République Algérienne Démocratique et Populaire

Ministére de l'Enseignement Supérieur et de la Recherche Scientifique

Université Mohamed Khider - BISKRA

Faculté des Sciences et de la Technologie

Département: Génie Electrique

Thèse présentée en vue de l'obtention Du diplome de :

Doctorat LMD en génie électrique

Option : Energies renouvelables

Conception du dimensionnement optimal d'un système d'énergie renouvelable intégré dans un microgrid

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Algerian People's Democratic Republic

Ministry of Higher Education and Scientific Research

Mohamed Khider University - BISKRA

Faculty of Science and Technology

Department of Electrical Engineering

PhD Thesis

In Electrical Engineering

Option: Renewable Energies

Optimal sizing design of renewable energy system integrated in a microgrid

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ملخص

تناولت هذه الأطروحة إشكالية التحجيم الأمثل لنظام الطاقات المتجددة في شبكة صغيرة، حيث قدمت تحليلاً شاملاً مبنياً على الجوانب الاقتصادية والتقنية باستخدام معايير ومؤشرات متعددة. ركزت الدراسة على التقييم المالي باعتبار أن نظام الطاقات المتجددة في الشبكات الصغيرة يمثل مشروعا اقتصاديا يتطلب دراسة جدوى اقتصادية دقيقة وتقييما شاملاً للاستثمار. ولتطوير التصميم الأمثل للتحجيم، تم استعراض التحديات الرئيسية التي تواجه هذه العملية، وعلى رأسها مشكلة عدم اليقين الناتج عن أخطاء القياس والحساب أو الطبيعة المتغيرة لأنظمة الطاقات المتجددة. تم معالجة هذه الإشكالية باستخدام عدة أساليب، منها تحليل الحساسية، ومحاكاة مونت كارلو، بالإضافة إلى توظيف النماذج العشوائية للتنبؤ بالقيم والمسارات المستقبلية في ظل عدم اليقين لمختلف المعايير. وقد ساهمت هذه الأساليب في بناء منهج فعال لعملية التحجيم على المدى الطويل. كما قدمت الأطروحة نظرة شاملة على أداء النظام من حيث الإنتاج الطاقوي، التكاليف، والأرباح المتوقعة، وذلك من خلال دراسة حالة شملت ثلاثة أنظمة طاقوية مختلفة في شبكات صغيرة بمنطقة بسكرة . أظهرت الدراسة أن المنهج المقترح فعال في تحقيق التحجيم الأمثل لهذه الأنظمة على صعيد الإقتصادي والطاقوي ؛ وبالتالي تحسين كفاءة الأنظمة على المدى الطويل و جذب المستثمرين في هذا القطاع وتعزيزالثقة بين المنتج والمستهلك.

الكلمات المفتاحية: نظام الطاقات المتجددة ؛ التحجيم الأمثل؛ التقييم المالي ؛ الشبكة الصغيرة ؛ عدم اليقين

Abstract

This thesis addresses the issue of optimal sizing for a renewable energy system in a microgrid, providing a comprehensive analysis based on economic and technical aspects using multiple criteria and indicators. The study focuses on financial evaluation, considering that a renewable energy system in microgrids represents an economic project that requires a thorough feasibility econom and a comprehensive investment assessment.
To develop an optimal sizing design, the research introduces the main challenges associated with this process, particularly the uncertainty resulting from measurement and calculation errors or the variable nature of renewable energy systems. This issue is addressed using several methods, including sensitivity analysis, Monte Carlo simulation, and stochastic modeling to predict future values and trends under uncertain conditions across different criteria. These methods contribute to building an effective long-term sizing approach.
Additionally, the thesis provides a comprehensive evaluation of system performance in terms of energy production, costs, and expected profits through a case study involving three different energy systems in microgrids within the Biskra region. The findings indicate that the proposed approach effectively achieves optimal sizing for these systems from both economic and energy perspectives. Consequently, it enhances system efficiency in the long term, attracts investors to this sector, and fosters trust in renewable energy projects.

Keywords: Renewable energy system, Microgrid, Sizing,Financial assessement, Optimization, Uncertainty

Résumé

Cette thèse traite du dimensionnement optimal des systèmes d'énergie renouvelable dans les micro-réseaux, en s'appuyant sur une analyse économique et technique. Elle met l'accent sur l'évaluation financière, considérant ces systèmes comme des projets nécessitant une étude de faisabilité et d'investissement. Le travail identifie les principaux défis liés aux incertitudes de mesure, de calcul et à la variabilité des énergies renouvelables. Pour y répondre, il mobilise des méthodes telles que l'analyse de sensibilité, la simulation de Monte Carlo et la modélisation stochastique, permettant d'élaborer une approche de dimensionnement efficace à long terme.Une étude de cas sur trois systèmes de micro-réseaux dans la région de Biskra montre que la méthode proposée atteint un dimensionnement optimal, améliore l'efficacité énergétique et économique, attire les investisseurs et renforce la confiance dans les projets d'énergie renouvelable.

Mots-clés: Système d'énergie renouvelable, Micro-réseau, Dimensionnement,Évaluation financière, Optimisation, Incertitude.

This doctoral dissertation has been examined by a committee as follows:

The jury was chaired by **Professor Boumeheraz Mohamed**, President of the jury, from the Department of Electrical Engineering at the University of Biskra.

The examination was conducted by **Professor Rahmani Lazhar**, from the Department of Electrical Engineering at the University of Sétif 1.

And by **Professor Naimi Djemai**, from the Department of Electrical Engineering at the University of Biskra.

The supervisor was **Dr. Tegani Ilyes**, from the University Center of Barika, and the co-supervisor was **Professor Kraa Okba**, from the Department of Electrical Engineering at the University of Biskra.

This PhD thesis is affiliated with the Laboratory of Electrical Engineering **(LGBE)** at the University of Biskra.

Acknowledgements

*I thank **Allah** Almighty for His guidance and success. All praise and thanks are due to Allah .*

I also thank myself for my strength and patience, and for loving challenges and success.

I would like to thank the thesis director, Dr. Tegani Ilyes from the University Center of Barika, and the co-director, Prof. Kraa Okba from the University of Biskra.

I sincerely thank Dr.Benhamadouche Abdelouahab from the University of M'sila for all his help and support during my doctoral journey.

Dedication

To myself

To my family

To my primary school teacher Mr. Djemai,
who encouraged me to love science.

Ardjouna chebabhi

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INTRODUCTION

Motivation

The electricity sector is exposed to significant risks from various sources, such as fuel markets, climate and energy policy, technology advancements, weather fluctuations, and climate change. Gaining a comprehensive understanding of the effects and unpredictability of these various factors is essential for making informed decisions on long-term energy system planning and investment. The uncertainty surrounding these factors can significantly impact the shift towards renewable energy sources and the formulation of policies to facilitate this transition [1].

In recent years, the integration of renewable energy sources into microgrids has grown significantly worldwide.This expansion is primarily driven by advancements in renewable technologies and decreasing component costs. IRENA (International of Renewable Energy Agency) reports that the growing popularity of solar photovoltaic systems has led to a substantial decrease in installation costs, ranging from 48% to 88 %. Similarly, onshore wind installations have seen price reductions of 69 % to 88 % [2]. At sime time, climate change has emerged as a global emergency, predominantly driven by the extensive use of fossil fuels. Consequently, governments are increasingly investing in new renewable technologies and actively promoting the adoption of renewable energy.

Nevertheless, global energy consumption is projected to reach 38,700 TWh by 2050 [3]. This significant energy requirement highlights the imperative to prioritize renewable energy sources. The microgrid power system is proposed as a powerful approach for reducing carbon intensity and achieving global decarbonization goals.

Furthermore, the orientation towards electricity generation is shifting towards decentralized systems, which offer benefits in reducing energy losses. Today, microgrids represent an effective solution for critical infrastructures, campuses, remote communities, island grids, or individual buildings such as factories, shopping malls, or academic institutions [4].

Therefore, choosing the most efficient renewable energy system sizing necessitates meticulously evaluating factors such as solar radiation, wind speed, and hydrological conditions. The energy potential of these resources is contingent upon factors such as geographical location, prevailing weather conditions, and the specific technology utilized. Algeria maintains one of the most remarkable solar energy capacities worldwide, with 2,000 hours of sun radiation per year and up to 3,900 hours in the highlands and Sahara region [5].

The yearly worldwide horizontal irradiation in the northern zone is recorded at 3,000 Wh/m^2; in the southern region, it surpasses 5,000 Wh/m^2 [5]. In addition, NASA meteorological data shows that wind speeds in Algeria vary between 4 m/s and 8 m/s [6]. Despite the significant solar and wind potential in regions like Algeria, renewable energy adoption remains limited, with only 1.5 % of its electricity generated from these sources [5]. Therefore, this difference highlights the critical need for optimized renewable energy solutions, particularly through microgrids, where solar and wind power are increasingly favored for sustainable energy generation. This thesis aims to explore the optimal integration of these energy sources into microgrids, focusing on enhancing efficiency, sustainability, and economic feasibility. Algeria is a significant case study owing to its renewable energy potential, offering a practical framework for assessing and designing efficient renewable energy systems.

Consequently, it is essential to determine the optimal dimensions for a renewable energy system that can be effectively integrated into a microgrid. A thorough analysis of each component's specific environmental factors and costs is necessary to achieve optimal efficiency and sustainability.

Research questions

- **Research Question 1**:

  What is the process for determining the optimal dimensions and specifications for incorporating renewable energy sources into microgrids? How can a systematic approach be developed to achieve the most efficient size and design of renewable energy systems in a microgrid?

- **Research Question 2**:

  The second question concerns the factors that should be considered when determining the methodology for achieving the optimal sizing of renewable energy systems (RES) in a microgrid.

- **Research Question 3**:

  What are the implications of ignoring uncertainty factors in the sizing of renewable energy systems for microgrids, and which decision-making frameworks are most effective in addressing these gaps to ensure optimal system performance and economic feasibility?

- **Research Question 4:**

  How can energy system investment planning enhance the integration of renewable energy systems into microgrids by optimizing their sizing and operation to ensure a reliable, cost-effective, and sustainable energy supply?

Objectives and Contributions of Dissertation

Objectives

The aims of this doctoral dissertation are outlined in the subsequent bullet points:

i. The primary goal is to propose a systematic approach for choosing the most suitable microgrid configuration by assessing the economic feasibility of different combinations of renewable energy sources in a region with abundant renewable energy resources and a significant inflation rate. What are these projects' financial feasibility, and what are the reasons for their lack of investment?

ii. The second includes a comprehensive financial analysis emphasizing investment decision-making and risk analysis. The process involves assessing multiple financial indicators such as NPV, IRR, and DPB and conducting risk analysis. It also entails defining cost criteria and economically feasible setups to promote a sustainable and ecologically conscious energy future while mitigating financial risks.

iii. Enhance the sizing design by considering the issue of uncertainty. It may be achieved by creating a model that captures the behavior of the factors influencing the future design of hybrid renewable energy systems. Discuss the elements that affect the sizing and design of renewable energy hybrid systems in the long term, considering the uncertainty and volatility nature of these parameters over time. More precisely, the parameters that have been chosen include information on renewable resources such as wind speed and solar radiation, the demand for power (load), and the inflation rate of the country for installations.

iv. It is crucial to use a stochastic process to describe and depict uncertainty related to these aspects. Where the approach is widely used in forecasting and controlling the risk associated with dynamic investments. By incorporating Geometric Brownian motion into a stochastic process, the model accurately accounts for the uncertainties related to these elements and improves the forecast parameters for renewable energy systems (RES).

Contributions

The structure of this thesis highlights the key contributions of this research. It begins by exploring renewable energy systems and microgrids, emphasizing the critical role of sizing and design before their implementation. A comprehensive literature review is provided to clarify the study's scope and the methodology applied.

This research introduces a systematic approach to sizing renewable energy systems (RES) in microgrids. The methodology consists of three main phases: techno-economic assessment, financial analysis, and reliability evaluation through sensitivity analysis. These steps ensure accurate and reliable outcomes, fostering trust among investors and consumers.

Additionally, the thesis examines the challenges posed by uncertainty in microgrid design. Various sources of uncertainty are identified, along with strategies to mitigate their impact at both input and output stages. The proposed approach includes risk assessment for financial metrics such as Net Present Value (NPV), sensitivity analysis for discrete variables, and deterministic Monte Carlo simulations. To enhance forecasting accuracy under fluctuating conditions, stochastic uncertainties are modeled using Geometric Brownian Motion (GBM).

A case study conducted in Biskra demonstrates the proposed methodology by analyzing three different microgrid configurations. This case study provides valuable insights into renewable energy microgrid projects' technical and financial viability and showcases the practical application of the approach.

This PhD research presents a comprehensive framework for designing and sizing renewable energy systems in microgrids of different scales. It offers an in-depth analysis of both technical and financial aspects, reinforcing confidence among investors and consumers. Furthermore, it advocates for increased public funding to support microgrid projects, promoting their broader adoption and long-term sustainability.

CHAPTER 1

RENEWABLE ENERGY SYSTEMS INTO MICROGRID

Chapter One presents an overview about the utilization of renewable energy systems (RES). Through an examination of the obstacles and benefits of incorporating renewable energy sources into microgrids, the chapter highlights the essential significance of the sizing phase in the development and implementation of renewable energy systems. The chapter examines diverse studies and methodologies for attaining optimal size. By reviewing related works and identifying research gaps for a more profound comprehension of the intricacies associated with sizing renewable energy systems.

1.1 Introduction

Recently, an estimated 1.1 billion people lack access to electricity, representing approximately 17 % of the global population. Around 22 % of the total population living in remote areas of impoverished and developing countries do not have access to electricity [7]. Germany has improved its power grid by incorporating various renewable energy sources into its planned system. Consequently, it has successfully increased its proportion of renewable energy sources (RESs) by 30 % but has yet to encounter significant problems. It anticipates a complete transition to a 100 % renewable energy system by 2050 [8]. Renewable Energy Sources (RESs) have played a critical role in supplying electrical loads and reducing greenhouse gas emissions [9]. Their global adoption has increased significantly due to the growing availability of diverse renewable energy resources, as illustrated in the next paragraph. Despite the numerous benefits of renewable energy systems, several challenges remain in integrating RES, which will be addressed in the next section. After mentioning the significant keys for introducing the renewable energy system, the primary step before planning and installing the RES is the sizing stage. Therefore, the central question is : Why is sizing the RES important, particularly in microgrids? This will be explored by reviewing related works and identifying research gaps in this PhD thesis.

1.1.1 Challenges and Issues

Several challenges faced by renewable energy systems are related to the nature of resources, types of applications, and socioeconomic factors.

The first challenge related to natural resources is the integration of photovoltaic (PV) systems. Equipment failures can be seamlessly incorporated into the reliability assessment process using the same methodology for analyzing fossil fuels.

However, assessing the effect of short-term unpredictable fluctuations in solar energy on the uninterrupted provision of power is considerably more difficult. At small time intervals, the fluctuation of PV output is still subject to significant uncertainty, which is a primary cause of power imbalances in the electrical grid. Techniques for measuring and predicting sudden changes in energy production over short periods are currently being developed, along with models that consider how the dispersion of power generation across different locations can impact these fluctuations.

Accurate models are essential for adequately planning industrial microgrids, as the influence of solar variability becomes more significant with increasing penetration rates. Flexibility mechanisms to offset fluctuations in renewable energy generation are crucial for maintaining system resilience. Storage systems are receiving more research attention, while fossil fuel technologies are being overlooked because they are well-established. However, how these technologies respond to consecutive ramps is still uncertain, as it could substantially impact their lifespan and fuel usage. Only a few models consider or incorporate their dynamic behavior in long-term evaluations [10].

The second issue relates to economic challenges. Hybrid systems generally involve higher initial costs compared to single-source systems. Another challenge pertains to regulatory and policy obstacles precisely, policy discrepancies. Different energy sources may be subject to distinct policies and regulations, complicating the system design. Integrating Hybrid Renewable Energy Systems (HRES) into existing electricity grids may face regulatory hurdles, particularly if the policies governing the grids require revision. The lack of standardized legislation for HRES might lead to ambiguity over licensing and operation [11], as depicted in Figure 1.1 [12].

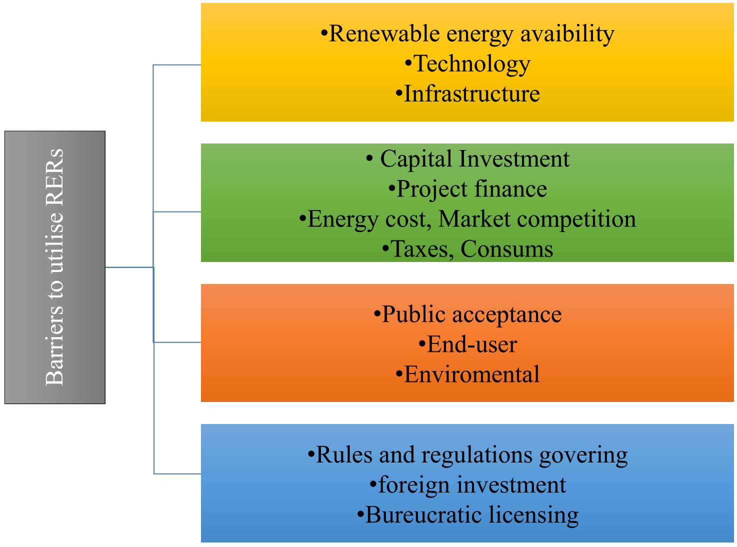


Figure 1.1: Obstacles to renewable energy resources deployment

1.2 Global Overview of RES: Usage, Technologies, Pricing, and Potential

The utilization of renewable energy technologies has increased dramatically in recent years, according to the International Renewable Energy Agency (IRENA) [13]; Figure 1.2 illustrates the global electricity generation capacity by major renewable energy technologies. It highlights hydropower as the leading source, followed by solar and wind energy. Between 2010 and 2023, these technologies experienced substantial growth. In 2023, hydropower reached a capacity of 1.26 million MW, solar power 1.4 million MW, and wind power 1.07 million MW.

This increasing reliance on renewable energy, particularly solar and wind, has driven many countries to implement supportive policies to enhance their adoption. Figure 1.3 displays the adoption rates of solar PV and onshore wind technologies in selected countries. For example, Algeria utilizes solar PV at 11 % and onshore wind at 11.4 %. Argentina reports solar PV and onshore wind adoption rates of 13.8 %, while Australia registers both technologies at 2.9 %. In Brazil, solar PV and onshore wind stand at 6.3 % and 4.9 %, respectively. These figures underscore the growing global reliance on renewable energy sources for electricity generation.

While the expansion of renewable energy continues, global electricity consumption has also witnessed substantial growth across various sectors, highlighting the urgent need for sustainable energy solutions. Over the past 30 years, electricity demand has surged across industries, households, and commercial establishments. The industrial sector accounts for a substantial portion, consuming approximately 37 million TJ, while the residential sector consumes around 23 million TJ, and commercial and public services contribute 17 million TJ.

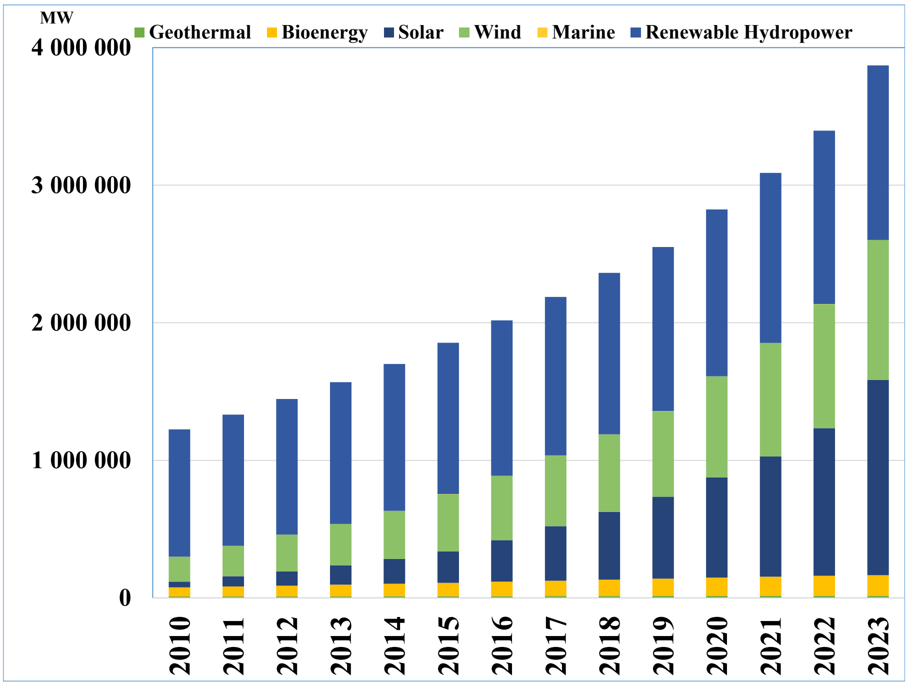


Figure 1.2: The cumulative electricity capacity of the main technology of RES.

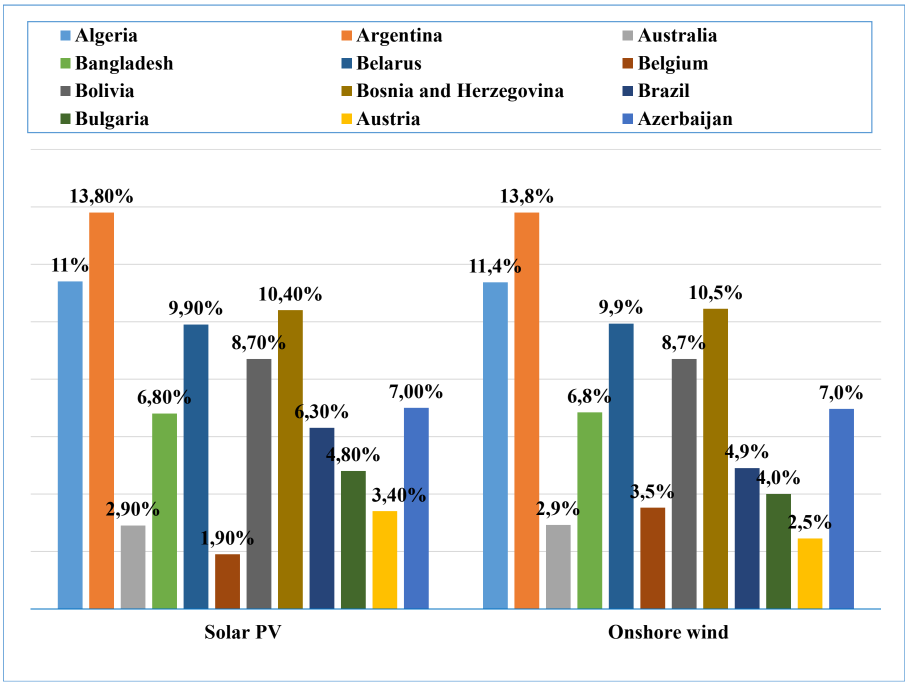


Figure 1.3: The exploitation of Solar PV and onshore wind in countries

Global energy consumption varies across sectors, with fishing, transportation, and agriculture showing comparatively lower usage, as illustrated in Figure 1.4. Notably, the mining industry accounts for 38 % of total industrial energy use and 11 % of global energy consumption. Without new regulatory measures, global energy demand could potentially double by 2050, underscoring the need for sustainable energy solutions [14].

In response to this growing demand and the need for cleaner alternatives, hybridization has become essential in modern energy systems. By integrating technologies like photovoltaic (PV) panels, wind turbines, and energy storage systems ensures a stable and continuous power supply. Solar and wind resources, which fluctuate due to time of day, weather, and seasonal conditions, can be complemented by energy storage systems. These systems store surplus energy generated during peak production for use during low-output periods, enhancing energy reliability and efficiency.

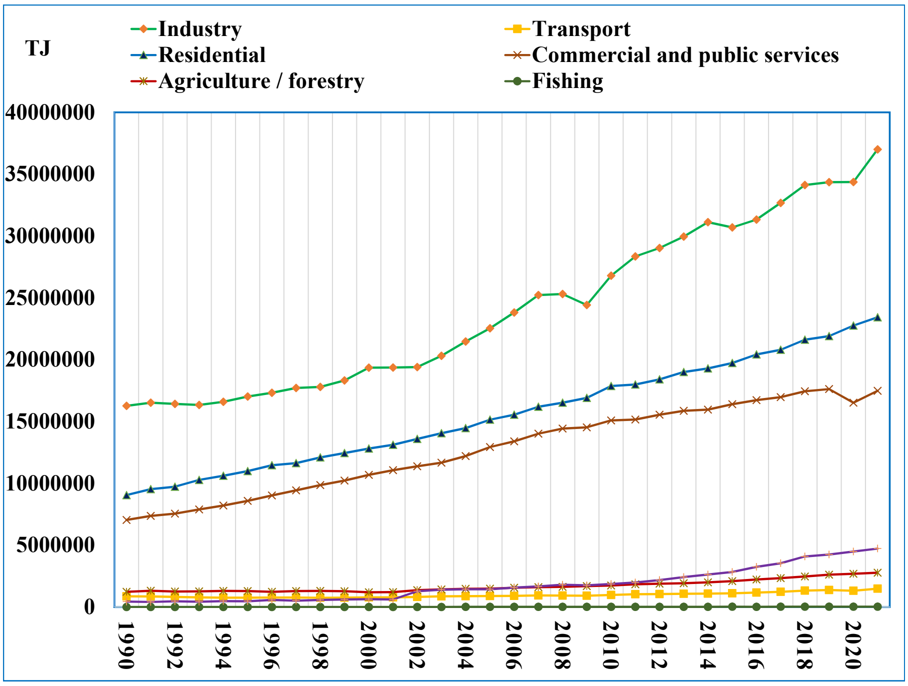


Figure 1.4: Consumption of electricity by sector in the world (IEA, 2023)

In addition to enhancing energy reliability and efficiency, the economic viability of renewable energy has significantly improved. A major contributor to this progress is the decreasing levelized cost of electricity (LCOE), which has strengthened the competitiveness of renewable energy compared to traditional fossil fuel generation. This reduction is primarily driven by technological advancements, economies of scale, and improvements in energy generation and storage systems.

Furthermore, hybrid renewable energy systems (HRES) have become increasingly feasible solutions for meeting global energy demands while mitigating climate change impacts. The global average cost of electricity from installed solar systems and offshore wind has dropped to approximately 0.1 USD/kWh, reflecting substantial progress in reducing renewable energy costs, as illustrated in Figure 1.5.

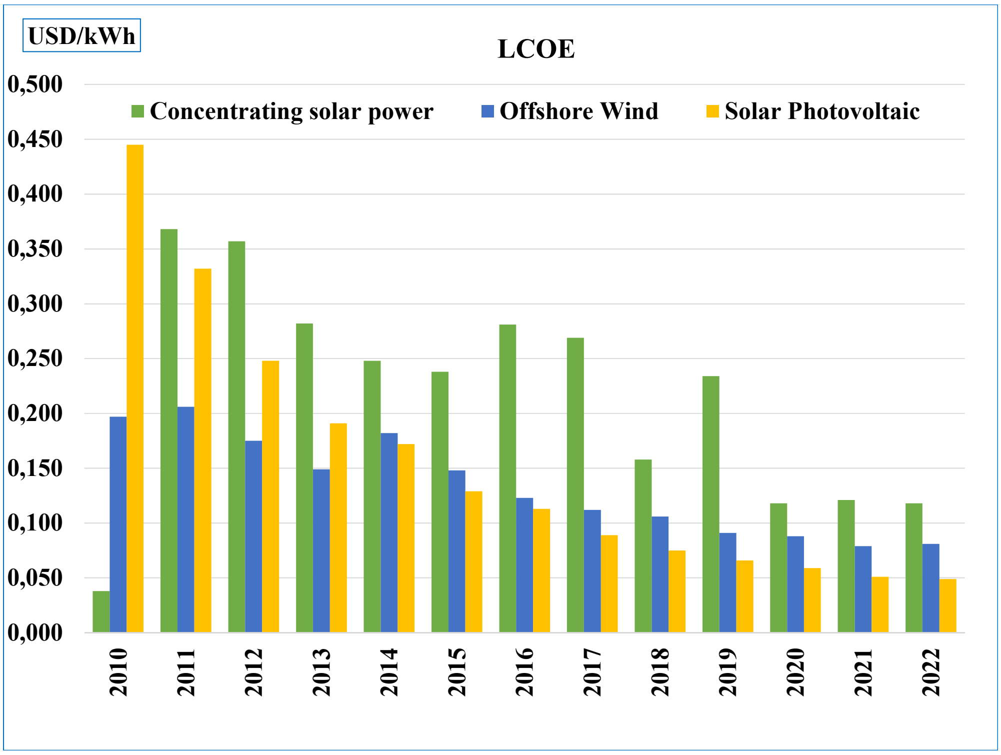


Figure 1.5: Levelized cost of electricity of installed solar and wind

In addition to economic advantages, renewable energy resources offer substantial environmental benefits.Advanced technologies are essential for enhancing system reliability and maximizing energy output, leveraging a diverse range of resources such as solar, wind, hydropower, and biomass. On the other hand, there exist different types of photovoltaic (PV) technologies, including monocrystalline (m-Si), polycrystalline (p-Si), thin films such as amorphous silicon (a-Si), cadmium telluride (CdTe), copper indium gallium selenide (CIGS), and the latest generation technologies known as organic photovoltaics. However, the environmental characteristics of a region are a crucial factor in determining and implementing PV technology in microgrids [15].

Furthermore, the prices of different components have fallen following. Figure 1.6 shows the cost of several solar panel technologies, data from 2010-2022 demonstrates the price fluctuation [13]. The decrease in PV panel prices has a crucial role in determining investment costs, as the cost of PV panels is a substantial portion of the initial capital required for solar microgrids.

