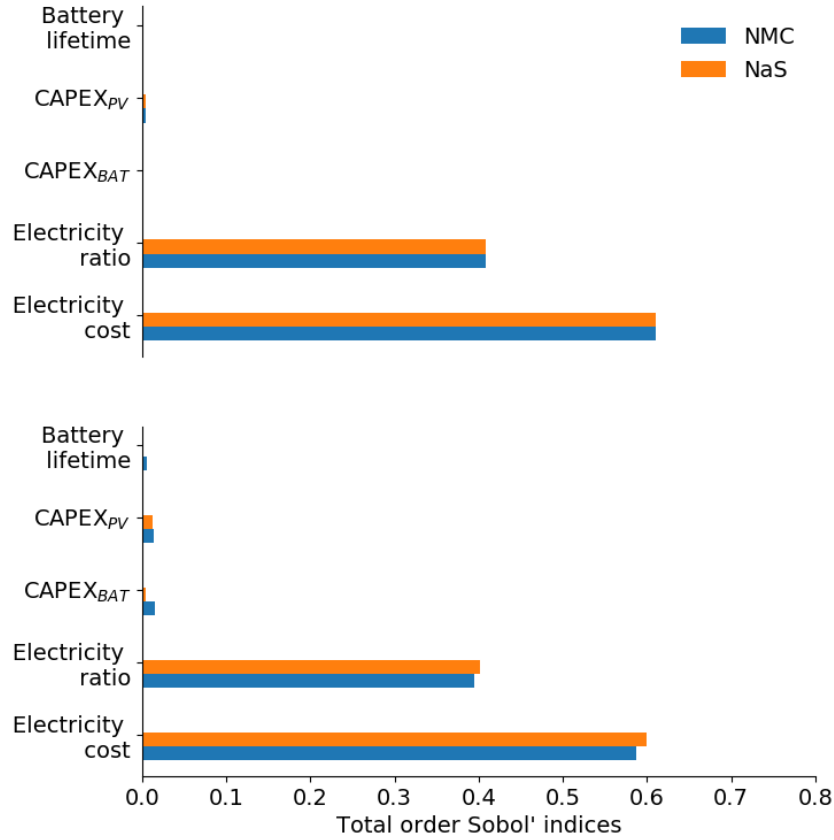


Figure 4.20: Sobol' indices comparison between the minimum mean designs (upper plot) and between the robust designs (lower plot) for the different batteries in Stockholm when optimizing LCOE for a community scaled energy system. The most driving parameters are the ones characterizing the grid electricity both for the minimum mean designs and the robust designs and regardless of the battery used.

As it could have been expected having in mind all the previous point discussed that highlight the important similarities on the results between the use of NMC battery and NaS battery, the stochastic performances achieved when using NaS battery are very close to the ones achieved when using NMC battery. Furthermore, the lowest mean design, PV-exclusive design, achieves, just like in the end-user scale case, the best performances (same kind of analysis between the different CDFs as it was made for the end-user scale can, also, be realized in this case).

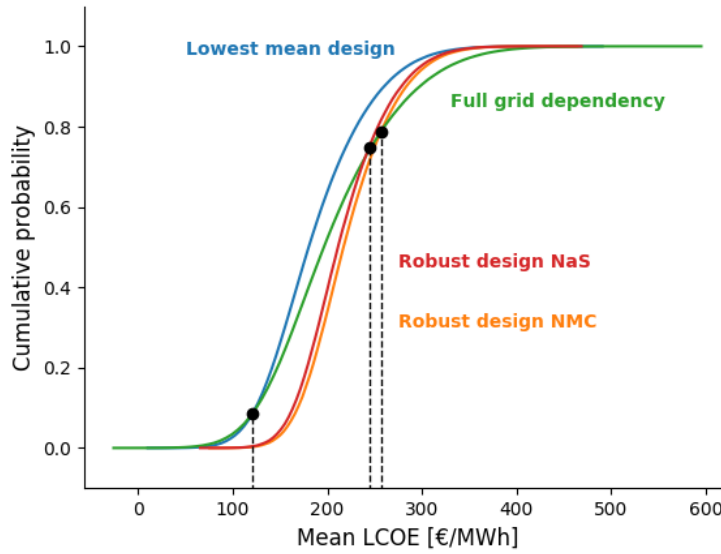


Figure 4.21: CDF comparison between three optimal designs (the minimum mean design which and the two robust designs) and the full grid dependency in the case of Stockholm when optimizing LCOE for community scaled systems. Lowest mean design achieves the best stochastic performances.

Environmental evaluation

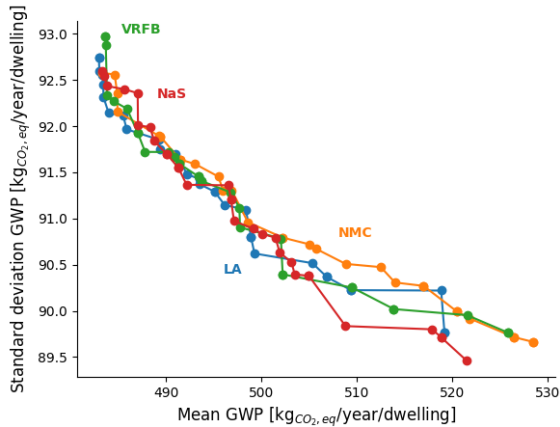


Figure 4.22: Pareto fronts comparison for the different batteries in Stockholm when optimizing GWP for a community scaled system. A reduced trade-off is observed, and the achieved performances are the same regardless of the battery technology used.

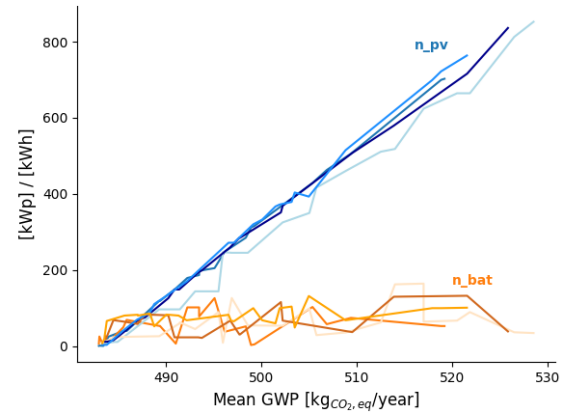


Figure 4.23: Design variables comparison for the different batteries in Stockholm when optimizing GWP for a community scaled system - traditional colors are for LA, light colors are for NMC and dark colors are for VRFB. No battery stack is never used.

The exact same analysis can be conducted with the environmental impact as objective. When considering the batteries available as storage technologies for end-user scaled system, the full grid reliance was, by far, the best choice to limit the GHG emissions. Thus, the

interest lies in knowing if deployment of NaS battery can compete the Swedish grid. From Figure 4.22, the different Pareto fronts appear to be superimposed. In fact, only PV panels are deployed in order to engage a reduction of the GWP standard deviation while no battery stack is never used (Figure 4.23). The PV array power increases up to 700 kWp to reach the robust system design. Detailed analysis of such PV-exclusive design and its comparison with the Swedish electrical grid having already been conducted in the end-user scale section. In the absence of NaS battery deployment in optimal designs, no further analysis will be made for the environmental evaluation in the case of community scaled energy system.

General discussion

After considering a wide variety of batteries, PV-battery systems do not achieve to be competitive either from the economic point of view or from the environmental point of view compare to a PV exclusive system (economically) or to the full grid dependency (environmentally). However, depending on the system's owner interest into a more self-sufficient system, PV-battery system can, therefore, become economically interesting. In this case, NaS battery achieves globally the same performances as NMC battery. Therefore, its use is interesting to replace NMC battery especially from an economic point of view. Also, as it was seen in the introduction, lithium-ion batteries are expected to increase drastically in years to come which rises important concerns in raw material depletion. Therefore, there is a major interest in turning to other types of battery.

4.2.3 Kigali

Self-sufficiency ratio evaluation

The performance of a single end-user scale system composed of a PV array with a battery stack is evaluated. As it has been previously developed, especially in chapter 3 when developing the three objectives of interest, reaching high SSR value in developing areas and especially Kigali in this work, is of particular interest given that the access to a reliable electrical grid is not acquired. Thus, optimization of SSR will be analyzed first before going for the two other objectives that are of primary interest.

A single result is reached when optimizing SSR which means that no trade-off between the maximization of SSR mean and minimization of SSR standard deviation is present. The two objectives are not really conflicting since deploying large energy system will maximize the mean SSR and minimize the risk of needing the electrical grid to meet the demand for electricity. Also, it is interesting to point that a multitude of system designs leads to this optimal point. In fact, there is nothing new to say that the solar potential, in Kigali, is huge and that relatively low load demand is faced in Kigali compared to Stockholm making it easy to obtain high SSR. Table 4.5 takes one combination that leads to 100% self-sufficiency but, of course, other possibilities like increasing the PV array power (although increasing costs) lead also to the same result regarding the optimization of SSR. A significant deployment of battery is needed beside the PV panels in order to fulfil the demand during the night or, even, during days with low solar radiation. Thanks to the abundant solar potential, PV panels easily generate big amount of extra electricity that can be used to charge the battery stack.

System components	Optimum SSR design
PV array power [kWp]	≈ 7
Battery stack capacity [kWh]	9.64
PV DCDC converter power [kW]	0.9
Battery DCDC converter power [kW]	0.7
Characteristic values	
μ_{LCOE} [€/MWh]	475.55
σ_{LCOE} [€/MWh]	85.39
μ_{GWP} [kgCO _{2,eq} /year]	623.96
σ_{GWP} [kgCO _{2,eq} /year]	160.00
μ_{SSR} [%]	99.97
σ_{SSR} [%]	0
$\mu_{lifetime}$ [years]	23.08

Table 4.5: Optimal SSR design

Knowing that the population of Kigali needs to rely on reliable energy sources and that a PV-Battery system can bring them 100% reliance, SSR reached by the system will be a factor of choice in order to decide between systems that optimize the environmental impact or the economic aspect. The population of developing regions, such as Rwanda, are certainly inclined to accept performance slightly lower than the performance reached by optimal solutions in order to be able to benefit from electricity with greater reliability.

Economic evaluation

An economic optimization of a single end-user energy system has been performed through the optimization of the LCOE objective for Kigali. Results are presented in Figure 4.24 and Figure 4.25, respectively for the Pareto fronts comparison and the design variables comparison. Single Pareto fronts for each battery as well as design variables are presented in Appendix D in order to have a more precise vision on each result. For each battery type, a very reduced trade-off can be observed as it is represented in the zoom out square plot in Figure 4.24. Explanations for this reduced trade-off can be found by having a look at the solar irradiance and load demand profiles (Figure 3.7 and Figure 3.9 in section 3.2) that have been previously presented. The constant behavior of these profiles throughout the year, leads a little bit to an extreme situation where the same day is repeated 365 times. Therefore, one specific system design can be the optimal one for the entire year. Due to the combined result of the low electricity demand with a high solar potential, PV exclusive system design with reliance on the grid when needed makes a single optimal result with LCOE perspective.

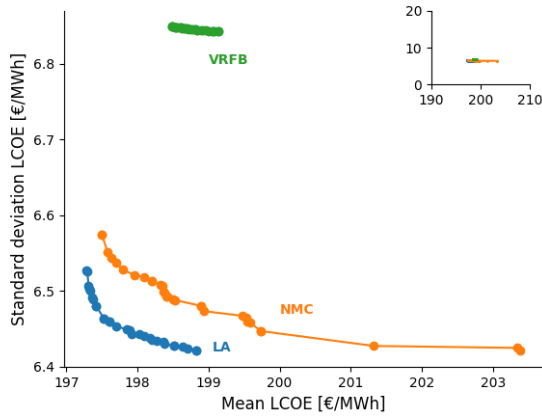


Figure 4.24: Pareto fronts comparison for the different batteries in Kigali when optimizing LCOE. The sets of optimal designs are the same regardless of the battery used.

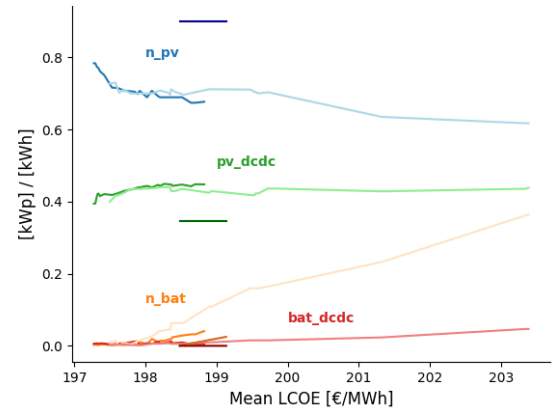


Figure 4.25: Design variables comparison for the different batteries in Kigali when optimizing LCOE - traditional colors are for LA, light colors are for NMC and dark colors are for VRFB.

Slight differences between the different Pareto fronts can be observed in Figure 4.24 but having a look at the design variables (Figure 4.25), the optimal designs are composed exclusively of PV panels. In fact, one could think that NMC batteries are used by looking at the light color curves in Figure 4.25 but two reasons lead to the conclusion that they are not used. Firstly, the DC-DC convertor connected to the battery stack does not differ from zero. Battery stack can, thus, not be filled if the converter does not allow it. Secondly, this deployment of battery exclusively leads to a horizontal extension of the Pareto front and, thus, to uninteresting system designs. There is no point in going for a system design that significantly increases the mean LCOE without a sensible decrease of the standard deviation. Thus, given that no battery is used in the optimal designs, no difference between the optimizations should be present. In fact, by zooming out, it appears that all the curves are approximately superimposed. The slight differences observed when zooming in are simply due to the randomness of the starting samples with which the algorithm and its optimizer, characterized by a crossover probability of 0.9 and a mutation of 0.1 guaranteeing respectively exploitation and exploration, makes the superimposition not 100% perfect.

The robust designs, which minimize the standard deviation, do not achieve significant reduction of the output standard deviation with regards to the increase of the LCOE mean. The minimum mean designs are, consequently, the ones of interest. As already explained, the differences being weak from one optimization to another, a single system will be used in order to proceed to uncertainty quantification. The considered system design composition as well as some characteristic values on this design are taken in Table 4.6.

