REPUBLIQUE ALGERIENNE DEMOCRATIQUE ET POPULAIRE
الجـمـهـوريـة الجـزائـريـة الديـمـقـراطيــة الشـعـبـيــة

MINISTRY OF HIGHER EDUCATION
AND SCIENTIFIC RESEARCH

HIGHER SCHOOL OF APPLIED SCIENCES
--TLEMCEN--

وزارة التعليـم العالـي والبحـث العلمـي

المـدرسـة العليـا في العلوم التطبيقيــة
-تلمسان-

End of study thesis

For of obtaining the Engineering degree

Field : **Electrotechnics**
Specialty : **Energy and environment**

Presented by:
TELLAB Souleyman
BOUAZDIA Wail

Theme

Sizing and optimization of a hybrid photovoltaic/wind energy system with a storage system using genetic algorithms

Publicly defended on 02/07/2023, before the jury composed of:

Mme N. Benahmed	Pr	ESSA. Tlemcen	President
Mr M. Mebrouki	MCA	ESSA. Tlemcen	Thesis Supervisor
Mr A.K. Chemidi	MCA	ESSA. Tlemcen	Examinator 1
Mr A.K. Ghezouani	Doctor	Univ. Bechar	Examinator 2

College year : 2022/2023

Abbreviations

1. PV : Photovoltaic
2. ESSs : Energy Storage Systems
3. DC : Direct Current
4. AC : Alternating Current
5. LP : Linear Programming
6. NLP : Non-Linear Programming
7. QP : Quadratic Programming
8. GA : Genetic Algorithm
9. DNA : Deoxyribonucleic Acid
10. GSA : Generalized Simulated Annealing
11. PSO : Particle Swarm Optimization
12. ACO : Ant Colony Optimization
13. HSA : Harmony Search
14. TS : Tabu Search
15. ABC : The Artificial Bee Colony
16. HRESs : Hybrid Renewable Energy Systems
17. DP : Dynamic Programming
18. RET : Region Elimination Technique
19. SA : Simulated Annealing
20. HBB-BC : The Hybrid Big Bang-Big Crunch Algorithm
21. HGA : Hybrid Genetic Algorithm
22. MILP : Mixed Integer Linear Programming
23. MOPSO :Multi-Objective Particle Swarm Optimization
24. NSGA-II : Non-Dominated Sorting Genetic Algorithm
25. ACO : Ant Colony Optimization

26. CDIP : Continuous Domain Integer Programming
27. MPPT : Maximum Power Point Tracker
28. NOCT : Nominal Operating Cell Temperatue
29. SOC : State Of Charge
30. DOD : Depth Of Discharge
31. LPSP : The Loss Of Power Supply Probability

Abstract

The increasing demand for clean and sustainable energy sources, coupled with the need to mitigate climate change, has driven the widespread adoption of renewable energy systems. Among these, hybrid photovoltaic (PV)/wind/batteries systems have emerged as a promising solution to address the intermittent nature of solar and wind energy sources. This dissertation focuses on the optimization and performance evaluation of hybrid PV/wind/batteries systems using genetic algorithms (GA). The objective is to minimize system costs while ensuring reliable power supply by integrating PV panels, wind turbines, and energy storage batteries. The study considers multiple sites and factors such as solar irradiance, wind speed, load demand, and storage capacity to determine the optimal system configurations. Through extensive simulations and analysis, the research provides insights into the cost-effectiveness, reliability, and performance of hybrid energy systems.
Keywords: Renewable energy, hybrid systems, photovoltaic, wind, batteries, genetic algorithms, optimization, performance evaluation, solar irradiance, wind speed, load demand, storage capacity, cost-effectiveness, reliability, performance.

Résumé

La demande croissante de sources d'énergie propres et durables, associée à la nécessité de lutter contre le changement climatique, a conduit à l'adoption généralisée de systèmes d'énergie renouvelable. Parmi ceux-ci, les systèmes hybrides photovoltaïques (PV)/éolien/batteries se sont imposés comme une solution prometteuse pour pallier la nature intermittente des sources d'énergie solaire et éolienne. Cette thèse se concentre sur l'optimisation et l'évaluation des performances des systèmes hybrides PV/éolien/batteries en utilisant des algorithmes génétiques (GA). L'objectif est de minimiser les coûts du système tout en garantissant une alimentation électrique fiable en intégrant des panneaux solaires PV, des éoliennes et des batteries de stockage d'énergie. L'étude prend en compte plusieurs sites et des facteurs tels que l'irradiance solaire, la vitesse du vent, la demande en énergie et la capacité de stockage pour déterminer les configurations optimales du système. Grâce à des simulations approfondies et à des analyses, la recherche apporte des éclairages sur l'efficacité économique, la fiabilité et les performances des systèmes d'énergie hybride.
Mots clés: Énergie renouvelable, systèmes hybrides, photovoltaïque, éolien, batteries, algorithmes génétiques, optimisation, évaluation des performances, irradiance solaire, vitesse du vent, demande en énergie, capacité de stockage, efficacité économique, fiabilité, performances.