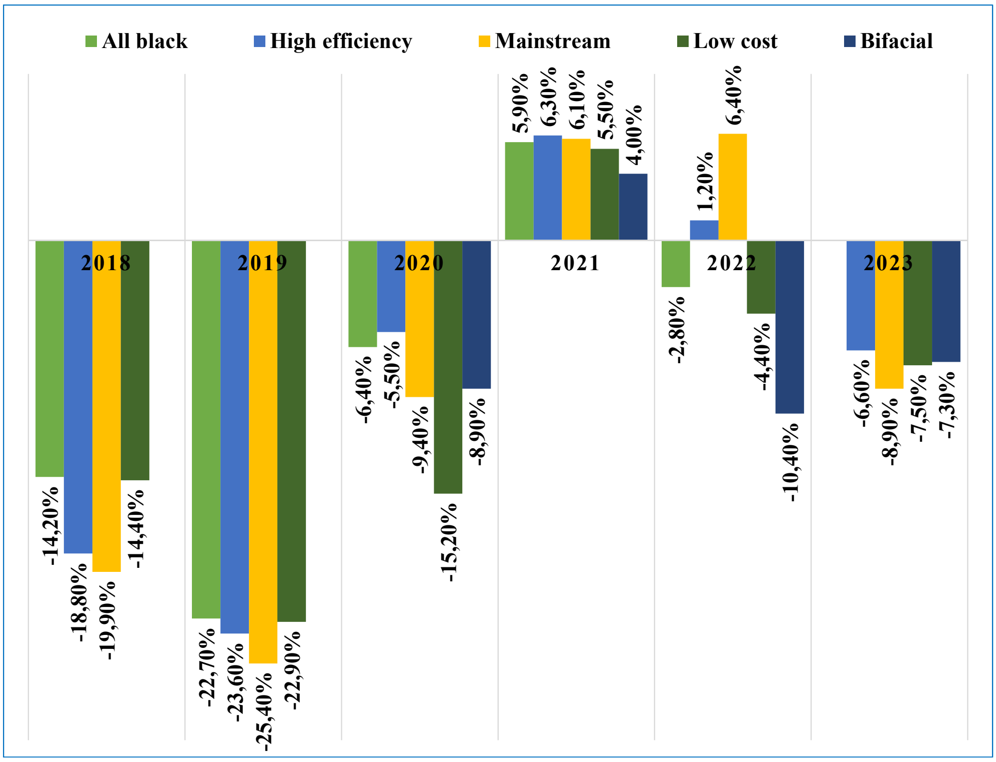
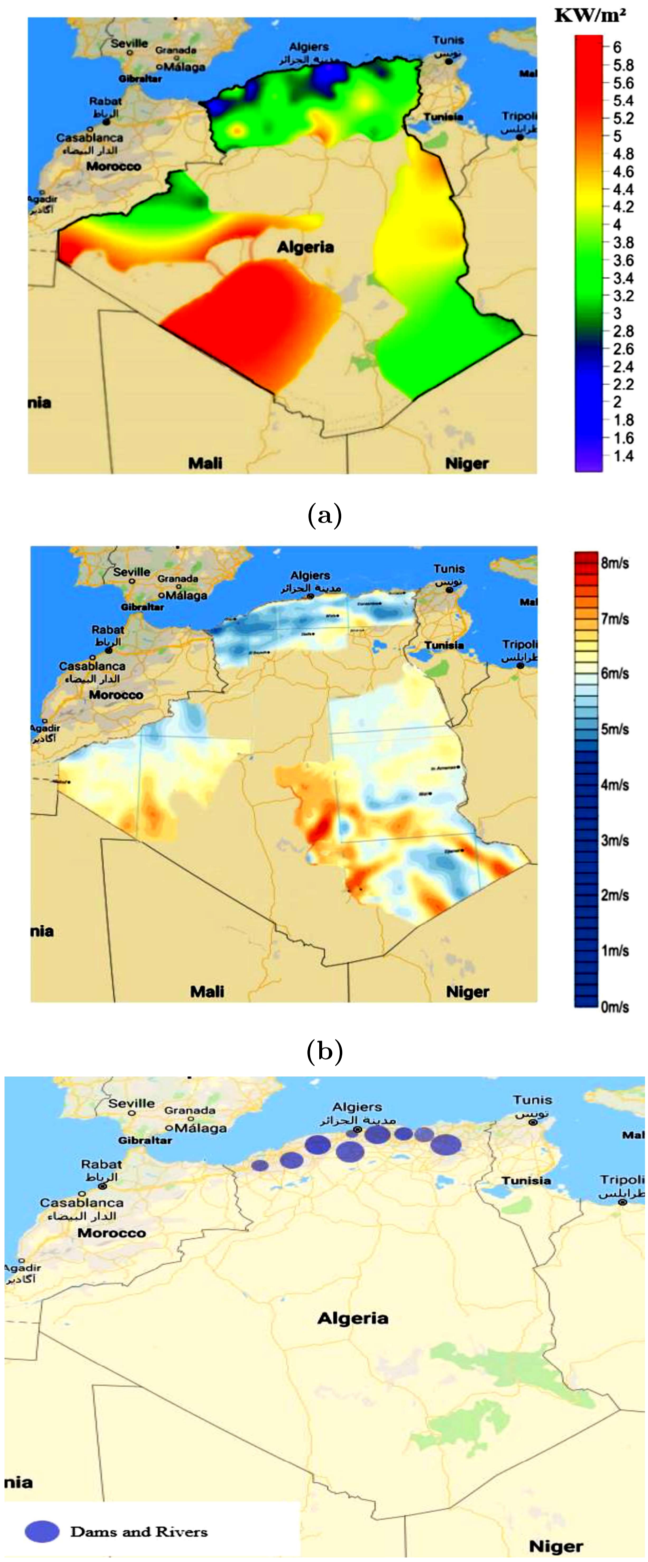


Figure 1.6: Average yearly percentage increase for Solar PV module price (2010-2022)

1.2.1 Renewable Energy Potential in Algeria

The region's potential is crucial to installing renewable energy systems. Algeria possesses significant renewable energy potential, including solar, wind, hydro, geothermal, and biomass resources. The country aims to increase solar power production by 2030 substantially. However, progress in this field has been slow as of 2020. Energy consumption has risen due to population and economic growth, increasing carbon dioxide emissions. Algeria's geographical location offers substantial opportunities for renewable energy development, as it receives a high amount of direct sunlight with an estimated irradiation of 169,440 kW/m^2 /year. The potential for energy generation in Algeria is predicted to exceed 3,000 kWh/year [16].

The desert in Algeria is known to have highest average solar irradiation and temperature levels worldwide. The country also has favorable conditions for hydropower generation due to suitable dam locations and a consistently large amount of rainfall. Algeria has significant wind energy potential in various regions, including M'Sila, Bou Chekif, Djelfa, and Mecheria. Where wind conditions are favorable throughout the year. However, despite having high wind speeds, Ain Salah and Adrar are unsuitable for wind generator installation due to topographical constraints and the need for an electrical transmission network. The abundance of hot springs in Algeria makes geothermal power a highly viable option for enhancing the integration of renewable energy sources. Figure 1.7 illustrates the renewable energy potential in Algeria.



(a)

(b)

(c)

Figure 1.7: Renewable energy potential in Algeria: a) Solar irradiation, b) Wind speed, c) Hydropower

[16]

1.3 Microgrids

1.3.1 Inception of Microgrids

The global electricity landscape is undergoing a significant transformation characterized by the "three Ds": decentralization, decarbonization, and democratization. This transition is motivated by the necessity to decrease electricity expenses, upgrade obsolete infrastructure, improve resilience and reliability, reduce carbon emissions to combat climate change and expand dependable electricity access to underserved regions [17].

The historical development of electricity systems has been dynamic. The inception of small-scale distributed generation, initiated by Thomas Edison in the late 19th century, signified the advent of the earliest DC microgrids. As energy demand increased, this system evolved into consolidated and centralized networks. Nonetheless, the centralized approach has encountered its constraints, confronting issues pertaining to environmental concerns, economic vulnerabilities, and deteriorating infrastructure. As a result, the energy sector is progressively transitioning to smaller, decentralized systems, facilitated by innovations in Distributed Energy Resource (DER) technology and the reorganization of utilities [18].

Beginning in the late 1990 s, researchers in the United States and Europe commenced the development of decentralized solutions to address the growing prevalence of distributed energy resources (DERs). These methods were formulated to enhance grid dependability and resilience against natural catastrophes, cybercrime, and cascading failures. This initiative established the microgrid, a localized grid system that regulates power generation and consumption inside segments of the primary grid. Microgrids can function autonomously (in island mode) or remain integrated with the larger grid, guaranteeing the continuity of key services during extensive outages [18].

The development of microgrids in areas with established grid infrastructure is chiefly driven by energy security, economic advantages, and the integration of clean energy. In the United States, microgrids have been established to improve resilience, which is defined as the capacity to recover from disruptions and reliability swiftly, guaranteeing consistent service availability. Essential infrastructures, including transportation, communication networks, healthcare services, water and wastewater management, emergency response systems, and food supply chains, significantly gain from these enhancements.

1.3.2 Microgrid Definitions

Microgrids are gaining global popularity due to their ability to create versatile, dependable, efficient, and intelligent electrical grid systems. They also have the potential to provide energy to areas not connected to the primary power grid while offering economic advantages. Various definitions and functional classifications of microgrids are available in the literature. The Microgrid Exchange Group provides one widely used definition.

Definition 1 : A microgrid is a collection of interconnected loads and dispersed energy resources, clearly defined within electrical boundaries. It functions as a single controllable entity concerning the grid [18].

Definition 2 : A microgrid can connect to and disconnect from the primary power grid, allowing it to operate either as part of the grid or independently in island mode. This description outlines three specific criteria [18]. The capacity to distinguish the microgrid segment of the distribution network from the remainder of the system.The management of resources within the microgrid as opposed to external resources. And the microgrid's capacity to function autonomously from the primary grid.

Definition 3 : Microgrids, also known as multi-energy systems, are rapidly becoming a viable commercial solution for achieving resilience, cost reduction, and decarbonization [19]. Additionally, MGs are characterized as low-voltage distribution networks consisting of interconnected Distributed Energy Resources (DERs), controlled loads, and critical loads. These systems can function in either a grid-connected or islanded mode, depending on the operational characteristics of the primary grid [20].

Definition 4 : Microgrids, being smaller than utility grids, are more sensitive to power variations. Consequently, developers must consider power dynamics, adaptability, and production uncertainty. Microgrids may have varying technology preferences as localized energy systems depending on the specific use case, such as commercial, residential, military or industrial units [10].

1.3.3 Benefits of Microgrids

The factors that contribute to the creation and implementation of microgrids in areas with established electrical grid infrastructure can be classified into three main categories: energy security, economic benefits, and integration of clean energy. Investing in microgrid solutions offers numerous benefits, including maintaining price stability by reducing risk. Microgrids can safeguard against unexpected and potentially excessive contingency or emergency energy costs and unpredictable variations in electricity expenses. MGs can provide economic benefits by leveraging local market regulations and initiatives. They can reduce peak load pricing, participate in demand response markets, and offer frequency control services to the broader grid [21].

Additionally, they can generate revenue by reducing expenses during periods of high demand, participating in demand response markets, and providing frequency regulation services to the primary power grid. Although the electrical infrastructure in most modern nations is generally reliable, any interruption can result in significant expenses and potential dangers. The nation's energy infrastructure faces increasing threats from extreme weather, aging, and physical attacks. Operating in island mode allows for a continuous and uninterrupted supply of electricity by disconnecting from the primary power grid and relying on on-site power generation.

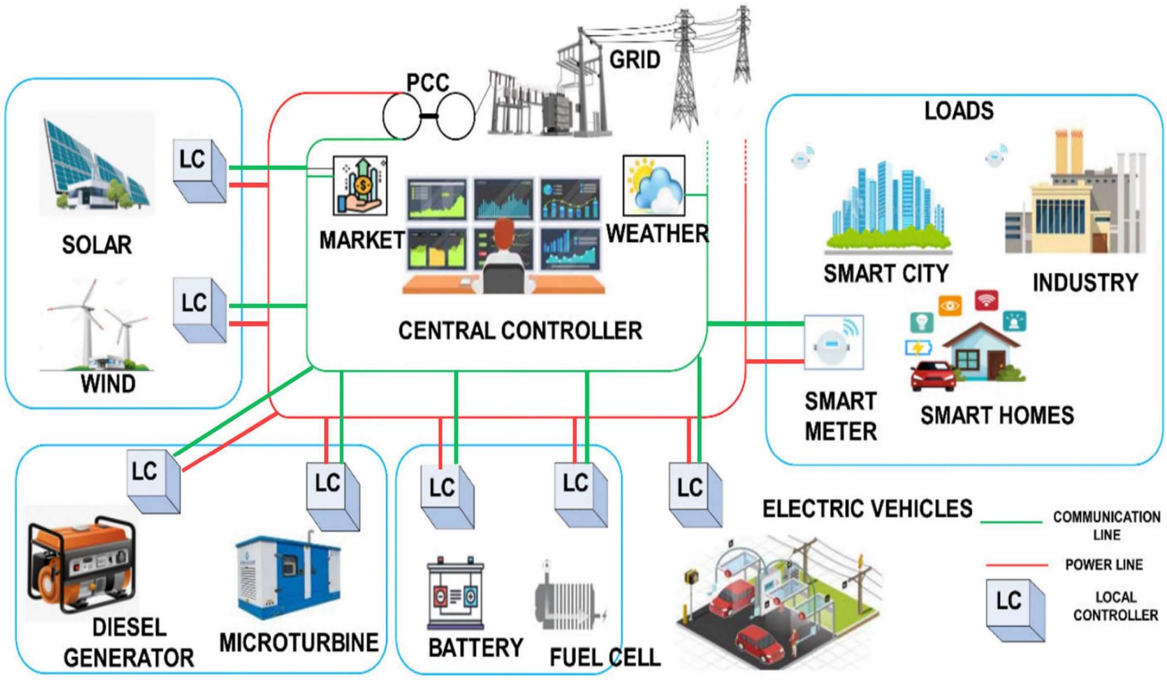


Figure 1.8: General structure of microgrid
[21]

Furthermore, intelligent microgrids (MGs) have significantly increased the utilization of renewable energy systems (RES). The extensive implementation of RESs offers multiple advantages in addressing environmental concerns and the depletion of fossil resources. However, this growing trend must be carefully regulated in light of two distinct concerns [22]. Therefore, renewable energy sources (RESs) substantially contribute to meeting global energy needs. The current worldwide energy shortage has created an unprecedented drive for RESs. Introducing microgrids might disrupt the conventional centralized energy system and shift control to local communities.

Microgrids are characterized by local entities' ownership and control of power generation and distribution, as opposed to large, centralized utilities. Microgrids can facilitate the development of new business models and ownership arrangements that benefit local communities economically. For instance, specific microgrid initiatives enable local communities to own and manage the microgrid, creating opportunities for residents to generate income and secure jobs. Moreover, the enhanced energy autonomy and resilience of microgrids can reduce the vulnerability of local populations to energy-related interruptions, thus laying the foundation for broader economic progress [21]. Figure 1.8 illustrated the basic structure of microgrids.

1.3.4 Types of Microgrid System

Microgrids can be categorized into three size-based classifications: small, medium, and large-scale. Microgrid systems provide electricity with limited capacity by harnessing renewable energy sources (RESs). However, some microgrids may also use diesel generators (DGs) as an alternative power source in conjunction with or instead of RESs.

- A small-scale microgrid has the potential to generate up to 10 (MW) of power. It is suitable for providing electricity to residential structures, small regional power systems, islands, and rural areas.

- Medium-scale microgrids provide power with moderate capacity, harnessing both RESs and conventional sources like oil or coal. The power generation capacity of a medium-scale microgrid ranges from approximately 10 MW to 100 MW, making it capable of supplying electricity to industrial areas.

- Large-scale microgrids produce power with significant capacity, typically using fossil fuels such as oil or coal. The maximum power output of a large-scale microgrid exceeds 100 MW, as noted by [17].

On the other hand, the classification of microgrids corresponds to the applications for MGs, encompassing island and remote "off-grid" MGs, commercial and industrial MGs, institutional and campus MGs, community and utility MGs, and advanced applications.

- Campus and institutional microgrids consist of buildings located within a specific geographic area, each with unique requirements for power supply reliability. Similar to institutional microgrids, commercial and industrial microgrids involve multiple participants, facilitating quick decision-making and using various energy sources.

- Community and utility microgrids comprise private residential consumers and occasional commercial and industrial customers. These systems may include several distributed energy sources powered by either fossil fuels or RESs.

- Military microgrids offer a cost-effective approach to ensuring energy and fuel availability while addressing the complexities of community management.

- Residential microgrids assess the optimal size for energy aggregation, determining whether to connect individual customers to larger microgrids.

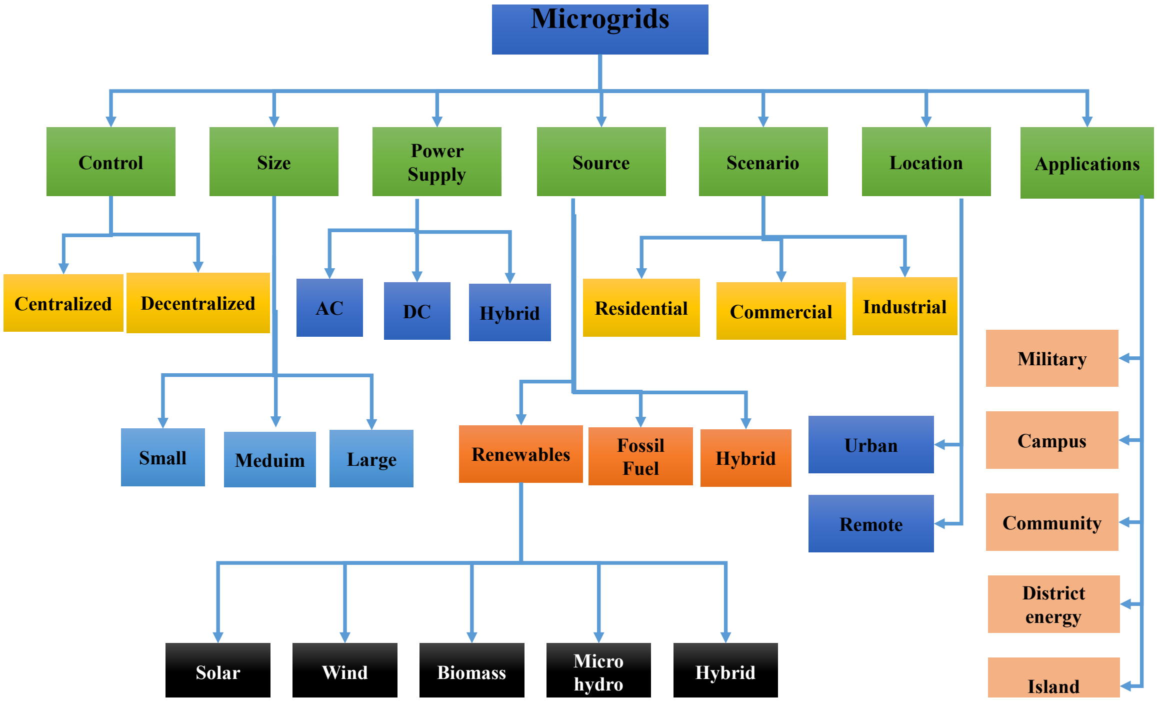


Figure 1.9: Flowchart of microgrid classification
[17]

Utilizing a decentralized coordinated system enables more efficient management of energy assets and the seamless integration of various households into the power distribution system. Decentralized private systems provide benefits such as reduced costs, enhanced efficiency, and improved voltage stability in the power grid [17, 18].

Based on their associated power source, MGs can also be categorized into three distinct types: hybrid, DC, and AC microgrids. Integrating alternating current microgrids (AC MGs) into existing power systems is straightforward and does not require additional control mechanisms. On the other hand, DC MGs have superior efficiency, produce and store energy in direct current (DC), and require less conversion for powering DC loads. The primary goal of hybrid MGs is to minimize the number of interface devices and conversion stages while maintaining cost-effectiveness by integrating both AC and DC power sources [23].

Hybrid microgrids enhance system reliability and efficiency by reducing conversion steps and interface devices. Hybrid MGs allow users to customize their power consumption by combining and switching between AC and DC loads. Power electronic converters isolate the AC and DC components of a microgrid. However, this arrangement only sometimes results in decreased energy losses. Hybrid MGs have lower reliability than AC MGs and require more complex controllers and management systems, mainly operating in islanded mode. To ensure a consistent and uninterrupted power flow, employing appropriate control mechanisms for MGs is crucial. Microgrids are managed by MG Central Controllers (MGCC) and are often located at distribution substations or local control centers. Control techniques must meet the power balance, transition, protection, power transmission, optimization, synchronization, and stability criteria. In summary, Figure 1.9 illustrated a flowchart overview of the various categories of microgrids.

1.3.5 Smart Microgrid

In recent years, the concept of smart microgrids has emerged as an advanced form of traditional microgrids. The following section provides an overview of their features and relationship with smart grid systems. The smart microgrid system, predominantly implemented by the national grid, combines energy storage with nearby renewable energy sources to provide electricity for industrial and residential requirements while maintaining the stability of the national grid. Smart microgrids with safety, stability, and robust regulating capabilities are urgently required [24]. While smart grids (SGs) and microgrids (MGs) can be differentiated from a technical standpoint, this study employs the term Smart MicroGrids (SMGs) to address the shift in electric systems specifically. The term "smart power distribution network" refers to a system that includes different loads, Distributed Energy Resources (DERs), and energy storage devices.

This system can operate connected or disconnected from the main utility in a controlled and coordinated manner, according to the definition provided by the US Department of Energy (DOE) [25]. Smart grids are equipped with cutting-edge technologies and devices, including the Internet of Things (IoT), smart metering infrastructure, advanced transmission and distribution systems, subsystems, mechanisms for demand response, dynamic pricing schemes, energy management systems (EMS), flexible loads, and sophisticated security structures. These systems effectively regulate the equilibrium between power generation and demand, optimize utility expenses, and ensure protection against cyber-crime.

The SGs' SM infrastructure examines the power usage of end-users and determines a utility fee using dynamic pricing. This information is then communicated to both end-users and service providers. It allows them to make efficient decisions on the scheduling of load and generation [26].

1.3.6 Examples of Microgrid

Microgrids are a growing trend in renewable energy systems; there are several installations of microgrids in the world, with the US and Asia having the highest market share of miniaturized scale cluster systems.

The United States and Asia currently have 42% of the market, while Europe, Latin

America, the Middle East, and Africa hold only 1%. The total power generation capacity is expected to reach around 5.7 GW or 8.7 GW by 2024. Microgrids are divided into five segments: remote (54 %), business/mechanical (5 %), network (13 %), dispersion of open services (13 %), institutional/grounds (9 %), and military (6 %) [27]. The United States currently has a minimum of 676 microgrids, generating a reliable electrical capacity of 4,132 MW. The Department of Energy (DOE) has documented a total of 620 microgrids that are connected to the electrical grid and 56 microgrids that operate independently from the grid in the United States. Then, some installations are illustrated in Table 1.1.

Table 1.1: Examples of Microgrid Installations and Their Characteristics

Installation Microgrid	**Region**	**Energy Resources**	**Characteristics**
Alcatraz Island Microgrid (Clean Coalition, 2024)	United States	Solar energy and diesel	• Solar and energy storage: 305 kW solar PV / 1,920 kWh of battery energy storage • Other energy generation: Two diesel generators • Date online: 2012- 989 solar panels- 8 power inverters, 100 kW each- 480 batteries- 1 controller device to coordinate generator operation
MCAS Miramar Microgrid [28]	United States	Solar energy, diesel, and natural gas	• Solar and energy storage: 1.3 MW solar photovoltaics / 3 MW energy storage (microgrid system level) / 157 kW thermal energy storage / 390 kW building level energy storage (Lithium Ion and zinc flow batteries and vehicle-to-grid bi-directional hybrid vans) • Other energy generation: 3.2 MW landfill gas, 6.45 MW diesel, and natural gas power plant- 1.6 MW HVAC demand response- EV charging station control
Changoi Tea Farm Solar Project [29]	Kenya	Solar energy	• Power: 1 MW

1.4 Why Size Renewable Energy Systems?

The explanation of this point needs to address the following question: Why is sizing the RES (Renewable Energy Systems) in a microgrid necessary? Microgrids offer various advantages to electric power systems, including reducing line losses, promoting high levels of renewable energy integration, and enhancing power quality, reliability, and efficiency. Photovoltaic panels (PV) and wind generators are commonly used as renewable energy sources in stand-alone hybrid systems. However, other viable options include hydrogen fuel cells, supercapacitors, superconducting magnetic energy storage, and flywheel systems. These devices also correct power imbalances and enhance stability [30].

Despite these advantages, the unpredictable, intermittent, and seasonal behavior of solar radiation or wind speed presents challenges. Therefore, a microgrid's energy conversion sources (ECS) and energy storage sources (ESS) must be carefully selected, designed, and sized to ensure economic and reliable performance and guarantee an adequate energy supply for the load. Sizing a microgrid is particularly challenging due to the nonlinearity and complexity of the design requirements and the modeling of ECS and ESS components [30].

In addition to gathering data on energy potential and local demand, the sizing process involves defining design criteria based on implementation constraints and objectives. Therefore, a multi-objective optimization problem is formulated using these input variables, and the optimal configuration is determined based on the selected criteria. Furthermore, when these sources operate together to meet an electrical load, the challenge lies in determining the optimal size of each component [31].

1.4.1 Load Fluctuation

Microgrids (MGs) typically include two primary types of loads: (i) critical loads, which must be supplied under all circumstances, and (ii) deferrable loads, which can be adjusted to support load balancing within the MG, thereby optimizing economic power generation [17]. Microgrid-generating sources must address the imbalance between power generation and demand. Unlike more significant geographical regions, microgrids have a limited load diversity, resulting in higher relative variability [18]. Consequently, distributed energy systems incorporating various energy sources are crucial for meeting fluctuating customer needs. Recently, there has been a growing trend toward adopting hybrid distributed energy systems to enhance system reliability and improve power quality. This shift aims to reduce reliance on a single traditional energy source, such as diesel generators. While these hybrid systems offer benefits, their widespread implementation is challenged by the unpredictable and variable nature of renewable energy sources, such as solar radiation. One potential solution to this issue is the integration of energy storage devices, which help align energy generation with demand [32].

Accurate load prediction is essential for new and existing projects, as it is critical in optimizing solutions. Estimating the load profile with precision is challenging due to its variability and dependence on unknown consumption patterns. The accuracy of load estimation is closely tied to the operational efficiency and reliability of the system. Analyzing load profiles over specific periods can aid in forecasting high-demand periods and identifying usage patterns.

Moreover, to avoid underperforming microgrids and additional project investments, it is crucial to prevent load consumption profiles that are either too small or too large [33]. Hourly load forecasting is crucial for the optimal design of a hybrid renewable energy system, necessitating the assessment of future load behavior changes. The predictive model analysis is necessary to provide more precise estimations of the load profile [34].

1.4.2 Availability of Energy Resources

Understanding the availability and variability of energy resources, such as solar irradiance and wind patterns, is crucial for determining the optimal amount of renewable energy components within a microgrid. Solar power systems are significantly reliant on the availability of sunlight, which fluctuates daily and seasonally. In areas possessing

Insufficient radiation or variable wind conditions may necessitate photovoltaic (PV) or wind generation capacity to fulfill energy demands, as output becomes increasingly vulnerable to these fluctuations. By precisely evaluating these variances, one may design a microgrid with optimally sized renewable energy systems that correspond to the specific environmental attributes of the site, so providing dependable and sustainable energy generation.

1.4.3 Renewable Energy Market

The assessment of investment expenditures and calculating the most efficient power cost are crucial in determining the appropriate sizing of renewable energy systems (RES). Furthermore, proficient knowledge of component prices, cutting-edge technology, and the intricacies of the electrical market is essential for making accurate size decisions. Several countries encounter difficulties determining a sustainable long-term approach for their energy alternatives, given that no universally ideal renewable energy source exists. Countries are motivated to investigate various renewable energy solutions due to significant economic, technical, and environmental differences.

Hence, it is imperative to carefully choose the most suitable technology or mix of technologies to maximize the advantages. Energy planning is an intricate and diverse process that necessitates the examination of various variables instead of relying on determinants for decision-making [35].

Moreover, the price of energy in the market is impacted by various elements, such as the expenses associated with power generation, local weather patterns, government financial aid, transmission and distribution facilities, industry laws, market mechanisms, and rules [36]. Understanding these variables is essential for making informed decisions regarding renewable energy technology selection and overall energy planning.

1.4.4 Energy Storage

Fluctuations in energy generation present difficulties in maintaining the stability and dependability of the power grid. Consequently, to incorporate energy storage devices and modern grid management techniques to ensure a consistent and reliable energy supply [18]. The technical characteristics of a storage system will vary based on its objectives, necessitating a precise selection of the suitable technology. The wide range of storage technologies available allows for the coverage of many applications, ranging from small, uninterruptible power systems to large-scale utility systems like pumped hydro. Storage systems must have several megawatts capacity to meet the demands of industrial microgrids and accompanying production units.

It is essential to ensure that the systems can supply services with response times ranging from a few seconds to hours. Depending on the unique energy requirements, Li-Ion batteries, flywheels, and supercapacitors are the most acceptable solutions for these applications. For example, heat storage may be ideal if the ultimate service demands heat, as illustrated in Table 1.2 [10].

Furthermore, the hybrid solar, wind, and energy storage (PV-WT-ES) system is a viable alternative for isolated and rural locations. It connects PV panels and wind turbines to a storage device, minimizing power fluctuations and fulfilling load demands. The hybrid PV-WT-BS system is the most cost-effective for islands and isolated locations compared to other hybrid systems.

Hydrogen tanks are another possibility, but they are less cost-effective due to high initial costs and the necessity for a fuel cell. Pumped hydro storage systems can also be reliable but have low energy capacity compared to other methods. Supercapacitors, with excellent power density and efficiency, have not been widely used due to their expensive cost and restricted capacity compared to batteries or other comparable energy storage technologies [37].