System components	Lowest mean design
PV array power [kWp]	≈ 0.80
Battery stack capacity [kWh]	0
PV DCDC converter power [kW]	≈ 0.40
Battery DCDC converter power [kW]	0
Characteristic values	
μ_{LCOE} [€/MWh]	197.50
σ_{LCOE} [€/MWh]	6.57
μ_{GWP} [kg $_{CO_2,eq}$ /year]	764.36
σ_{GWP} [kg $_{CO_2,eq}$ /year]	157.19
μ_{SSR} [%]	34.47
σ_{SSR} [%]	1.99

Table 4.6: System optimal design in Kigali for the different batteries when optimizing LCOE

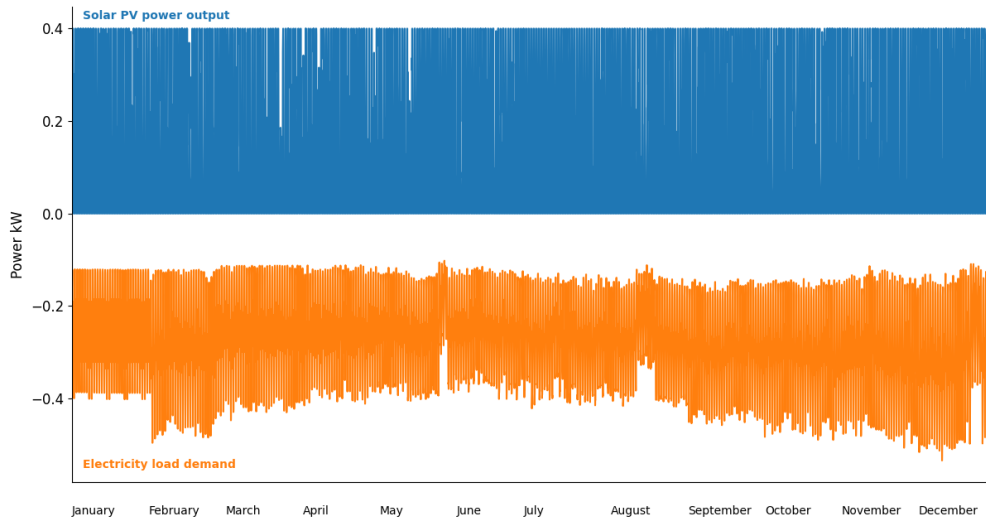


Figure 4.26: Power curves for the optimal LCOE design. PV output power is shortened by the DC-DC converter power.

The values of the PV array and the PV DC-DC converter can be understood, partially, by looking in Figure 4.26 as already explained in the case of Stockholm (except the reasons specific to Stockholm). However, some additional pieces of information that are specific to Kigali need to be pointed. First, as expected, the solar energy production is constant throughout the year. Also, in Kigali, the solar condition that are close to the condition that allows to characterize the kWp unit (i.e., 1000 W/m², 25 °C and clear sky [44]) can, often, be met during the year. Then, one could wonder why the PV DC-DC converter power is still not equal to the PV array power. During the early morning or even late in the

afternoon, conditions are further from the kWp standard conditions and then, the PV array does not reach its nominal power (similar reason than for Stockholm). At these times, DC-DC converter power does not need to be equal to the PV array power. During the day, conversely, conditions closer to the standard ones are reached but, opting for a DC-DC converter with more power will only increase the costs of the system and create surplus of electricity that can not be stored given the absence of battery stack.

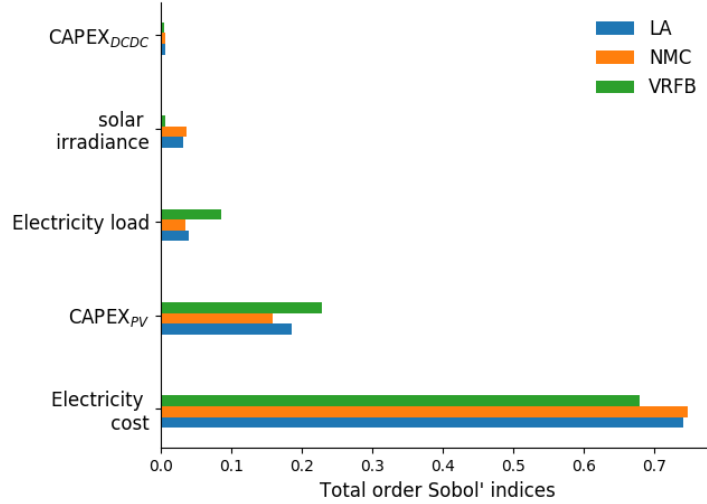


Figure 4.27: Sobol' indices comparison between the minimum mean designs for the different batteries in Kigali when optimizing LCOE. The cost of electricity from the grid and the investment costs of PV panels are the most driving parameters.

From the Sobol' indices in Figure 4.27, without surprise, the parameters characterizing the grid electricity price (Sobol' indices higher than 70% is reached) and the investment costs for the PV panels (around 20%) are the main drivers of the output variability. The solar irradiance and the load demand also have non-negligible impact since they have an influence on the need to buy additional electricity from the grid to fulfil the demand, but their impact does not reach values higher than 10%. Thus, the electricity price being already well characterized given the situation in Rwanda, it would be interesting to carry out additional work in order to refine the uncertainty range on the investment costs of PV panels. This would be an effective way to reduce the LCOE standard deviation and more specifically, the one of the PV system. Furthermore, this could potentially impact the percentage of system reliance since the uncertainty on the solar system LCOE would be therefore reduced.

Stochastic performances of the optimal system can also be analyzed. The latter achieves an important reduction of the mean LCOE compared to the full grid dependent design. Indeed, mean LCOE slightly below 200 €/MWh are reached while the grid electricity price lies around 260 €/MWh which corresponds to a reduction of 23%. Besides, it keeps a low value of standard deviation which ensures important robustness (value of LCOE in reality will always lie around the mean value without important variations). Moreover, reduction of the environmental impact is also achieved even if it is not an objective of the optimization. Electrical grid relying actually on carbon intensive energy sources, the actual yearly emissions of a typical dwelling were, as previously mentioned, about 1,100 kg_{CO₂,eq}/year. Going for the optimized design allows to engage a reduction of 30% to reach climate impact of 765 kg_{CO₂,eq}/year. Concerning the self-sufficiency of the system, one could wonder why such low values (i.e., 35%) are reached while, in Stockholm, SSR of 20 to 30% could, already,

be reached. Although the solar potential is huge and the electricity demand is rather low (2,330 kWh/year for a typical dwelling in Kigali compared to 9,500 kWh/year in Stockholm), the Rwandan electrical grid is very particular as it has already been explained above. The absence of electricity market greatly reduces the uncertain nature of electricity price which has the consequence of favoring a still important use of the grid. In fact, when optimizing the LCOE, minimization of the mean value as well as the standard deviation is pursued.

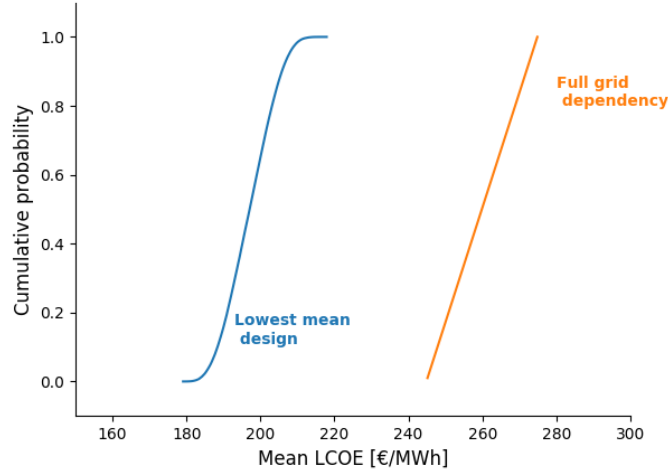


Figure 4.28: CDF comparison between three optimal designs (the three minimum mean designs) and the full grid dependency case in Kigali when optimizing LCOE. Full grid dependency case is, completely, outdrawn by a PV exclusive energy system from an economic point of view.

Comparison of the CDF is presented in Figure 4.28.¹ It turns out that, for any predefined LCOE upper threshold imposed by the owner, opting for a PV-exclusive energy system offers higher probability to be below this threshold than depending fully on the grid². In fact, the full grid dependency case is completely outdrawn by the solar system. As it was expressed in Table 4.6 and developed previously, alongside a greatly reduced LCOE, the standard deviation is particularly reduced and, thus, the CDF is rather steep. For instance, if the upper limit of LCOE is fixed by the owner at 190 €/MWh, the probability to be below is 16% while, for an upper threshold of 200€/MWh, the probability, already, reaches 66%. Already mentioned before, the economically optimized design achieving a reduction of the GWP compared to the grid, this makes it an advantageous choice from all points of view.

To conclude, the economically optimal design achieves interesting performances both on the LCOE as well as the GWP. However, the low reached SSR makes this system particularly vulnerable to potential power cuts that are of major concerns in Rwanda. Moreover, going for such designs may decrease the reliability of the grid and assess power quality issues. Indeed, in the case where a lot of single end-users adopt this solution, when sudden low solar irradiance and high consumption are combined, fast energy response are needed which may fragile the grid and cause severe and frequent power outages. Thus, important credits could

¹The PDF comparison between the different optimal solutions is presented in Appendix D to provide the interested reader with a different representation of stochastic performances.

²The linear shape of the grid electricity CDF is due to the uniform distribution used to characterize its stochasticity (i.e., $\mathcal{U}(245, 275)$ [€/MWh]). See Table A.2 in Appendix A

be given to system that increases the SSR at the expense of an increase of the LCOE (of course, trying to keep its value below the one of the actual grid price).

Environmental evaluation

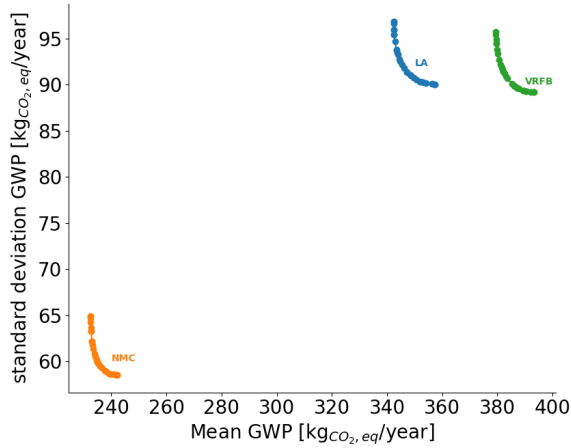


Figure 4.29: Pareto fronts comparison for the different batteries in Kigali when optimizing GWP. The use of NMC battery in the solar system achieved the best performances both for mean and standard deviation value.

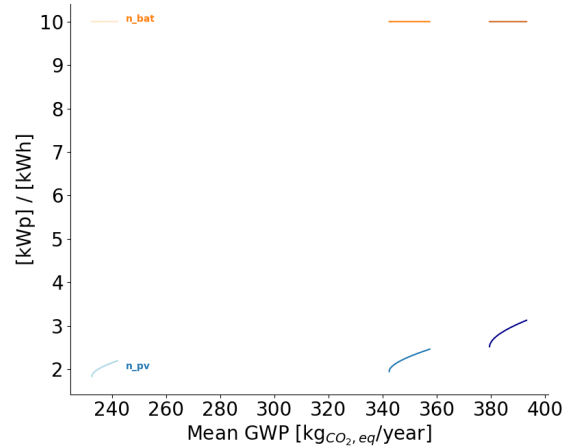


Figure 4.30: Design variables comparison for the different batteries in Kigali when optimizing GWP - traditional colors are for LA, light colors are for NMC and dark colors are for VRFB.

As it was the case for Stockholm, optimization with the objective of reducing the environmental impact has also been conducted in the case of Kigali. It is easily observed that results are far different from those obtained in Stockholm. Each battery has its own distinctive Pareto front and the system composed of a NMC battery outdraws the two others (Figure 4.29). Each Pareto fronts are included in small mean GWP and standard deviation GWP ranges as they are driven solely by the installed system. Single Pareto fronts for each battery as well as design variables are presented in Appendix D in order to have a more precise vision on each result. Besides, uncertainty quantification is conducted on the minimum mean designs as well as on the robust designs only for NMC battery and LA battery (Table 4.7). In fact, VRF battery achieves, by far, the worst results among the possible batteries.

More specifically on the designs of interest. It appears that the studied designs that are optimal from the environmental point of view, achieve rather bad results on the economic point of view (see Table 4.6). Indeed, mean LCOE around 200 €/MWh was reached by the economically optimized design while the environmentally optimized designs achieve a mean value around 357.83 €/MWh and 416.84 €/MWh respectively for the NMC and LA battery. Also, LA battery is cheaper than NMC (i.e. $\mathcal{U}(102, 354)$ €/kWh for LA compared to $\mathcal{U}(190, 500)$ €/kWh for NMC). One could, thus, wonder why the LCOE is higher when using LA battery. This can be understood by having a look at the deterministic lifetime values of the batteries inside the energy system. With deterministic value of 21.5 years, NMC battery has a high chance to not be replaced during the system lifetime. Conversely, LA battery will most likely be replaced twice or even three times (deterministic lifetime of 6.35 years).

System components	Lowest mean design		Robust design	
	LA	NMC	LA	NMC
PV array power [kWp]	1.95	1.83	2.46	2.19
Battery stack capacity [kWh]	10	10	10	10
PV DCDC converter power [kW]	1.60	1.55	1.60	1.55
Battery DCDC converter power [kW]	1.10	1.05	1.10	1.05
Characteristic values				
μ_{LCOE} [€/MWh]	416.84	357.83	427.58	363.92
σ_{LCOE} [€/MWh]	87.79	58.08	90.45	60.33
μ_{GWP} [kg _{CO₂,eq} /year]	342.45	232.5	357.40	242.03
σ_{GWP} [kg _{CO₂,eq} /year]	96.73	64.92	90.06	58.57
μ_{SSR} [%]	96.26	97.20	98.51	98.75
σ_{SSR} [%]	4.04	3.23	1.99	1.70
$\mu_{lifetime}$ [years]	6.35	21.5	6.34	21.5

Table 4.7: Comparison of system optimal designs in Stockholm for the different batteries when optimizing GWP

From the Sobol' indices illustrated in Figure 4.31, it is observed that two of the main driving stochastic parameters are the electricity load as well as the PV panels' carbon footprint. On the other hand, Sobol' index of the grid's carbon footprint is rather negligible. These three results can be easily explained. First of all, as the grid's carbon footprint is very high (i.e. $\mathcal{U}(0.39, 0.53)$ kg_{CO₂,eq}/kWh, see Table A.2 in Appendix A) and the system tries to diminish as much as possible the GWP, thus, the optimizer will converge towards a system that tries to be as self-sufficient as possible as it can be seen from the values in Table 4.7 (mean SSR of about 97% and 98.5% are reached respectively by the minimum mean designs and the robust designs). Therefore, the dwelling's carbon footprint is mainly driven by the electricity load that varies in a range of $\pm 30\%$, since a higher yearly consumption results in bigger emissions, and the installation of PV system with its respective carbon footprint. It, obviously, appears that additional work on improving the uncertainty range of the PV panels emissions would be an effective way to improve the robustness of the obtained results. Especially since the latter uncertainty is quite important. One could wonder why the solar irradiance is not a driving stochastic parameter as the system entirely relies in a PV-Battery system. This is simply the combined result of high solar irradiance presence in Kigali with low electricity consumption, making it thus a negligible stochastic parameter as well as a well-defined uncertainty range for the solar irradiance (i.e. $\mathcal{U}(100, 2.4)$ %). In fact, the solar potential does not need to be fully used to fulfil the load demand. On the other hand, the battery energy density as well as the battery lifetime of the LA battery are significant driving parameters. This comes from the fact that it has a low mean life cycle as well as a low mean energy density. Thus, for these parameters, being at the upper bound of their range makes them more competitive with NMC battery while being at the lower bound makes them completely outperformed by

NMC battery. This makes them driving parameters in the GWP objective since variability inside the range induces important variability in the competitiveness of LA battery.