ملخص

الطلب المتزايد على مصادر الطاقة النظيفة والمستدامة، إلى جانب الحاجة للتصدي لتغير المناخ. في هذا السياق، ظهرت الأنظمة الشمسية الضوئية والرياح والبطاريات الهجينة كحلاً واعدًا للتعامل مع طبيعة الطاقة المتقطعة لمصادر الطاقة الشمسية والرياح. تركز هذه الأطروحة على تحسين وتقييم أداء الأنظمة الهجينة باستخدام خوارزميات التحسين الجيني. الهدف هو تحقيق أقل تكلفة للنظام مع ضمان توفير طاقة موثوقة من خلال دمج الألواح الشمسية ومحولات الرياح وبطاريات التخزين. يأخذ البحث في الاعتبار مواقع متعددة وعوامل مثل أشعة الشمس وسرعة الرياح والطلب على الطاقة وسعة التخزين لتحديد التكوينات النظام الأمثل. من خلال المحاكاة والتحليل المتعمق، يوفر هذا البحث رؤى قيمة حول الكفاءة من حيث التكلفة والموثوقية وأداء أنظمة الطاقة الهجينة.

الكلمات المفتاحية: الطاقة المتجددة، الأنظمة الهجينة، الطاقة الشمسية، الرياح، البطاريات، خوارزميات التحسين الجيني، التقييم الأداء، أشعة الشمس، سرعة الرياح، الطلب على الطاقة، سعة التخزين، الكفاءة من حيث التكلفة، الموثوقية، أداء

Dedication

To my cherished family,
To my dearest friends,
To my esteemed mentors and advisors,
And to all those who have stood by my side throughout this journey.

Your unwavering support and encouragement have been invaluable
in my pursuit of knowledge and the completion of this thesis.
You have been my guiding lights, offering guidance
and uplifting me during moments of doubt and challenge.

I am deeply grateful for your presence in my life
and for the profound impact you have had on my path.
Your belief in my abilities has fueled my determination,
and I carry your faith and encouragement within me always.

This work is dedicated to each and every one of you
as a tribute to the power of genuine connections,
unyielding support, and shared aspirations.
Thank you for being the pillars of strength in my journey.

With heartfelt appreciation,
TELLAB Souleyman

Dedication

To my family, friends, and mentors,
whose unwavering support and encouragement
have been invaluable throughout my journey.

This work is dedicated to all of you,
as a token of my gratitude
for your belief in me and constant inspiration.

Thank you for always being there
and for making this achievement possible.

With deepest appreciation,
BOUAZDIA Wail

Acknowledgments

We would like to express our sincere appreciation to our supervisor, Mebrouki Mohamed, for his valuable guidance and support throughout this dissertation. We are grateful for his expertise and dedication, which have greatly contributed to the completion of this research. We also extend our thanks to the members of our jury, N. Benahmed, A.K. Chemidi, and A.K. Ghezouani, for their time and insightful feedback. We would like to acknowledge the support and resources provided by the Higher School of Applied Sciences of Tlemcen, which have been instrumental in the completion of this dissertation.