Table 1.2: Technologies for reliability-constrained microgrid

Technology	**Advantages**	**Drawbacks**
Li-ion batteries	High energy density, high cycling efficiency, rapid response time, low self-discharge, applicable to other uses (energy shifting)	Life cycle degradation due to cycling and thermal effects.
Flywheels	Quasi-infinite number of cycles	Low energy density, high self-discharge rate
Supercapacitors	High power density, long lifetime, and limited aging	High self-discharge rate (up to 40% a day)

1.4.5 Energy Management

Energy management includes various operational strategies that consider factors such as resource operation and maintenance costs, energy transactions, battery degradation, outages, interruptions, demand response incentives, costs or losses, penalties for load shedding, emissions, and the levelized cost of renewable energy systems. Additionally, the Energy Management System (EMS) may incorporate technical constraints such as electrical network capacity, energy balance, maximum output of renewable energy sources, demand response, reactive power support, reliability, and physical resource limitations [18].

Moreover, the establishment of microgrids requires assessing the dimensions of interconnected assets and developing an effective Energy Management System (EMS) to reduce energy consumption and costs while maintaining a reliable supply. Efficient control mechanisms are essential for resolving the challenges related to the integration of Renewable Energy Resources (RERs) and Energy Storage Systems (ESSs) in microgrids. Effective power management control and energy management system control are essential, with parameters such as voltage, current, and frequency being pivotal.

The Energy Management System (EMS) is crucial for safeguarding Energy Storage Systems (ESSs), optimizing renewable energy utilization, ensuring a reliable power supply, and minimizing operational, maintenance, fuel, and replacement costs [4]. Renewable Energy Systems (RES) are a highly promising but relatively challenging asset in the global energy grid [38].

1.5 Sizing and Optimization

The optimization of renewable energy systems is essential for attaining economic efficiency and environmental sustainability. This technique emphasizes two primary objectives: reducing costs while enhancing system performance and advantages. A variety of optimization techniques are utilized to attain these objectives, encompassing classical methods, artificial intelligence (AI), hybrid approaches, and software-based tools.

Minimization aims to decrease annual expenses, net current costs, electricity expenditures, land utilization, emissions, and the likelihood of power supply failure. By addressing these factors, renewable energy systems enhance their financial viability and environmental sustainability. Conversely, maximization emphasizes the augmentation of power generation, renewable proportion, profits, longevity, and overall revenue, guaranteeing optimal system efficacy and financial returns. These objectives are clearly illustrated in Figure 1.10.

Diverse strategies are utilized to optimize these systems efficiently. Classical techniques depend on mathematical models and deterministic optimization procedures, yielding definitive results while occasionally encountering difficulties with intricate variables. These methodologies encompass numerical, iterative, analytical, and probabilistic techniques. Numerical techniques employ economic and reliability models to estimate solutions for hybrid energy systems, whereas iterative methods forecast the most cost-efficient configurations. Probabilistic methods address multi-objective functions, non-linear system responses, and long-term weather fluctuations, whereas analytical methods employ computational models to evaluate economic viability.

Conversely, artificial intelligence (AI) methodologies incorporate machine learning and sophisticated algorithms, providing rapid, adaptable, and globally scalable solutions. Hybrid optimization methods incorporate classical and AI-based techniques, improving accuracy, computing efficiency, and solution reliability through the integration of diverse methodology. Moreover, software tools are essential for modeling, simulation, and data-driven decision-making, facilitating accurate optimization of energy systems.

A variety of sophisticated metaheuristic optimization algorithms have been developed to tackle complex multi-dimensional problems efficiently. These include the Social Spider Optimizer, Grey Wolf Optimizer, Jaya Algorithm, Dragonfly Algorithm, Pity Beetle Algorithm, Coyote Optimization, Deer Hunting Optimization, Forensic-Based Investigation Algorithm, Golden Eagle Optimizer, Tunicate Swarm Algorithm, and Jellyfish Optimizer. These algorithms enhance optimization performance and prevent solutions from becoming trapped in local optima. However, they are not without limitations, as some may prioritize suboptimal solutions, fail to explore diverse possibilities effectively, or converge prematurely [34].

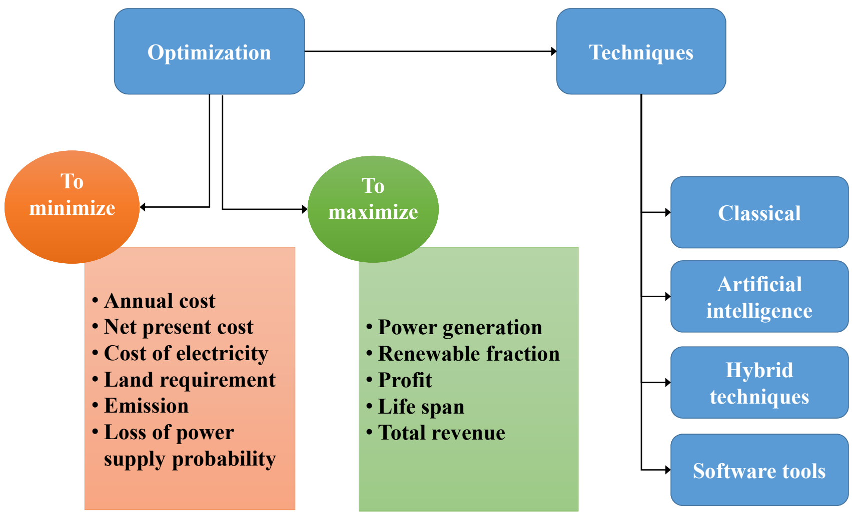


Figure 1.10: The strategy of optimization for sizing RES

1.5.1 Related Works

Addressing and improving the sizing problem in planning Renewable Energy Systems (RES) requires careful consideration of multiple vital aspects. These include selecting appropriate sizing methods, identifying key indicators, and incorporating crucial considerations throughout the renewable energy project sizing process.

The issue of sizing was resolved by utilizing evolutionary multi-objective optimization techniques and metaheuristic algorithms. For instance, in [39], a genetic algorithm was employed to achieve optimal PV/battery system sizing, addressing the techno-economic aspects. Similarly, the bee algorithm was utilized in [40], and [41] Introduced the levy flight moth flame algorithm. Other studies, such as [42]employed multi-objective algorithms.

Furthermore, a novel crow algorithm was proposed by [43], and a new hybrid metaheuristic algorithm was published in [44]; this algorithm, called the hybrid grey wolf optimizer-sine cosine algorithm, was used to find the optimal size of system components. Additionally, the multiple-design methodology was implemented for off-grid systems [45], and a novel multi-objective approach with online Pareto pruning was employed for the multi-year optimization of rural microgrids [46].

In the literature, the sizing operation for renewable energy systems is often determined using key economic indicators. One of the most commonly employed indicators is the Net Present Cost (NPC), which represents the total cost of establishing a renewable energy system. It defined as the total system cost, this includes expenditures for construction, operation, and maintenance. or life cycle cost of the system [47]. Another crucial metric is the Levelized Cost of Electricity (LCOE), which calculates the cost of generating a kilowatt-hour (kWh) of electricity in dollar terms, or it is the ratio of net annual payment to the net annual electricity consumption. As discussed in this work, these indicators provide a comprehensive basis for evaluating and optimizing the financial feasibility of renewable energy systems.

Several papers have introduced these indicators as critical criteria for optimal sizing of renewable energy systems. These studies use various methods and optimization algorithms to minimize economic indicators, such as Net Present Cost (NPC) and Levelized Cost of Electricity (LCOE) [48–50].

In addition, multiple articles employed specialized software, particularly the HOMER optimizer, to determine microgrid systems' lowest Cost of Energy (COE). These studies utilized various resource systems, such as Photovoltaic (PV), Wind turbine (WT), diesel, hydrogen, and the electrical grid.

The work in [51] provides a techno-economic analysis for a hybrid PV/wind microgrid and investigates the viability of a grid-connected microgrid [52]. The planning and design of renewable energy systems (RES) involved determining the most efficient size based on the lowest Net Present Cost (NPC) and reducing the Levelized Cost of Energy (LCOE).

Recent studies have thoroughly investigated financial indicators related to profitability and reliability. Key metrics such as Net Present Value (NPV) of a power system is the difference between the present values of the total profit and total cost of the system within its operational lifetime. Obviously, the higher the NPV, the higher economic benefit, Internal Rate of Return (IRR), and Discounted Payback Period (DPB) have been identified as critical for evaluating the economic feasibility of projects. These indicators, shaped by factors such as cash flow, discount rates, and project lifespan, serve as fundamental tools for in-depth economic analysis. Their significance is further emphasized in developing academic strategies for the optimal sizing and performance evaluation of renewable energy systems, ensuring both financial sustainability and operational efficiency.

Table 1.3: Some studies about sizing and optimization

References	Configuration	Metaheuristic /Algorithm	Homer Software
[39]	PV/batt	X	
[40]		X	
[41]		X	
[51]	PV/WT		X
[44]		X	
[43]		X	
[46]	PV/WT	X	
[42]		X	
[49]	PV/batt		X
[53]	PV/WT/Bio-gene		X
[54]	PV/DG/fuel cell	X	
[55]	PV/DG/WT	X	
[45]	PV/Fuel gen/batt	X	
[56]	PV/batt/On-Grid	X	

When examining the parameters to consider when assessing RES investment in [57], it was discovered that economic parameters play a crucial role in energy projects. As stated by [58], a study comparing various objective functions for the optimal design of a microgrid found that the external rate of return, discounted payback duration, and discounted profitability index are all financial measures.The NPV (Net Present Value) and IRR (Internal Rate of Return) are utilized to evaluate the energy investment to maximize profitability. These metrics are calculated based on the projected cash flow [59].

Alternatively, certain researchers employed decision-making techniques to analyze the investment in energy projects [60] and assess quantitative and qualitative risks in energy investment [61]. Summarize all this in Tables; Table 1.3 summarizes various studies focusing on optimizing configurations through advanced techniques, while Table 1.4 presents research on economic indicators related to RES sizing.

Table 1.4: Some studies about economic indicators

Study	NPC	LCOE	NPV
[62]	X	X	
[63]	X		
[50]	X	X	
[45]	X		
[48]	X	X	
[64]	X		
[57]		X	X
[65]			X
[39]			X
[66]		X	
[58]	X	X	X
[67]	X	X	X
[68]			X

1.5.2 Research gaps

Following the comprehensive literature evaluation presented in Section 1.5.1 and encapsulated in Table 1.3 and Table 1.4, the investigation gaps that have been identified are:

Several studies have applied economic metrics to assess the financial performance of various Renewable Energy Systems (RES). Others have concentrated on evaluating investment projects for renewable energy integration. However, no research has introduced a comprehensive, systematic approach that provides a detailed, step-by-step methodology for determining the optimal sizing of RES into a microgrid.

- Lack of Comprehensive Methodology: While many studies have examined economic metrics and investment project evaluations for RES, none have presented a structured, step-by-step framework for the optimal sizing of RES with a focus on long-term planning.

- Integration of Economic and Technical Aspects: Previous research often treats economic analysis and technical design as separate entities, neglecting the interconnection between the two. Bridging this gap by integrating these dimensions is essential for creating a holistic and effective system design, particularly in the context of long-term investment planning and sustainability.

- Addressing Long-Term Uncertainties:

  Most existing studies fail to incorporate uncertainties in sizing design of renewable energy systems. To address this gap, a comprehensive methodology must integrate uncertainty modeling and financial investment considerations to ensure robust and adaptable system design.

The dissertation aims to address these limitations by incorporating a long-term perspective that accounts for uncertainties and financial investment considerations. Additionally, the research integrates financial investment metrics to ensure that the optimal sizing framework aligns with sustainable economic goals and provides robust solutions that remain viable under various future scenarios.

1.6 Conclusion

This chapter presented a comprehensive overview of renewable energy systems and microgrids, focusing on various sizing techniques through an extensive literature review. It highlighted existing research gaps and emphasized the critical importance of the sizing process in designing efficient and reliable renewable energy systems. The subsequent chapter will outline the proposed sizing methodology and the techno-economic assessments conducted in this study.

CHAPTER 2

COMPREHENSIVE STUDY OF OPTIMAL SIZING OPERATION FOR RENEWABLE ENERGY SYSTEMS IN MICROGRID

Chapter Two introduces sizing operations and develops an optimal sizing for incorporating renewable energy systems into microgrids. The chapter presents a thorough framework for examining sizing operations, including important factors for attaining the best possible integration. We aim to comprehensively comprehend the optimal sizing of renewable energy systems in microgrids, guaranteeing efficiency, dependability, and sustainability.

2.1 Introduction

In the design of renewable energy systems, essential components encompass solar radiation, wind speed, and hydrological conditions. The energy potential of these resources depends on variables such as geographical location, climatic conditions, and the technology utilized. Therefore, an optimal sizing methodology guarantees the proficient and economical use of integrated renewable energy sources. This entails establishing the optimal size to minimize expenses while maximizing the use of PV panels, wind turbines, hydro, biomass, and battery storage. The objective is to function under optimal circumstances, balancing system investment and power efficiency.

Through optimization methods, financial goals are considered to identify the most optimal solution regarding dependability and cost while assessing the system's long-term performance. The size of the system is optimized by regulating the energy flow to achieve optimal integration of renewable energy systems. Energy management systems, encompassing both demand-side and production-side approaches, aim to fulfill energy requirements while minimizing operating expenses and environmental impact. The main goal is to reduce the costs associated with expanding the power system by determining the most efficient size and position for the feeders and substations in the distribution system [14].

Furthermore, Hybrid Renewable Energy Systems (HRES) offer a potential solution to the issues posed by the intermittent nature of renewable energy. These systems integrate many energy sources, such as wind and solar energy, to compensate for the limitations of one source by leveraging the advantages of another [34]. HRES can incorporate a more reliable energy source, such as biomass fuel, which can be used whenever needed. It can function independently in isolated regions where generating electricity from fossil fuels or extending the power grid is impractical. Energy storage technologies, such as batteries, fuel cells, flywheels, electrochemical/super/ultracapacitors, compressed air energy, and pumped hydro storage, can effectively deal with fluctuations in renewable energy [54].

The hybrid renewable energy system can operate independently of the power grid or in a connected mode to the power grid, offering versatility and dependability. By maximizing the benefits of hybrid energy systems, microgrids serve as a key component in facilitating the efficient distribution of power generation. They are vital for ensuring smooth operations and maintaining high reliability within the power system [32]. Therefore, the analysis of hybrid systems for optimization purposes is challenging due to various generating systems. The objective is to achieve the most favorable operating conditions and perform an economic assessment, ensuring that the system's performance adheres to all economic and technical constraints. The effective utilization of sustainable energy sources depends on the techno-economic evaluation of the hybrid system. The efficient and successful design of hybrid renewable energy systems relies on the application of optimal sizing methodologies, which are becoming increasingly common. This research framework focuses on developing a sizing methodology for renewable energy systems, whether standalone or hybrid.

2.2 Sizing Concept

Determining the appropriate capacity for renewable energy systems (RES) is crucial before installation. The process entails assessing the system's expenses and energy generation to guarantee the reliable fulfillment of local demand, even in the face of probable disruptions in production and storage. Microgrids that have significant storage capability necessitate high investment and maintenance expenses. Therefore, it is crucial to maintain a careful equilibrium between operational costs and energy system expenses to guarantee profitability.

Sizing optimization uses different objective functions to find the most efficient and high-performing solutions while considering unique limitations, developing renewable energy sources inside microgrid systems entails several economic factors such as expenses, financial viability, and energy efficacy. Optimization is the systematic Procedure of determining a mathematical function's lowest or highest value by carefully choosing suitable variables while considering any limitations or restrictions. Simulation tools are commonly employed for this purpose. Nevertheless, optimization techniques only sometimes ensure the identification of an optimal solution owing to the intricacy of the problem.

The selection of the optimization method is contingent upon the specific cost function being targeted. The ultimate dimensioning of a microgrid can vary considerably depending on the optimization methodology employed [58]. The HES optimization problem is to achieve the optimal capacity of components by minimizing/maximizing objective functions with considering system constraints as depicted in Figure 2.1.

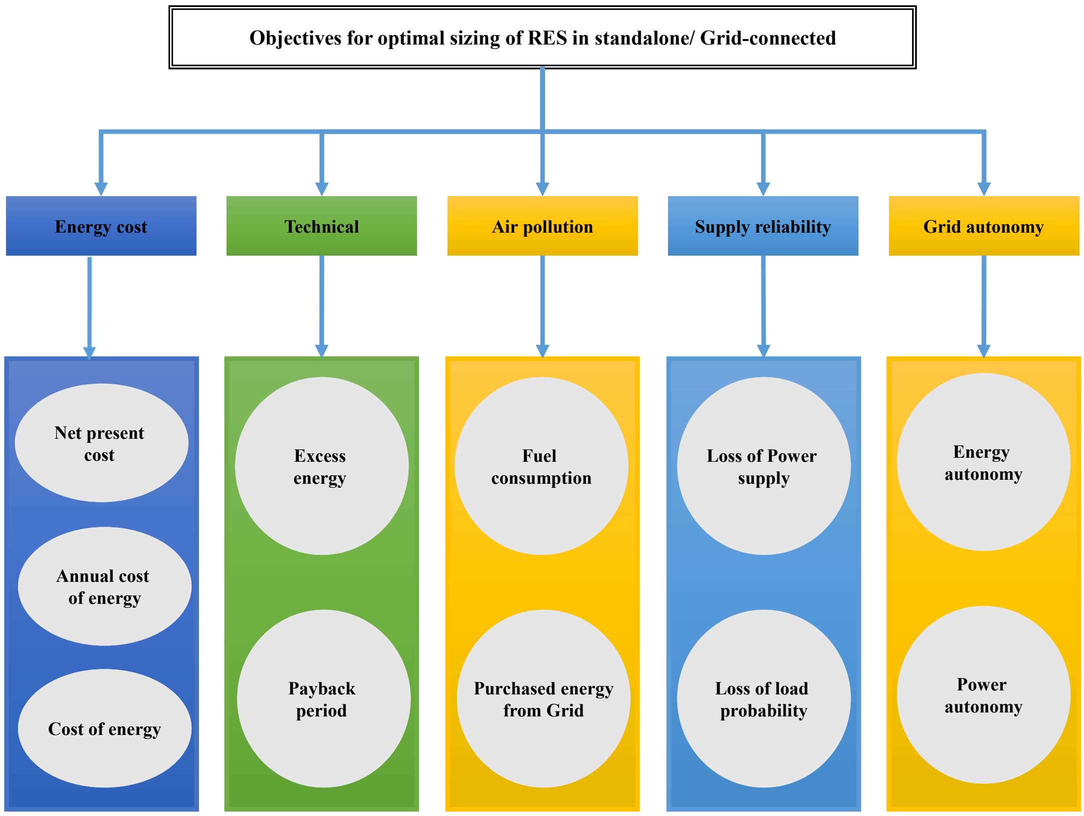


Figure 2.1: Objective functions for optimal sizing of HRES
[47]

2.2.1 Environmental Assessment

The environmental assessment of integrating renewable energy sources (RES) into microgrids is a crucial step in the sizing process. This assessment is considered to reduce air pollution, which varies depending on the operational mode of the hybrid energy system (HES). In a standalone HES, air pollution can be minimized by reducing diesel generator (DG) fuel consumption, while in a grid-connected HES, it is achieved by decreasing reliance on energy imports from fossil-fuel-dominated grids [47].

A critical factor influencing emissions in both modes is the renewable fraction (RF), as higher RF values are directly associated with lower pollutant emissions. By incorporating these environmental and operational considerations into the sizing process, the system can achieve optimal economic and technical performance while ensuring long-term sustainability.

Furthermore, Life Cycle Assessment (LCA) is widely used to evaluate the energy consumption and environmental impact of a system throughout its entire lifespan. This approach was applied to a hybrid microgrid (MG) system that combined diesel, photovoltaic (PV), and wind energy sources for rural electrification on an island. The analysis revealed that, among various environmental impacts, the hybrid MG system exhibited the lowest global warming potential, particularly when compared to acidification and human toxicity potential [69].

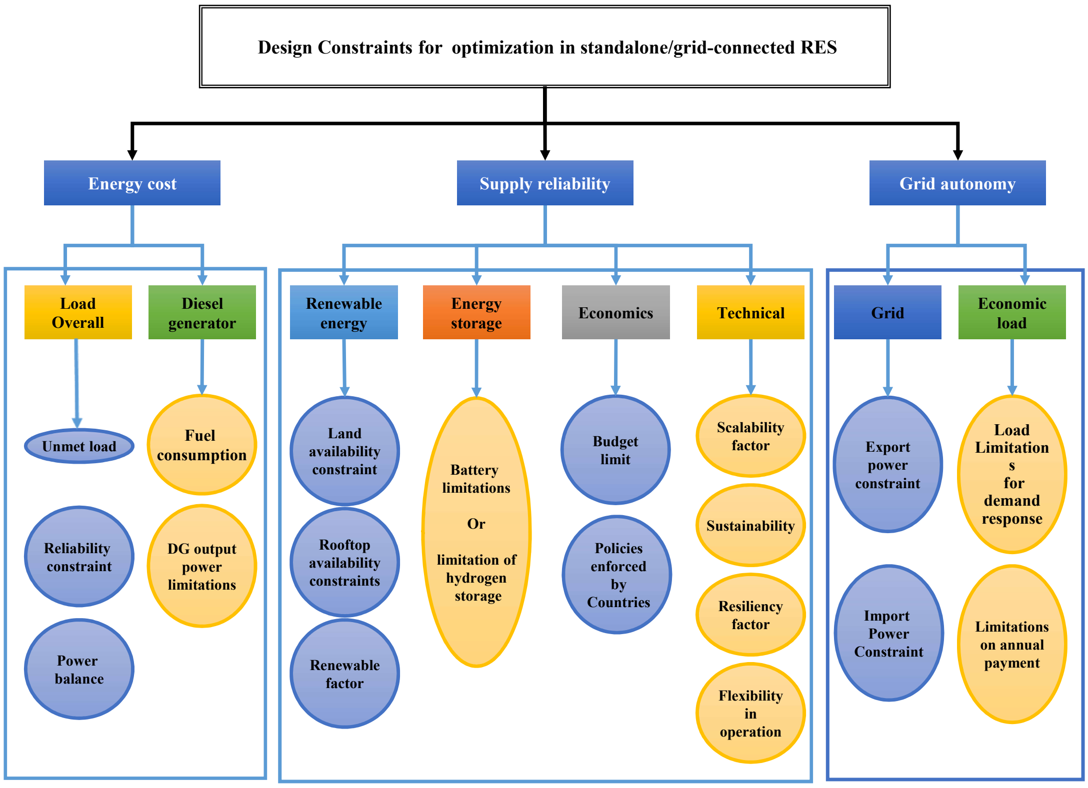


Figure 2.2: Constraints for optimal sizing of standalone/grid-connected HRES

2.2.2 Economic and Reliability Assessment

An essential aspect of effectively and economically harnessing renewable energy resources (RER) is the use of an optimal sizing approach [70]. RES optimization takes into account many techno-economic parameters, including net present cost (NPC), annualized system cost (ASC), life cycle cost (LCC), and cost of energy (COE). sizing primarily examines the ability of energy production to meet load demands, utilizing technical indicators such as loss of load expectation (LOLE), loss of energy expectation (LOEE), deficiency of power supply probability (DPSP), loss of load hours (LOLH), unmet load (UL), equivalent loss factor (ELF), loss of power supply probability (LPSP), and renewable energy fraction (RF) in both standalone and grid-connected systems.

The constraints for Hybrid Energy Systems (HES) are categorized based on their application to standalone, grid-connected, or combined systems. For grid-connected HES, constraints include import/export power limitations and load restrictions to facilitate demand response. Where the primary constraint in optimizing standalone HES is the power equilibrium between generation and consumption. By considering reliability limits, a targeted decrease in load can be achieved, resulting in reduced system costs as illustrated in Figure 2.2.

Moreover, the renewable energy system can function autonomously or be linked to the power grid, and limitations are classified according to their relevance to either standalone, grid-connected, or both types of energy system. Typical limitations involve batteries' state-of-charge (SOC), which must be kept within specific minimum and maximum levels. The availability of land and rooftops is a substantial constraint for installing wind turbines (WT) and photovoltaic (PV) systems due to their space requirements. Investment limits and national policies may impose some limitations and technical constraints are another common consideration in optimal sizing procedures. One such constraint is the scalability factor, which ensures the designed system can be scaled effectively. Resiliency constraints enhance the robustness of the system, making it capable of withstanding severe disturbances like grid outages or natural disasters. Additionally, operational flexibility is crucial, particularly given the increasing integration of renewable energy sources into power systems [47, 49].

2.3 Proposed Method

The proposed method thoroughly examines the financial and technical viability of different combinations of renewable energy sources in microgrid systems. Moreover, this methodology is adaptable to any renewable energy system and can be applied to microgrids of different scales. This study combines the distinctive geographical features of a region known for its substantial solar and wind energy capacity. It incorporates a sensitivity analysis to ascertain the influence of input parameters on different expenses, such as solar radiation, wind speed, power demand, inflation rate, and discount rate.

Moreover, this doctoral dissertation comprehensively examines the practicality of technology and economics and evaluates the potential risks associated with investing. The use of HOMER software enables the optimal sizing of renewable energy systems (RES) through three different combinations:

- Isolated Photovoltaic Microgrid: Exclusively reliant on photovoltaic energy.
- The Hybrid Renewable Microgrid is a technology that integrates solar and wind power generation with a storage system.
- The Hybrid Renewable System with Backup Diesel Generator combines solar and wind power sources with energy storage capabilities, supplemented by a diesel generator for backup purposes.

As shown in Figure 2.3, the proposed framework outlines the process for selecting the most efficient combination by considering the lowest Cost of Energy (COE) and the Net Present Cost (NPC) of the system configuration. Each microgrid is regarded as an economic project, evaluating financial metrics and determining investment choices. It involves examining the cash flow and assessing the levels of financial indicators. In addition, the risk analysis of Net Present Value (NPV) is performed by utilizing Monte Carlo simulation, as explained in the next chapter.

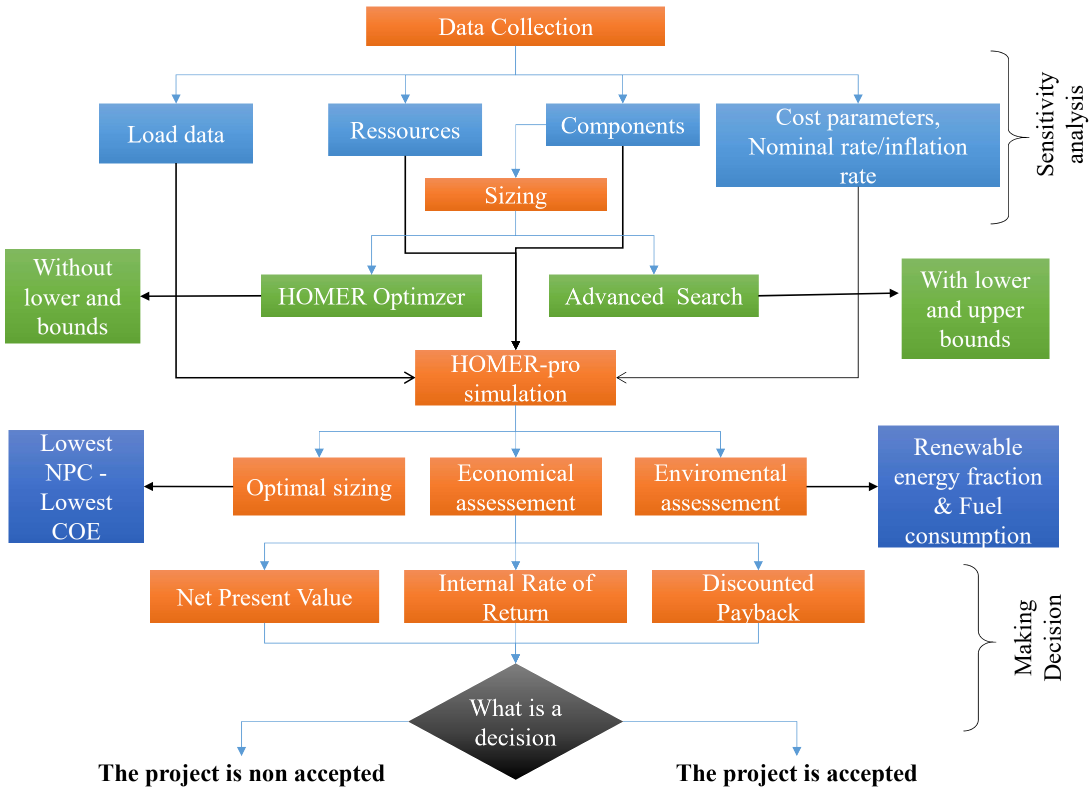


Figure 2.3: Procedure of financial analysis of the RES

2.3.1 Techno-Economic Analysis

The HOMER program employs two main optimizing approaches. The grid search algorithm systematically evaluates every potential system configuration inside the Search Space. Subsequently, the HOMER Optimizer employs a distinctive methodology that does not depend on derivatives to determine the system configuration, which results in the minimum cost. Afterward, the software presents a list of configurations, arranged based on their Net Present Cost (NPC), allowing for assessing different system design options. HOMER is utilized for techno-economic analysis of hybrid renewable energy systems, evaluating them based on practical criteria and constraints to determine the system's net present cost [62].

2.3.1.1 Costs

Researchers in various fields of economics, including energy, environmental economics, energy system modeling, and finance, are focused on understanding the investment and financing of renewable energy assets. These academics hold varying conceptualizations on the cost of capital or discount rates [71]. To improve the intelligibility of our subject matter, we will provide a concise explication of financing frameworks. Capital expenditures (CAPEX) are the expenses incurred while investing in the initial capital components, as indicated by equation 2.1 [72].

$$\text{CAPEX}_{i,y} = \sum_{i=1}^{n} \text{CRF} \cdot C_{\text{comp},i} \tag{2.1}$$

Moreover, it can be defined as the primary cost associated with generating power and storing energy in a microgrid. This includes the charges for the necessary equipment and the costs related to its installation. In annual calculations, two economic terms determine the objective function: the capital recovery factor (CRF) and the sinking fund factor (SFF). The capital recovery factor calculates the present worth of annual costs, while the sinking fund factor (SFF) calculates the annuity of any future value. The capital recovery factor (CRF) is calculated using the following formula (equation 2.2) [73].

$$\text{CRF}(i_r, y) = \frac{i_r(1+i_r)^y}{(1+i_r)^y - 1} \tag{2.2}$$

Where the discounted rate $(\mathbf{i_r})$ is correlated with all economic variables, as seen in equation (2.1) to (2.6), the nominal/discount rate is calculated by combining the risk-free rate and the risk-premium rate, as these rates have a significant effect on the values of economic indicators that are influenced by the inflation rate $(\mathbf{i_{inf}})$ and the nominal discount rate $(\mathbf{i_n})$ [74].