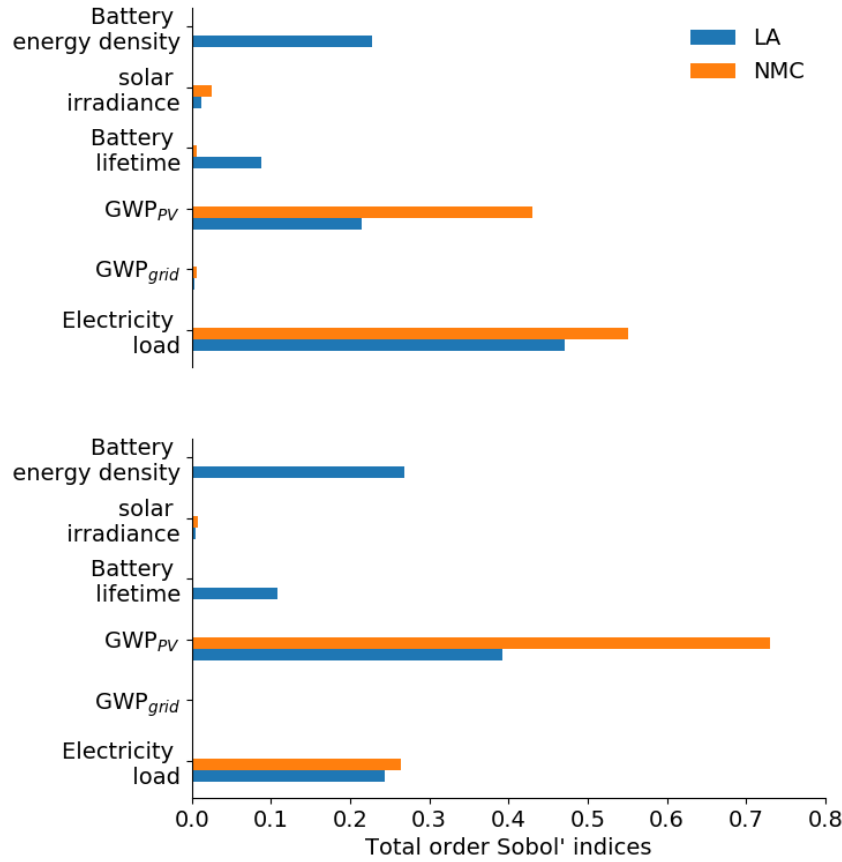


Figure 4.31: Sobol' indices comparison between the minimum mean designs (upper plot) and between the robust designs (lower plot) for the different batteries in Kigali when optimizing GWP. Uncertainty on parameters characterizing the energy system as well as load demand uncertainty drives the GWP standard deviation.

Comparison of stochastic performances between the different optimal designs when considering LA and NMC battery as well as the full grid dependency design is made via CDF comparison (Figure 4.32 and Figure 4.33).¹ The full grid dependent dwelling is completely outdrawn by the other systems as the grid's carbon footprint has a significant high value and the NMC outdraws as well the system equipped of LA battery. However, as the system with the LA battery still has a significant lower GWP impact than the typical household with 100% grid dependency, it can still be interesting to pursue a system with this battery type. Besides, it is better in diversifying battery types since they engage different materials and avoid depletion. Concerning the NMC battery, it can be seen that globally the lowest mean design is better than the most robust design as the most robust design's CDF curve crosses the lowest mean design around the cumulative probability of 85% for mean GWP around 300 kg_{CO₂,eq}/year. It is not to forget that the NMC lowest mean design achieves a slightly lower mean LCOE as well as a slightly lower LCOE standard deviation which makes it a better solution than the robust one.

¹PDF comparison between different interesting optimal solutions are available for the different battery types in Appendix D

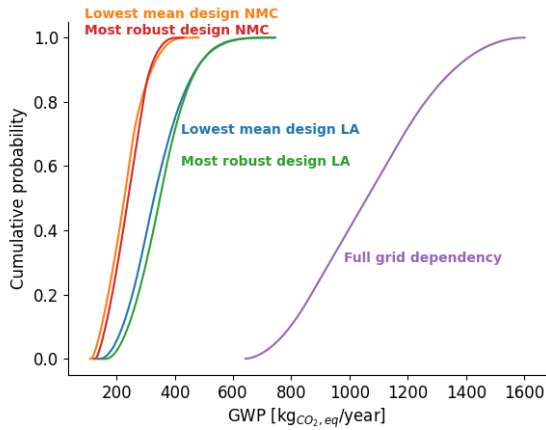


Figure 4.32: CDF comparison between five designs (the two minimum mean designs, the two robust designs and the full grid dependency) in the case of Kigali when optimizing GWP. The entire grid reliance design is completely outdraws by solar energy systems regardless of the battery used.

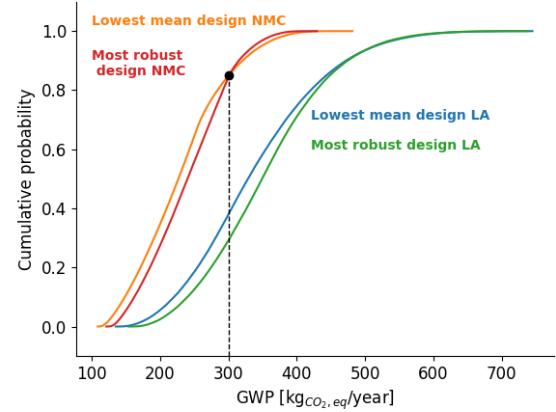


Figure 4.33: CDF comparison between four optimal designs (the two minimum mean designs and the two robust designs) in the case of Kigali when optimizing GWP. Use of NMC battery leads to the best performances

System components	Optimum LCOE design	Optimum GWP design
PV array power [kWp]	0.80	1.83
Battery stack capacity [kWh]	0	10
PV DCDC converter power [kW]	0.40	1.55
Battery DCDC converter power [kW]	0	1.05
Characteristic values		
μ_{LCOE} [€/MWh]	197.50	357.83
σ_{LCOE} [€/MWh]	6.57	58.08
μ_{GWP} [kgCO _{2,eq} /year]	764.36	232.5
σ_{GWP} [kgCO _{2,eq} /year]	157.19	64.92
μ_{SSR} [%]	34.47	97.20
σ_{SSR} [%]	1.99	3.23
$\mu_{lifetime}$ [years]	/	21.5

Table 4.8: Comparison of system optimal designs depending on the optimization

General discussion

Remembering the full grid dependent design, it is hard to imagine that the optimal GWP is a viable solution as it provides a system with a higher electricity cost even though it proposes a solution that drastically reduces the electricity's carbon footprint. On the other hand, the LCOE optimum design presents a much lower electrical cost as well as a reduced carbon footprint compared to the full grid dependent design. Indeed, the full grid dependent design has a cost of electricity and a yearly carbon footprint characterized by the following respective distributions:

- $\mathcal{U}(245, 260)$ [€/MWh]
- $\mathcal{N}(1072.70, 208.97)$ [$\text{kg}_{\text{CO}_2, \text{eq}}/\text{year}$]

which are indeed higher than the characteristic values obtained for the optimum LCOE design expressed in Table 4.8. Also, this design achieves an average SSR around 34.47% which enables to be released from some of the frequent power outage. Some could be interested in adding batteries to increase their SSR and become a bit more released from these power outages that can be annoying and penalizing. Thus, an intermediate optimal design is presented. This design is composed of a 1 kWp PV installation with a 0.7 kW PV DC-DC power conversion as well as a 1 kWh battery stack with a 0.2 kW DC-DC power converter. It allows to achieve a 46.06% mean SSR with a 3.45% standard deviation while keeping the cost of electricity close to the optimal PV design as well as reducing the carbon footprint. Thus, the intermediate design seems to be a good compromise between these three objectives. PDF of these respective designs are illustrated below on LCOE and GWP basis in Figure 4.34, Figure 4.35. CDF on LCOE and GWP basis of these designs are illustrated in Appendix D, Figure D.28 and Figure D.29 respectively.

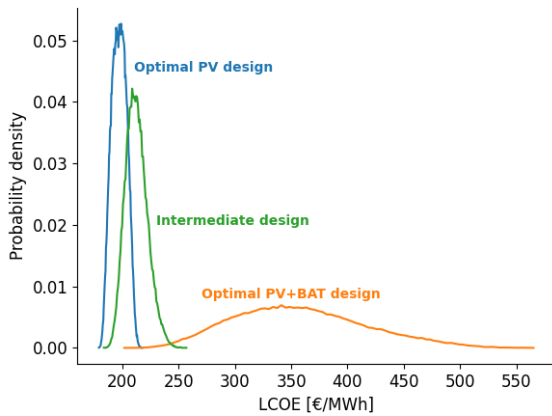


Figure 4.34: PDF comparison between the economical optimum design (PV-exclusive), the intermediate design (PV+BAT) and the environmentally optimum design (PV+BAT) on LCOE basis

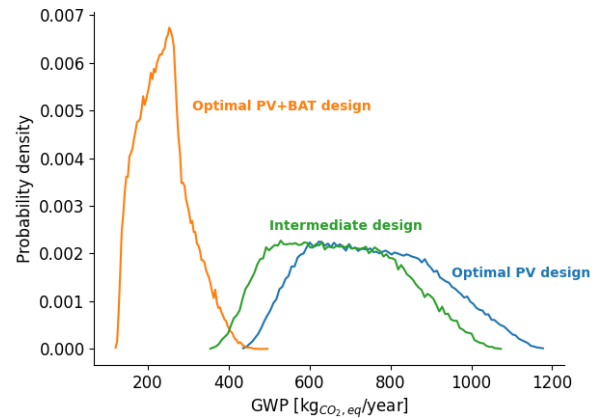


Figure 4.35: PDF comparison between the economical optimum design (PV-exclusive), the intermediate design (PV+BAT) and the environmentally optimum design (PV+BAT) on GWP basis

Chapter 5

Conclusion

The primary goal of this thesis was to optimize from an economic and environmental point of view a renewable energy system composed of solar PV panels with different battery types. The consistency in integrating such energy systems in very different contexts was also of particular interest. The search for the optimal system was accompanied by the introduction of input parameters' stochasticity in order to obtain a solution that behaves as close as possible to reality and that is less sensible to real world uncertainties. A Python-based model representing the energy system has been used with the help of polynomial chaos expansion.

In order to achieve the desired objectives, several optimizations have been conducted to evaluate the optimal system designs from an economic and environmental point of view. In addition, these optimizations were performed for two different contexts, namely Stockholm and Kigali. Firstly, in Stockholm, it has been shown that, economically, an energy system composed exclusively of PV panels with approximatively 5 kWp nominal power achieves the most important reduction of the LCOE and provides the highest probability to be under a LCOE threshold fixed by the owner of the system. On the other hand, an entire reliance on the grid allows to generate the lowest GHG emissions. Besides, if a significant self-sufficiency is sought by the owner, the PV-battery system, which is the system design that leads to the higher SSR value, is in all cases surpassed in both LCOE and GWP minimization objectives. Secondly, in Kigali, a PV exclusive energy system with a nominal power slightly below 1 kWp is the economically optimal solution and allows achieving a lower GHG impact than a dwelling relying solely on the grid. However, the environmentally optimal design opts for a system composed of important amount of energy storage batteries with a higher PV installation than the economically optimal result (1.83 kWp PV array combined with 10 kWh battery stack). This latter also achieves a total self-sufficiency. From these specific results obtained through the robust optimizations, several general conclusions that applied more globally can be drawn.

First of all, deploying renewable energies (PV in this case) in single end-user scale are interesting from a LCOE point of view when optimizing this objective whatever the considered geographical context (Stockholm and Kigali in this case with different solar irradiance) linked with its initial energy context (load consumption and electricity price). The system design is only composed of solar PV panels and does not present a battery. However, deploying renewable energies in single end-user scale are not always interesting from a GWP perspective when optimizing this objective. It depends on the grid's carbon footprint. Stockholm which disposes of a large amount of high-scale renewable energies achieves lower environmental impact (at least $\text{CO}_{2,eq}$) which makes the PV single-end user design completely uninteresting

from a GWP objective as it contributes negatively in $\text{CO}_{2,eq}$ emissions. On the contrary, in the case of Kigali, high reduction of $\text{CO}_{2,eq}$ are achieved thanks to the use of batteries. The simple use of PV panels without batteries (when optimizing LCOE) already allows achieving lower carbon footprint than a dwelling relying solely on the grid. However, batteries, besides decreasing even more the environmental impact, help achieving higher SSR which may be interesting for the single end-user in Kigali due to frequent and long duration of power outages.

Then, globally, NMC seems to be the best battery both at end-user scale and community-scale alongside NaS battery even though the ranges of uncertainty on the characterizing parameters are greater than the LA one. They have a longer lifetime making the system less costly than with a LA one. VRF being a new technology, efforts have to be made for it to be less cost and green house gas intensive in order to be able to compete the other two batteries. Regarding the two optimal batteries, it seems judicious to favor the deployment of NaS battery instead of NMC battery for stationary applications at community scale in order to avoid as much as possible the impact on the raw materials depletion.