Contents

List of Figures

List of Tables

General introduction

The escalating global energy demand, coupled with the urgent need to reduce greenhouse gas emissions, has prompted a shift towards renewable energy sources. Photovoltaic (PV) and wind energy have emerged as leading contenders in the transition to a sustainable energy future. PV systems harness the sun's energy to generate electricity, while wind turbines capture the kinetic energy of the wind. Both sources offer abundant availability and produce minimal greenhouse gas emissions during operation.
However, one of the main challenges associated with PV and wind energy is their intermittent nature. Solar energy generation is dependent on daylight hours and weather conditions, while wind energy production relies on the strength and consistency of wind patterns. This intermittency introduces fluctuations in energy supply, making it difficult to meet the constant energy demands of modern societies.
To address this issue, hybrid PV/wind systems, also known as renewable energy hybrid systems, have gained traction. By integrating PV and wind technologies, these hybrid systems can harness the complementary nature of solar and wind resources, maximizing energy generation potential. Moreover, to ensure a continuous power supply, energy storage systems, such as batteries, are incorporated into these hybrid systems. Batteries store excess energy during periods of high generation and discharge it when energy demand exceeds the renewable energy generation capacity.
The integration of batteries into hybrid PV/wind systems introduces flexibility and enhances system resilience. Excess energy generated during peak periods is stored for use during periods of low generation, effectively mitigating the intermittent nature of solar and wind sources. This storage capability ensures a reliable and stable power supply, reducing reliance on conventional energy sources and increasing the overall penetration of renewable energy.
To optimize the performance and economic viability of hybrid PV/wind/batteries systems, sophisticated optimization techniques are employed. Genetic algorithms (GA) have proven to be effective in solving complex optimization problems by simulating natural selection processes. By iteratively evaluating different system configurations, GA algorithms can identify the most optimal combinations of PV panels, wind turbines, and batteries. These optimized configurations aim to maximize energy generation, minimize system costs, and maintain a high level of reliability in meeting energy demands.
This thesis aims to contribute to the advancement of hybrid PV/wind/batteries systems through the application of genetic algorithms for system optimization. The study focuses on evaluating the performance and cost implications of these systems at various sites, taking into account factors such as solar irradiance, wind speed, load demand, and storage capacity.
By optimizing hybrid PV/wind/batteries systems, we can harness the full potential of renewable energy sources while ensuring a reliable and sustainable power supply. The integration of these systems offers a promising pathway towards a decarbonized energy future, reducing greenhouse gas emissions and promoting long-term energy security.
This thesis is organized into three main chapters. In Chapter 1, we review the various sizing methods and optimization techniques used for stand-alone hybrid systems, specifically focusing on photovoltaic-wind systems with storage for isolated sites. Chapter 2 delves into the mathe-

matical models of the components studied within the hybrid system. Finally, in Chapter 3, we present and analyze the results of our work, highlighting key findings and their implications. Through this structure, the thesis contributes to the understanding of sizing methods, mathematical modeling, and the evaluation of hybrid photovoltaic-wind power systems with storage for isolated sites.

Chapter 1

Sizing hybrid photovoltaic-wind power systems: an introduction to methods and concepts

1.1 Introduction

In recent years, there has been increasing focus on hybrid power systems, which combine two or more power supplies to provide more reliable and cost-effective power. Hybrid systems offer many advantages, including increased energy reliability, cost savings, reduced environmental impact, increased energy independence and flexibility in energy use. For example, a hybrid system that combines solar panels and battery backup can provide power during periods of low solar radiation or blackouts, reducing reliance on the grid or other external energy sources. However, the optimal configuration of a hybrid system depends on many factors, including the user's specific energy needs and available resources.

As society becomes more aware of the environmental impact of conventional energy sources, renewable energy systems are gaining popularity as a cleaner and more sustainable alternative. However, the intermittent nature of renewable energy can present challenges in meeting energy demands and achieving optimal system performance.Hybrid systems that combine multiple renewable energy sources such as wind and photovoltaics can address these challenges by providing more reliable and consistent energy.A critical aspect of designing a successful hybrid renewable energy system is the precise sizing of its components. This phase determines the optimal sizing of various system components and has a significant impact on system performance, efficiency and overall cost-effectiveness. Therefore, careful consideration and accurate sizing are critical to realizing the full potential of a hybrid renewable energy system.

1.2 Renewable energies vs fossil fuels: a comparative study

1.2.1 Environmental impact

Renewable energy sources have been shown to have a lesser environmental impact when compared to fossil fuels. This conclusion is supported by various measures such as the reduction in air and water pollution, decreased harm to public health, lessened wildlife and habitat loss, lowered water and land use, and minimized global warming emissions that are associated with renewable energy sources. In summary, the available scientific evidence indicates that renewable energy sources are a more environmentally sound choice than fossil fuels [1].

1.2.2 Resource availability

Renewable energy sources, such as solar and wind power, are naturally replenished and have become widely recognized as a crucial component of the transition to clean energy and climate change mitigation. However, the intermittency of renewable energy, which relies on weather and time of day, necessitates the use of energy storage systems to ensure a dependable electricity supply. In addition, the implementation of renewable energy requires a significant amount of land and appropriate transmission infrastructure. In contrast, fossil fuels have a limited reserve that will eventually be depleted, leading to a non-renewable energy crisis [2] [3] [4].