According to the Bank of Algeria, the nominal discount rate will be 3 % in 2022, with the inflation rate ranging between 10 % and 11 % [75].

Furthermore, Operational Expenditures (OPEX) are defined explicitly as the expenditures associated with the maintenance and operation of components, as represented by equations (2.1) to (2.3) [76].

$$\text{OPEX}_{i,y} = \sum_{i=1}^{n} \left(C_{\text{o\&m},i,y} + \sum_{i=1}^{n} \text{SFF} \cdot C_{\text{rep},i} \right) \tag{2.3}$$

The variables used in this equation are as follows: C_{rep} represents the replacement cost, $\text{C}_{\text{o\&m}}$ represents the operational cost, and n represents the number of components. The life cycle cost of replacing the microgrid system's primary components is considered. The replacement cost is determined as the ultimate stage of a microgrid system's Life Cycle Cost (LCC) study. The sinking fund factor (SFF) measures the relationship between the component's lifespan and the annual replacements. The formula for it is as follows equation 2.4 [77] :

$$\text{SFF} = \frac{i_r}{(1+i_r)^y - 1} \tag{2.4}$$

The operation and maintenance costs of each component of the planned microgrid are included in the Life Cycle Cost (LCC). One can estimate the O&M expenditures for each component by considering its projected lifespan. The operational and maintenance (O&M) expenses of a microgrid system during its entire lifespan encompass the fuel costs of the diesel generator, which constitute the majority of the running expenses for the reciprocating engine. The operation and maintenance costs of the microgrid system are contingent upon the inflation rate and interest rate and are subject to change based on the system's utilization [7].

Furthermore, the maintenance of the energy mix system, capital expenditure (CAPEX), and operating expenditure (OPEX) might vary significantly based on the load conditions. For instance, batteries may require replacement due to increased demand and limited durability, and the cost of batteries may fluctuate periodically, depending on demand and the discharge procedure [72].

2.3.1.2 Economic Indicators

Economic indicators such as Net Present Cost (NPC) and Levelized Cost of Electricity (LCOE) are crucial for determining the optimal size and cost of Renewable Energy Systems (RES) in a microgrid. The NPC provides a comprehensive measure of the total cost of a system over its lifetime, including initial capital costs, operation and maintenance costs, and the cost of fuel and replacements. In contrast, the LCOE reflects the average cost per unit of electricity the system generates, accounting for all expenses over its operational life. By analyzing these indicators, decision-makers can optimize the design and operation of the microgrid to minimize costs and maximize efficiency, ensuring the economic viability and sustainability of the RES microgrid.

A) **Net present cost (NPC)**: The primary goal of determining the size of the microgrid system is to minimize the Net Present Cost (NPC), which is computed by subtracting the entire cost from the revenues generated throughout the project's lifespan, as indicated by equation 2.5 [64, 78].

$$\text{NPC}(i,y) = \frac{1}{\text{CRF}(i,y)} \sum_{y=0}^{N_{ni}} (\text{CAPEX}_{i,y} + \text{OPEX}_{i,y} - C_{\text{salvage},i,y}) \tag{2.5}$$

Where the C_{Salvage} is the salvage cost. The equation 2.6 is utilized to compute the residual value of the power components upon the completion of the project's lifespan [79]. L_{rem} represents the remaining duration of the project, while L_{com}

represents the component's lifespan.

$$C_{\text{salvage}} = C_{\text{rep}} \frac{L_{\text{rem}}}{L_{\text{com}}} \tag{2.6}$$

B) **Levelized cost of electricity**: The term "levelized cost of energy" denotes the mean revenue generated per energy unit produced, which is utilized to cover the costs linked to the design and operation of the system throughout its anticipated financial duration and operational cycle. It is regarded as an economic indicator that is utilized to evaluate the economic feasibility of the project [76, 80] , as expressed in equation 2.7.

$$LCOE_T = \frac{\sum_{y=0}^{N_y} C_y}{\sum_{y=0}^{N_y} \text{ES}_y} \tag{2.7}$$

C_y represents the system's expenses, whereas ES represents the energy served or he amount of electricity (kWh or MWh) that the system successfully delivers to the load [58]. The Levelized Cost of Energy is the ratio of all discounted expenses incurred over a system's usable lifetime to the discounted total of the actual energy values distributed.

2.3.2 Objective Function and Constraints

2.3.2.1 Objective Function

Several factors must be considered when designing renewable energy systems integrated into microgrid systems. These include economic considerations such as cost, profitability, and energy efficiency, particularly when the system generates the anticipated electricity. The primary purpose of this work is to enhance the efficiency of the microgrid system by optimizing multiple objective functions. The objectives include minimizing the Net Present Cost (NPC) during the system's lifespan, lowering the Levelized Cost of Energy (LCOE), and reducing fuel usage and CO_2 emissions.

2.3.2.2 Constraints

The proposed optimization model has several design limitations that must be addressed for technical and environmental considerations.

a. The power balance and battery charge constraints are critical from a technical perspective. These constraints can be mathematically represented in equation 2.8, which ensures that the total power consumption does not exceed the maximum power generated from available energy sources [81]:

$$\sum_{j=1}^{N} (P_E + P_{bat} - P_{load}) = 0 \tag{2.8}$$

P_E represents the power generated by energy resources, while P_{bat}denotes the battery's power output. A positive P_{bat} value indicates the battery discharges, whereas a negative value indicates charging. Additionally, it is essential to adhere to the operational limits of power generation units and battery systems. The terms $P_{\text{charge max}}$ and $P_{\text{discharge max}}$ define the upper bounds for the battery's charging and discharging power, respectively, as defined in equation 2.9.

$$P_{\text{charge}}^{\text{max}} \leq P_{bat} \leq P_{\text{discharge}}^{\text{max}} \tag{2.9}$$

b. From an environmental standpoint, diesel generators contribute significantly to greenhouse gas emissions, with carbon dioxide (CO_2) being the predominant byproduct. The amount of CO_2 emissions generated by a unit of type **n** during time **t** (in ton/MWh) is denoted by E_n , while g_n represents the energy produced by the non-renewable generation units during the same period (in MWh) [82]. As expressed in equation 2.10.

$$E_t = \sum_{t} \sum_{n \in N} g_{n(t)} E_n(t) \tag{2.10}$$

c. The loss of power supply probability (LPSP) measures the likelihood of experiencing a power shortage. It is determined by comparing the combined output of stored energy and energy needs to the load demand divided by the total load demand [14]. LPSP is the proportion of power supply that cannot meet the load demand. Currently, it is the most widely used measure for assessing the dependability of HRESs. There are two approaches to calculating LPSP: the first method relies on chronological simulation, which is computationally complex and requires data over a specific time; the second method utilizes probabilistic techniques that account for load and energy fluctuations, eliminating the need for time-series data [82]. The term 100 % LPSP refers to a hybrid power system (HRES) that is reliable and free from capacity shortages. To attain 90 %, the maximum annual capacity shortage specified for HOMER as an input variable is set to zero.

d. Various measures evaluate how much renewable energy contributes to the system. Renewable fraction (RF) is used to decrease the amount of non-renewable energy in the context of diesel-powered hybrid renewable energy systems (HRES) [73]. The renewable fraction (RF) helps determine the percentage of renewable energy sources in the total energy supplied for a specific demand. RF is the proportion of energy provided to the load that originates from renewable power sources, and it may be expressed mathematically as equation 2.11 [81]:

$$\mathrm{RF} = \left(1 - \frac{E_{\text{non-ren,ann}}}{E_{t,\text{ann}}}\right) \times 100\% \tag{2.11}$$

$E_{t,a\,nn}$ represents the total amount of electricity consumed annually, while $E_{non-ren,a\,nn}$ refers to the total yearly electricity generation not derived from renewable sources. In this study, the purpose is to maximize the function RF, which is subject to constraints. Specifically, RF cannot exceed 100 % or be less than 50 %.

2.3.3 Load Profile and System Modeling

Accurately determining the required amount of energy and the accessibility of renewable resources are essential in determining the appropriate size of renewable energy systems (RES) in a microgrid. Precise estimation guarantees that the system is adequately sized to fulfill energy requirements while maximizing the use of accessible renewable resources. This entails gathering and examining past consumption data to comprehend patterns and highest demands and constructing load profiles based on the time of day, season, and specific customer needs. Assessing the availability of renewable resources involves evaluating solar radiance levels by satellite data, ground measurements, and meteorological data for solar resource. It also includes utilizing wind speed data, anemometer readings, and geographical information for wind resources.

Furthermore, it is crucial to examine fluctuations in seasons and daily cycles to comprehend the fluctuations in resource availability over time and to consider the collective potential of numerous renewable resources to improve dependability and consistency. After estimating the load demand and resource availability, the mathematical models for each constituent of the microgrid, such as solar systems, wind energy systems, storage systems (batteries), and backup systems (diesel generators). By integrating these models, microgrid operations can be optimized by maintaining energy balance, prioritizing renewable sources, and effective management of battery cycles.

2.3.3.1 Photovoltaic System

The output power of the photovoltaic (PV) panels manufactured by Solar Max Inc. is calculated using a specific equation implemented within the HOMER software, which is based on mathematical modeling as expressed in equation 2.12. This calculation considers various factors such as solar irradiance, temperature, and panel efficiency to accurately estimate the power generated under different conditions. Detailed simulation results and their implications are thoroughly discussed in Chapter Four.

$$P_{\mathrm{PV}}(t) = R_{\mathrm{PV}} \cdot f_{\mathrm{PV}} \left[\left(\frac{I_T(t)}{I_S} \right) \left(1 + \alpha_p \left(T_c(t) - T_{c,\mathrm{STC}}\right)\right) \right] \tag{2.12}$$

R_{PV}: Rated capacity of the PV array, meaning its power output under standard test conditions [kW]

f_{PV} : PV derating factor [%]

I_T: Solar radiation incident on the PV array in the current time step [kW/m^2]

I_S : Incident radiation at standard test conditions [1 kW/m^2]

α_P : Temperature coefficient of power [%/°C]

T_c : PV cell temperature in the current time step [°C]

$T_{c,STC}$: PV cell temperature under standard test conditions [25° C]

2.3.3.2 Wind Power

The study examines the power generated by the Gaia WT, a wind turbine with a capacity of 11 kW and a hub height of 18 m. The turbine has a lifetime of 25 years and does not require any replacement costs. The power output can be mathematically represented by a function that takes wind speed (v) as input, as shown in equation 2.13 [83].

$$P_{\mathrm{WT}}(t) = \begin{cases} 0, & \text{if } v < V_{\mathrm{in}} \text{ or } v > V_{\mathrm{out}} \\ p_{\mathrm{WTr}} \cdot \frac{V(t) - V_{\mathrm{in}}}{V_r - V_{\mathrm{in}}}, & \text{if } V_{\mathrm{in}} \leq v < V_r \\ P_{\mathrm{WTr}}, & \text{if } V_r \leq v < V_{\mathrm{out}} \end{cases} \tag{2.13}$$

The power output of wind turbines at simulation step t is denoted as P_{WT}(t), whereas the wind speed at that same step is denoted as v(t). The power output of a wind turbine grows linearly as the wind speed increases from the cut-in wind speed (V_{in}) to the rated wind speed (V_r) when the wind speed (v) reaches the cut-in wind speed (V_{in}). When the velocity v falls inside the interval [V_r, V_{out}], where V_{out} represents the cut-off speed, the wind turbines (WTs) will consistently operate at the rated power P_{WTr}. When the velocity (v) is greater than the output velocity (V_{out}), the wind turbines (WTs) are deactivated as a safety measure. This deactivation indicates the wind turbines' performance under standard temperature and pressure conditions (STP). To adapt the wind turbine power to the existing conditions, the expected power value is multiplied by the power curve, considering the air density ratio, as indicated by the equation 2.14 [84].

$$P_{\mathrm{WTG}} = \left(\frac{\rho}{\rho_0} \right) \cdot P_{\mathrm{WTG,STP}} \tag{2.14}$$

Where:

P_{WTG}: Wind turbine power output [kW]

$P_{WTG,STP}$: Wind turbine power output at standard temperature and pressure (kW)
ρ: Actual air density [kg/m^3]
ρ_0: Air density at standard temperature and pressure (1.225 kg/ m^3)

The values of speed are measured at a certain level of height, and then these measured values are transformed according to the real turbine height using the following formula [85]:

$$V_{\text{hub}} = V_0 \times \left(\frac{Z_{\text{hub}}}{Z_0}\right) \times \lambda \tag{2.15}$$

Where V_{hub} is the wind turbine speed, V_o is the wind speed at reference height, Z_{hub} is the actual height of the wind turbine, Z_o is the height of wind speed measurement and λ is a power law.

2.3.3.3 Diesel Power

Equation 2.16 mathematically represents the diesel generator (DG). The fuel curve slope α for a 100 kW capacity is 0.253 L/hr/kW, and β is the coefficient fuel curve intercept [85]. R_{DG} represents the rated capacity of 100 kW, whereas P_{DG} represents the power generation within a specific time.

$$F_{\text{DG}}(t) = \alpha R_{\text{DG}} + \beta P_{\text{DG}}(t) \tag{2.16}$$

2.3.3.4 Storage System

Lead-acid batteries are employed for modeling. They can absorb surplus energy and subsequently replenish power when there are inadequate resources to fulfill the load demands. Equations 2.17 and 2.18 mathematically depict the behavior of these batteries.

$$P_{(b,ch)}(t) = \frac{kQ_s(t)e^{-k} + Q(t)k_c\left(1 - e^{-k\Delta t}\right)}{1 - e^{-k\Delta t} + c\left(k\Delta t - 1 - e^{-k\Delta t}\right)} \tag{2.17}$$

$$P_{(b,d)}(t) = \frac{-k_c Q_{\max} + k_c Q(t) e^{-k\Delta t}}{1 - e^{-k\Delta t} + c\left(k\Delta t - 1 - e^{-k\Delta t}\right)} \tag{2.18}$$

Q_s(t) represents the amount of charge available at the beginning of the time step, which is more than the minimum state of charge (SOC_{min} is 40%). Equation 2.17 defines Q(t) as the initial total energy at the beginning of the time step. The variables **c**, **k**, and **t** represent the storage capacity ratio, storage rate constant, and time step, respectively. Q_{max} is the total capacity storage used to calculate power discharge in Equation 2.18 [49, 50]. The selected replacement cost of the batteries is 300 USD per unit, as determined by equation 2.3, including SFF.

2.3.3.5 Data Collection

Figure 2.4 displays a dataset requiring specific inputs. It represents the electricity consumption for the commercial load at site Biskra in July, with a peak load of 460 kW. The output power of the PV generator can be determined by considering the global solar radiation values depicted in Figure 2.5, which range from 0.2 kW/m^2 to 0.88 kW/m^2. The wind speed is acquired from a meteorological station operated by NASA [6].

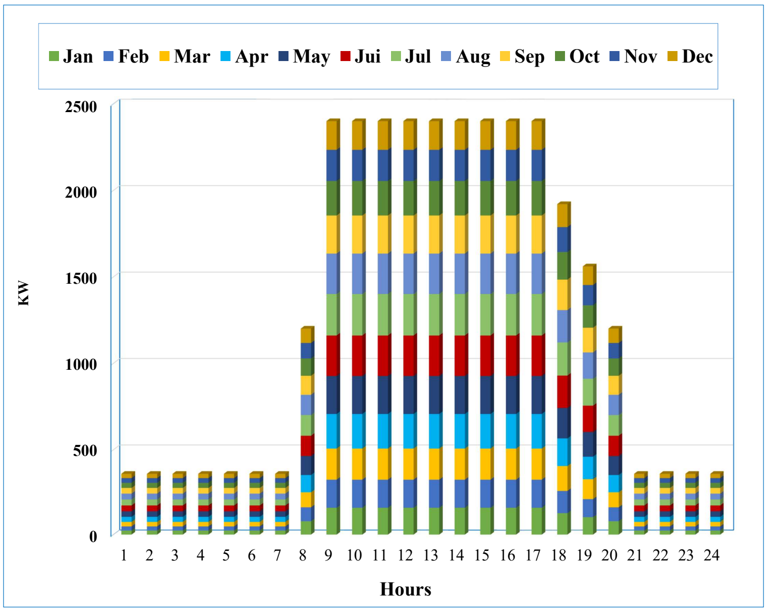


Figure 2.4: Day profile in monthly demand load

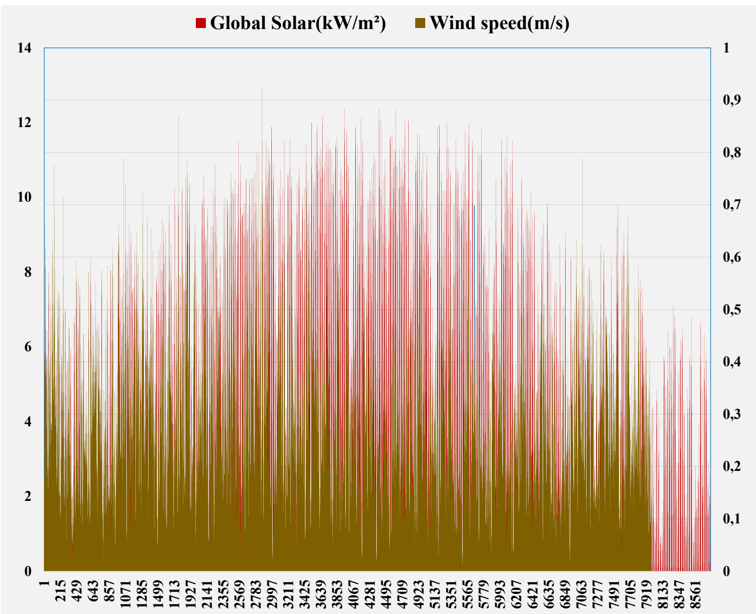


Figure 2.5: Daily climatic data for Biskra region

2.3.4 Sensitivity Analysis

Sensitivity analysis is performed to assess the impact of any significant or moderate changes on the results obtained, thereby evaluating the effectiveness of the findings. Examining the accuracy of renewable energy alternatives is crucial, as even a slight variation in weight can lead to significant fluctuations in the conclusions drawn [86].

Furthermore, sensitivity analysis is conducted to evaluate the resilience of the method. This study involves the creation of various configurations of renewable energy systems (RESs) and applying sensitivity analysis to examine how design variables influence economic metrics. Additionally, a thorough sensitivity analysis is carried out to assess the impact of altering economic variables on different components. This approach is the most direct method for capturing uncertainties. Sensitivity analysis involves adjusting individual input parameters of the model and evaluating their impact on the output. This assessment allows for determining the effects of parameter variability on the results [87].

In this dissertation, sensitivity analysis is utilized to assess the influence of both economic and technical input variables on economic indicators such as NPC and LCOE to optimize the design of system sizing. The findings of this analysis are presented in Chapter Four.

2.3.5 Investment Evaluation Criteria

The construction of a microgrid system is considered an investment project, where economists establish procedures and criteria for selecting the most favorable projects to support [88]. They employ financial metrics such as Net Present Value (NPV), Internal Rate of Return (IRR), and Discounted Payback Period (DPB) [57]. The goal is to identify the most suitable microgrid project, make informed decisions while considering uncertainty, and conduct sensitivity analysis [57].

NPV and IRR are used to evaluate energy investments to maximize profitability. These metrics are calculated based on the projected cash flows. A group of researchers has applied decision-making techniques to assess investments in energy projects [60].

2.3.5.1 Financial Metrics

Financial metrics are essential for assessing a project's projected expenses and possible income. They provide vital insights that are necessary for making educated decisions. The measures, including Net Present Value (NPV), Internal Rate of Return (IRR), and Discounted Payback Period (DPB), enable stakeholders to evaluate the financial feasibility of a project by forecasting future cash flows and comparing them to the initial and ongoing investments. These indicators assist in estimating the anticipated financial results, identifying the most lucrative projects, managing risk, and ensuring that the selected investments comply with the leading financial objectives and strategy. Therefore, financial analysis that relies on these indicators is crucial in the decision-making process, as it helps choose and support initiatives that provide the highest returns while maintaining an acceptable level of risk.

1) **Net present value**: Is the sum of the annual cash flow returned to the project's starting value, as stated in equation 2.19, where cash flow (CF) represents the difference between income and expenses associated with system/project operation (OPEX), and C_0 is the number of one-time investment costs, as revealed in equation 2.20 [45, 57, 88].

$$\mathrm{NPV} = \sum_{y=1}^{N_y} \frac{CF_y}{(1+i_r)^y} - C_0 \tag{2.19}$$

The net present value (NPV) approach, also known as the discounted cash flow approach, utilizes the concept of the time worth of money to transform a series of annual cash flows generated by a project into a single value at a specific discount rate. This technique also includes income tax ramifications and other fluctuating cash flows. The discounted cash flow or net present value approach calculates the cumulative present value by discounting a series of cash flows over a specific period.

Furthermore, the NPV is a valuable tool when evaluating different investment options. When comparing several investment options, the project with the largest cumulative Net Present Value (NPV) is the most appealing. An important constraint of this technique is that it is unsuitable for comparing projects with different durations.

$$CF_y = C_{\mathrm{in},y} - C_{\mathrm{ex},y} \tag{2.20}$$

2) **Internal rate of return (IRR)**: This discount rate corresponds to a value that neutralizes the net present value of (NPV). Using this indicator yields a more accurate return than the investment cost for each project, providing the investor with some insight into potential returns. It has much potential for more profitable microgrid systems based on energy storage systems [89]. The IRR is calculated using the subsequent formula (equation 2.21).

$$\mathrm{IRR}\,(\mathrm{NPV}=0) = \sum_{y=1}^{N_y} \frac{CF_y}{(1+i_r)^y} - C_0 = 0 \tag{2.21}$$

The internal rate of return (IRR) is a critical financial metric that represents the rate at which the net present value (NPV) of all cash flows from a project equals zero. Essentially, it indicates the actual profitability of a system for a project, providing a time-adjusted measure of return on investment (ROI). By calculating the IRR, investors can gain valuable insights into the potential returns of a project compared to its initial investment cost, making it an essential tool for decision-making. This metric is particularly promising for microgrid systems incorporating energy storage solutions, as these systems often yield higher profitability. However, while the IRR is useful for determining whether a project is worth pursuing, it has limitations. One significant drawback is that the IRR does not account for the project size when comparing different investment opportunities, potentially leading to biased comparisons [89].

Additionally, the IRR is widely used in feasibility studies as a criterion for assessing the economic viability of a project. It identifies the interest rate at which the NPV of a project's cash flows becomes zero, serving as a benchmark for investors. An investment is considered economically viable if the IRR exceeds a predefined acceptance threshold [90]. This makes the IRR a valuable metric for evaluating potential investments, though it should be used with other financial indicators to provide a comprehensive analysis.

3) **Discounted paybacks (DPB)**: DPB indicates the time required after an investment to recover the initial costs. The project is considered economically unavailable when the PB is longer than the evaluated systems' useful lifetime and is used as an alternative to NPV. However, it does not consider the value of money over time. In other words, it is a more straightforward criterion with a more significant potential for imprecision. It is interesting to highlight that this indicator was used in a way that was complementary to others considered more accurate, or else, it was adopted as a financial indicator in the optimization of more comprehensive mathematical models, which justifies its relatively high occurrence [90]. Using equation 2.22, the DPB is defined as the amount of time required to reach the initial investment, which corresponds to the point at which the sum of the discounted cash flows equals zero [57,58].R_y is the annual revenue from electricity, and **m** is a percentage of $\mathbf{C}_0$.

$$DPB = \frac{-\ln\left(1 - \frac{C_0}{R_y - mC_0}\right)}{\ln(1 + i_r)} \tag{2.22}$$

4) **Return on investment (ROI)**: It has become increasingly popular to guide investment decisions. As a result, investors have found it helpful to have a standard measure to compare the benefits of their investments [66]. It was calculated

using the following equation 2.23 :

$$ROI = \frac{(PVC - PVB)}{PVC} \times 100\% \tag{2.23}$$

PVC denotes the cost's present value, and PVB is the present value of the benefits. ROI is another essential metric that describes and evaluates the return on investment.

2.3.6 NPV Rule

Net Present Value (NPV) is a widely used metric for evaluating investment projects. According to the traditional NPV rule, a project should be accepted if its NPV ;the sum of its discounted cash flows is positive, while projects with a negative NPV should be rejected. However, this approach has limitations, as it does not account for the inherent uncertainties of investment projects. Investors often consider various criteria, including the NPV rule, the Internal Rate of Return (IRR) rule, and the payback period [88]. Each of these metrics provides different insights and can be used to provide a more comprehensive assessment of an investment's potential.

2.4 Conclusion

The chapter has introduced an approach to determining the most efficient size of renewable energy systems (RES) in microgrid system. It has provided a structured approach to identifying the optimal dimensioning and arrangement of renewable energy system components, including economic and technical factors. The methodology commences with a comprehensive examination of energy requirements and the accessibility of resources, subsequently employing diverse financial measures to assess the viability and cost-efficiency of distinct renewable energy systems (RES). Net Present Value (NPV), Internal Rate of Return (IRR), and payback period are used to evaluate the economic feasibility of renewable energy system (RES) projects. The chapter also covers the technical aspects of incorporating renewable energy sources (RESs) into the microgrid, which includes evaluating the energy balance, reliability, and performance. The methodology proposes optimizing the microgrid system's efficiency and sustainability by integrating financial and technical evaluation.

CHAPTER 3

RISK ANALYSIS AND UNCERTAINTY MODELING IN SIZING DESIGN

The Chapter focuses on improving the sizing design by evaluating risk using Net Present Value (NPV) and incorporating uncertainty through stochastic modeling of different components in microgrid renewable energy systems.

3.1 Introduction

Renewable energy sources (RESs) have a favorable environmental impact and are increasingly accepted; however, their implementation encounters various problems, such as the lack of reliability in accurately measuring and consistently designing power systems. In addition, the rapid development of renewable energy production, specifically photovoltaic (PV) and wind power (WP), has resulted in substantial variations and a high degree of unpredictability in electricity production [91]. Multiple sources contribute to the emergence of various unknown aspects, including demand predictions, wind and solar energy generation, hydro inflow, fuel costs, CO_2 prices, market dynamics, and the availability of generating and transmission infrastructure [92].

Another important category of uncertainty, the size uncertainties in renewable energy systems pertain to the difficulties in accurately determining the optimal capacity and arrangement of the infrastructure needed for generating renewable energy [10].

The variability in energy demand exacerbates these issues, as the variable availability of resources and technological advancements can contribute to increased complexity and ultimately lead to inefficient system design.

In addition to sizing uncertainties, these problems are worsened by the uncertainty in determining the anticipated efficiency of renewable energy sources (RESs). Assessing the integration of renewable energy is of utmost importance, considering sustainability and technological perspectives. Factors such as energy efficiency and operational expenses should be considered.

Therefore, it is crucial to tackle the challenges of sizing and implementing a hybrid energy system [93]. Thus, to reduce the unpredictable fluctuations in power generation from renewable energy sources (RESs), a microgrid can integrate traditional power generating and energy storage technologies, resulting in a more stable and dependable hybrid microgrid [9]. A notable utilization of Renewable Energy Systems (RES) involves the implementation of microgrids to supply energy in rural areas and communities.

In addition to technical uncertainties, economic uncertainties must also be assessed, the assessment of investment based on the financial metric of net present value (NPV) is impacted by several aspects related to the system's inputs. The intermittent nature of these factors creates uncertainties, leading to a problem. The diffusion of renewable sources has impacted electricity prices and prompted the investigation of the relationship between the penetration of renewable sources and the detrended system electricity price [94].

As a result, the system's Net Present Value (NPV) has been impacted since NPV is directly linked to cash flow. In addition, the price has affected energy components since the market prices for various renewable technologies present significant obstacles to the shift to renewable energy sources [95] [1]. Neglecting the influence of these uncertainties could have a detrimental effect on the operation schedule, potentially leading to the projected optimal solution not being the perfect operating point in reality. The fluctuation in the load impacts decision-making and long-term investment for determining the appropriate size, as stated by [33]. Subsequently, the unpredictability of solar radiation significantly impacts the optimal sizing of microgrids, leading to increased uncertainty [96].

The presence of uncertainty in a system generates a state of constant change. It significantly affects important indicators essential for economic viability and decision-making, which is necessary for stakeholders. Hence, it is crucial to mitigate uncertainties in the dimensioning and modeling of Renewable Energy Systems (RES) to guarantee the viability and effectiveness of renewable energy initiatives. A sufficient risk evaluation can result in below-par system performance, heightened costs, and failure to meet sustainability goals. These uncertainties present substantial risks to investors, policymakers, and stakeholders involved in renewable energy projects, ultimately eroding trust in the reliability and effectiveness of renewable energy solutions.

The literature has put forth many solutions employing theoretical methodologies to solve and depict these uncertainties. In the context of microgrids, it is no longer practical to depend on deterministic energy scheduling methods that ignore uncertainties. Several studies have shown that using probabilistic methodologies reduces operational expenses compared to deterministic solutions. Creating and testing fuzzy mathematical programming models and extensions have been conducted effectively [97]. The probability density function (PDF) is used to determine the distribution of the design variables, considering their continuous nature. The samples used to determine the optimal size of the microgrid are chosen based on appropriate probability density functions (PDFs) and Monte Carlo simulation, with the statistical method as presented by [66].

Furthermore, the stochastic method utilizes a mathematical model, specifically Markov chain Monte Carlo simulations, to effectively capture and handle risk by representing many scenarios and modeling uncertainty [98].

In addition, the strategies used to forecast and resolve uncertainty in microgrid planning are significantly impacted by different approaches to modeling uncertainty [99]. Stochastic frameworks, which utilize probability distributions to depict uncertainty, are more prevalent and have shown considerable efficiency in modeling uncertainty.