In conclusion, deploying renewable energies comes with consistency. It is not necessarily less carbon intensive as it was seen in the results. Deploying renewable technologies in a country where a lot of renewables are already present at high scale may just contribute negatively to the GWP. It is not to forget that only the green house gases were considered in this study while there exist different sorts of environmental impacts such as acidification, toxicity and resource depletion. Also, except for LA battery type, recycling and waste disposal were not taken into consideration during the assessment of the batteries' carbon footprint. Finally, further improvements can be made with the parameters' uncertainty ranges.

Appendices

Appendix A

Stochastic parameters

A.1 Values

Table A.1: Techno-economic stochastic parameters of the solar PV panels

Parameter	Unit	Min.	Max.	Ref.
Solar irradiance ^a	%	100	Sweden: 4.2 Rwanda: 2.4	/
T_{amb}	%	Sweden: -40 Rwanda: -10	Sweden: +40 Rwanda: +10	/
Power tolerance	%	0	5	[33]
CAPEX	€/kW _p	430	780	[33]
OPEX	€/kW _p /year	16	19	[33]
GWP	kg _{CO₂,e,q} /kW _p	800	2368	[45],[46]

^a This parameter is not uniformly distributed and minimum and maximum values do not correspond to upper or lower limit. It is a Gaussian distribution. Minimum and maximum values correspond respectively to mean and standard deviation values in percentage as the distribution is multiplied by the hourly solar irradiance values.

Table A.2: Techno-economic stochastic parameters of Sweden and Rwanda

Country	Parameter	Unit	Min.	Max.	Ref.
Sweden	Electrical load	%	-30	+30	[47]
	Electricity grid price ^a	€/MWh	40	15	[48]
	Grid emission	kg _{CO₂,e,q} /kWh	0.02	0.04	[27]
	Electricity cost ratio	/	0.2	0.4	[49],[50]
Rwanda	Electrical load	%	-30	+30	[47]
	Electricity grid price	€/MWh	245	275	[38]
	Grid emission	kg _{CO₂,e,q} /kWh	0.39	0.53	[37]
	Electricity cost ratio	/			

^a This parameter is not uniformly distributed and minimum and maximum values do not correspond to upper or lower limit. It is a Gaussian distribution. Minimum and maximum values correspond respectively to mean and standard deviation values.

Table A.3: Techno-economic stochastic parameters of the different battery types

Battery type	Parameter	Unit	Min.	Max.	Ref.
PbA	GWP	kg _{CO₂,e.q} /kg	2.3	2.5	[14], [7]
	Energy density	Wh/kg	15	45	[51]
	Roundtrip efficiency	%	80	83	[13]
	Cycle life at 80% DoD	/	500	2000	[13]
	self discharge	%/day	0.1	0.3	[52]
	CAPEX	€/kWh	102	354	[13]
	OPEX	€/kWh/year	15	28	[33]
	BOP	€/kWh	30	80	[53], [54]
NMC	GWP	kg _{CO₂,e.q} /kg	14.12	16.13	[7]
	Energy density	Wh/kg	130.3	139.1	[7], [55], [15]
	Roundtrip efficiency	%	92	97	[7], [45], [15]
	Cycle life at 80% DoD	/	2000	5000	[7], [13], [52]
	self discharge	%/day	0.1	0.3	[33]
	CAPEX	€/kWh	190	500	[7]
	OPEX	€/kWh/year	20	30	[7]
	BOP	€/kWh	30	80	[54]
NaS	GWP	kg _{CO₂,e.q} /kg	11	18	[14], [56]
	Energy density	Wh/kg	70	250	[51], [57]
	Roundtrip efficiency	%	71	90	[13]
	Cycle life at 80% DoD	/	2500	5000	[13]
	self discharge	%/day	18	22	[52]
	CAPEX	€/kWh	178	400	[13]
	OPEX	€/kWh/year	15	28	[58]
	BOP	€/kWh	30	80	[59]
VRFB	GWP	kg _{CO₂,e.q} /kg	2.5	3.2	[14], [7]
	Energy density	Wh/kg	10	20	[60], [15]
	Roundtrip efficiency	%	70	80	[13], [15]
	Cycle life at 80% DoD	/	10000	15000	[13], [15]
	self discharge	%/day	12	16	[61]
	CAPEX	€/kWh	110	809	[13]
	OPEX	€/kWh/year	9	30	[62], [63]
	BOP	€/kWh	20	60	[53], [59]

Table A.4: Common techno-economic stochastic parameters of the different battery types

Parameter	Unit	Min.	Max.	Ref.
Degradation	%/year	3.5	4	[33]
Inflation rate	%	1	3	[33]
Discount rate	%	6	8	[33]
Nominal interest rate	%	4	8	[33]

Table A.5: Techno-economic stochastic parameters of the auxiliary equipments

Power electronic auxil- iary	Parameter	Unit	Min.	Max.	Ref.
DCDC Converter	CAPEX	€/kW	100	200	[33]
	OPEX	% of CAPEX	1	5	[33]
	Efficiency	%	95	96	[64]
DCAC Inverter	CAPEX	€/kW	140	200	[65],[66]
	OPEX	% of CAPEX	1	5	[33]
	Efficiency	%	89	91	[67]

Appendix B

Context



This appendix is dedicated to the description of the procedure taken to characterize the specific contexts. The focused parameters in this appendix are the yearly solar irradiance, temperature and load demand profile as well as the cost of electricity bought from the grid and its carbon footprint.

B.1 Sweden

In the objective of finding the hourly solar irradiance and temperature, TMY data will be used. Ten consecutive years were taken from 2007 to 2016. These data come from the European commission joint research center (JRC) [68]. The exact chosen coordinates were:

$$\begin{aligned} latitude &= 59^{\circ}19'58.8'' \\ longitude &= 18^{\circ}4'1.2'' \end{aligned}$$

which is located in the Norrmalm district in Stockholm, the city center. Stockholm being a 188 km² city, the average irradiance and temperature throughout the year will be approximated by the conditions at these coordinates.

B.1.1 Irradiance

The global horizontal irradiance $G(h)$ is used. In fact, this gives the total solar irradiance on the earth surface what is the power concentration a PV panel will receive if it lies on the ground. It is not realistic to use the global normal irradiance for domestic PV panels since these PV panels do not have an orientation system relative to the sun's rays due to economical purposes.

The hourly data for the irradiance in Stockholm from the TMY is shown in the right-hand side, Figure B.1 [68]. It can be clearly seen that the solar potential is spread between the late winter, the spring, the summer and the early fall while being almost zero during the rest of the year.

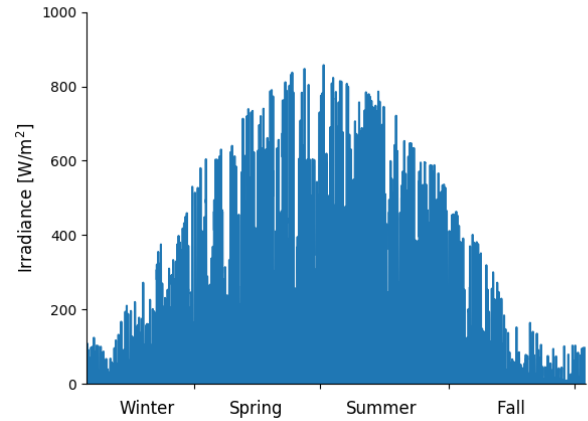


Figure B.1: Hourly distribution of the global horizontal irradiance along the year in Stockholm

The uncertainty on the solar irradiance typical year profile will be applied as a scaling. Regarding the low number of historical measurements available (i.e., 11 years of measurements), probability plot and maximum likelihood method are both applied to evaluate if a normal distribution catches well the uncertainty. Proceeding this way ensures double-check of the obtained result. The result obtained using the probability plot is shown in Figure B.2. Given that each of the two methods returns a similar result added to a high value for the R^2 coefficient from the probability plot ($R^2 = 0.95$), the normal distribution is kept to characterize the uncertainty with the parameters taken in Table A.1.¹

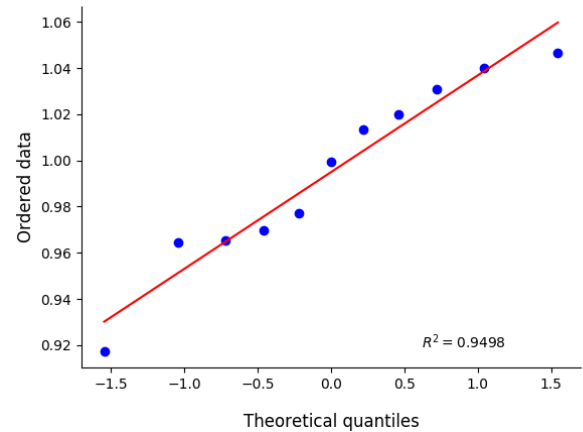


Figure B.2: Probability Plot for solar irradiance in Stockholm

¹ R^2 coefficient is a measure of the prediction quality of a linear regression.

B.1.2 Temperature

The hourly temperature profile in Stockholm taken from TMY is shown in Figure B.3 [68]. The uncertainty is applied as a scaling on the entire temperature profile. The determination of the values for this scaling is made using past measurements also available on [68]. Since the quantity of past measurements is not sufficient to consider representative range of the potential values taken by the temperature (i.e., 11 years of measurements), a security on the range we obtain is taken. If the temperature turns out to be an influencing parameter, further works on reducing this uncertainty will be needed. Values are taken in Table A.1.

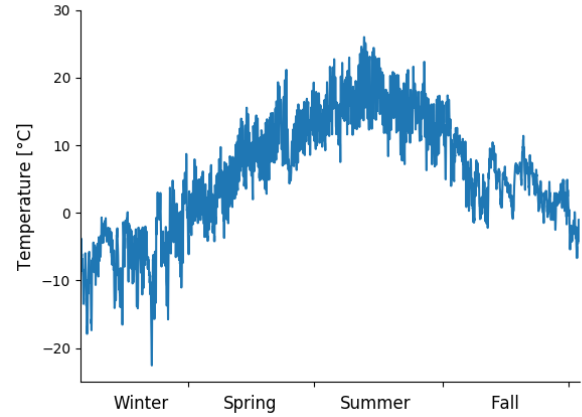


Figure B.3: Hourly distribution of the temperature along the year in Stockholm

Characterization of the temperature uncertainty is made through uniform distribution and the values are taken in Table A.1.

B.1.3 Load demand

The hourly load demand profile is computed by scaling the load from a different city to the requested location. To achieve it, the method developed in [69] is used.

First, the website Codeminders gives 99% similarity with US city Idaho Spring in Colorado [70]. Then, from Open Energy Information we have hourly electricity data for residential users in different cities across the US based on a TMY [71]. Finally, a scale factor needs to be applied so that the load demand for Stockholm can be obtained from the Idaho Spring's load demand. In fact, the electricity consumption is not only dependent on the weather but also on the habits, behavior of the users. The scale factor is the ratio between the average electricity consumption by the residential sector in the country of the wanted city and the one in the US. The average electricity consumption per dwelling in Sweden is equal to 9,494 kWh/dwelling [72] and in the US is equal to 10,649 kWh/dwelling [73]. The scale factor is, then, easily obtained:

$$\begin{aligned} s.f. &= 9,497/10,649 \\ &= 0.89182 \end{aligned}$$

Applying the found scale factor, the hourly load demand in Stockholm is obtained and represented below in Figure B.4.

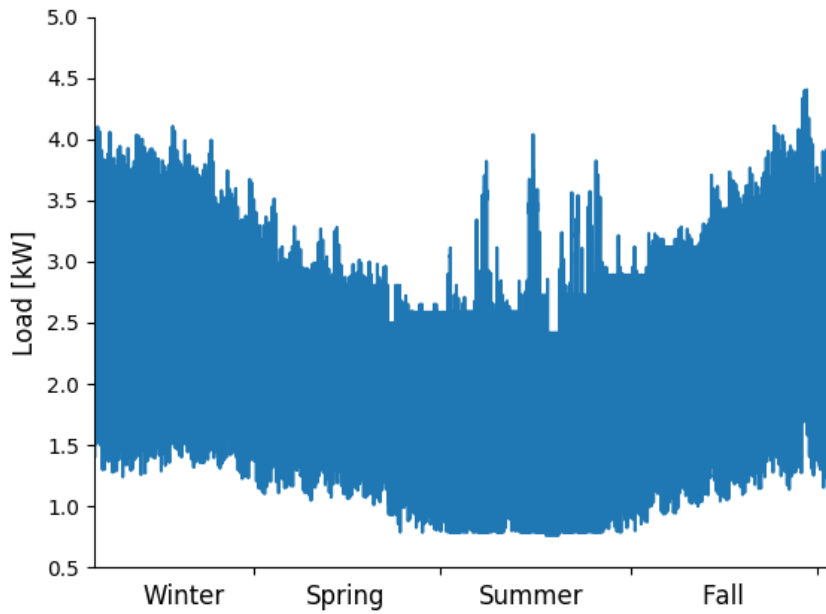


Figure B.4: Hourly distribution of the load demand along the year in Stockholm

Concerning the uncertainty applied on this parameter, a typical variation of within a $\pm 30\%$ range is used [47]. These information are included in Table A.2.

B.1.4 Electricity cost and emissions

The first parameter to gather is the price of the electricity itself, the market price of electricity. The need to have the market price is due to the willingness to represent in the more realistic way possible the uncertainty on the end-user cost of electricity. Besides, it would allow to easily add the possibility to sell electricity to the grid for further work. Then, in this case, the market price can be directly used for the price at which electricity is sold. On the opposite, when electricity needs to be bought from the grid, the end-user cost needs to be known. To this end, the electricity cost ratio which is the percentage of the received bill directly due to the electricity price itself needs, also, to be characterized.

Concerning the electricity market price. To reduce the computational cost, only a mean price on which a probabilistic uncertainty is applied will be used and not a typical daily or even yearly distribution like it is done for the irradiance, the temperature and the load demand. In order to determine the mean price as well as the probabilistic uncertainty, data from the NordPool Group that is active in the European power market are used [48]. 2020's data are not used due to their specific characteristic given the Covid-19 crisis.