1.2.3 Cost

The cost competitiveness of renewable energy sources in comparison to fossil fuels is increasing. Recently, the International Energy Agency reported that the cost per megawatt to construct solar plants worldwide is now less than that of fossil fuels for the first time. The cost of large-scale solar plants is about $45 per megawatt-hour, while new onshore wind costs approximately $46 per megawatt-hour. By contrast, the construction of new coal-fired plants has a cost of $74 per MWh, while gas plants have an expense of approximately $56 per MWh [5] [6].

1.3 Why hybrid energy systems

1.3.1 Increasing energy efficiency

Hybrid energy systems have the potential to increase energy efficiency by integrating multiple energy generation, storage, and conversion technologies, resulting in enhanced capabilities, cost savings, improved environmental performance, and greater value when compared to independent alternatives. The integration of different energy sources and storage technologies in hybrid systems can lead to increased system efficiency and flexibility, which can help plants optimize their revenue and create new and valuable products. Hybridization has become an attractive solution in the power sector due to its ability to offer a range of benefits to both the energy providers and consumers [7].

1.3.2 Reliability

Hybrid energy systems, which integrate renewable energy sources with backup energy storage solutions, have the potential to provide a continuous and reliable power supply without interruptions. When there is a power outage, the energy storage units connected to hybrid solar systems can store the excess energy generated by the renewable sources. These energy storage units can also function as inverters, enabling them to supply continuous power even during outages. This ensures that the power supply remains stable, thereby increasing the reliability of the energy system [8].

1.4 Components of hybrid energy system

1.4.1 Photovoltaic panels

Photovoltaic (PV) panels are electrical devices that convert solar energy into usable electricity. They are composed of semiconductor materials, with mono-crystalline and poly-crystalline silicon being the most commonly used [9].

1.4.1.1 Operation

The photovoltaic effect is the process by which a photovoltaic cell converts sunlight into electrical energy. The cell is made of two types of semiconductors that form a pn junction. When photons of an appropriate wavelength are absorbed, valence electrons are promoted to the conduction band, generating an electron-hole pair. The built-in electric field of the pn junction separates these carriers, creating a flow of electrical current [10].

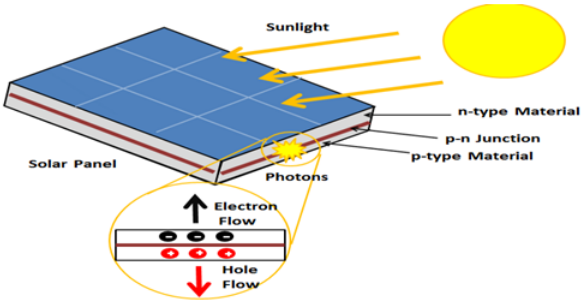

Figure 1.1: A Diagram showing the photovoltaic effect [11].

1.4.1.2 Factors affecting current and power output in PV cells

The amount of current and power produced by a photovoltaic (PV) cell is influenced by various factors, including environmental, PV system, installation, cost, and miscellaneous factors. Environmental factors such as solar irradiance, temperature, and shading conditions affect energy harvesting, while PV system factors like panel size and orientation impact energy conversion. Installation factors such as proper placement and orientation, and cost factors such as initial investment and maintenance costs can also affect efficiency. Miscellaneous factors like soiling of panels, spectral effects, and mismatch losses can further reduce power output [12].

1.4.1.3 Types of photovoltaic panels:

1. **Monocrystalline polar panel :**
   A monocrystalline solar panel is composed of monocrystalline solar cells. These cells are named after a cylindrical silicon ingot grown from high-purity single-crystal silicon in the same way as a semiconductor. Because the cell is made of a single crystal, the electrons have more space to move, which ensures better flow of electricity. The cylindrical ingot is sliced into wafers that form the cells. To maximize the utility of the cells, the circular wafers are wire cut into octagonal-shaped wafers. These cells have a unique appearance due to their octagonal shape, and they also have a uniform color [13].

   Monocrystalline solar panels have advantages such as high efficiency levels ($17\% - 22\%$), requiring less space, and a 25-year warranty. They also perform well in low levels of sunlight and have greater heat resistance. However, they are the most expensive type of solar panel and their performance tends to decline with temperature. The manufacturing process generates waste due to cutting the silicon [13].