3.2 Risk Analysis and Decision Making

Energy investment decisions are complex and uncertain due to their variable and stochastic nature, which introduces risks. The energy sector is transforming quickly, primarily driven by market dynamics, regulatory frameworks, and technological advancements. Hence, performing risk analysis with other evaluations is crucial while making energy investment decisions [100]. A risk-neutral and profit-maximizing economic agent who possesses a power-generating asset or a possible investment project can either sell the asset or invest in the project later. This agent faces the risk of uncertain revenue and uncertainty about future scenarios. The revenues generated by the asset before the project is closed after investment are calculated based on the future values of risk variables such as fuel, electricity, and carbon prices. The evolution of these risk factors is uncertain, and their distribution relies on the actual transition scenario, as discussed by [101].

Moreover, computational modeling has employed several methods to simulate investment choices in the presence of uncertainty and risks. Investments in the real option-based analysis are a risk-neutral mechanism and thus do not allow for examining how the interplay of uncertainty and risk aversion affects investment decisions. The fundamental principle is that, at a specific anticipated return level (the mean), an investment portfolio is constructed to minimize risk (measured by variance or standard deviation) or at a specific risk level [102].

3.2.1 NPV Risk

Investments frequently entail a remote future characterized by uncertainty. Risk is a type of uncertainty involving knowledge about future occurrences but with a probability of less than one. There are four distinct levels of uncertainty: precise enough future, alternate futures, continuous uncertainty, and real uncertainty. In the contemporary global landscape, many variables influence economic mechanisms, complicating economic choices when knowledge is limited. The scientific challenges of decision-making in uncertain and risky economic situations are significant. Research efforts focused on creating robust methodologies for measuring the financial risks of investment projects in uncertain conditions are of great significance [103].

The risk analysis must include Probability Distribution Functions (PDF) for critical metrics such as Net Present Value (NPV), Levelized Cost of Energy (LCOE), and Internal Rate of Return (IRR) To ensure the evaluation of the project. This is especially beneficial when addressing pertinent uncertainties. The risk analysis is performed through Monte Carlo simulation, employing random sampling techniques based on the probability distributions specified for each input. The convergence requirement determines the delay conditions for the Monte Carlo method, which has a tolerance of 1 % and a confidence level of 95 %. Multiple studies validate the correlation among net present value (NPV), internal rate of return (IRR), and payback period.

This PhD thesis also focuses on risk analysis concerning Net Present Value (NPV). The findings of this simulation are outlined in Chapter Four. Monte Carlo Simulation (MCS) is a statistical sampling technique that effectively addresses quantitative problems by modeling random variables. The random net present value is estimated by considering the time series of cash flows (CF) and the anticipated probability distribution of NPV.

3.2.2 Treatment of Uncertainty Problem

The PhD thesis focuses on addressing the issue of uncertainty to enhance the design of optimal size for renewable energy systems incorporated into microgrids. Uncertainty can occur at different levels, such as input variables, sizing considerations, and financial measures. This thesis addresses uncertainty at many levels, utilizing diverse methodologies, as depicted in Figure 3.1. Sensitivity analysis is used to capture the uncertainty of input variables, as explained extensively in Chapter Two. The thesis analyzes financial indicators using the Net Present Value (NPV) rule. It incorporates risk analysis at the NPV level by employing deterministic Monte Carlo Simulation. In addition, the thesis suggests using stochastic modeling to represent for the uncertainty associated with different input elements. These methods jointly improve the dependability and precision of the size design for renewable energy systems in microgrids.

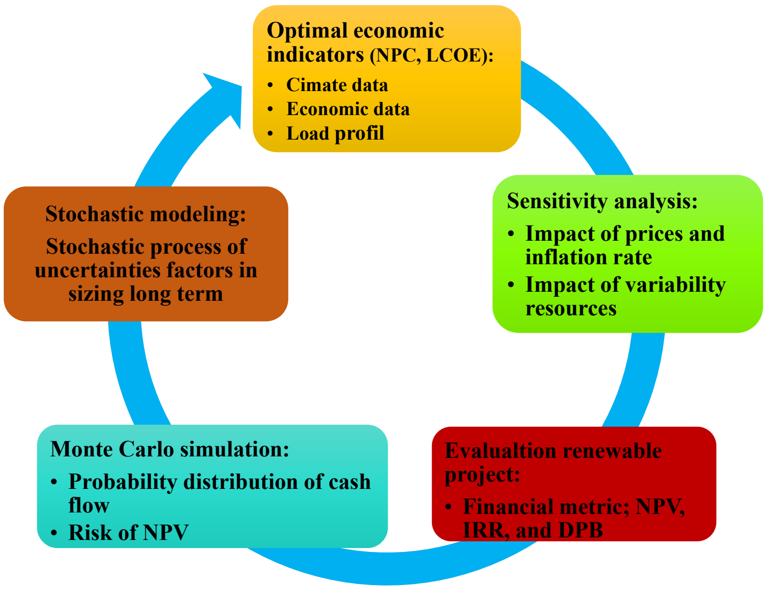


Figure 3.1: The framework of treatment of the uncertainty problem

3.3 Stochastic Optimization and Uncertainties

Stochastic optimization provides numerous potential solutions that more precisely represent real-world conditions, assisting operators and customers in assessing the risks linked to the uncertainties of renewable energy generation. Thus, the characteristics of stochastic optimization methods are more suitable for tackling the variable and sporadic nature of renewable energy systems [104]. This thesis presents the issue of uncertainties and underscores the significance of uncertainty modeling in stochastic optimization for robust design sizing and long-term planning of microgrids.

3.3.1 Overview of Stochastic Optimization

In electric power systems, optimization is employed for several functions, encompassing real-time operation and long-term planning. System operators, generation businesses, and consumers depend on diverse input data to establish parameters in the development of a mathematical optimization model that facilitates optimal decision-making.

Parameters of this nature encompass projections of load and renewable energy, insights into forthcoming electricity pricing, and enduring climate change patterns. Unfortunately, numerous parameters remain unclear. The prediction of load and renewable energy generation is influenced by uncertainties in weather forecasts, whereas electricity prices are determined by fluctuations in load and renewable energy generation, as well as the actions of other market participants. Predicting future climate change trends is challenging due to insufficient understanding of emission trajectories and their consequent effects on the grid. Despite the lack of precise values for these ambiguous characteristics, we must proceed with decision-making at this time [105]. Furthermore , decision-making in electricity systems must account for the unique characteristics of EMDE (emerging markets and developing economies) countries from three critical perspectives: engineering (power delivery), policy (regulation), and financial (cost recovery). Key decisions, such as choosing between on-grid and off-grid generation, expanding the grid, undertaking maintenance, or investing in renewable energy coupled with battery storage, must incorporate relevant uncertainties to ensure effectiveness [106].

Uncertainty, by its nature, limits the ability to predict outcomes with precision. Two primary types of uncertainty influence decision-making: exogenous and endogenous. Exogenous uncertainty is external to the decision process and includes factors like weather forecasts or technology costs. In contrast, endogenous uncertainty depends on the decisions made, such as demand growth influenced by supply reliability, generation technology choices, or tariff structures. In both cases, decision-making can be conceptualized as an agent responding to observations and inputs from its surrounding environment [106].

Stochastic optimization is a mathematical methodology employed to achieve optimal decisions under uncertainty by integrating random variables into the optimization framework. Stochastic optimization in microgrid sizing and design mitigates uncertainty associated with renewable energy output, load demand, fuel prices, and meteorological variables. This approach guarantees that the microgrid system is economically efficient and robust against fluctuations.

3.3.2 Uncertainty Modeling

Demonstrating uncertainty is essential in stochastic optimizations. Every uncertainty modeling technique yields a unique representation of the systems. Thus, the careful selection of uncertainty modeling approaches is crucial. Uncertainty modeling is a conventional method to depict the stochastic nature of renewable systems. Rather than presuming complete knowledge of the parameters (such as wind speed, solar irradiation, and load demand) in contrast to a deterministic method, random distributions are incorporated as inputs into a stochastic optimization framework to replicate the probabilistic nature of a renewable energy system [104].

Therefore, uncertainty modeling often focuses on several techniques to assess the influence of uncertain input parameters on system output parameters. Soroudi and Amraee suggest a classification of uncertainty modeling for decision-making in energy systems, encompassing probabilistic, possibilistic, hybrid possibilistic–probabilistic techniques, information gap decision theory, resilient optimization, and interval analysis [92].

The use of Monte Carlo Simulation (MCS) in renewable energy applications has been a topic of interest. MCS is a method that minimizes economic risks and maximizes financial returns by analyzing random variables such as water inflow, wind speed, solar irradiance, PV panel temperature, and average generation capacity. It has been applied to investigate the economic risk analysis of decentralized renewable energy infrastructures and has been implemented in various studies.

Furthermore, the MCS model is a prevalent method that has been used to predict the stochastic behavior of uncertainty sources in the planning of stand-alone RES-based microgrids [98]. Stochastic models may be structured as either single-stage or multi-stage situations. Decisions are made at the start of the planning phase before uncertainty is realized, and there are no recourse options available in single-stage formulations. In multi-stage formulations, decisions are made at various temporal intervals as uncertainty is progressively disclosed, allowing for adjustments when new information emerges [92].

3.4 Proposed Modeling

The sizing operation has been assessed utilizing metrics such as net present cost (NPC), net present value (NPV), and levelized cost of electricity (LCOE). These variables, which pertain to energy production and load demand, are influenced by uncertainties and risks associated with the inputs of renewable energy systems, as demonstrated in many articles. This proposed solution mitigates these risks using mathematical techniques commonly employed in the literature.

Stochastic systems necessitate meticulous approaches due to uncertainty and probability, which define decision-making in such situations. Stochastic dynamics employ stochastic elements, such as Geometric Brownian Motion (GBM), to represent the unexpected temporal evolution of a system. The selection of GBM is based on its effectiveness in capturing the unpredictable and random characteristics of different inputs [107]. Using stochastic differential equations allows for a dynamic representation of power systems that accounts for continuous time uncertainties, including a GBM component [108].

Furthermore, the stochastic characteristics of GBM are vital for accurately representing the inherent uncertainties in the system, and prediction models are also crucial for investors to mitigate investment risk [109]. Consequently, given the system's unpredictable character, the design of renewable energy systems necessitates analyzing the behaviors shown by different components. This method employs a stochastic framework to model and simulate the uncertainty associated with many factors affecting renewable energy systems' sizing and design.

The stages of this work include determining the most suitable criteria for the system's design, which involves identifying key aspects that significantly impact the system's performance. After identifying these factors, the next step is to gather historical data. This data provides a factual basis for understanding the behavior of the selected elements over time. Following data collection, the volatility and drift are computed. Volatility measures the extent of variation in the components, while drift represents the average rate of change over time. These calculations are essential for accurately replicating the behavior of the elements. Subsequently, the GBM (Geometric Brownian Motion) modeling technique is applied, using the obtained volatility and drift values to predict the future behavior of the factors. GBM is a commonly used stochastic process that represents the continuous-time behavior of variables.

A Monte Carlo simulation uses the GBM model to explore several possible results. This procedure involves producing numerous simulated trajectories by random sampling, which helps to understand the potential variations and uncertainties inside the system.

3.4.1 Stochastic Model

The stochastic model is based on the stochastic differential equation with geometric Brownian motion (GBM), which accurately represents real-world occurrences as they evolve. This model has been extensively employed in the dynamic investment sector to accommodate the fluctuation of prices and market models, and the GBM is distinguished by its drift μ and volatility σ .

In this context, X(t) denotes the input parameter as it changes over time, while W(t) represents a Wiener process that follows a normal distribution η (0,1), with a mean of 0 and a variance of 1. The equation 3.1 represents the stochastic differential equation using the Geometric Brownian Motion (GBM) model, with the term dW representing Brownian motion [107].

$$dX(t) = \mu X(t)\, dt + \sigma X(t)\, dW(t) \tag{3.1}$$

Where:

- μ is the drift coefficient,
- σ is the diffusion coefficient,
- $W(t)$ is a Wiener process (or Brownian motion).

3.4.2 GBM Parametres Estimation

The Geometric Brownian Motion (GBM) model is a stochastic variable restricted to positive values only [68]. To simulate the trajectories of factors using the Geometric

Brownian Motion (GBM) model. Which requires estimating the sample mean and variance for the GBM model by computing the average and standard deviation of the logarithmic returns R (t $_i$) for i=1,. . . . . . .N [108].

Definition 1: Let X represent the value of the data, t represents the time moment within the interval (0, T), T represents the total time, and Δt represents the time lag, which equals the reciprocal of T. The logarithmic return R(t) of x inside the time interval $(t, t + \Delta t)$ is accurately determined according to the references cited [110,111]. In equation 3.2, the function R(t) is defined as the natural logarithm of the ratio between $X(t + \Delta t)$ and X(t).

$$R(t) = \ln\left(\frac{X(t + \Delta t)}{X(t)}\right) \tag{3.2}$$

Definition 2: Brownian motion is a stochastic process $\{W(t), t \geq 0\}$ that fulfills the following conditions [110]:

- The differences $\{W(t_{i+1}) - W(t_i), i = 1, \ldots, n-1\}$ are statistically independent, where $0 < t_i \leq t_{i+1}$.
- $W(0) = 0$.

The solution to equation 3.1 for any arbitrary initial value X (0) is provided in equation 3.3 [109]:

$$\begin{cases} X(t) = X(0)\exp\left(\mu t - \frac{1}{2}\sigma^2 t + \sigma W(t)\right) \\ \mu = \text{mean}(R(t)), \quad \sigma = \text{Std}(R(t)) \\ W = \sqrt{t} \cdot \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, 1) \end{cases} \tag{3.3}$$

Furthermore, Monte Carlo simulation (MCS) captures the uncertainty and forecasts future behavior. It offers a viable approach to simulated intricate dynamics due to their unpredictable and stochastic nature [110].

3.4.3 Renewable Energy System

The characteristics of the installation area, specifically Biskra, Algeria, are crucial in examining the factors that impact the selection of renewable energy systems. The integrated system comprises solar panels, wind turbines, and a battery energy storage device. It is essential to identify the most relevant variables while thoroughly analyzing the architecture of this renewable energy system (RES). The discussion has focused on three main elements: climatic variables, economic issues, and load demand. The initial categorization concerning climatic elements encompasses unpredictable and variable aspects such as sun radiation and wind speed. Gaining a comprehensive understanding of the characteristics of these components is essential for maximizing the efficiency of the renewable energy system (RES). The size and efficiency of photovoltaic (PV) panels and wind turbines are directly impacted by the strength of solar radiation and wind patterns.

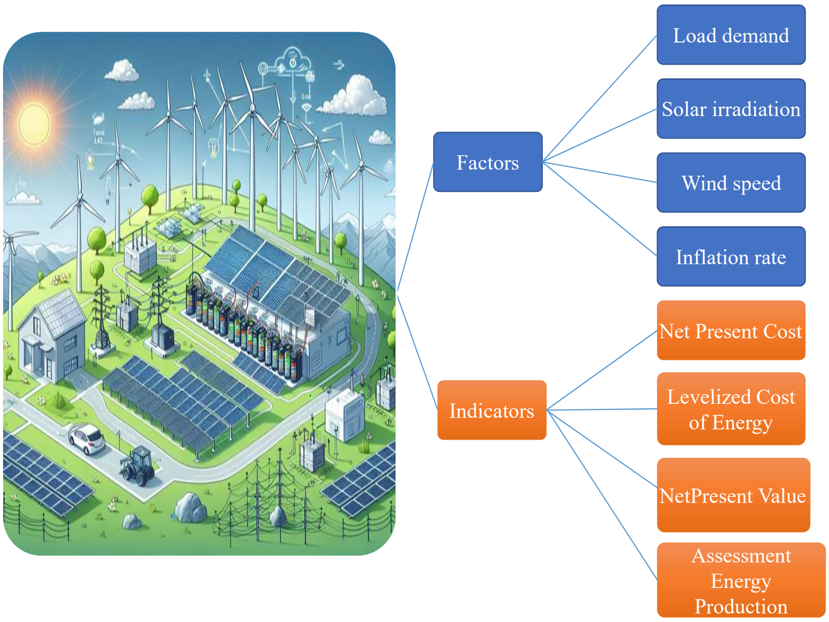


Figure 3.2: Factors and indicators for the planning of RES into microgrid

The economic aspect of the second category is affected by factors such as the inflation rate. Economic factors substantially influence renewable energy projects and long-term viability, as shown in Figure 3.2.This figure presents the criteria and indicators used to determine the appropriate size and design of the renewable energy system, including the levelized cost of electricity (LCOE), net present cost (NPC), net present value (NPV), and energy production.

Furthermore, load demand specifically pertains to the quantity of electrical energy utilized. Precisely forecasting the load demand profile is crucial for determining the appropriate capacity of Renewable Energy Sources (RESs). The system's sizing and design are influenced by peak demand hours, seasonal swings in energy consumption, and load fluctuations. A comprehensive analysis of these components using several parameters guarantees the most suitable sizing and structure of the renewable energy system (RES), improving reliability, cost-effectiveness, and sustainability in fulfilling energy requirements.

3.4.4 Historical Data

Collecting data from numerous factors is essential to assess the anticipated change in value for each data point. This step facilitates the calculation of the drift term and volatility in the Geometric Brownian Motion (GBM) model. To achieve precise modeling and analysis, data should be collected at latitude 34.9 ° and longitude 5.81°.

Figure 3.3 depicts the variations in solar irradiance and wind speed over time. The data used for this analysis was received annually from NASA [6]; the data from NASA's 2023 report reveals that solar irradiance saw variations ranging from 5.1 kWh/m^2/d to 6 kWh/m^2/d during the years 1984 and 2022. Concurrently, the wind speed fluctuated, including values between 4.8 m/s and 5.7 m/s over time. The wind speed range spans 11 m/s to 20 m/s, covering its broader variation.

Furthermore, Figure 3.4 depicts the hourly-monthly statistics of wind speed and solar radiation for each month throughout 24 hours. Through data analysis, it is evident that there is a continuous pattern in solar radiation levels. The lowest values, which average 0.04 kWh/m^2/d, are typically appreciated in January and continue throughout winter. The maximum values measured in July were 0.6 kWh/m^2/d. The wind speed exhibited significant variability, spanning from 0.5 m/s to 8 m/s.

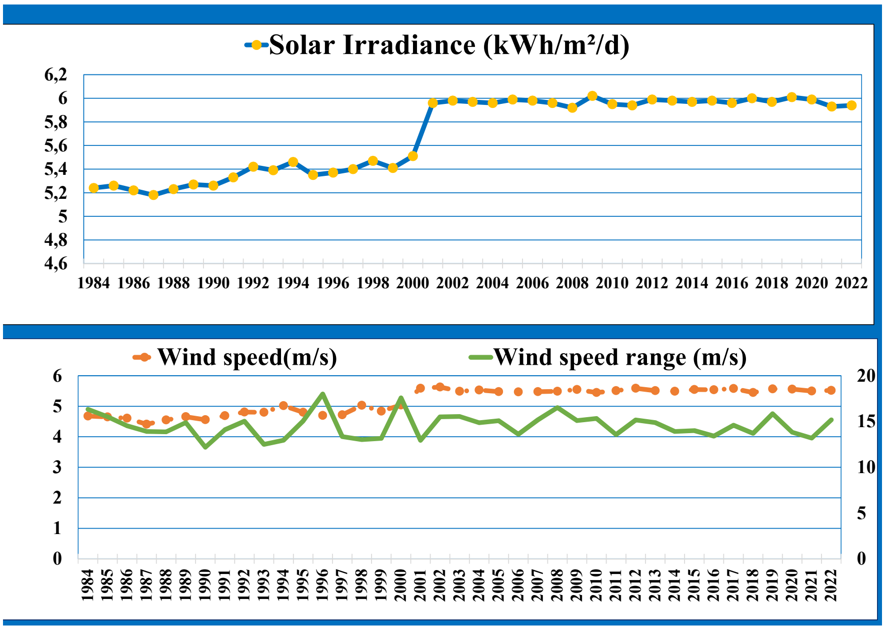


Figure 3.3: Annual climate data for Biskra, Algeria

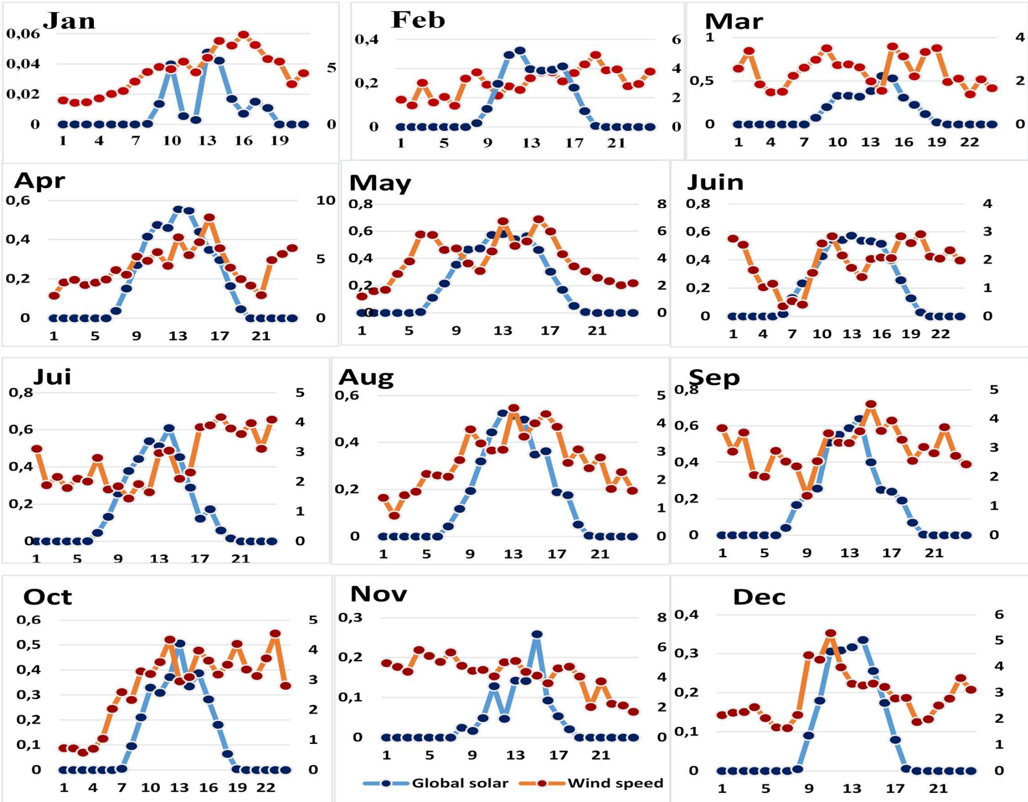


Figure 3.4: Solar radiation and Wind speed during 24 h in months (Biskra, Algeria)

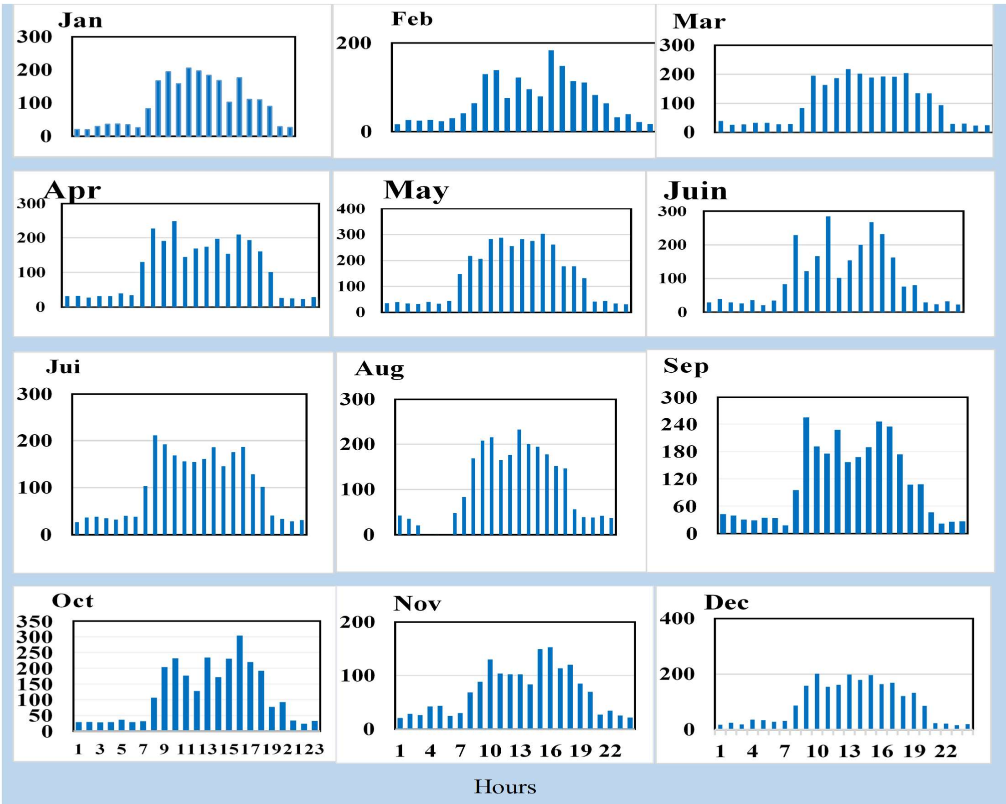


Figure 3.5: Monthly load demand in kWh/d

Regarding the load demand statistics, Figure 3.5 displays an average monthly day, illustrating substantial hour-to-hour variability. The maximum power usage between

10:00 and 16:00 is 300 kWh/day, while the minimum power usage is 50 kWh /day. Typically, the highest value occurs during the summer season. However, this demonstrates the inconsistency and instability in selecting days to depict this fluctuation.

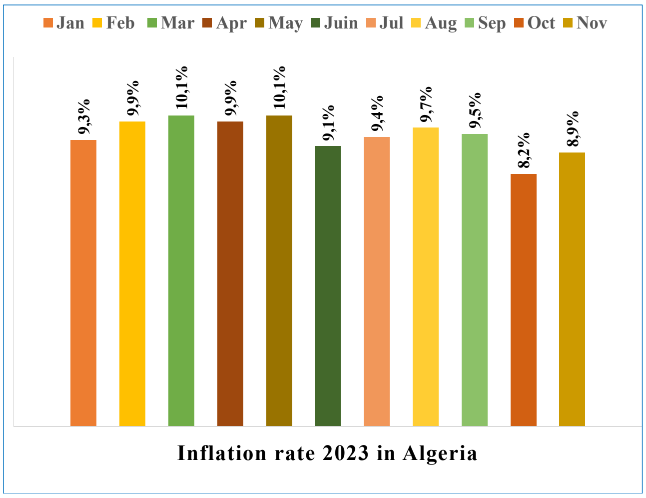


Figure 3.6: Inflation rate for Algeria in 2023

Moreover, the economic dimension, which has been considered essential, encompasses the inflation rate data for 2023, as illustrated in Figure 3.6. The inflation rate exhibited irregular fluctuations within the range of 8.2 % to 10.1 % over the months. The fluctuation of this factor underscores its significance in economic research. Furthermore, Figure 3.7 presents the historical statistics on the inflation rate in Algeria spanning from 1970 to 2023 [112]. Exhibiting significant variations over time. This variation underlines the substantial instability in the inflation rate. This data is crucial for conducting analysis, allowing for a more profound comprehension of long-term patterns and variations, thereby providing vital insights into the dynamics of the financial system over time.

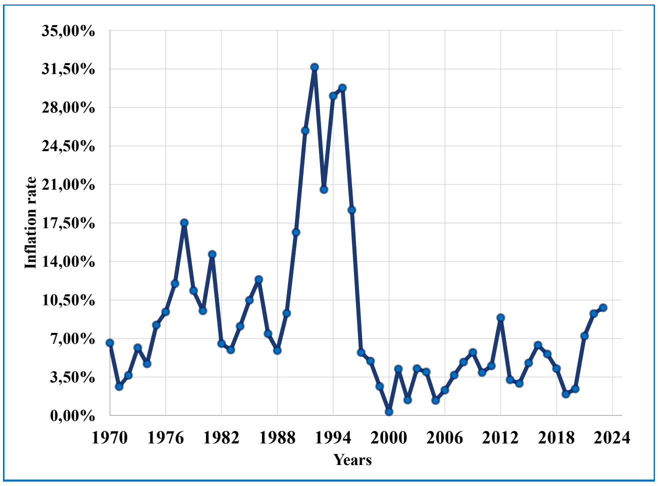


Figure 3.7: Historical data of annual inflation rate for Algeria

3.5 Results

The results were obtained by employing geometric Brownian motion for elements involved in planning and sizing the microgrid's renewable energy system (RES). The Monte Carlo simulations of the Geometric Brownian Motion (GBM) model were conducted for individual factors across periods of 5 years, 10 years, 15 years, and 25 years. The process commences with estimating the drift and volatility values for each element. Afterward, Python code executed in a Jupyter Notebook generates pathways for these factors using simulation parameters shown in Table 3.1.