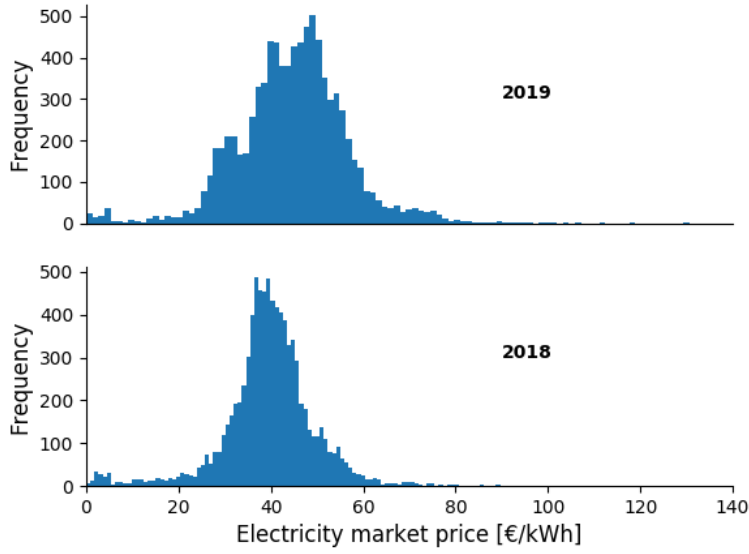


Figure B.5: Electricity Market price distributions for 2018 and 2019

Therefore, the data from 2018 and 2019 are used. Figure B.5 clearly highlights that uniform distribution is not really representative of the electricity market price variability while a normal distribution is. Probability plot method is used to obtain the parameter of the probabilistic distribution for the uncertainty (see Figure B.6). The normal distribution represents particularly well values of electricity market prices when laying around the mean value. Concerning the electricity ratio and the grid electricity's $\text{CO}_{2,\text{eq}}$ emissions, the information are directly taken from [27]. The results are presented in Table A.2.

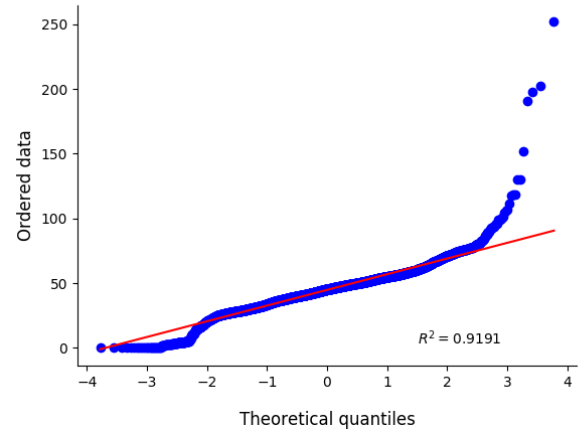


Figure B.6: Probability Plot for the electricity market prices in Stockholm

B.2 Rwanda

In the objective of finding the hourly solar irradiance and temperature, TMY data will be used. Ten consecutive years were taken from 2007 to 2016. These data come from the European common joint research center (JRC) [68]. The exact chosen coordinates were:

$$\begin{aligned} \text{latitude} &= -1^{\circ}57'18'' \\ \text{longitude} &= 30^{\circ}3'50.4'' \end{aligned}$$

which is located in the district of Kiyovu in Kigali. Kigali being a 730 km² city, the average irradiance and temperature throughout the year will be approximated by the conditions at these coordinates.

The method used to characterize the uncertainties in the case of Stockholm is applied in the same way for Kigali.

B.2.1 Irradiance

As it is observed from the figures below (Figure B.7 and Figure B.8), the irradiance is constant throughout the year.

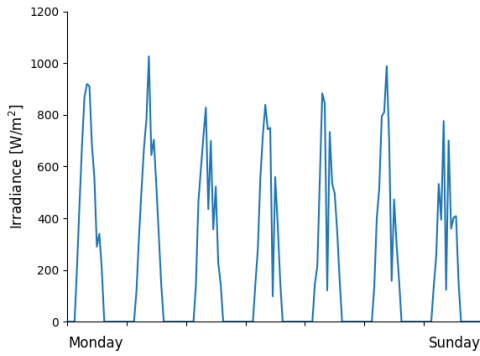


Figure B.7: Hourly distribution of the global horizontal irradiance along a week in Kigali

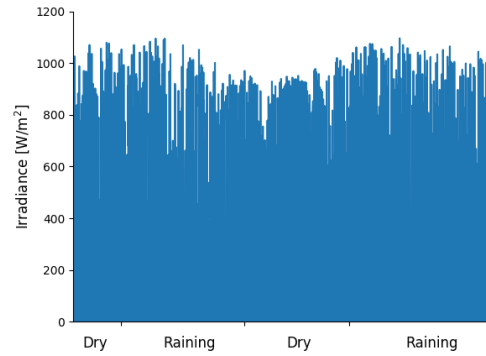


Figure B.8: Hourly distribution of the global horizontal irradiance along the year in Kigali

B.2.2 Temperature

The same remark as the one made for the solar irradiance can be made for the temperature throughout the year (Figure B.9 and Figure B.10).

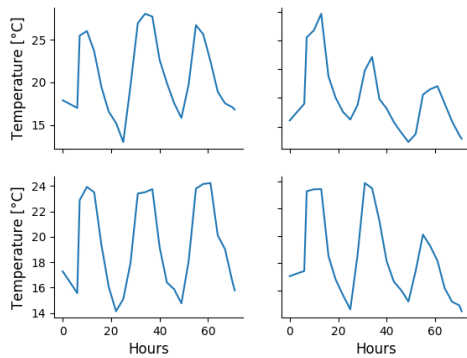


Figure B.9: Temperature profile for 3 random consecutive days profile with 3 months separating them in Kigali

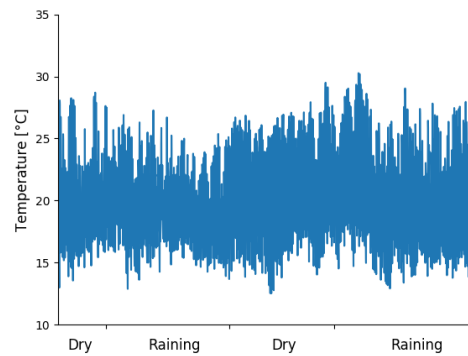


Figure B.10: Average temperature yearly profile

B.2.3 Load demand

Here, it is important to understand the hypothesis chosen, as already explained in sub-section 3.2.2. Because Rwanda is still a developing country, strong inequalities in terms of energy consumption are observed even in its capital. Rural areas suffer even more from absence of electrification, but the focus of this study will be the capital city of Kigali. This

inequalities in energy consumption can be observed in Table B.1 for different housing types and, thus, different socio-economic groups.

Building type	Electricity	LPG	Charcoal	Total
Rudimentary	79	165	1,290	1,534
Villa house	530	355	1,532	2,417
Luxury villa	689	419	1,329	2,437
Local type	442	2,426	0	2,868

Table B.1: Dwelling's consumption in kWh/capita/year [74]

Because of these mentioned reasons, the load scaling will not be done exactly as it was with the case of Sweden due to the important socio-economic cleavage in Rwanda. One assumption is here made: the household must be able to afford a PV-Battery system. Also, the luxury villa being a too much restrained percentage of Kigali's households (and even more of Rwanda), the villa house is then chosen in order to take into account a more global situation. Besides, the city of Hilo in Hawaii was found to be climate relative of 98%. Therefore, the electric consumption¹ of this city was taken. Its annual electric consumption per dwelling is around 14,500 kWh. A scale factor is then applied:

$$\begin{aligned} s.f. &= 2,332/14,500 \\ &= 0.160828 \end{aligned}$$

The hourly load throughout the year is presented below as it was already presented in subsection 3.2.2

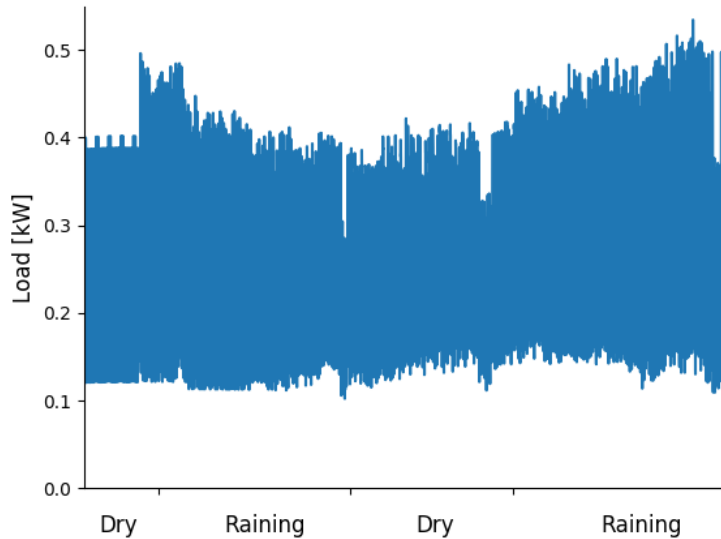


Figure B.11: Hourly distribution of the electric load demand (villa house) along the year in Kigali

Concerning the uncertainty applied on this parameter, a typical variation of within a +/- 30% range is used [47]. These information are included in Table A.2.

¹<https://openei.org/datasets/files/961/pub/>

B.2.4 Electricity cost and emissions

As Rwanda is an emerging country, the situation of energy is a bit different from the one encountered in Stockholm. Also, the energy sector is a monopoly detained by the government leading thus to lack of competitiveness in the energy market. Therefore, electricity price is fixed and people buy their monthly consumption in advance. The electric price for a residential consuming more than 50 kWh, which is the case in our assumption, equals 249 Rwandan francs per kWh, equivalent to 0.26 €/kWh [38]. Next to that, real questions remain when questioning how could the selling from a stand-alone PV can be carried out when no market exist and that there is an excess of production and personal battery storage is fully charged. At this time, this possibility can not be considered.

Figure B.12 comes from a study of 2018 that extrapolates the grid's emission based on the energy sector planning. Since Rwanda is a fast-emerging country, we believed that it was important to take into account this transition. Therefore, it was decided to take into consideration the carbon footprint calculated in 2018 and the estimated value in 2024 such that we take into account values estimated in a near future. Thus stochasticity of the parameter GWP_{grid} is characterized by the following distribution: $\mathcal{U}(0.39, 0.53)$ $\text{kg}_{\text{CO}_2,eq}/\text{year}$ as presented in Table A.2.

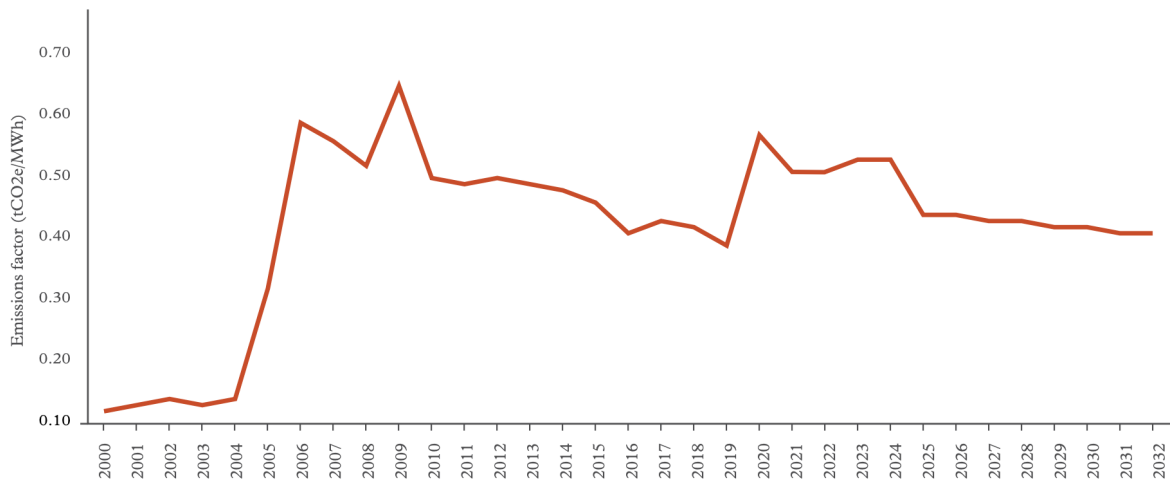


Figure B.12: Emissions factor of grid electricity in Rwanda, 2000 to 2032. This emissions factor includes the effects of imported electricity. [37]

Appendix C

Determining polynomial order and reducing the uncertainties

C.1 Negligible stochastic parameters

Note: Sobol' indices are here computed with the case of a LA battery. As the stochasticity of $OPEX_{BAT}$ and battery efficiency are relatively of the same order of magnitude for the different batteries, it is assumed that Sobol' indices order will be relatively of the same order of magnitude. However, self-discharge stochasticity is higher for VRF and NaS battery but regarding the magnitude of the total order Sobol' indices with LA, results won't be sensitive to this parameter compared to the considered stochastic parameters presented in section 3.6. Thus, by proving that these parameters are negligible for a specific kind of battery applies for the others. Also, stochastic parameters related to LCOE for GWP are presented. It just proves, that LCOE related parameters can be set as deterministic when considering GWP optimization. Same applies with GWP stochastic parameters when doing a LCOE optimization. Thus, considering the optimization they will be set as deterministic as already explained in section 3.6.

Stockholm

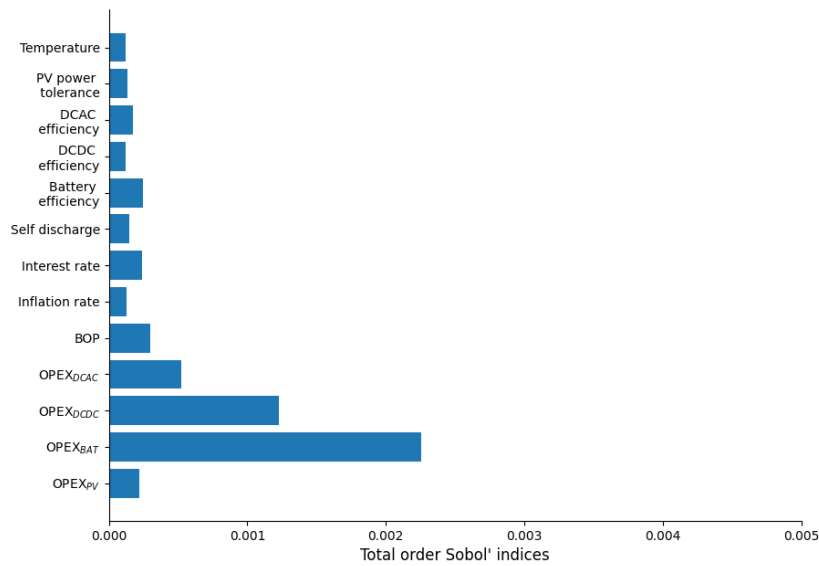


Figure C.1: Unconsidered Sobol' indices in Stockholm LCOE polynomial order determination. Looking at the order of magnitude of these Sobol' indices, it is easily verified that these stochastic parameters are negligible.