2. **polycrystalline solar panel :**
   Polycrystalline or multicrystalline solar panels are made up of multiple fragments of silicon that are melted together to form the wafers of the panel. These panels have a mosaic-like surface and a square shape with a shining blue hue. The molten silicon used to produce

the cells is allowed to cool on the panel, resulting in multiple silicon crystals in each cell. As a result, polycrystalline panels have limited electron movement within the cells. These solar panels absorb solar energy and convert it into electricity [13].

3. **Thin-film solar panels:**
Thin-film solar panels use the photovoltaic effect to convert light energy into electrical energy and are made of multiple thin layers of photovoltaic materials. They are lightweight and flexible, making them ideal for portable applications. Each cell is composed of a photovoltaic material, a conductive sheet, and a protective layer. Thin-film panels offer unique advantages in terms of flexibility and weight compared to traditional monocrystalline and polycrystalline panels [14].

1.4.2 Wind turbine generator

Wind turbines are devices that convert the kinetic energy of wind into electrical energy. There are two main types of wind turbines: horizontal-axis turbines and vertical-axis turbines. The size of wind turbines can vary widely, with small wind turbines designed for a single home having an electricity generating capacity of 10 kilowatts and the largest utility-scale wind turbines generating up to 15 megawatts. Multiple large turbines are often grouped together to create wind farms that can provide electricity to local or regional electricity grids [15].

1.4.2.1 Horizontal-axis turbines

Horizontal-axis wind turbines are equipped with blades that resemble airplane propellers and typically have three blades. The largest horizontal-axis turbines can reach heights equivalent to 20-story buildings and feature blades that extend over 100 feet in length. These turbines generate more electricity due to their greater height and longer blade length. The vast majority of wind turbines that are currently being utilized are horizontal-axis turbines [15].

1.4.2.2 Vertical-axis turbines

Vertical-axis wind turbines are equipped with blades that are attached to the top and bottom of a vertical rotor. The most widely used type of vertical-axis turbine is the Darrieus wind turbine, which was patented in 1931 by the French engineer Georges Darrieus. The Darrieus turbine has a distinctive appearance, resembling a large, two-bladed egg beater. Some versions of vertical-axis turbines can be as large as 100 feet tall and 50 feet wide. However, the performance of vertical-axis turbines is generally inferior to that of horizontal-axis turbines, which is why they are not widely used [15].

1.4.3 Storage system

The emergence of new energy storage technologies promises to improve the reliability and productivity of renewable energy sources. Energy storage systems (ESSs) enable the balancing of supply fluctuations and provide backup power during outages, resulting in a more stable and reliable power grid. A range of electric storage technologies, including batteries, supercapacitors, and hydrogen storage, have been developed, each with their own advantages and limitations in terms of efficiency, cost, and environmental impact. Electric batteries, which utilize electrochemical reactions to store and deliver energy, are a vital component of hybrid renewable energy systems and require continuous research and innovation for the advancement of sustainable energy. Understanding the principles of battery operation and selecting the most suitable storage solution for a particular application are essential for the development of efficient energy storage systems [16].

1.4.4 Charge controller

A charge controller (regulator) plays a crucial role in ensuring and regulating the battery charging process. It helps to optimize the performance of solar panels and wind turbines while also preventing the occurrence of deep discharges or overcharges [17].

1.4.5 Inverter

Inverters play a crucial role in the conversion of direct current (DC) electricity generated by solar panels into alternating current (AC) electricity, which can be used by the electrical grid. They are essential in converting DC electricity from sources such as batteries, fuel cells, or solar panels to AC electricity. This is done by rapidly switching the direction of the DC input back and forth, effectively transforming it into an AC output. The primary goal of an inverter is to facilitate this DC-to-AC conversion process [18].

1.5 Configuration of hybrid energy system

1.5.1 Series architecture

1.5.1.1 Configuration with direct current bus

In a series architecture, all energy sources are connected to a common direct current (DC) bus.In this architecture, the alternating current (AC) voltages generated by the wind turbine and modules are rectified into direct current voltages using AC/DC converters. The load is then supplied by an inverter (DC/AC converter) [19].

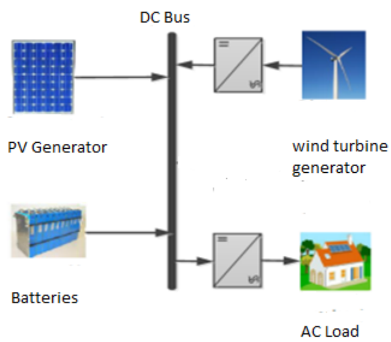

Figure 1.2: Configuration with direct current Bus [19].