Table 3.1: Simulation parameters of MCS

N	Number of paths
T	5, 10, 15, 25 years
X(0)	The initial value of each state
Number of steps	50

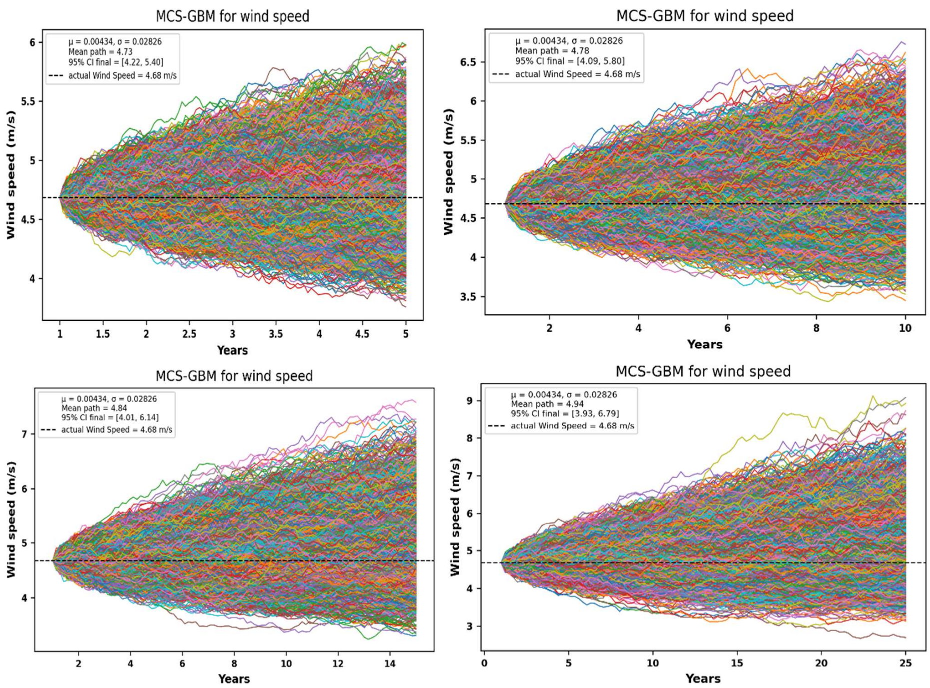


Figure 3.8: Forecasting the paths for future wind speeds

Figure 3.8 illustrates the Monte Carlo Simulation (MCS) showing the change in wind speed over five years, ranging from 4 m/s to 5.8 m/s. The simulation includes a drift value of 2.8 % and a volatility of 0.4 %. The expected wind speed values range from 4 m/s to 6.5 m/s during ten years. Significantly, 60 % of the expected values are within a more limited range of 4 to 5.5 m/s. Over ten years, the anticipated wind speeds range from 3 m/s to 6.5 m/s. This underscores the dependability and uniformity of the anticipated wind velocities, underscoring assurance in forecasts for energy generation.

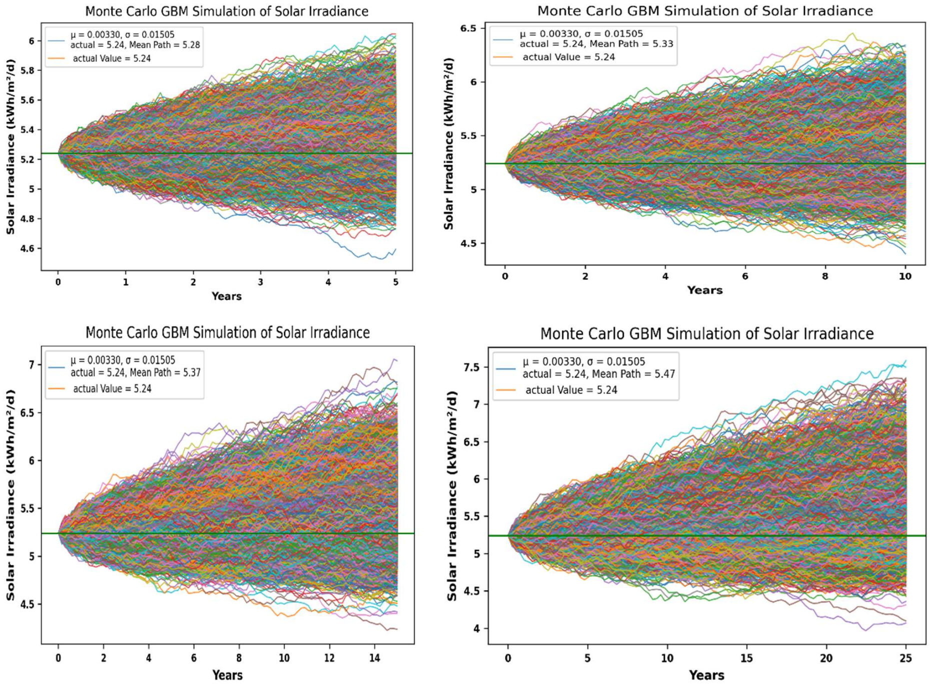


Figure 3.9: Forcasting uncertainties for solar irradiance

Furthermore, Figure 3.9 illustrates the probabilistic paths that predict the future of solar irradiation. The volatility 0.015 signifies a substantial degree of unpredictability in solar irradiation compared to the anticipated pattern. According to the model, solar irradiation levels will range from 5 to 5.6 kWh/m^2/d over the next five years. This forecast considers solar irradiation's expected path (drift) and inherent variations (volatility).

About the 10-year forecast, the projected range of solar irradiation is anticipated to be similar to the short-term estimate, indicating constant growth within the same time frame. Solar irradiation levels are predicted to stay between 5 to 5.6 kWh/m^2/d for the next 25 years. This projection considers incremental shifts in the fundamental pattern and unexpected fluctuations in unforeseen circumstances. The calculated values aid in reducing risks in strategic energy planning and environmental impact evaluations. Therefore, stakeholders can improve their decision-making process by using stochastic modeling to account for the inherent uncertainty in future solar irradiation predictions.

Additionally, Figure 3.10 illustrates the projected trajectories of inflation rates throughout different periods, characterized by a descending trend of **-0.0006** and a level of volatility of **0.049**. The GBM projection predicts that inflation rates will range from 9 % to 16 % during the next five years. This range encompasses the inherent decrease in value over time and the unpredictability of the inflation rate. During the next decade, the projected inflation rates will range from 9 % to 18 %. This analysis examines the long-term influence of inflation patterns and instability on investment choices. The model predicts that inflation rates will vary between 7 % and 20 % during the next 20 years. A long-term perspective provides investors with significant insights into possible inflation rates and how they impact project economics. Precisely forecasting inflation rates is essential for investors in renewable energy projects since they directly affect project costs, net present cost (NPC), levelized cost of energy (LCOE), net present value (NPV), investment risk, and profitability. By comprehending the anticipated trajectories of the inflation rate, investors can enhance their decision-making, risk mitigation, and dependability of renewable energy projects in the long term.

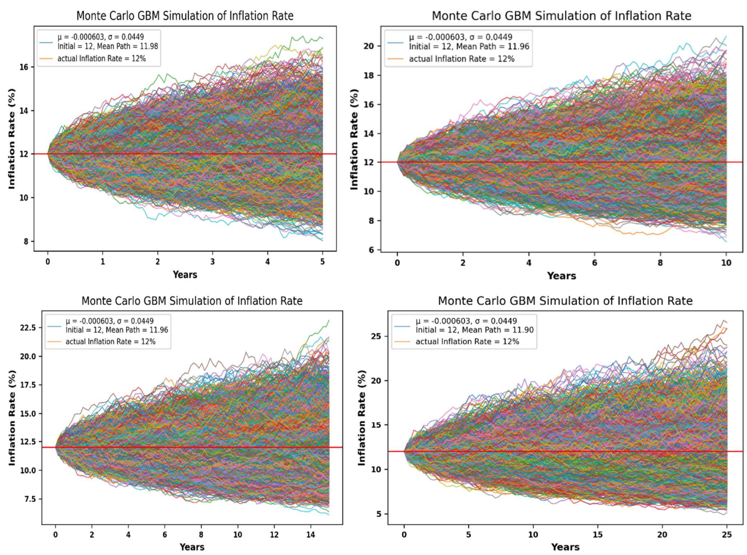


Figure 3.10: Forecasting uncertainties for the inflation rate

In addition, Figure 3.11 provides a detailed depiction of Geometric Brownian Motion (GBM) trajectories to reliably predict anticipated power usage based on historical data. The GBM model incorporates a drift value of **-0.057** and a volatility of **0.28**. These elements are crucial for precisely capturing the underlying pattern and fluctuations in power consumption over time. The depicted trajectories depict the projected rise in demand for electricity, emphasizing the planned increase in consumption levels by 50 %. This tool is valuable for understanding the potential trajectories of electricity use. It facilitates decision-making about resource allocation, infrastructure development, and risk management in the energy project.

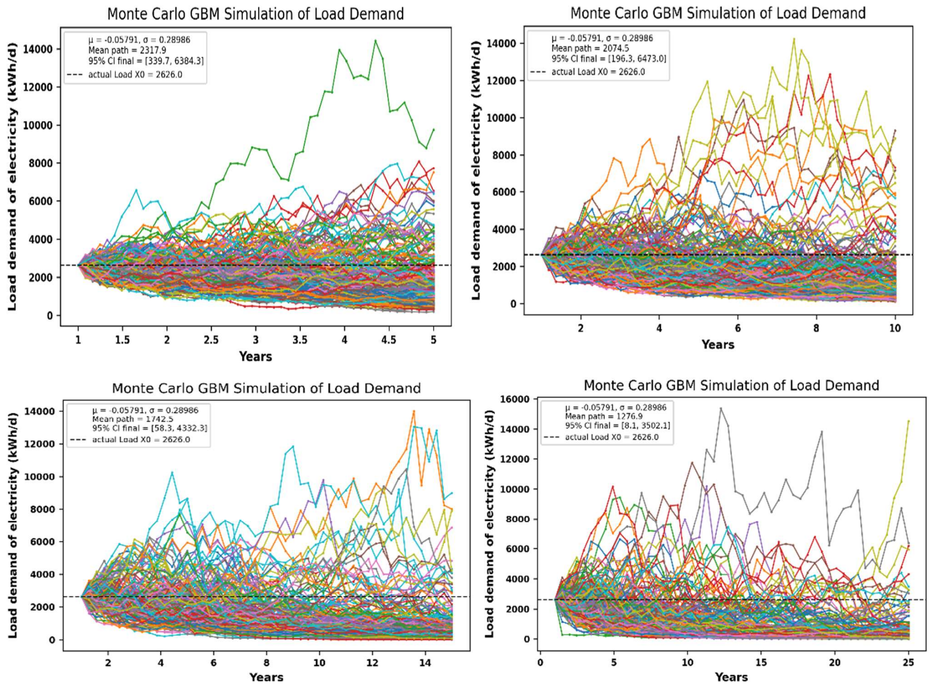


Figure 3.11: Uncertainties evolution for load demand

3.6 Conclusion

Long-term planning and sizing are necessary for designing microgrids that rely on renewable resources to assess investment costs and electricity production. This procedure entails evaluating multiple indicators, including net present cost (NPC), levelized cost of electricity (LCOE), and net present value (NPV). The availability of renewable resources impacts these parameters, the level of energy consumption (load demand), and the inflation rate.

Moreover, the sizing and design of renewable energy systems are subject to uncertainties arising from the inherent characteristics of these components, the quantification of risks, and government economics. This study presents a technique for describing and capturing the uncertainty involved in the size and planning of renewable energy systems (RES) in a microgrid. Resolving these uncertainties is achieved by utilizing a mathematical methodology that is frequently employed to effectively handle the risk associated with dynamic investments and the fluctuations in the stock market.

Stochastic modeling employs Geometric Brownian Motion (GBM) with historical data for each element. The approach starts by calculating the critical components of

GBM, namely drift and volatility, to forecast the random fluctuations of size factors over time intervals of 5, 10, 15, and 25 years. The choice of factors is contingent upon the particular microgrid system. The hybrid renewable microgrid utilizes both wind and solar energy sources. Hence, the elements considered include wind speed, solar irradiation, power demand, and the inflation rate.

Stochastic Monte Carlo simulations with 10,000 paths illustrate future predictions of various behavior characteristics. This technique effectively captures uncertainty at the individual factor level, successfully predicting pathways with an accuracy of 60 %. Furthermore, it offers enduring perspectives on these aspects by fostering trust among investors in the renewable energy sector and supporting the dependability of renewable energy sources within microgrids. Consequently, it plays a crucial role in determining the viability of renewable energy projects.

CHAPTER 4

OPTIMAL DESIGN AND SIZING OF RENEWABLE ENERGIES IN MICROGRIDS WITH FINANCIAL CONSIDERATIONS A CASE STUDY OF BISKRA, ALGERIA

In this chapter, we present a detailed discussion of the results obtained from the comprehensive sizing procedure proposed in Chapter Two. The method focuses on the optimal sizing of three renewable energy combinations. Our approach incorporates multiple considerations to ensure robustness and practicality, including financial analysis, sensitivity analysis, and handling uncertainties and decision-making processes.

4.1 Introduction

To accomplish the objective of this doctoral research, we conducted simulations of the proposed approach for determining the most efficient configuration of renewable energy systems within microgrids. This chapter presents the primary findings by examining expenses, energy generation, economic indicators, and financial measures. We evaluate the economic feasibility of renewable energy projects by utilizing essential financial metrics, such as the Net Present Value (NPV) criterion, to determine their profitability. We utilize the Monte Carlo simulation to mitigate the risks and uncertainties associated with renewable energy projects. This simulation effectively simulates and analyses the effects of different uncertainties on the outcomes of the projects. These visual aids improve understanding of the data, allowing stakeholders to make well-informed decisions based on thorough insights. By incorporating economic and risk assessments into the decision-making process, we enhance the design of the most efficient dimensioning for renewable energy sources (RES) in microgrids. This chapter provides the efficacy of the suggested approach in facilitating improved decision-making for renewable energy projects.

4.2 Cost and Evaluation of Energy

For this investigation, three energy sources were used and integrated into three different configurations, as shown in Figure 4.1. The choice of these arrangements was motivated by the region's characteristics, including abundant solar energy potential and many remote locations that require off-grid microgrid solutions. The configurations are as stated below:

- Photovoltaic (PV) systems combined with battery banks: This configuration utilizes photovoltaic panels in conjunction with battery storage.
- PV/WT/Battery Banks integrates solar panels and wind turbines with battery storage.
- The system combines photovoltaic panels, wind turbines, battery storage, and a diesel generator to provide backup power.

The selected configurations were particularly adapted to coordinate with the energy consumption and generation patterns of the place under consideration while addressing the social and economic requirements of the Biskra region. In this case study, the demand corresponds to the commercial load for the Biskra site in July, with a peak load reaching 460 kW. Table 4.1 displays the values for the fundamental simulation inputs. The solar scale average is selected as a moderate value of 3 kWh/m^2/day, while the fuel cost is determined to be 0.214 USD/L based on local prices [113].

In addition, this analysis presents numerous values and parameters sourced from the Homer library [114] in Table 4.2.

Table 4.1: Variables and Values

Variable	**Value**
Inflation rate	9.8%
Average solar	3 kWh/m^2/d
Wind speed	3 m/s
Fuel price	0.214 $/L

Table 4.2: Component Characteristics

Component	Lifetime	O&M	Capital cost
PV generator	25 years	10 $/yr	3000 $/kW
Battery	10 years	10 $/yr	300 $
Wind turbine	25 years	850 $/yr	60 k$
Diesel generator	15000 h	2 $/h	40 k$

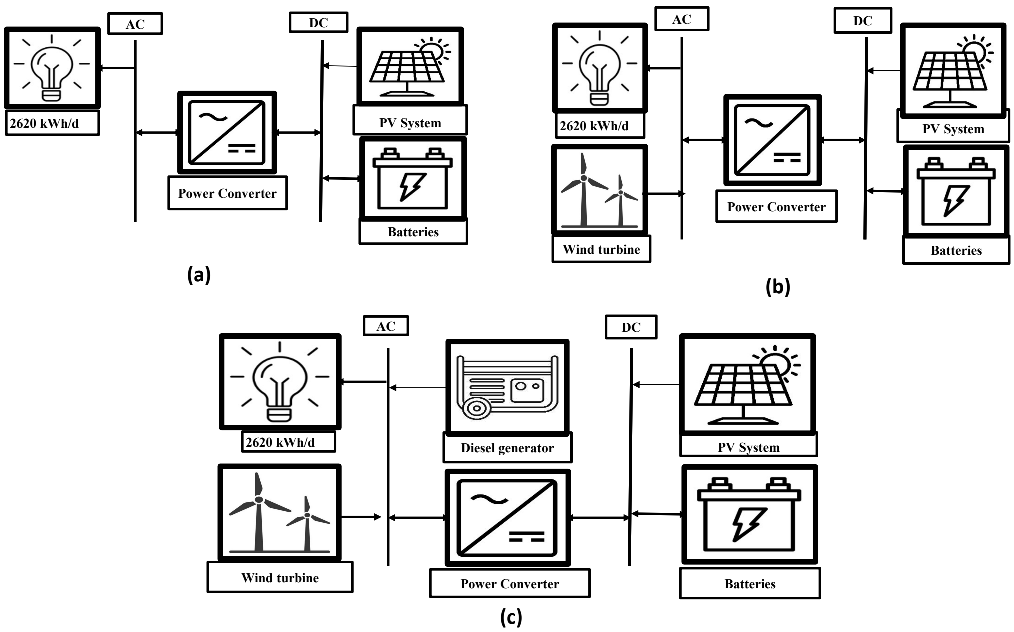


Figure 4.1: RES combinations of microgrids: (a) PV MG, (b) PV/WT MG, (c) PV/WT/DG MG

4.2.1 Cost Analysis

The ensuing paragraphs explain the important findings of the simulation for the suggested combinations. Figure 4.2 illustrates the annual costs associated with the first project, consisting of capital expenditure of 66,000 k USD and operational expenses totaling 14,600 USD. The PV generator does not require any expenses for replacement. However, the batteries and system converter require repair because of their limited lifespans, resulting in additional costs. The batteries carry a replacement value of 82 k USD, whereas the system converter has a replacement value of 5,000 k USD. The combined salvage cost for both components amounts to 41 k USD.

Figure 4.3 depicts the annual costs linked to the different elements of the second project. The PV system requires an initial investment of 245.5 k USD while the wind turbines are expected to have operating expenses of 28.05 k USD. The batteries possess a notable expense for replacement, with a salvage value of 599 k USD reflecting the worth of the potential reserve.

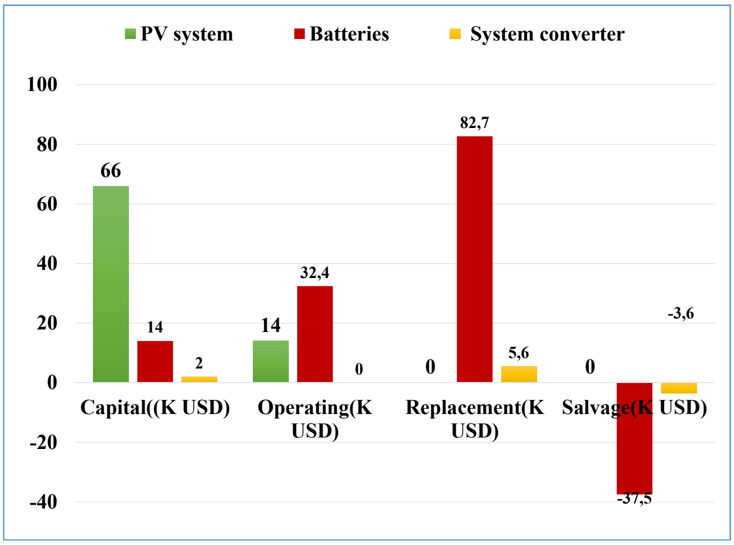


Figure 4.2: The annual costs for Project N°1

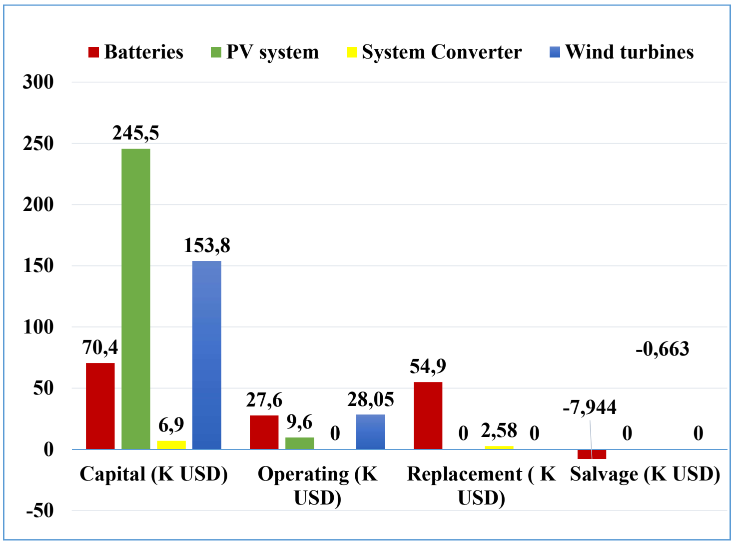


Figure 4.3: The annual costs for Project N°2

According to Figure 4.4, the yearly costs for the third project show substantial starting expenses for the photovoltaic (PV) system and the highest expenditures for battery replacement. Furthermore, the diesel generator necessitates a resource outlay of 40 k USD and carries a capital expense of 581.350 k USD. One of the most critical economic indicators is the total net present cost (NPC), which assesses the system's financial viability over time.

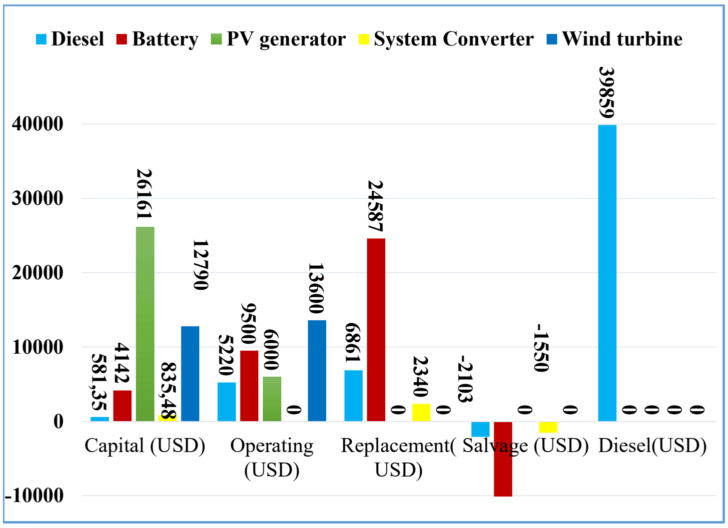


Figure 4.4: The annual costs for Project N°3

Figure 4.5 shows the system's minimum NPC over 25 years for the first project. The project involves high capital costs for the PV system, at 4.4 million USD, high operating costs for batteries, at 2.13 million USD, and a total salvage value of 2.73 million. The high NPC for batteries is primarily due to their replacement cost, given their 9 to 10 years lifespan.

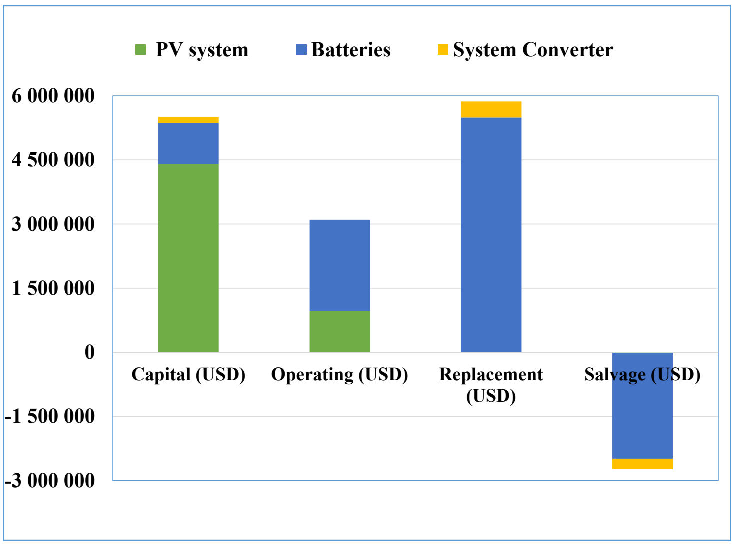


Figure 4.5: NPC of project N°1

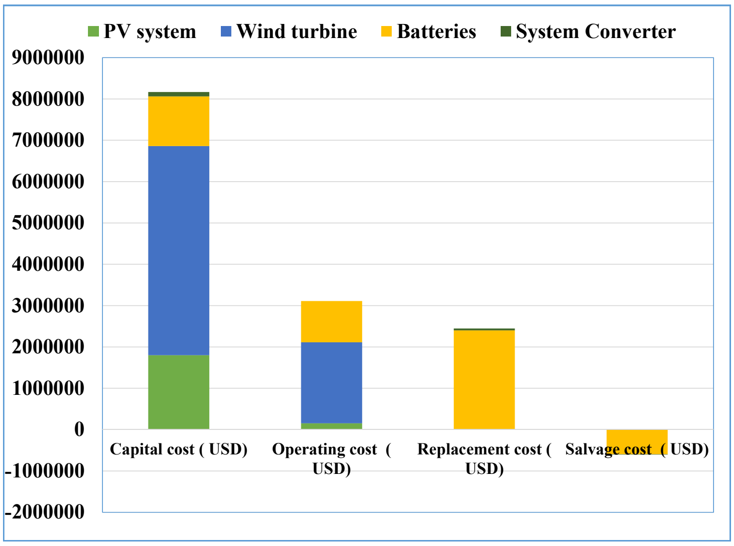


Figure 4.6: NPC of project N°2

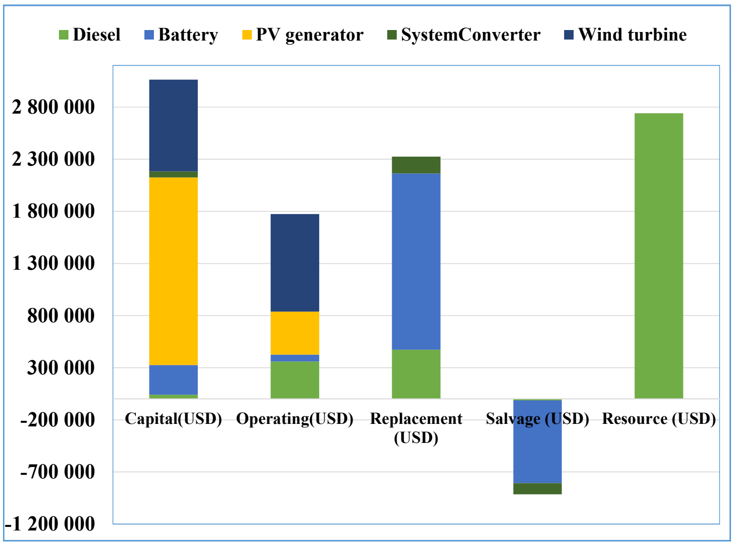


Figure 4.7: NPC of project N°3

Similarly, Figure 4.6 illustrates the second project's optimal configuration with the minimum NPC of each component over 25 years. The NPC for capital costs ranges from 1 million to 5.06 million USD, while the operating costs for wind turbines are high at 1.96 million USD. This analysis highlights the significant impact of each component on the overall cost. For the third project, the simulation results indicate that the NPC for the diesel generator is 2.7 million USD, and the capital NPC is 3 million USD. Figure 4.7 shows that the operational costs for this project are substantial, exceeding 2.3 million USD. These results provide a comprehensive understanding of the economic impact of each component in the microgrid configurations, offering valuable insights for optimizing costs and enhancing system performance.

4.2.2 Optimal Indicators

Net Present Cost (NPC) and Levelized Cost of Energy (LCOE) are essential indicators in choosing the best system configuration to achieve cost efficiency. Table 4.3 displays the most favourable indicator values for each project configuration:

First Project: The total NPC (Net Present Cost) is 11 million USD, while the LCOE(Levelized Cost of Electricity) is 0.197 USD/ kWh.

Second Project: The project's net present cost (NPC) is 13 million USD, with a levelized cost of electricity (LCOE) of USD/kWh. This project is entirely fuel-free and produces no CO_2 emissions, as it achieves a 100% renewable percentage (RF).

Third Project: The Net Present Cost (NPC) is 9.45 million USD, and the Levelized Cost of Electricity (LCOE) is 0.188 USD/kWh. The current setup utilizes 39,000 L of fuel annually and releases 104,321 kg of CO_2 annually, with 85% of the energy coming from renewable sources. The third project exhibits the most favourable Levelized Cost of Electricity (LCOE) and the lowest Net Present Cost (NPC) compared to the previous configurations. However, it also substantially influences CO_2 emissions due to its fuel use.

Table 4.3: Comparison of Project Indicators

Indicators	1^{st} Project	2^{nd} Project	3^{rd} Project
NPC (M USD)	11.7	13.3	9.45
Capex (M USD)	5.50	8.25	3.06
Opex (K USD)	94.6	201	92.7
LCOE (USD/kWh)	0.197	0.728	0.188
CO_2 emitted (kg/yr)	0	0	104,321
Fuel consumption (L/yr)	0	0	39,000

4.2.3 Energy Produced

In order to assess the technical performance of the suggested configurations in meeting the required load, a time-based simulation was carried out to analyze the sufficiency of the power generated from all sources in each configuration. Figure 4.8 displays the power generated by the PV-only configuration over 72 hours. During this time, electricity production is solely derived from the photovoltaic (PV) source. The maximum power output reaches around 500 kW at noon, which completely satisfies the fluctuating load requirement that ranges from 100 kW to 200 kW throughout the day. The battery system has a stored energy capacity ranging from 2300 kWh to 2800 kWh. The battery's State of Charge (SOC) varies between 80 % and 100 %, offsetting the changes in PV power output. It guarantees that the load demand is consistently fulfilled, regardless of the fluctuations in solar power generation.

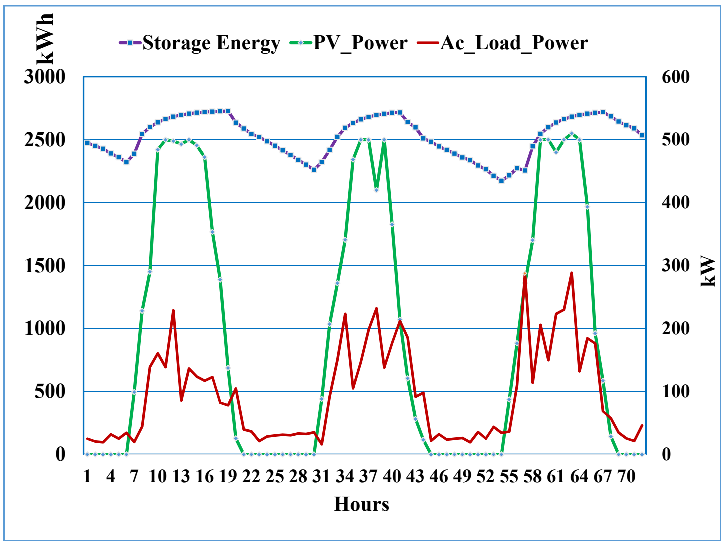


Figure 4.8: 72 hours of system's power and battery capacity for the 1st project

Furthermore, Figure 4.9 presents a comprehensive depiction of energy generation from various sources throughout a 72-hour duration in the winter season: - During the initial 24-hour period, wind energy is the primary source of energy generation. In contrast, solar energy production is low, mainly when the demand for electricity does not surpass 200 kW. As a result, the battery's storage capacity swings between 1100 and 1200 kWh as it adjusts to the changing energy inputs. Following days: Solar energy output experiences a substantial increase, especially during daylight hours, reaching its highest point in the afternoon. During this period, intense energy generation of over 200 kW guarantees sufficient coverage of the load demand even in the absence of solar energy, such as during nighttime hours. The technology efficiently employs battery storage to fill gaps and ensure a steady supply.