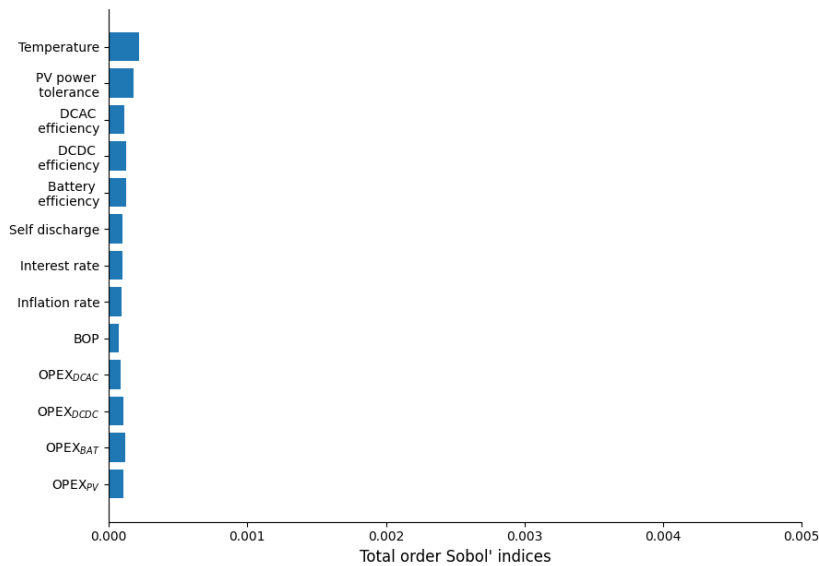


Figure C.2: Unconsidered Sobol' indices in Stockholm GWP polynomial order determination. Looking at the order of magnitude of these Sobol' indices, it is easily verified that these stochastic parameters are negligible.

Kigali

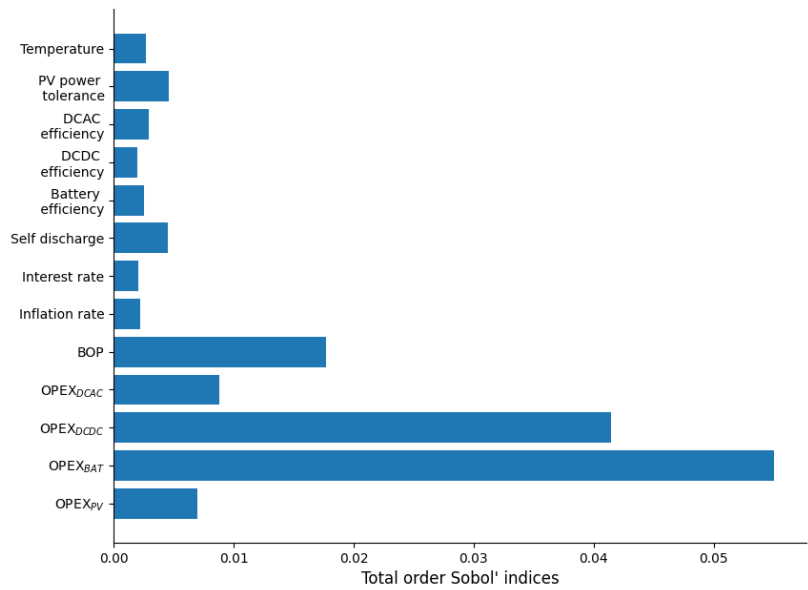


Figure C.3: Unconsidered Sobol' indices in Kigali LCOE polynomial order determination

Unconsidered Sobol' indices in Kigali LCOE polynomial order determination. Looking at the order of magnitude of these Sobol' indices, it is easily verified that these stochastic parameters are negligible. The order of magnitude of these Sobol' indices are significantly higher than those in Stockholm but are still quite negligible as the other considered stochastic parameters presented in section 3.6 are higher than these in the case of Kigali.

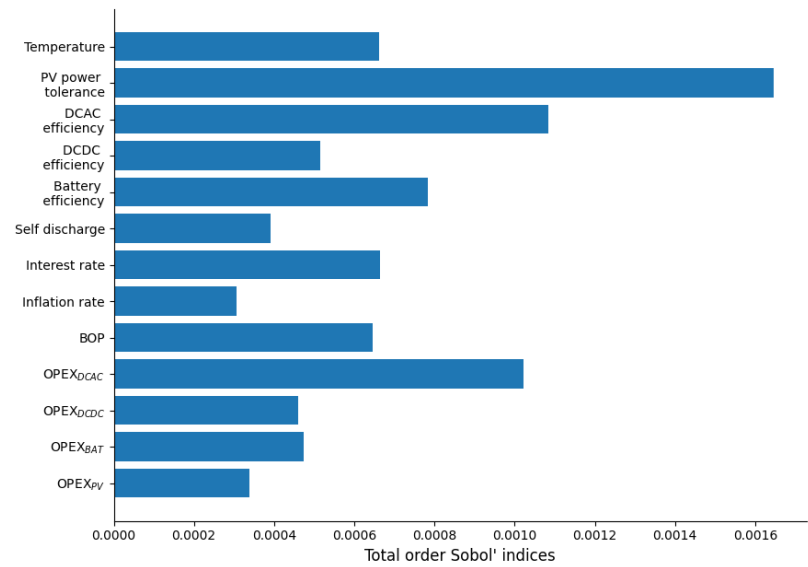


Figure C.4: Unconsidered Sobol' indices in Kigali GWP polynomial order determination

Unconsidered Sobol' indices in Kigali GWP polynomial order determination. Looking at the order of magnitude of these Sobol' indices, it is easily verified that these stochastic parameters are negligible.

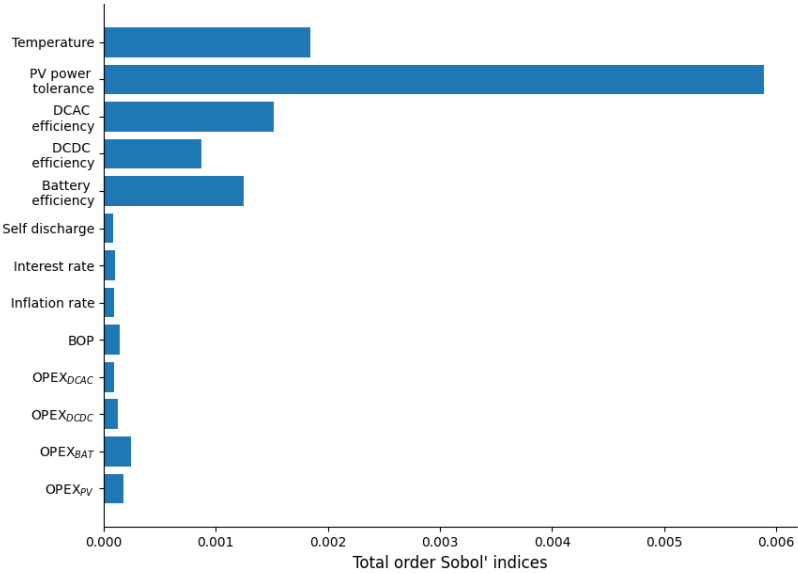


Figure C.5: Unconsidered Sobol' indices in Kigali SSR polynomial order determination

Unconsidered Sobol' indices in Kigali SSR polynomial order determination. Looking at the order of magnitude of these Sobol' indices, it is easily verified that these stochastic parameters are negligible. Besides, it is observed that parameters related to the system performances are the highest Sobol' indices, logically, despite still being negligible.

C.2 NaS battery

	LCOE	GWP
Order 1	16.55	3.62
Order 2	0.24	0.01

Table C.1: Maximum LOO error in the case of Stockholm in [%] for NaS battery

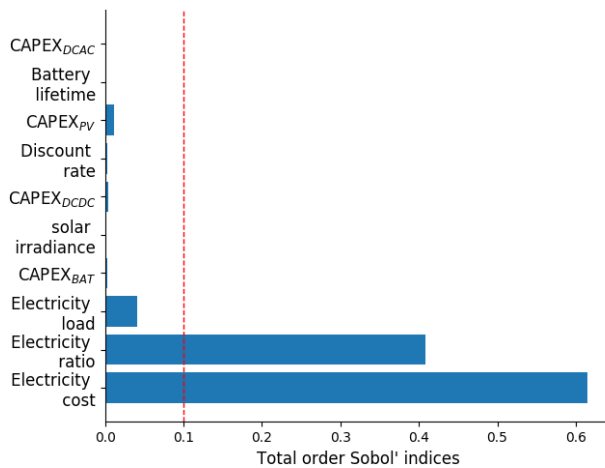


Figure C.6: Total order Sobol' indices in the case of Stockholm for a LCOE optimization with NaS battery

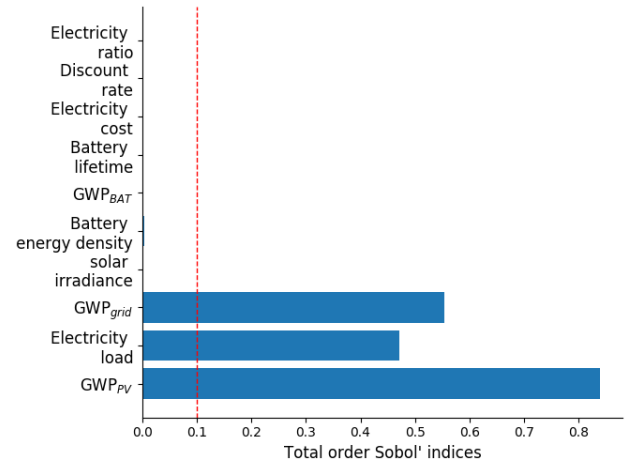


Figure C.7: Total order Sobol' indices in the case of Stockholm for a LCOE optimization with NaS battery

Electricity cost	Electricity ratio	GWP _{PV}	Electricity load	GWP _{grid}
CAPEX _{PV}	CAPEX _{BAT}	CAPEX _{DCDC}	Discount rate	Battery's energy density

Table C.2: Stochastic parameters for NaS battery in the case of Stockholm

Appendix D

Results

D.1 Stockholm

Lead-acid battery

LCOE optimization

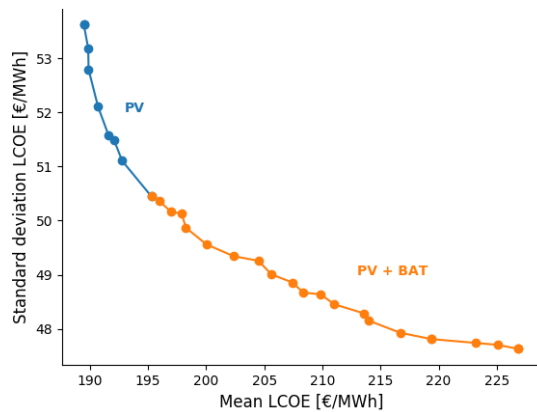


Figure D.1: Pareto front from LCOE robust optimization in Stockholm with lead-acid battery presenting separation between PV-exclusive designs and PV-Battery designs

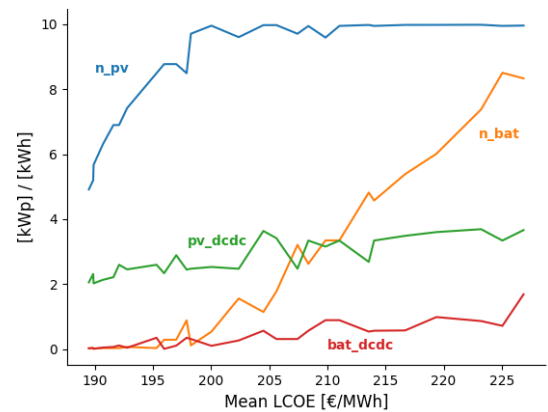


Figure D.2: Design variables from LCOE robust optimization in Stockholm with lead-acid battery

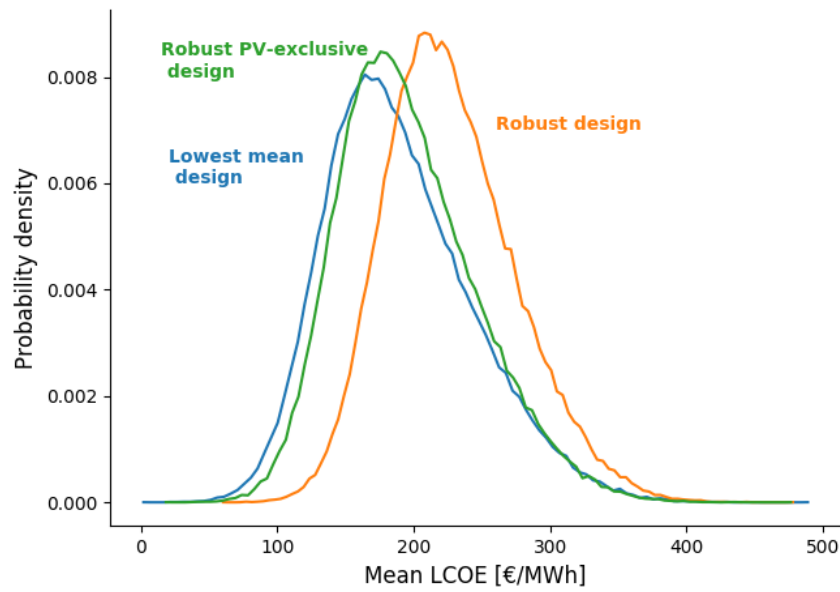


Figure D.3: Comparison between 3 different designs' PDF in Stockholm with lead-acid battery when optimizing LCOE

NMC battery

LCOE optimization

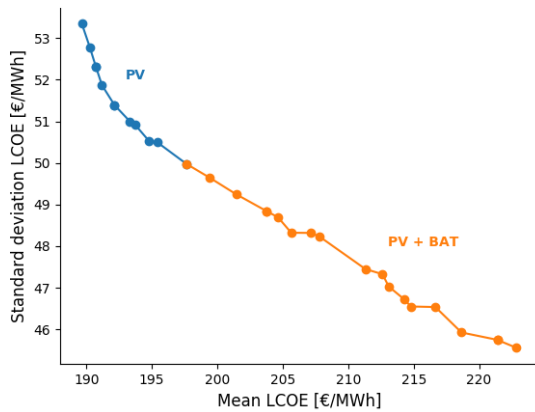


Figure D.4: Pareto front from LCOE robust optimization in Stockholm with NMC battery presenting separation between PV-exclusive designs and PV-Battery designs