1.5.1.2 AC bus configuration:

The AC bus architecture has emerged with the development of power electronics and the availability of more efficient inverters. This architecture features a single AC bus to which all hybrid system modules are connected [19].

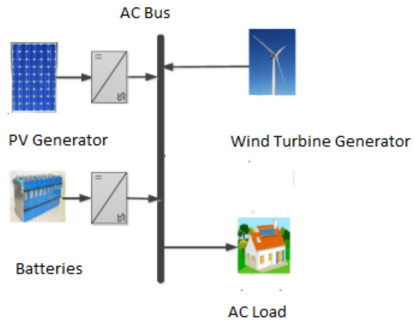

Figure 1.3: Configuration of a hybrid system with an AC bus [19].

1.5.2 Parallel architecture :

The parallel configuration of a hybrid system utilizes two buses, a DC bus for direct current sources such as batteries and PV panels, and an AC bus for the wind turbine and load. These two buses are connected through a bidirectional converter which operates in rectifier mode when the load is supplied by the PV panels or batteries and charges the energy storage system, and in inverter mode when the load is supplied by the wind turbine. This configuration allows for the load to be supplied by both buses at the same time, increasing the flexibility and reliability of the system [19].

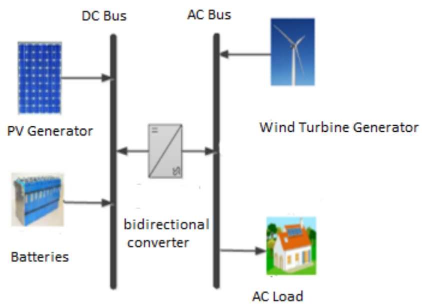

Figure 1.4: Parallel architecture [19].

1.6 Methods for sizing hybrid systems

1.6.1 Classical techniques

1.6.1.1 Analytical approaches

Analytical optimization approaches involve creating numerical equations through theoretical and mathematical analysis. They can be combined with simulation models to ensure convergence and offer the benefits of quick computing time and ease of implementation. However, simplifying assumptions may limit accuracy in complex problems. An effective use of analytical methods was seen in power systems where continuous power flow analysis identified buses prone to voltage drop, resulting in improved voltage profile, reduced power loss, and increased transfer capacity. [20]

1.6.1.2 Linear and non-linear programming (LP & NLP)

Linear programming (LP) and nonlinear programming (NLP) are mathematical tools utilized to optimize objective functions subject to a set of constraints. LPs and NLPs are widely used in diverse fields, including computer science, mathematics, business, economics, engineering, and the sciences. While LPs can be solved using a finite procedure, no such method exists for NLPs. However, the Kuhn-Tucker condition method has proven to be an effective approach for solving NLP problems, and it allows for reducing QP problems to the form of an LP problem, which can be solved using simplex-type algorithms such as Wolfe's Algorithm. Therefore, the use of LP and NLP models, along with their associated optimization methods, has become essential in various fields to enhance decision-making processes and improve system performance [21].

1.6.1.3 Fuzzy logic

The concept of partial truth, where truth values may range between completely true or false, is at the core of fuzzy logic. It uses membership functions, which assign truth values to variables between 0 and 1, to represent degrees of truth. Fuzzy logic provides an inference structure that closely mimics human reasoning, called a fuzzy inference system. The Mamdani method, which uses fuzzy sets, rules, and logic, is a popular decision-making process based on fuzzy logic. Fuzzy logic has wide-ranging applications, including air conditioning, transportation planning, medical diagnosis, and various branches of engineering and research [22].

1.6.1.4 Graphical construction method

The method is based on the condition that the average demand must be met by the average solar radiation and wind speed for a given size of PV generator and wind turbine. The seasonal variation of demand and resource availability is analyzed for winter and summer months. Based on the analysis, a sizing curve is developed between the available various sizes of wind turbines and PV generators. If data are collected for a larger number of times, a more refined curve can be obtained [23].