Moreover, Figure 4.10 comprehensively depicts the power flow dynamics in the third arrangement within a 72-hour. This arrangement typically supports an electrical load ranging from 200 kW to 300 kW. The primary sources of electricity to meet the overall demand are renewable, specifically photovoltaic (PV) panels and wind turbines (WT). Renewable energy sources significantly fulfil the load demand when generating electricity at their highest capacity. A diesel generator is utilized to complement the system to guarantee uninterrupted power supply when there is a shortage of renewable energy. The system's output varies from 50 kW to 100 kW, efficiently maintaining a stable power flow and assuring a continuous supply of electricity to match fluctuations in demand. The hybrid arrangement demonstrates the adaptability and dependability of combining renewable energy sources with backup diesel power in microgrid systems. It showcases the capabilities of these systems to efficiently handle fluctuating energy supply while ensuring operational stability and satisfying electricity demand over diverse time intervals.

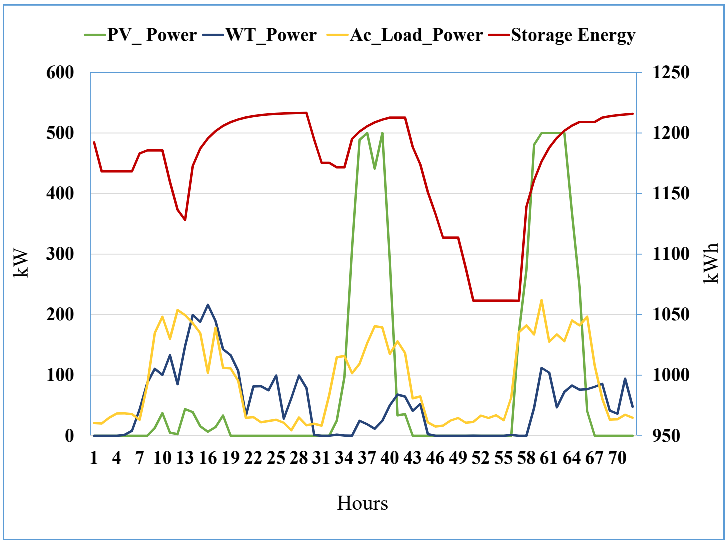


Figure 4.9: 72 hours system's power and battery capacity for the 2nd project

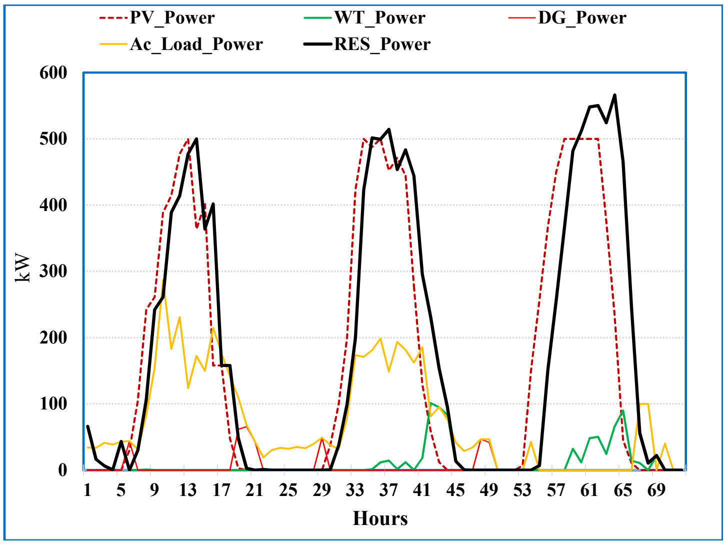


Figure 4.10: 72 hours system's power for the 3rdproject

Furthermore, Figure 4.11 illustrates the electrical summary, emphasizing notable distinctions among the projects examined. The First Project depends exclusively on a single energy source, most likely solar power. Consequently, its output fluctuates more, resulting in a more significant deficit in capacity compared to projects with several sources. The second project, in contrast, utilizes a combination of photovoltaic (PV) and wind turbine (WT) power generation, resulting in additional benefits. The data indicates a significant surplus of 63 % in energy and a deficit of 4.8 % in capacity. This excess highlights the effectiveness of incorporating various renewable energy sources to supply the electricity demand more dependably. The third project shows a reduced unmet load since the PV, WT sources, and diesel generator complement each other. This hybrid structure helps reduce the unpredictability inherent in individual renewable sources, improving the system's reliability. In addition, the battery capacity for these systems is specified. The first project is expected to handle around 130,692 kWh/y, and the battery's expected lifespan is approximately 9 years. These measurements highlight the essential importance of energy storage in stabilizing and optimizing energy usage in microgrid systems, especially in fluctuating renewable energy sources.

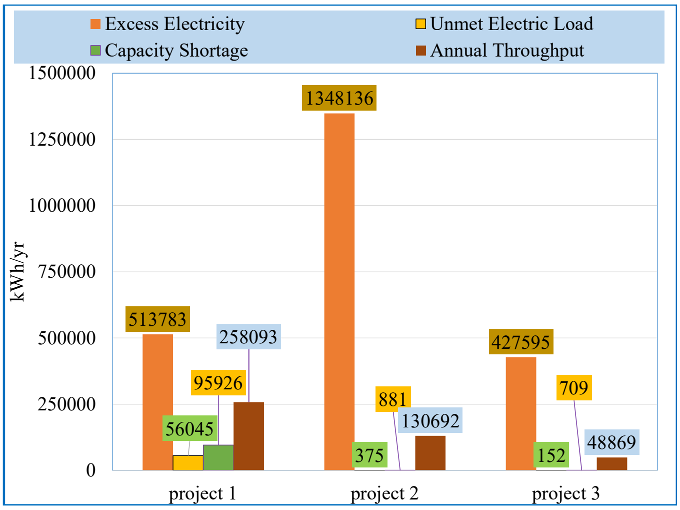
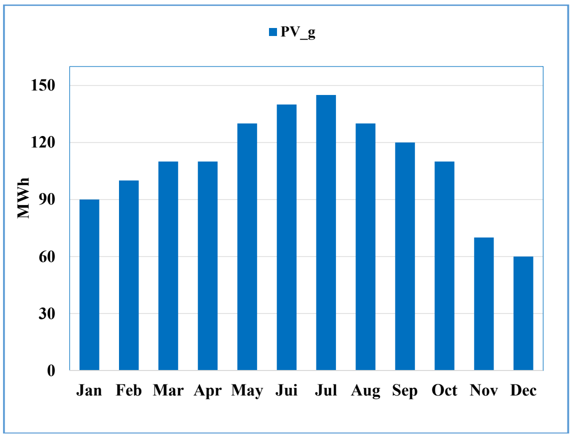
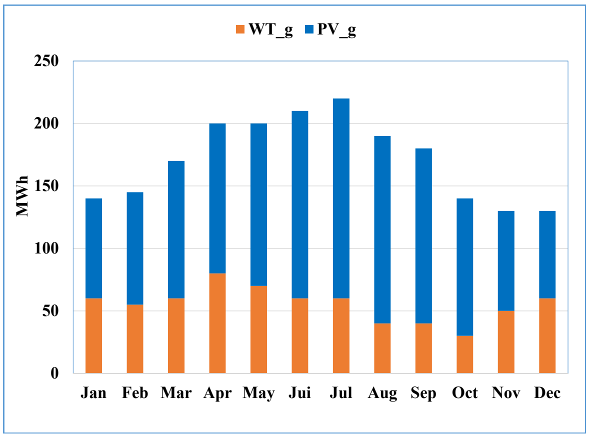


Figure 4.11: Electric production summary for each configuration

Additionally, Figure 4.12 illustrates the monthly electricity generation for each power source in the three examined setups. The first chart (Figure 4.12a) shows that the electric power is solely derived from photovoltaic sources, reaching a peak of 145 MWh in July. The second chart, depicted in Figure 4.12b, illustrates the electricity generation in the second project, which reaches 220 MWh. Notably, the project exhibits significant photovoltaic power output throughout the year. In Figure 4.12c, the photovoltaic (PV) power source accounts for over 60 % of the total power generated. The wind turbine (WT) generates between 20 MWh and 40 MWh, and the backup diesel generator (DG) produces between 5 MWh and 10 MWh every month to compensate for the intermittent nature of renewable energy.



(a)



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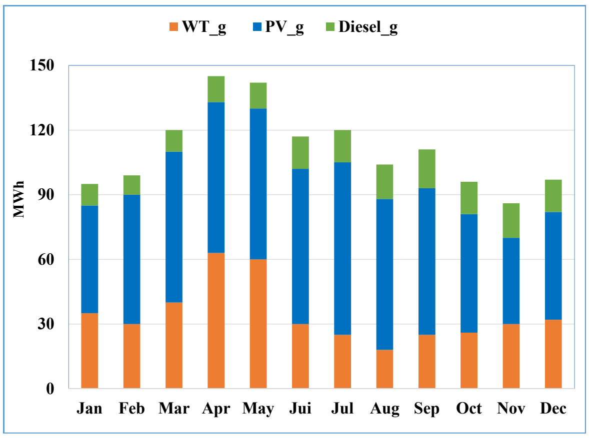

(c)

Figure 4.12: Monthly electric energy output

4.2.4 Cost Analysis Assessment

The assessment of the three proposed configurations can be based on Comparing earlier studies with comparable structures. Three configurations have been identified as possible combinations with the lowest levelized cost of electricity (LCOE). These configurations include a PV-battery combination with an LCOE of 0.502 USD/kWh and a PV/Wind/Diesel/battery combination with an LCOE of 0.27 USD/kWh, as observed in the examples analyzed in Bangladesh [50].

A PV/Wind/Diesel/battery system was implemented in Popova island, resulting in a Levelized Cost of Electricity (LCOE) ranging from 0.24 USD/kWh to 0.7 USD/kWh [72]. In Thailand, the levelized cost of electricity (LCOE) for different photovoltaic (PV) and battery scenarios ranges from 0.24 USD/kWh to 0.275 USD/kWh [48]. The levelized cost of electricity (LCOE) for the PV/Wind setup varied between 0.341 USD/kWh and 0.69 USD/kWh across different sites [51].

4.2.5 Sensitivity Analysis

Sensitivity analysis is essential for assessing the reliability of the proposed method, particularly by examining uncertainties related to renewable energy sources, load demand, and economic inputs. This analysis evaluates the influence of changing these parameters for each combination examined in this work, offering a valuable understanding of the system's performance in diverse situations.

Figure 4.13 depicts the first project's Net Present Cost (NPC) across load demand and average solar irradiation scenarios. The load demand fluctuates between 2400 kWh and 2850 kWh. In contrast, the average solar irradiation varies from 3 kWh/m^2/day to 5.8 kWh/m^2/day, with a 25% deviation in solar input. The results indicate that increased average solar irradiation leads to a drop in the Net Present Cost (NPC) and the Levelized Cost of Energy (LCOE) due to enhanced solar energy availability.

On the other hand, when load demand rises, the net present cost (NPC) also increases. This is mainly because the expenses for replacing and operating the system increase.

The second experiment investigates the impact of PV and wind power output variations on the system's costs, as shown in Figure 4.14. The operational expenses linked to energy generation extensively impact the NPC (Net Present Cost) and LCOE (Levelized Cost of Energy). As the wind speed and the intensity of solar radiation rise, the energy production of wind turbines and photovoltaic (PV) panels also increases, impacting the system's total cost. The number of wind turbines and photovoltaic (PV) power generation capacity are crucial factors in determining the results. Although the Levelized Cost of Electricity (LCOE) is somewhat affected by these variations, the Net Present Cost (NPC) generally rises as the quantity of wind turbines increases, primarily because of increased capital and operational costs.

Table 4.5 shows the inputs that impacted the third project. The average load demand increased from 2460 kWh/d to 2850 kWh/d, resulting in a shift in the NPC from 13.2 M USD to 16.2 M USD. Additionally, the LCOE changed slightly from 0.216 USD/kWh to 0.255 USD/kWh.

In addition, capital expenditure (CAPEX) and operational expenditure (OPEX) are increasing as the demand load rises. At the same time, the levelized cost of electricity (LCOE) and net present cost (NPC) remain in equilibrium. The second factor determining its impact is the inflation rate, which ranges from 9 % to 11%. During this range, all economic indicators experienced a significant increase while still maintaining appropriate values. Subsequently, the analysis examines the impact of fuel price on other parameters. It is shown that CO_2 emissions increase in direct proportion to the rise in power demand while they decrease in inverse proportion to wind speed and solar radiation.

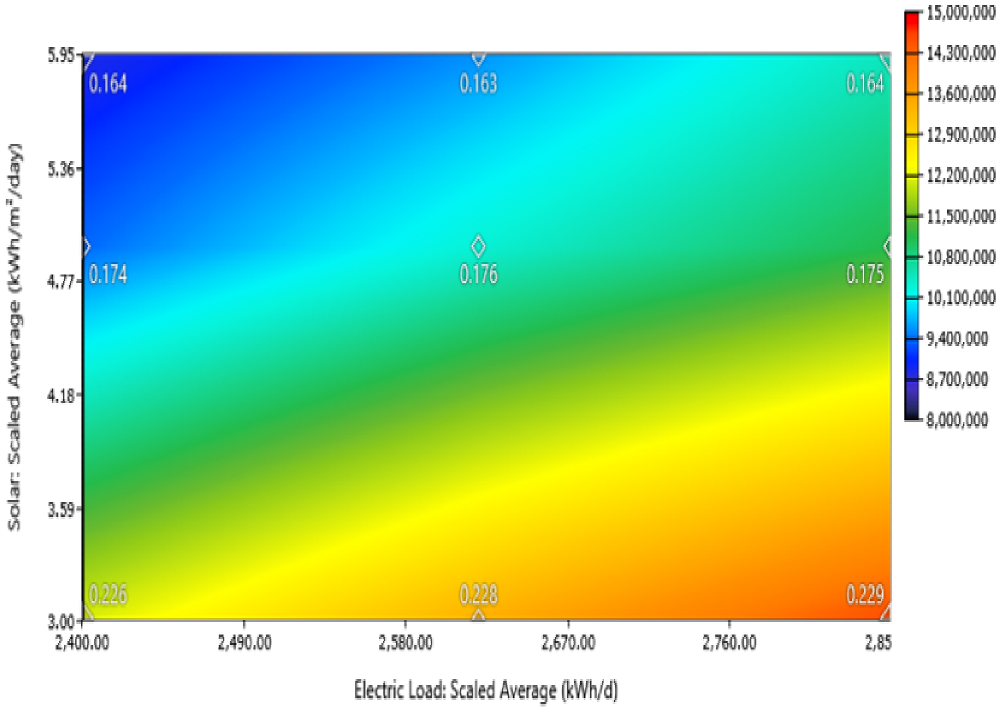

Figure 4.13: NPC and LCOE with average load sensitivity and solar irradiation for the 1st project

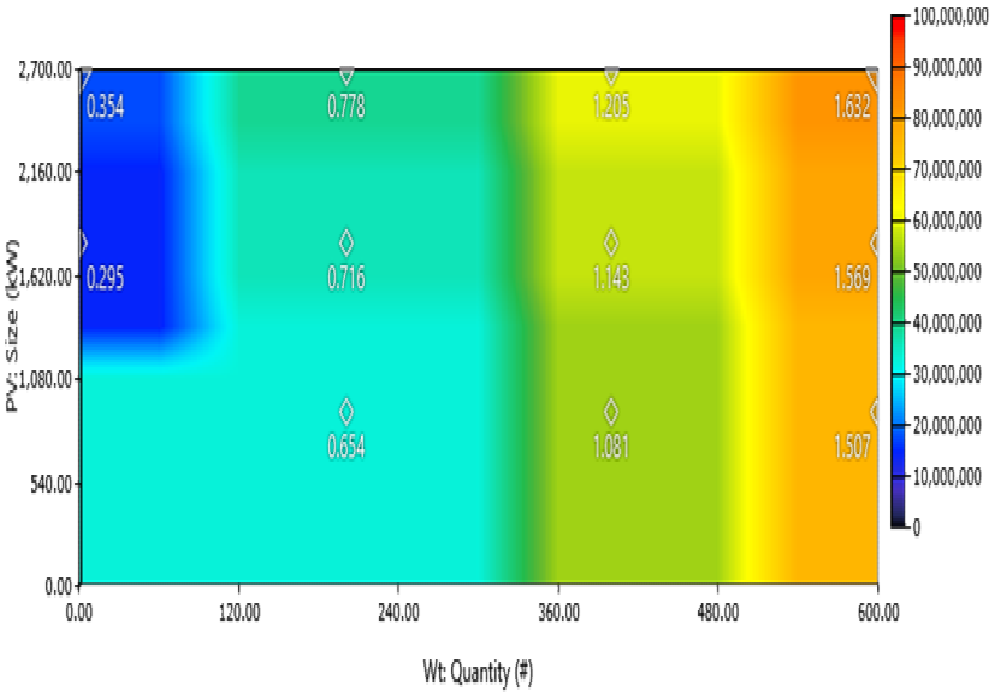

Figure 4.14: NPC and LCOE in different sizes of WT and PV for the 2nd project

4.3 Metrics Influencing Financial Decision-Making

This part examines crucial financial metrics necessary for making well-informed decisions in project investments, specifically focusing on assessment and evaluation concepts. Essential economic procedures such as Net Present Value (NPV), Internal Rate of Return (IRR), and Payback Period (DBP) are based on the analysis of annual cash flows.

Net Present Value (NPV): NPV is a financial metric determining the current value of all cash inflows and outflows during a project's duration. This calculation considers the project's cost of capital and applies a discount rate to adjust for the time value of money. A positive net present value (NPV) signifies that the project is anticipated to yield more significant cash inflows than outflows, suggesting profitability. Its purpose is to compare projects and evaluate their financial appeal based on their ability to generate profits.

The Internal Rate of Return:(IRR) is the discount rate that makes cash inflows' present value equal to cash outflows' present value. Essentially, it denotes the anticipated rate of return for the project and is employed to assess its profitability regarding capital expenditures. Higher internal rate of return (IRR) numbers generally indicate more advantageous investment prospects.

Payback Period (DBP): The Payback Period is a measure that determines the amount of time it takes for the total cash inflows to match the initial investment (cash outflow). It offers a direct assessment of the ease of converting an investment into cash and the level of uncertainty, showing the speed at which the investment can recover its initial expenses. Shorter payback times are typically favoured due to their ability to provide faster returns on investment and less risk.

The evaluation of renewable energy projects relies heavily on these essential financial parameters, which enable choices based on comprehensive financial analysis that considers the timing and size of cash flows. They assist stakeholders in evaluating the economic viability, profitability, and risk involved in proposed investments in sustainable energy solutions [88].

Thus, the second project has a higher Internal Rate of Return (IRR) of **15.8%**. The Payback Period (DBP) for all projects falls within the range of 6 to 9 years, and the Return on Investment (ROI) ranges from **20 %** to **29 %**, as depicted in Table 4.4. It calculates the duration required for investors to recover their initial investment expenses. The three projects have been approved based on a positive net present value (NPV) of zero, following the specified rule: A project is accepted if the following conditions are met:

$$\text{NPV}(p) > 0 \quad \text{and} \quad \text{IRR}(p) > i_r \quad \text{and} \quad \text{DPB}(p) < y \tag{4.1}$$

Moreover, Net Present Value (NPV) is a vital financial measure that is essential for making investment decisions, particularly in identifying the most effective project design. The Net Present Value (NPV), together with metrics such as Internal Rate of Return (IRR) and Payback Period (DPB), provide a thorough understanding of the financial feasibility of PV/wind turbine setups, whether they are integrated with diesel backup or not. Projects 1 and 2, which are distinguished by their lack of carbon emissions, have environmental advantages that increase their attractiveness as prudent investments. The inclusion of environmental sustainability further enhances the appeal of these initiatives, as they align with both financial and environmental objectives. The significance of NPV in assessing both financial returns and broader implications on sustainability and investment feasibility is emphasized by such factors.

Table 4.4: Project Evaluation Metrics

Projects	**NPV (M USD)**	**IRR (%)**	**ROI (%)**	**DPB (yr)**
Project 1	0.76	13.9	20	6.03
Project 2	2.31	15.8	24	9.61
Project 3	10.2	13.0	29	8.9

Table 4.5: Economic Sensitivity Analysis for 3 rd project

Parameters	**Demand load(kWh/d)**		**Inflation rate %**			**Average wind speed (m/s)**		**Average global solar (kWh/m^2/d)**		**Fuel price ($/l)**
	2460	**2850**	**9**	**10**	**11**	**3.95**	**4.8**	**4.95**	**3.00**	**1**
NPC(M USD)	13.2	16.2	8.8	8.54	9.78	5.99	8.3	10.6	6.39	9.11
LCOE (USD/kWh)	0.216	0.255	0.16	0.14	0.18	0.119	0.156	0.23	0.12	0.15
CAPEX(M USD)	4.02	8.14	3.12	3.29	10.4	2.19	2.90	3.67	2.69	4.35
OPEX(M USD)	0.13	0.16	0.095	0.17	0.20	0.055	0.077	0.07	0.085	0.105
CO_2 emission (kg/y)	98767	153200	102754	103113	100378	111849	102745	97768	112699	98625

4.3.1 Risk Analysis

The decision-making process entails a thorough risk analysis, where Net Present Value (NPV) plays a vital financial tool for evaluating investments. The probability values obtained from the distribution function indicate the reliability of forecasts and the degree of agreement between the calculated NPV and the simulated results. Standard deviation serves a dual purpose as both a measure of predictability and an indicator of risk. It represents the level of uncertainty in NPV values within a specific confidence range, usually about 60 %. The mean value criterion is used to choose profitable projects.

The Monte Carlo simulation of NPV utilized The mean values (μ), standard deviations (σ), and the minimum and highest NPV values from the three projects. This simulation evaluated each project's probability distribution function f(x,σ,μ) by producing 1000 samples. Projects 2 and 3 demonstrated a notable occurrence of favourable Net Present Value (NPV) values, suggesting they are profitable and appealing for investment. In contrast, Project 1 demonstrated occurrences of negative Net Present Value (NPV) figures, indicating substantial risk and demonstrating that hybrid systems generally surpass PV-only microgrid systems in terms of NPV.

Figure 4.15 demonstrates the approval of the PV project based on many factors, validating the decision-making process. Sensitivity analysis is another result of the risk analysis process. It helps identify the critical risk input variables that have the most significant impact on the uncertainty of NPV estimates. This all-encompassing strategy guarantees well-informed decision-making and effective risk management when assessing investments in renewable energy microgrids.

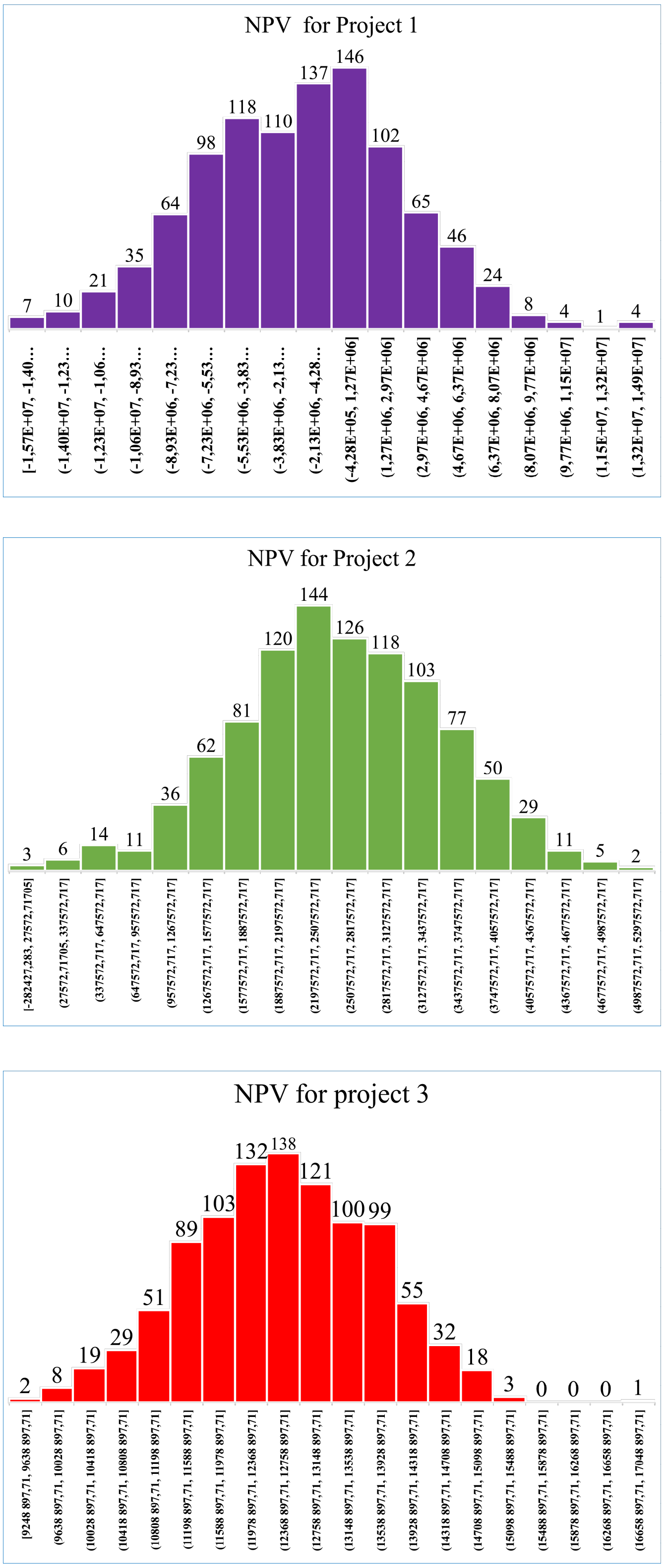

Figure 4.15: Monte Carlo simulation for NPV Risk analysis

4.4 Conclusion

This chapter presented the results of a systematic approach designed to enhance the sizing of renewable energy systems in microgrids, particularly emphasizing a comprehensive examination in the Biskra region of Algeria. It highlights three main dimensions:

i. Assessment of the cost: The analysis considers three different scenarios: independent photovoltaic (PV) systems, PV systems combined with wind turbines (PV/WT), and PV/WT systems enhanced by a diesel generator (PV/WT/DG). Every situation is evaluated to determine the most suitable size, considering important economic indicators such as Net Present Cost (NPC) and Levelized Cost of Energy (LCOE). The analytical model incorporates uncertainties and risks related to crucial input parameters. At the same time, sensitivity analysis finds the variables that influence Capital Expenditure (CAPEX), Operational Expenditure (OPEX), Levelized Cost of Electricity (LCOE), and Net Present Cost (NPC). The results indicate a decline in the net primary productivity (NPC) from Project 1 to Project 3. Notably, Project 3 is the only scenario where CO_2 emissions occur as a result of the operation of the diesel generator.

ii. Technical Feasibility Assessment: The study assesses the technical feasibility of these scenarios by analyzing comparative financial metrics such as Net Present Value (NPV), Internal Rate of Return (IRR), Return on Investment (ROI), and Payback Period (DPB). These metrics offer crucial insights for making well-informed investment decisions in renewable energy systems by considering both economic feasibility and technical efficiency.

iii. Risk Analysis: The risk assessment utilizes Monte Carlo simulation for NPV to evaluate the reliability and security of investment choices. Project 1 exhibits minimal risk; however, Project 2 stands out as the most beneficial choice regarding economic, environmental, and production aspects, emphasizing its appropriateness for maximizing the region's energy potential.

To achieve optimal sizing for microgrid renewable energy systems, costs must be optimized and financial aspects thoroughly evaluated, such as predicted cash flows and risk assessments of variable factors over time. This methodological approach provides essential direction to investors who assess and implement new renewable energy projects, ensuring that decisions align with economic feasibility and sustainability goals.

CONCLUSION AND FUTURE WORKS

Conclusion

The transition to renewable energy systems is essential for addressing the challenges related to energy demand, environmental sustainability, and economic viability. Planning and sizing renewable energy systems for their integration into microgrids is a complex study due to the interaction of technical, economic, and environmental factors.

This PhD dissertation proposes an analytical approach to tackle these challenges by focusing on the following aspects:

- **Techno-economic optimization**: Development of a comprehensive framework to optimize key economic indicators, including Net Present Cost (NPC) and Levelized Cost of Electricity (LCOE), using HOMER-Pro software.

- **Financial assessment**: Evaluation of the financial feasibility of renewable energy systems using indicators such as Net Present Value (NPV), Internal Rate of Return (IRR), and Discounted Payback Period (DBP) to assess cash flow and profitability.

- **Integrated design approach**: Adoption of an integrated design approach that considers environmental, technical, and economic factors to develop a comprehensive and practical sizing methodology, emphasizing the importance of selecting the optimal combination of energy resources.

- **Case study**: The proposed methodology was validated through a case study conducted in Biskra, Algeria, analyzing three renewable energy system combinations (PV/WT/Batt, PV/Batt, and PV/WT/DG/Batt).

  The results demonstrate that the proposed approach provides a practical and robust solution for optimizing renewable energy systems in microgrids, balancing cost-effectiveness, sustainability, and feasibility.

To address the uncertainties inherent in sizing renewable energy systems, this dissertation explores input-level and output-level analyses:

Input-level analysis

At the input level, the analysis focuses on key parameters that significantly influence the sizing process, such as wind speed, solar radiation, load demand, and inflation rate. To assess their impact, the dissertation employs the following methods:

- **Sensitivity analysis**: This method evaluates the impact of variations in deterministic factors such as solar irradiation, wind speed, inflation rate, load demand, and fuel price. By analyzing how these variables affect economic indicators like NPC and LCOE, sensitivity analysis provides a solid foundation for the proposed sizing methodology, ensuring its effectiveness under different conditions.