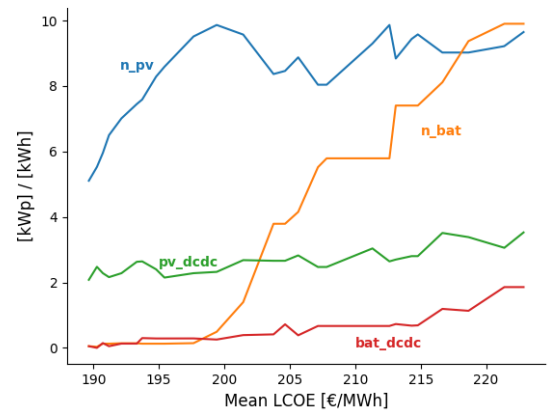


Figure D.5: Design variables from LCOE robust optimization in Stockholm with NMC battery

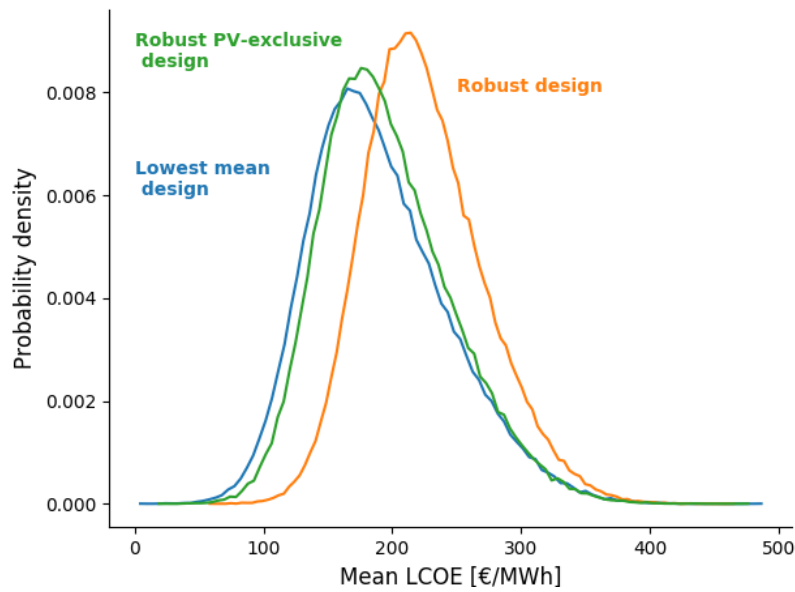


Figure D.6: Comparison between 3 different designs' PDF in Stockholm with NMC battery when optimizing LCOE

Vanadium redox flow battery

LCOE optimization

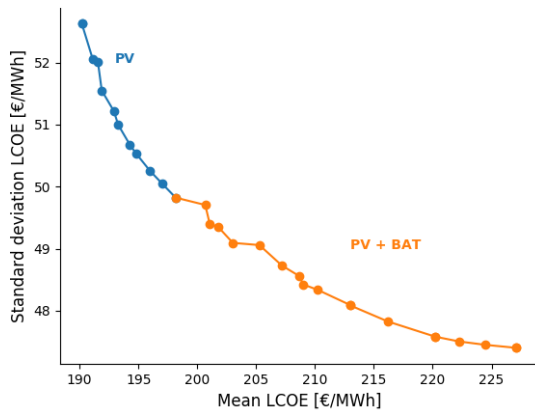


Figure D.7: Pareto front from LCOE robust optimization in Stockholm with VRF battery presenting separation between PV-exclusive designs and PV-Battery designs

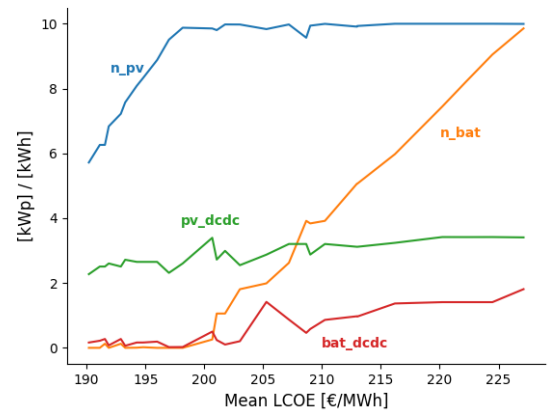


Figure D.8: Design variables from LCOE robust optimization of in Stockholm with VRF battery

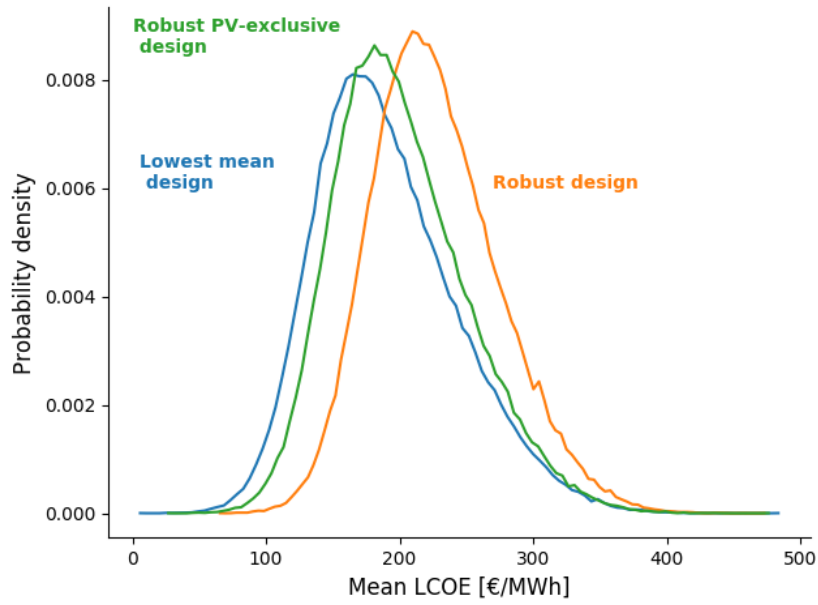


Figure D.9: Comparison between 3 different designs' PDF in Stockholm with VRF battery when optimizing LCOE

GWP optimization

As there are no batteries present when optimizing GWP whatever the battery considered as it was seen in chapter 4, a common subsection is dedicated to present the results obtained for the GWP optimizations.

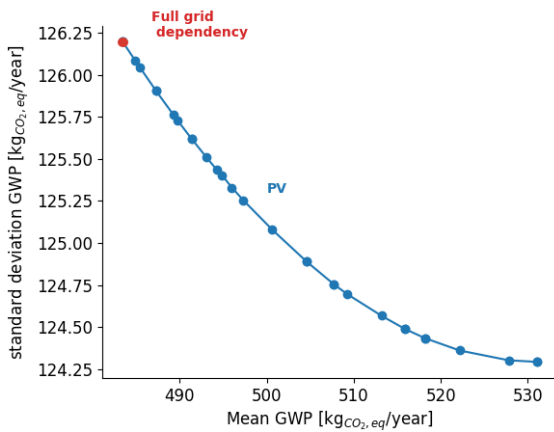


Figure D.10: Pareto front from GWP robust optimization in Stockholm with VRF battery presenting only PV-exclusive designs

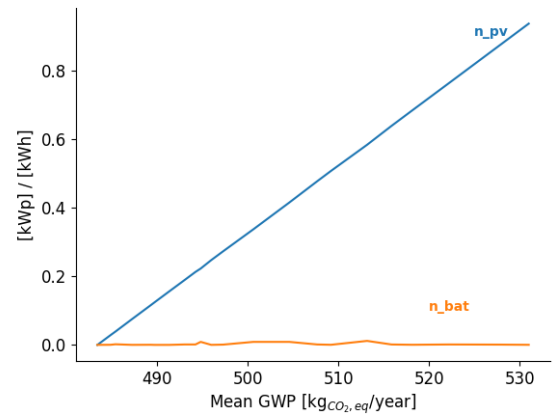


Figure D.11: Design variables from GWP robust optimization in Stockholm with VRF battery

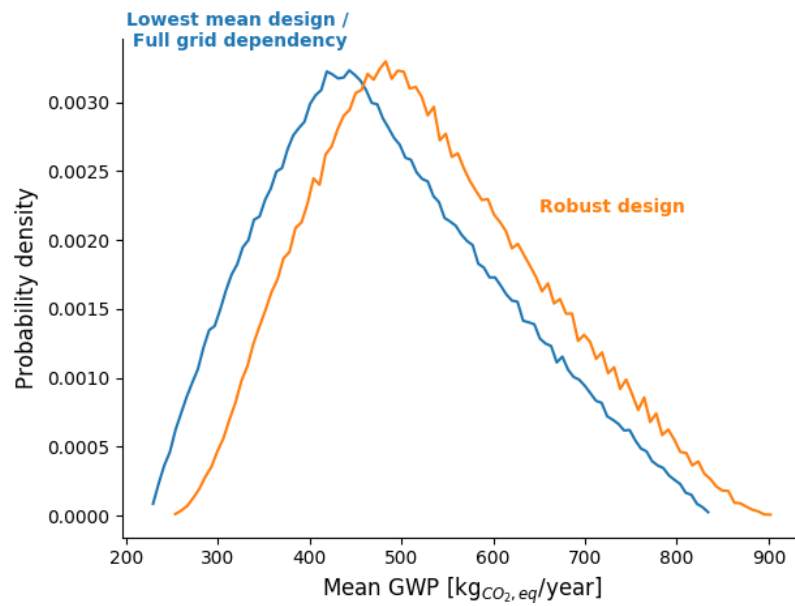


Figure D.12: Comparison between 3 different designs' PDF in Stockholm with VRF battery when optimizing GWP

Optimal design optimization

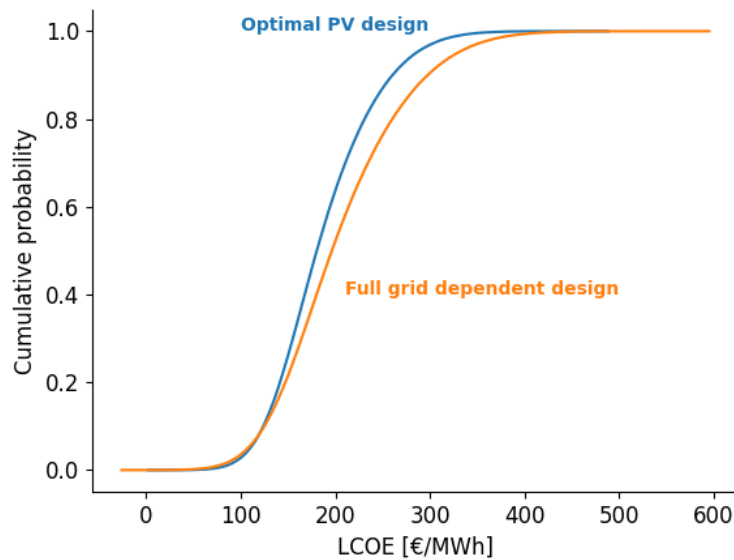


Figure D.13: Comparison of the LCOE between the PV and the full grid dependent designs' CDF in Stockholm (respectively, the LCOE and GWP optimization designs results)

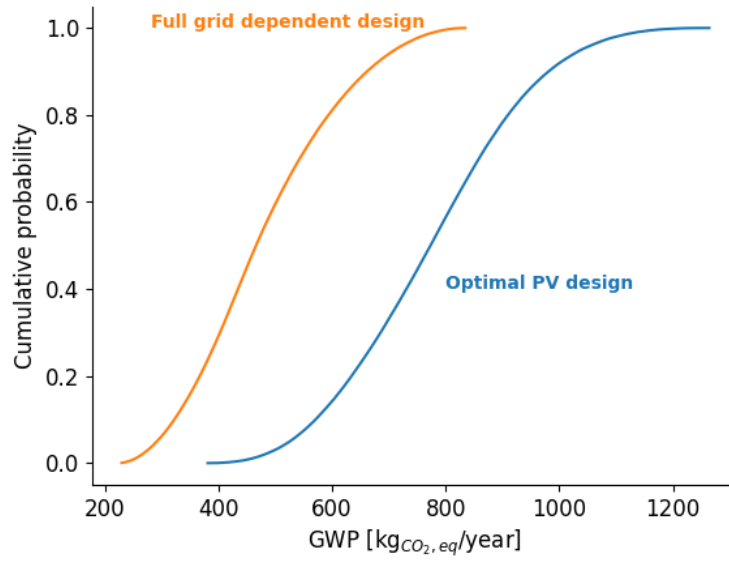


Figure D.14: Comparison of the GWP between the PV and the full grid dependent designs' PDF in Stockholm (respectively, the LCOE and GWP optimization designs results)

D.2 Kigali

LCOE optimization

Just as it was done with the GWP optimization in Stockholm presented in the appendix, the LCOE section will be grouped for the different optimizations as no batteries are used.