1.6.1.5 Iterative approach

The iterative approach for evaluating the performance of an integrated energy system involves using a recursive program that stops when the optimal system design is achieved. The optimization model used in this approach considers parameters such as the capacity of PV panels, rated power of wind system, and battery bank storage capacity to minimize the system cost while meeting the desired reliability level. However, this approach does not optimize other parameters such as PV area, PV module slope angle, wind turbine swept area, and wind turbine installation heights which can significantly impact system costs. Therefore, it may be necessary to reformulate the approach to include these parameters in the optimization model for a more accurate evaluation of the integrated energy system's performance. [24]

1.6.1.6 Probabilistic approaches

Probabilistic approaches for sizing integrated energy systems consider the effect of insolation and changes in wind speed when designing the system. However, these approaches have limitations in characterizing the dynamic changing performance of the integrated or hybrid system. To address this limitation, it may be necessary to reformulate the probabilistic approach by incorporating models that account for the system's response to changes in resource generation and demand, using time-series data, and accounting for interactions between the different components of the integrated energy system. By including these models, the probabilistic approach can provide a more accurate and comprehensive evaluation of the performance of the integrated energy system under varying conditions [24].

1.6.1.7 The trade-off approach:

The trade-off approach is a method that considers both the cost and reliability of hybrid energy systems. However, it is not commonly used in hybrid system sizing and has limited research available. The approach can provide robust designs but requires decision-makers to make the final decision, and it does not consider emission control. To address this limitation, incorporating models that account for emission control may provide a more accurate evaluation of hybrid system performance and help decision-makers make informed decisions [25].

1.6.2 Intelligent search methods:

1.6.2.1 Genetic algorithm :

Genetic algorithm (GA) is a search strategy that applies principles of evolutionary biology to address complex search spaces by utilizing crossover, mutation, and natural selection. By maintaining diversity through genetic operators such as crossover and mutation, the GA can find feasible solutions and prevent early convergence to a local maximum. The GA is highly effective in resolving combinatorial optimization problems and generating high-quality solutions for optimization problems. Its success is largely attributed to the evolution of diverse individuals within a population, following the principle of survival of the fittest. The genetic algorithm is used as an optimization tool to minimize a given function by generating a population of solutions and producing offspring solutions by combining two parental solutions, much like the combination of DNA in biological offspring [26].

1.6.2.2 Simulated annealing

Simulated annealing is an iterative, stochastic algorithm used to approximate the global optimum of a problem. It gradually converges to a near-optimal solution by accepting moves that may reduce the solution quality, based on a parameter called temperature. This algorithm has been proven to sample the parameter space more efficiently than other previous simulated annealing algorithms. An extended version of simulated annealing has been introduced for multiobjective optimization, which allows for the construction of near-Pareto optimal solutions through the use of an archive. Several variants of multiobjective simulated annealing have been proposed in the literature. Generalized simulated annealing (GSA) is an adaptation of simulated annealing that addresses the issue of suboptimal distribution by utilizing a distorted Cauchy-Lorentz distribution [27] [28].

1.6.2.3 Particle swarm optimization:

Particle Swarm Optimization (PSO) is a metaheuristic optimization method inspired by the collective behavior of biological systems such as bird flocks. PSO represents the potential solutions of an optimization problem as particles and updates the particle positions based on the personal best and global best particle positions ever found. However, the basic PSO algorithm has limitations in finding the global optimal solution due to local optima and difficulties in balancing exploration and exploitation, especially in complex functions. To overcome these issues, researchers have proposed various variants of PSO, including new parameters, adaptive methods, and using multiple best particle positions. PSO has been applied in various fields such as renewable energy systems, including photovoltaic systems, wind turbines, and hybrid systems, for tasks such as design, sizing, control, and maximum power point tracking [29] [30].

1.6.2.4 Ant colony optimization

Ant Colony Optimization (ACO) is a popular metaheuristic optimization method that mimics the behavior of ant colonies in finding the shortest path between their nest and food sources. ACO algorithms use indirect communication between ants through the deposition of pheromones on their trails to solve optimization problems. The idea is that ants use the trails with the strongest pheromone concentration to find the most promising route. ACO algorithms create solutions to an optimization problem and exchange information on their quality through a communication scheme that emulates the behavior of real ants. ACO has been applied successfully to solve complex and difficult optimization problems, and several strategies have been developed based on the ACO concept. Different variants of ACO have been proposed, including competitive ant colony optimization, artificial ant species, and multi-colony ant algorithm, to enhance the performance of ACO in solving optimization problems [31] [32].