- **Stochastic modeling**: Recognizing the need to account for continuous uncertainty, this dissertation applies a stochastic process based on Geometric Brownian Motion (GBM). This approach models the future trajectories of key input factors that could influence the long-term performance and cost-effectiveness of the renewable energy system. By forecasting these potential future trends, stochastic modeling enhances the reliability of the sizing process.

Output-level analysis

While input-level analysis focuses on managing uncertainties in the sizing process, this dissertation extends its scope to output-level analysis by conducting a risk assessment of NPV using Monte Carlo simulations. This probabilistic approach provides a detailed evaluation of the risks associated with the renewable energy project, offering valuable insights into the proposed system's efficiency, feasibility, and reliability. The Monte Carlo simulation results play a crucial role in decision-making processes, ensuring that the renewable energy system proposed in this dissertation accounts for uncertainties and remains sustainable.

Consequently, this PhD dissertation introduces a robust methodology for sizing renewable energy systems for microgrids and provides a comprehensive framework for addressing uncertainties and risks inherent in such projects. The research systematically examines the process of determining the optimal dimensions and specifications for integrating renewable energy systems into microgrids.

i. By developing a structured approach, this study ensures the efficient sizing and design of renewable energy systems, optimizing both technical performance and economic feasibility. The methodology incorporates key factors such as resource availability, load demand, and system components, emphasizing their role in achieving an optimal configuration for microgrid integration.

ii. To address uncertainties, the dissertation evaluates the implications of disregarding variability in renewable energy sources and proposes decision-making frameworks, including stochastic modeling and Monte Carlo simulations. These methods effectively capture and mitigate risks, confirming reliable system performance under varying conditions.

iii. The dissertation highlights the importance of investment planning in enhancing the integration of renewable energy systems into microgrids. It demonstrates how optimized sizing and operation can lead to a reliable, cost-effective, and sustainable energy supply, contributing to broader sustainability and energy efficiency goals.

The results and methods developed in this dissertation have significant implications for the design and sizing of renewable energy systems. They provide actionable insights for creating resilient, scalable, and economically viable microgrids that address global energy challenges.

Future works

Future work will prioritize enhancing the dynamic microgrid size and design process through advanced methodologies and sophisticated economic analysis. Which aims to improve the system's efficiency and cost-effectiveness by utilizing real-time data, predictive modeling, advanced machine learning, and resilient optimization techniques. The objective is to enhance dependability and durability and offer a more profound understanding for decision-makers in the energy sector.

BIBLIOGRAPHY

[1] E. Ogner, I. M. Trotter, T. Folsland, and M. Carlo, "Long term power prices and renewable energy market values in Norway – A probabilistic approach," vol. 112, no. May, 2022.

[2] IRENA, "Renewable Capacity Statistics," 2021.

[3] N. Alshammari and J. Asumadu, "Optimum unit sizing of hybrid renewable energy system utilizing harmony search, Jaya and particle swarm optimization algorithms," *Sustainable Cities and Society*, vol. 60, no. March, p. 102255, 2020.

[4] Y. J. Khawaja, "INVESTIGATIONS INTO MICROGRID," no. August, 2019.

[5] C. Ammari, D. Belatrache, B. Touhami, and S. Makhloufi, "Sizing, optimization, control and energy management of hybrid renewable energy system—A review," *Energy and Built Environment*, 2021.

[6] NASA, "Renewable energy data," 2023.

[7] T. Adefarati and R. C. Bansal, "Reliability, economic and environmental analysis of a microgrid system in the presence of renewable energy resources," *Applied Energy*, vol. 236, pp. 1089–1114, 2019.

[8] M. A. Hannan, M. Faisal, P. Jern Ker, R. A. Begum, Z. Y. Dong, and C. Zhang, "Review of optimal methods and algorithms for sizing energy storage systems to achieve decarbonization in microgrid applications," *Renewable and Sustainable Energy Reviews*, vol. 131, no. July, p. 110022, 2020.

[9] F. Tooryan, H. HassanzadehFard, E. R. Collins, S. Jin, and B. Ramezani, "Smart integration of renewable energy resources, electrical, and thermal energy storage in microgrid applications," *Energy*, vol. 212, p. 118716, 2020.

[10] L. Polleux, G. Guerassimoff, J. P. Marmorat, J. Sandoval-Moreno, and T. Schuhler, "An overview of the challenges of solar power integration in isolated industrial microgrids with reliability constraints," *Renewable and Sustainable Energy Reviews*, vol. 155, 2022.

[11] Q. Hassan, S. Algburi, A. Z. Sameen, H. M. Salman, and M. Jaszczur, "A review of hybrid renewable energy systems: Solar and wind-powered solutions: Challenges, opportunities, and policy implications," *Results in Engineering*, vol. 20, no. November, p. 101621, 2023.

[12] A. G. Olabi and M. Ali, "Renewable energy and climate change," *Renewable and Sustainable Energy Reviews*, vol. 158, no. November 2020, p. 112111, 2022.

[13] I. Renewable and E. Agency, *the Global Atlas for Renewable Energy a Decade in the Making.* No. April, 2024.

[14] O. Ellabban and A. Alassi, "Optimal hybrid microgrid sizing framework for the mining industry with three case studies from Australia," *IET Renewable Power Generation*, no. October 2020, pp. 409–423, 2021.

[15] D. Akinyele, J. Belikov, and Y. Levron, "Challenges of microgrids in remote communities: A STEEP model application," *Energies*, vol. 11, no. 2, pp. 1–35, 2018.

[16] Y. Zahraoui, M. R. Basir Khan, I. Alhamrouni, S. Mekhilef, and M. Ahmed, "Current status, scenario, and prospective of renewable energy in algeria: A review," *Energies*, vol. 14, no. 9, 2021.

[17] M. Uddin, H. Mo, D. Dong, S. Elsawah, J. Zhu, and J. M. Guerrero, "Microgrids: A review, outstanding issues and future trends," *Energy Strategy Reviews*, vol. 49, no. February, p. 101127, 2023.

[18] S. Fang and Y. Wang, *The role of energy storage systems in microgrids operation.* 2021.

[19] Z. K. Pecenak, M. Stadler, P. Mathiesen, K. Fahy, and J. Kleissl, "Robust design of microgrids using a hybrid minimum investment optimization," *Applied Energy*, vol. 276, no. July, p. 115400, 2020.

[20] M. Fahad Zia, E. Elbouchikhi, and M. Benbouzid, "MICROGRIDS ENERGY MANAGEMENT SYSTEMS: A CRITICAL REVIEW ON METHODS, SOLUTIONS, AND PROSPECTS Energy management system ESS Energy storage system EV Electric vehicle GA Genetic algorithm GHG Greenhouse gas LC Local controller LP Linear programming MAS Multi," 2018.

[21] S. Shahzad, M. A. Abbasi, H. Ali, M. Iqbal, R. Munir, and H. Kilic, "Possibilities, Challenges, and Future Opportunities of Microgrids: A Review," *Sustainability (Switzerland)*, vol. 15, no. 8, 2023.

[22] S. M. Hakimi, A. Hasankhani, M. Shafie-khah, M. Lotfi, and J. P. Catalão, "Optimal sizing of renewable energy systems in a Microgrid considering electricity market interaction and reliability analysis," *Electric Power Systems Research*, vol. 203, no. November 2021, 2022.

[23] M. S. Alam, M. A. Hossain, M. Shafiullah, A. Islam, M. S. Choudhury, M. O. Faruque, and M. A. Abido, "Renewable energy integration with DC microgrids: Challenges and opportunities," *Electric Power Systems Research*, vol. 234, no. June, p. 110548, 2024.

[24] Q. Yang, Q. Liu, Q. Fu, K. Yang, M. Zhang, and Q. Chen, "Smart microgrid construction in abandoned mines based on gravity energy storage," *Heliyon*, vol. 9, no. 11, p. e21481, 2023.

[25] F. Norouzi, T. Hoppe, L. R. Elizondo, and P. Bauer, "A review of socio-technical barriers to Smart Microgrid development," *Renewable and Sustainable Energy Reviews*, vol. 167, no. May, p. 112674, 2022.

[26] F. R. Badal, S. K. Sarker, Z. Nayem, S. I. Moyeen, and S. K. Das, "Microgrid to smart grid's evolution: Technical challenges, current solutions, and future scopes," *Energy Science and Engineering*, vol. 11, no. 2, pp. 874–928, 2023.

[27] A. Kumar, D. M. A. Hussain, and M. Z. U. Khan, "Microgrids Technology: A Review Paper," *Gyancity Journal of Electronics and Computer Science*, vol. 3, no. 1, pp. 11–20, 2018.

[28] C. coalition, "Microgrids across the united state," 2024.

[29] J. Namaganda-kiyimba, "DESIGN AND OPTIMIZATION OF A RENEWABLE ENERGY BASED SMART MICROGRID FOR RURAL ELECTRIFICATION A THESIS SUBMITTED TO THE UNIVERSITY OF MANCHESTER Table of Contents," 2020.

[30] J. M. Rey, P. P. Vergara, J. Solano, and G. Ordóñez, *Design and optimal sizing of microgrids.* 2018.

[31] F. Foroutan, S. M. Mousavi Gazafrudi, and H. Shokri-Ghaleh, "A Comparative Study of Recent Optimization Methods for Optimal Sizing of a Green Hybrid Traction Power Supply Substation," *Archives of Computational Methods in Engineering*, vol. 28, no. 4, pp. 2351–2370, 2021.

[32] A. M. Alzahrani, M. Zohdy, and B. Yan, "An Overview of Optimization Approaches for Operation of Hybrid Distributed Energy Systems with Photovoltaic and Diesel Turbine Generator," *Electric Power Systems Research*, vol. 191, no. September 2020, p. 106877, 2021.

[33] N. Stevanato, F. Lombardi, G. Guidicini, L. Rinaldi, S. L. Balderrama, M. Pavi, S. Quoilin, and E. Colombo, "Energy for Sustainable Development Long-term sizing of rural microgrids : Accounting for load evolution through multi-step investment plan and stochastic optimization," vol. 58, pp. 16–29, 2020.

[34] M. Thirunavukkarasu, Y. Sawle, and H. Lala, "A comprehensive review on optimization of hybrid renewable energy systems using various optimization techniques," *Renewable and Sustainable Energy Reviews*, vol. 176, no. February, p. 113192, 2023.

[35] N. Shatnawi, H. Abu-Qdais, and F. Abu Qdais, "Selecting renewable energy options: an application of multi-criteria decision making for Jordan," *Sustainability: Science, Practice, and Policy*, vol. 17, no. 1, pp. 210–220, 2021.

[36] D. Fateh, M. Eldoromi, A. Akbar, and M. Birjandi, *Chapter 9 - Uncertainty modeling of renewable energy sources*. Elsevier Inc., 2022.

[37] M. D. Al-falahi, S. D. Jayasinghe, and H. Enshaei, "A review on recent size optimization methodologies for standalone solar and wind hybrid renewable energy system," *Energy Conversion and Management*, vol. 143, pp. 252–274, 2017.

[38] G. Chebotareva, W. Strielkowski, and D. Streimikiene, "Risk assessment in renewable energy projects: A case of Russia," *Journal of Cleaner Production*, vol. 269, p. 122110, 2020.

[39] F. Ghayoor, A. G. Swanson, and H. Sibanda, "Optimal sizing for a grid-connected hybrid renewable energy system: A case study of the residential sector in Durban, South Africa," *Journal of Energy in Southern Africa*, vol. 32, no. 4, pp. 11–27, 2021.

[40] A. A. Kondratenko, M. Bergström, M. Suominen, and P. Kujala, "An Artificial Bee Colony optimization-based approach for sizing and composition of Arctic offshore drilling support fleets considering cost-efficiency," *Ship Technology Research*, 2022.

[41] S. Mohseni, A. C. Brent, D. Burmester, and W. N. Browne, "Lévy-flight moth-flame optimisation algorithm-based micro-grid equipment sizing: An integrated investment and operational planning approach," *Energy and AI*, vol. 3, p. 100047, 2021.

[42] H. U. R. Habib, U. Subramaniam, A. Waqar, B. S. Farhan, K. M. Kotb, and S. Wang, "Energy cost optimization of hybrid renewables based V2G microgrid considering multi objective function by using artificial bee colony optimization," *IEEE Access*, vol. 8, pp. 62076–62093, 2020.

[43] H. M. Farh, A. M. Al-Shaalan, A. M. Eltamaly, and A. A. Al-Shamma'A, "A Novel Crow Search Algorithm Auto-Drive PSO for Optimal Allocation and Sizing of Renewable Distributed Generation," *IEEE Access*, vol. 8, pp. 27807–27820, 2020.

[44] H. Kamyab, "New hybrid meta-heuristic algorithm for reliable and cost-effective designing of photovoltaic / wind / fuel cell ene ...," *Journal of Cleaner Production*, 2020.

[45] D. Fioriti, D. Poli, P. Duenas-Martinez, and A. Micangeli, "Multiple design options for sizing off-grid microgrids: A novel single-objective approach to support multi-criteria decision making," *Sustainable Energy, Grids and Networks*, vol. 30, p. 100644, 2022.

[46] M. Petrelli, D. Fioriti, A. Berizzi, C. Bovo, and D. Poli, "A novel multi-objective method with online Pareto pruning for multi-year optimization of rural microgrids," *Applied Energy*, vol. 299, 2021.

[47] R. Khezri and A. Mahmoudi, "Review on the state-of-the-art multi-objective optimisation of hybrid standalone/gridconnected energy systems," *IET Generation, Transmission and Distribution*, vol. 14, no. 20, pp. 4285–4300, 2020.

[48] A. Bhatt, W. Ongsakul, and N. Madhu M., "Optimal techno-economic feasibility study of net-zero carbon emission microgrid integrating second-life battery energy storage system," *Energy Conversion and Management*, vol. 266, no. May, p. 115825, 2022.

[49] R. Chaurasia, S. Gairola, and Y. Pal, "Technical, economic feasibility and sensitivity analysis of solar photovoltaic/battery energy storage off-grid integrated renewable energy system," *Energy Storage*, vol. 4, no. 1, pp. 1–18, 2022.

[50] B. K. Das, M. A. Alotaibi, P. Das, M. S. Islam, S. K. Das, and M. A. Hossain, "Feasibility and techno-economic analysis of stand-alone and grid-connected PV/Wind/Diesel/Batt hybrid energy system: A case study," *Energy Strategy Reviews*, vol. 37, no. December 2020, p. 100673, 2021.

[51] M. Nurunnabi, N. K. Roy, E. Hossain, and H. R. Pota, "Size optimization and sensitivity analysis of hybrid wind/PV micro-grids- A case study for Bangladesh," *IEEE Access*, vol. 7, pp. 150120–150140, 2019.

[52] S. Singh, A. Slowik, N. Kanwar, and N. K. Meena, "Techno-economic feasibility analysis of grid-connected microgrid design by using a modified multi-strategy fusion artificial bee colony algorithm," *Energies*, vol. 14, no. 1, pp. 1–20, 2021.

[53] S. Kumar, C. Sethuraman, and G. Chandru, "Sizing optimization and techno-economic analysis of a hybrid renewable energy system using HOMER pro simulation," *Journal of Scientific and Industrial Research*, vol. 80, no. 9, pp. 777–784, 2021.

[54] A. Ghaffari and A. Askarzadeh, "Design optimization of a hybrid system subject to reliability level and renewable energy penetration," *Energy*, vol. 193, 2020.

[55] B. Dey, B. Bhattacharyya, and F. P. G. Márquez, "A hybrid optimization-based approach to solve environment constrained economic dispatch problem on microgrid system," *Journal of Cleaner Production*, vol. 307, no. May, 2021.

[56] M. Najafi Ashtiani, A. Toopshekan, F. Razi Astaraei, H. Yousefi, and A. Maleki, "Techno-economic analysis of a grid-connected PV/battery system using the teaching-learning-based optimization algorithm," *Solar Energy*, vol. 203, no. February, pp. 69–82, 2020.

[57] D. Aussel, P. Neveu, D. Tsuanyo, and Y. Azoumah, "On the equivalence and comparison of economic criteria for energy projects: Application on PV/diesel hybrid system optimal design," *Energy Conversion and Management*, vol. 163, no. August 2017, pp. 493–506, 2018.

[58] D. Fioriti, S. Pintus, G. Lutzemberger, and D. Poli, "Economic multi-objective approach to design off-grid microgrids: A support for business decision making," *Renewable Energy*, 2020.

[59] C. S. Lai and G. Locatelli, "Economic and financial appraisal of novel large-scale energy storage technologies," *Energy*, vol. 214, p. 118954, 2021.

[60] R. Alizadeh, L. Soltanisehat, P. D. Lund, and H. Zamanisabzi, "Improving renewable energy policy planning and decision-making through a hybrid MCDM method," *Energy Policy*, vol. 137, 2020.

[61] E. M. Urbano, V. Martinez-Viol, K. Kampouropoulos, and L. Romeral, "Energy-investment decision-making for industry: Quantitative and qualitative risks integrated analysis," *Sustainability (Switzerland)*, vol. 13, no. 12, 2021.

[62] J. O. Oladigbolu, Y. A. Al-Turki, and L. Olatomiwa, "Comparative study and sensitivity analysis of a standalone hybrid energy system for electrification of

rural healthcare facility in Nigeria," *Alexandria Engineering Journal*, vol. 60, no. 6, pp. 5547–5565, 2021.

[63] D. Fioriti, D. Poli, P. Duenas-Martinez, and I. Perez-Arriaga, "Multi-year stochastic planning of off-grid microgrids subject to significant load growth uncertainty: overcoming single-year methodologies," *Electric Power Systems Research*, vol. 194, 2021.

[64] Z. Javid, K. J. Li, R. Ul Hassan, and J. Chen, "Hybrid-microgrid planning, sizing and optimization for an industrial demand in Pakistan," *Tehnicki Vjesnik*, vol. 27, no. 3, pp. 781–792, 2020.

[65] P. N. Premadasa and D. P. Chandima, "An innovative approach of optimizing size and cost of hybrid energy storage system with state of charge regulation for stand-alone direct current microgrids," *Journal of Energy Storage*, vol. 32, no. July, p. 101703, 2020.

[66] O. A. Dabar, M. O. Awaleh, M. M. Waberi, and A. B. I. Adan, "Wind resource assessment and techno-economic analysis of wind energy and green hydrogen production in the Republic of Djibouti," *Energy Reports*, vol. 8, pp. 8996–9016, 2022.

[67] L. Al-Ghussain, R. Samu, O. Taylan, and M. Fahrioglu, "Sizing renewable energy systems with energy storage systems in microgrids for maximum cost-efficient utilization of renewable energy resources," *Sustainable Cities and Society*, vol. 55, no. December 2019, p. 102059, 2020.

[68] F. Penizzotto, R. Pringles, and F. Olsina, "Real options valuation of photovoltaic power investments in existing buildings," *Renewable and Sustainable Energy Reviews*, vol. 114, no. January, p. 109308, 2019.

[69] P. H. Shaikh, A. Shaikh, Z. A. Memon, A. A. Lashari, and Z. H. Leghari, "Microgrids: A review on optimal hybrid technologies, configurations, and applications," *International Journal of Energy Research*, vol. 45, no. 9, pp. 12564–12597, 2021.

[70] F. A. Alturki, A. A. Al-Shamma'a, H. M. Farh, and K. AlSharabi, "Optimal sizing of autonomous hybrid energy system using supply-demand-based optimization algorithm," *International Journal of Energy Research*, vol. 45, no. 1, pp. 605–625, 2021.

[71] B. Steffen, "Estimating the cost of capital for renewable energy projects," *Energy Economics*, vol. 88, p. 104783, 2020.

[72] L. Uwineza, H. G. Kim, and C. K. Kim, "Feasibilty study of integrating the renewable energy system in Popova Island using the Monte Carlo model and HOMER," *Energy Strategy Reviews*, vol. 33, p. 100607, 2021.

[73] C. Mokhtara, B. Negrou, N. Settou, B. Settou, and M. M. Samy, "Design optimization of off-grid Hybrid Renewable Energy Systems considering the effects of building energy performance and climate change: Case study of Algeria," *Energy*, vol. 219, p. 119605, 2021.

[74] B. Steffen, "Estimating the cost of capital for renewable energy projects," *Energy Economics*, vol. 88, p. 104783, 2020.

[75] B. of algeria, "Indicators," 2022.

[76] M. Alramlawi and P. Li, "Design optimization of a residential pv-battery microgrid with a detailed battery lifetime estimation model," *IEEE Transactions on Industry Applications*, vol. 56, no. 2, pp. 2020–2030, 2020.

[77] A. S. Aziz, M. F. N. Tajuddin, M. R. Adzman, A. Azmi, and M. A. Ramli, "Optimization and sensitivity analysis of standalone hybrid energy systems for rural electrification: A case study of Iraq," *Renewable Energy*, vol. 138, pp. 775–792, 2019.

[78] D. Fioriti, R. Giglioli, D. Poli, G. Lutzemberger, A. Micangeli, R. Del Citto, I. Perez-Arriaga, and P. Duenas-Martinez, "Stochastic sizing of isolated rural mini-grids, including effects of fuel procurement and operational strategies," *Electric Power Systems Research*, vol. 160, pp. 419–428, 2018.

[79] L. Raji, Z. Y.I, and W. J, "Using Homer Software for Cost Analysis of Stand-Alone Power Generation for Small Scale Industry in Nigeria: A Case Study Lumatec Aluminium Products," *Current Journal: International Journal Applied Technology Research*, vol. 2, no. 2, pp. 90–102, 2021.

[80] M. Kharrich, S. Kamel, M. Abdeen, O. H. Mohammed, M. Akherraz, T. Khurshaid, and S. B. Rhee, "Developed approach based on equilibrium optimizer for optimal design of hybrid PV/Wind/Diesel/Battery Microgrid in Dakhla, Morocco," *IEEE Access*, vol. 9, pp. 13655–13670, 2021.

[81] H. U. R. Habib, S. Wang, M. R. Elkadeem, and M. F. Elmorshedy, "Design Optimization and Model Predictive Control of a Standalone Hybrid Renewable Energy System: A Case Study on a Small Residential Load in Pakistan," *IEEE Access*, vol. 7, pp. 117369–117390, 2019.

[82] J. Lian, Y. Zhang, C. Ma, Y. Yang, and E. Chaima, “A review on recent sizing methodologies of hybrid renewable energy systems,” *Energy Conversion and Management*, vol. 199, no. April, p. 112027, 2019.

[83] C. Shilaja, G. Nalinashini, N. Balaji, and K. Sujatha, “A Study on Optimal Power Solution through Optimization Technique in Solar Power,” *Journal of University of Shanghai for Science and Technology*, vol. 23, no. 06, pp. 565–587, 2021.

[84] R. S. Nuvvula, D. Elangovan, K. S. Teegala, R. M. Elavarasan, M. R. Islam, and R. Inapakurthi, “Optimal sizing of battery-integrated hybrid renewable energy sources with ramp rate limitations on a grid using ala-qpso,” *Energies*, vol. 14, no. 17, 2021.

[85] W. M. Hamanah, M. A. Abido, and L. M. Alhems, “Optimum Sizing of Hybrid PV, Wind, Battery and Diesel System Using Lightning Search Algorithm,” *Arabian Journal for Science and Engineering*, vol. 45, no. 3, pp. 1871–1883, 2020.

[86] Z. A. Baloch, Q. Tan, H. W. Kamran, M. A. Nawaz, G. Albashar, and J. Hameed, “A multi-perspective assessment approach of renewable energy production: policy perspective analysis,” *Environment, Development and Sustainability*, vol. 24, no. 2, pp. 2164–2192, 2022.

[87] À. Alonso-Travesset, H. Martín, S. Coronas, and J. De La Hoz, “Optimization Models under Uncertainty in Distributed Generation Systems: A Review,” *Energies*, vol. 15, no. 5, 2022.

[88] H. Dai, N. Li, Y. Wang, and X. Zhao, “The Analysis of Three Main Investment Criteria: NPV IRR and Payback Period,” *Atlantic Press*, vol. 648, no. Icfied, pp. 185–189, 2022.

[89] M. Kiehbadroudinezhad, A. Merabet, and H. Hosseinzadeh-Bandbafha, “Review of Latest Advances and Prospects of Energy Storage Systems: Considering Economic, Reliability, Sizing, and Environmental Impacts Approach,” *Clean Technologies*, vol. 4, no. 2, pp. 477–501, 2022.

[90] P. Rotella Junior, L. C. S. Rocha, S. N. Morioka, I. Bolis, G. Chicco, A. Mazza, and K. Janda, “Economic analysis of the investments in battery energy storage systems: Review and current perspectives,” *Energies*, vol. 14, no. 9, pp. 1–30, 2021.

[91] X. Fu, X. Wu, C. Zhang, S. Fan, and N. Liu, “Planning of distributed renewable energy systems under uncertainty based on statistical machine learning,” *Protection and Control of Modern Power Systems*, 2022.

[92] M. Haugen, H. Farahmand, S. Jaehnert, and S. Erik, *Representation of uncertainty in market models for operational planning and forecasting in renewable power systems : a review.* No. 0123456789, Springer Berlin Heidelberg, 2023.

[93] M. Farghali, A. I. Osman, Z. Chen, A. Abdelhaleem, and I. Ihara, *Social , environmental , and economic consequences of integrating renewable energies in the electricity sector : a review*, vol. 21. Springer International Publishing, 2023.

[94] O. O. Owolabi, T. L. J. Schafer, G. E. Smits, S. Sengupta, S. E. Ryan, L. Wang, D. S. Matteson, M. Getmansky Sherman, and D. A. Sunter, "Role of Variable Renewable Energy Penetration on Electricity Price and its Volatility across Independent System Operators in the United States," *Data Science in Science*, vol. 2, no. 1, pp. –, 2023.

[95] S. Chakraborty, R. Verzijlbergh, Z. Lukszo, M. Cvetkovic, and K. Baker, "The Role of Demand-Side Flexibility in Hedging Electricity Price Volatility in Distribution Grids," 2019.

[96] T. Schittekatte, M. Stadler, G. Cardoso, S. Mashayekh, and N. Sankar, "The impact of short-term stochastic variability in solar irradiance on optimal microgrid design," pp. 1–10, 2016.

[97] K. P. Kumar and B. Saravanan, "Recent techniques to model uncertainties in power generation from renewable energy sources and loads in microgrids – A review," *Renewable and Sustainable Energy Reviews*, no. December, pp. 1–11, 2016.

[98] H. Bakhtiari, J. Zhong, and M. Alvarez, "Predicting the stochastic behavior of uncertainty sources in planning a stand-alone renewable energy-based microgrid using Metropolis – coupled Markov chain Monte Carlo simulation," vol. 290, no. February, 2021.

[99] E. Oh and S. Y. Son, "Theoretical energy storage system sizing method and performance analysis for wind power forecast uncertainty management," *Renewable Energy*, vol. 155, pp. 1060–1069, 2020.

[100] B. Karatop, B. Taşkan, E. Adar, and C. Kubat, "Decision analysis related to the renewable energy investments in Turkey based on a Fuzzy AHP-EDAS-Fuzzy FMEA approach," *Computers and Industrial Engineering*, vol. 151, no. November, 2021.

[101] M. Flora, P. Tankov, and I. P. Paris, "Green investment and asset stranding under transition scenario uncertainty ," pp. 1–21, 2022.

[102] G. Lu, Y. Yang, Z. Li, and Y. Tang, “Optimal energy portfolio allocation method for regulable hydropower plants considering the impact of new energy generation,” *Frontiers in Energy Research*, vol. 11, no. March, pp. 1–15, 2023.

[103] A. Vasiliev, N. Vasilieva, and N. Tupko, “Development of a Systems Approach To Assessment of Investment Project Risks: Risks of Unacceptably Low Project Profitability,” *Eastern-European Journal of Enterprise Technologies*, vol. 1, no. 4-115, pp. 77–86, 2022.

[104] A. Zakaria, F. B. Ismail, M. S. H. Lipu, and M. A. Hannan, “Uncertainty models for stochastic optimization in renewable energy applications,” *Renewable Energy*, vol. 145, pp. 1543–1571, 2020.

[105] L. A. Roald, D. Pozo, A. Papavasiliou, D. K. Molzahn, J. Kazempour, and A. Conejo, “Power systems optimization under uncertainty : A review of methods and applications,” vol. 214, no. May 2022, 2023.

[106] C. Science, C. Science, T. Supervisor, C. Science, T. Supervisor, L. A. Kolodziejski, and C. Science, “Decision-making under uncertainty for electric power system operation and expansion planning by,” no. 2017, 2022.

[107] J. Sowinski, “Application of Real Options Approach to Analyse Economic Efficiency of Power Plant with CCS Installation under Uncertainty,” *Energies*, vol. 15, no. 3, 2022.

[108] H. Verdejo, A. Awerkin, W. Kliemann, and C. Becker, “Electrical Power and Energy Systems Modelling uncertainties in electrical power systems with stochastic di ff erential equations,” *Electrical Power and Energy Systems*, vol. 113, no. May, pp. 322–332, 2019.

[109] S. N. I. Ibrahim, M. Misiran, and M. F. Laham, “Geometric fractional Brownian motion model for commodity market simulation,” *Alexandria Engineering Journal*, vol. 60, no. 1, pp. 955–962, 2021.

[110] V. Brătian, A. M. Acu, D. M. Mihaiu, and R. A. Șerban, “Geometric Brownian Motion (GBM) of Stock Indexes and Financial Market Uncertainty in the Context of Non-Crisis and Financial Crisis Scenarios,” *Mathematics*, vol. 10, no. 3, 2022.

[111] M. Zhang, L. Liu, Q. Wang, and D. Zhou, “Valuing investment decisions of renewable energy projects considering changing volatility,” *Energy Economics*, vol. 92, p. 104954, 2020.

[112] W. Data, “Infaltion rate 1970-2022 Algeria,” 2023.

[113] G. petrolprices, “fuel prices,” 2023.

[114] HOMER, “The HOMER Pro® Microgrid Software.”