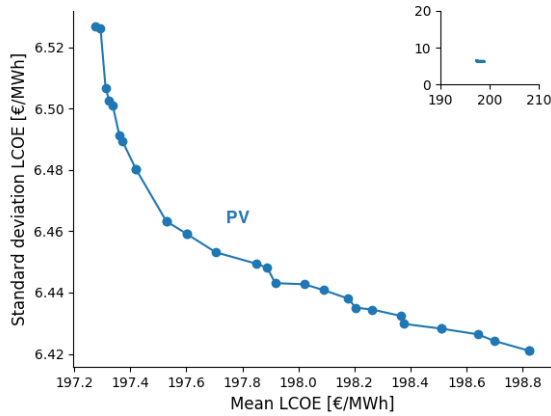


Figure D.15: Pareto front from LCOE robust optimization in Kigali with lead-acid battery

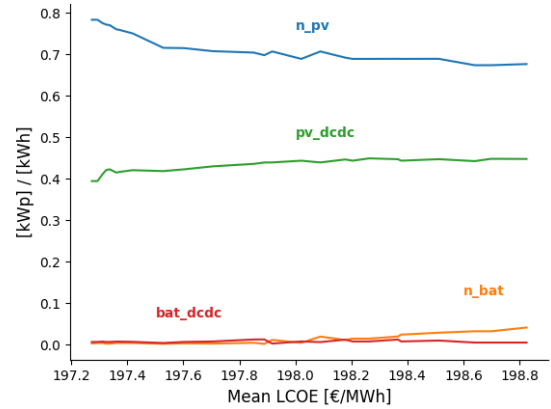


Figure D.16: Design variables from LCOE robust optimization in Kigali with lead-acid battery

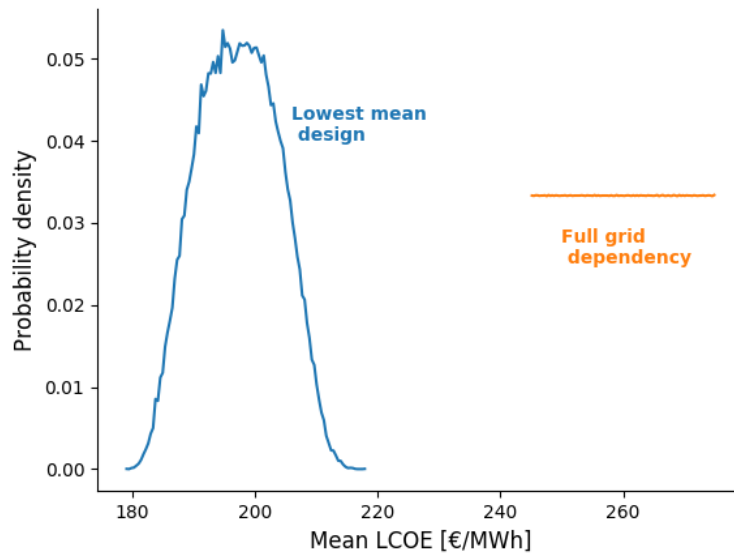


Figure D.17: Comparison between 2 different designs' PDF in Kigali with lead-acid battery when optimizing LCOE

Lead-acid battery

GWP optimization

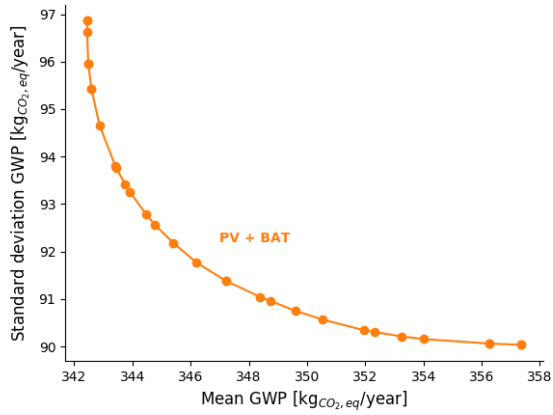


Figure D.18: Pareto front from GWP robust optimization in Kigali with lead-acid battery

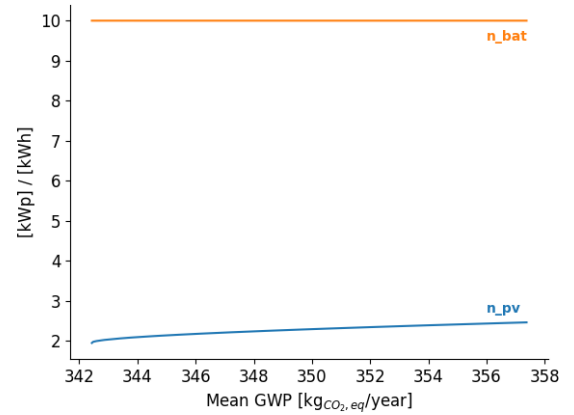


Figure D.19: Design variables from GWP robust optimization in Kigali with lead-acid battery

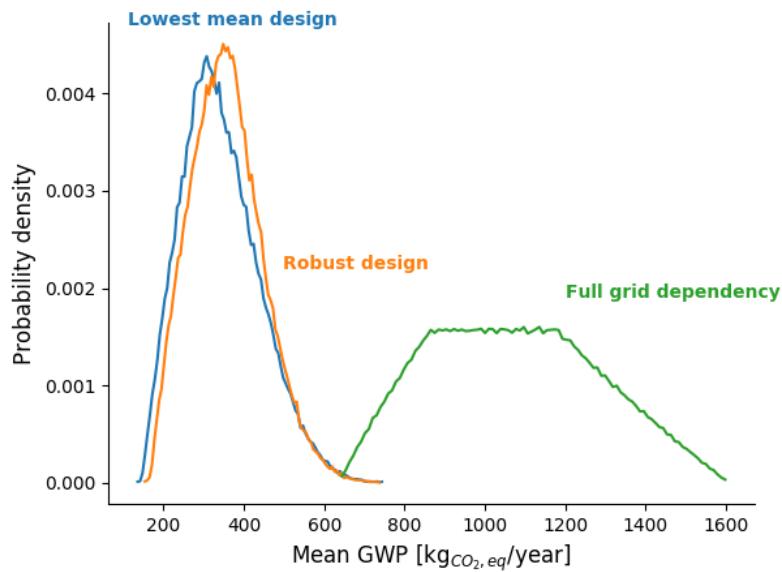


Figure D.20: Comparison between 3 different designs' PDF in Kigali with lead-acid battery when optimizing GWP

NMC battery

GWP optimization

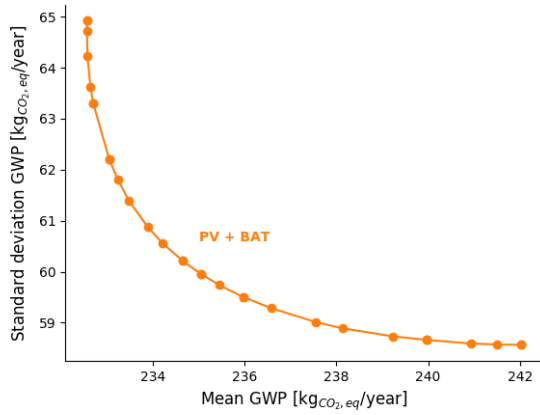


Figure D.21: Pareto front from GWP robust optimization in Kigali with NMC battery

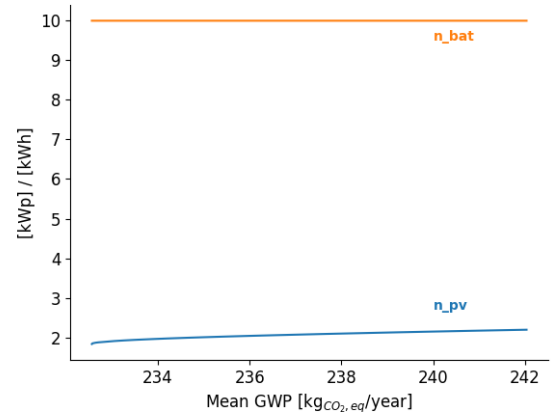


Figure D.22: Design variables from GWP robust optimization in Kigali with NMC battery

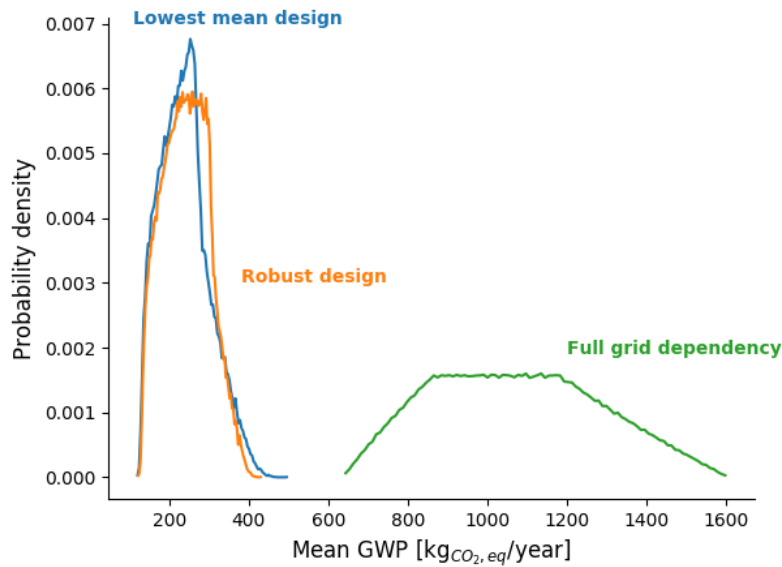


Figure D.23: Comparison between three different designs' PDF in Kigali with NMC battery when optimizing GWP

Vanadium redox flow battery

GWP optimization

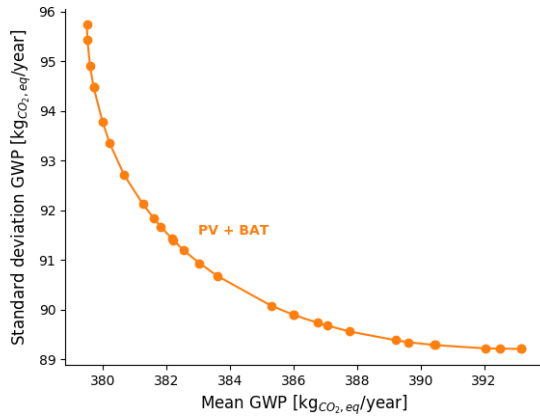


Figure D.24: Pareto front from GWP robust optimization in Kigali with VRF battery

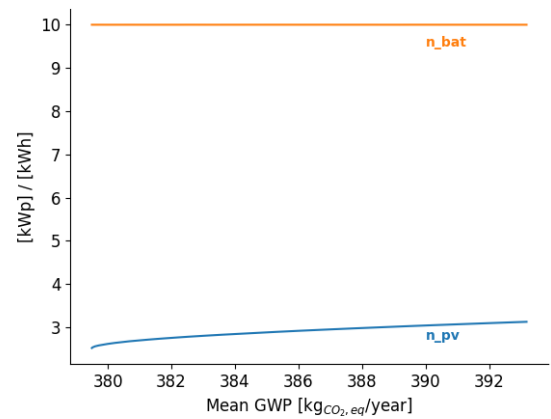


Figure D.25: Design variables from GWP robust optimization in Kigali with VRF battery

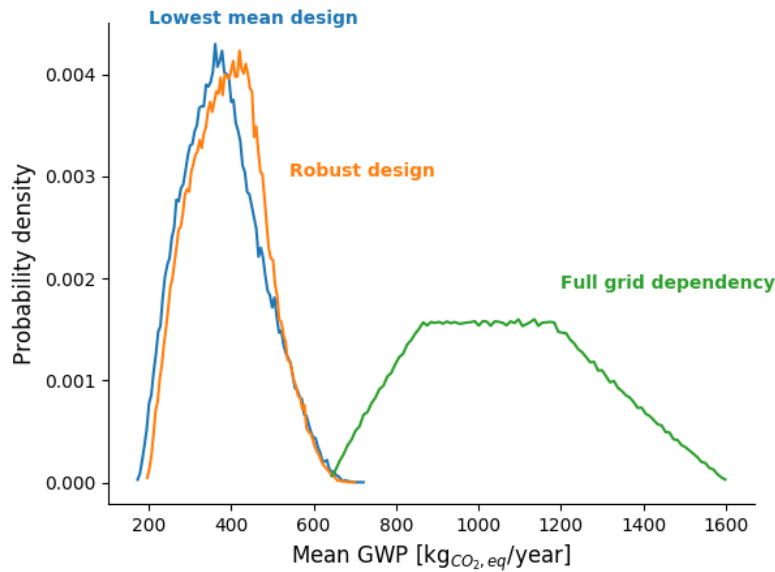


Figure D.26: Comparison between three different designs' PDF in Kigali with VRF battery when optimizing GWP

Additional information

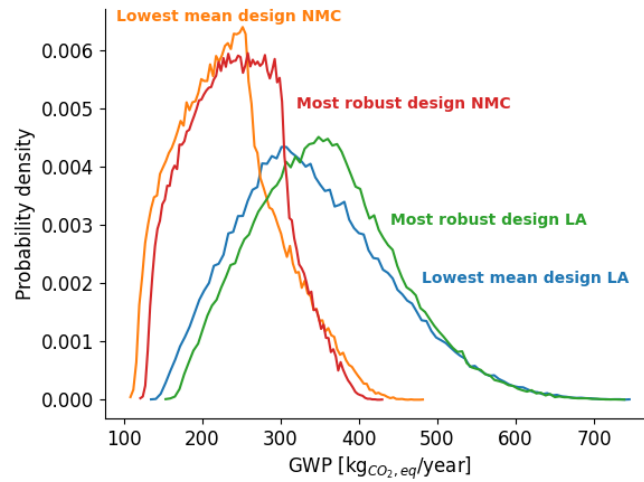


Figure D.27: Comparison between 4 different designs' PDF in Kigali when optimizing GWP

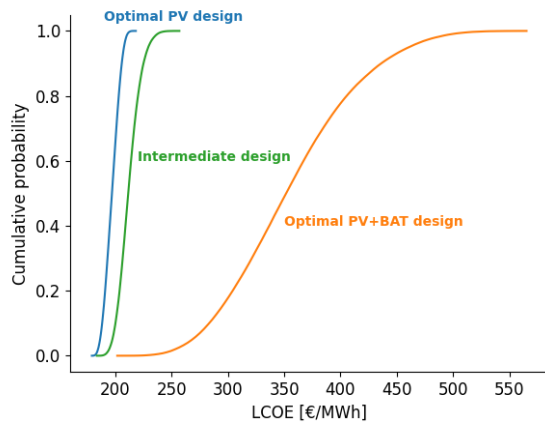


Figure D.28: PDF comparison between the economical optimum design (PV-exclusive), the intermediate design (PV+BAT) and the environmentally optimum design (PV+BAT) on LCOE basis in Kigali

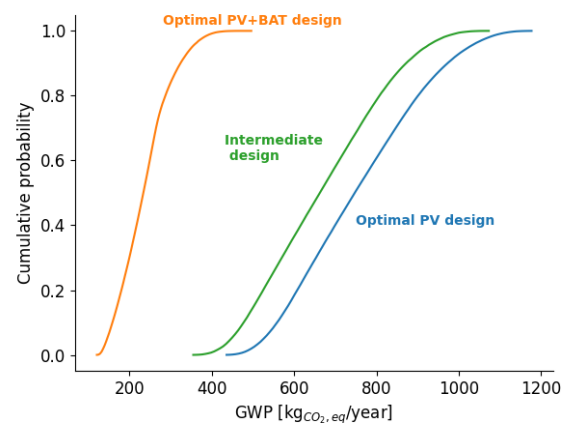


Figure D.29: PDF comparison between the economical optimum design (PV-exclusive), the intermediate design (PV+BAT) and the environmentally optimum design (PV+BAT) on GWP basis in Kigali

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