1.6.2.5 Harmony search

The Harmony Search Algorithm (HSA) is a recently developed metaheuristic optimization algorithm inspired by the behavior of a musician producing a perfect harmony. HSA is characterized by its ability to balance exploration and exploitation during the search process and its ease of implementation compared to other metaheuristics. As a result, it has been widely applied to solve a variety of real-life optimization problems, including clustering, unconstrained benchmark functions, and water distribution system pipe diameter design problems. To improve the performance of HSA, researchers have proposed several variants, such as the multi-layered harmony search algorithm and the hybrid harmony search differential evolution algorithm. A systematic review of HSA has been conducted to explore its natural inspiration, conceptual framework, control parameters, improvement and hybridization with other metaheuristics, and applicability in various problem domains. The review highlights the potential of HSA as a promising metaheuristic optimization algorithm and its ability to solve a diverse range of optimization problems in different problem domains [33] [34] [35].

1.6.2.6 Tabu search

Tabu Search (TS) est une approche méta-heuristique qui a été initialement proposée par F. Glover en 1986 pour résoudre des problèmes d'optimisation. L'approche est basée sur le principe de la mémoire adaptative et de l'exploration réactive, qui permettent de rechercher l'espace de solution de manière économique et efficace jusqu'à ce qu'aucune amélioration ne soit atteinte. [20]

1.6.2.7 The artificial bee colony

The Artificial Bee Colony (ABC) algorithm is a swarm intelligence-based optimization approach inspired by the foraging behavior of bees, proposed by Karaboga and Basturk in 2005. It has a quick convergence speed, making it useful in solving capacity allocation problems. In a study by Mohamed et al., which applied both ABC and GA to optimize an off-grid PV-battery system, the results showed that ABC was more effective. [36]

1.6.2.8 Cuckoo search

Cuckoo search is a powerful algorithm for solving global optimization problems. It was first introduced in 2009 by Yang and Deb and has since been successfully applied in various fields, including structural engineering, image processing, protein complex identification, power flow optimization, wind energy forecasting, side lobes reduction, milling operations, and feed forwarding applications. To further enhance the performance of cuckoo search in solving optimization problems, researchers have proposed several variants, such as the modified cuckoo search algorithm. A review of the original cuckoo search algorithm and its variants, a literature survey, and a comprehensive overview of the variants of cuckoo search algorithm and their applications have been presented. These resources summarize the key features of the algorithm and its variants, as well as the latest developments in the field and the diverse range of applications where cuckoo search has been successfully applied. The review highlights the potential of cuckoo search as an efficient metaheuristic optimization algorithm and its ability to solve various optimization problems in different application domains [37] [38].

1.6.2.9 Hybrid methods

Hybrid methods that combine two or more optimization algorithms have been proposed to overcome the limitations of single methods in efficiently solving the complex and multi-dimensional optimization problems of hybrid renewable energy systems (HRESs) sizing. Many studies have shown that hybrid methods can obtain a better capacity result compared to single methods. For example, dynamic programming (DP)-region elimination technique (RET) was combined by Berrueta et al. to realize the capacity allocation and management of energy storage on a roof PV system, resulting in greater economic benefits. Katsigiannis et al. used a hybrid simulated annealing (SA)-Tabu Search (TS) method to optimize the size of an independent autonomous system, with a shorter calculation time compared to SA and TS. The hybrid Big Bang-Big Crunch algorithm (HBB-BC) was applied to a standalone PV-wind-battery system design, showing better performance than other methods. Hybrid genetic algorithm (GA)-mixed integer linear programming (MILP) algorithm was used in configuring the capacity of a microgrid, while hybrid GA-exhaustive search algorithm was proposed to optimize the impact of social-demographic factors on system capacity. Lan et al. employed a multi-objective particle swarm optimization (MOPSO) and elite non-dominated sorting genetic algorithm (NSGA-II) hybrid algorithm to optimize both the total system cost and carbon dioxide emissions of an isolated ship system. Lastly, a hybrid optimization method of ant colony optimization (ACO) based on continuous domain integer programming (CDIP) was proposed, which had a fast convergence speed and high accuracy compared to GA and ABC [36].

1.7 Load estimation and energy management

1.7.1 Load estimation methods and techniques

In the realm of hybrid renewable energy systems, load estimation methods and techniques are crucial to optimize energy production and meet load demand with minimum cost and maximum reliability. Optimization techniques such as particle swarm optimization (PSO) and exponential smoothing method are utilized to determine the optimal size of system components and predict upcoming load peak values based on historical data. Load shifting and strategic conservation methods are used for demand-side energy management. Resource estimation and load estimation serve as primary inputs for designing Hybrid Renewable Energy Systems (HRES) to ensure sustainable energy, improved reliability, and stability. Accurate load estimation methods for distribution system analysis are now possible with advanced metering infrastructure (AMI) technologies, which result in significantly improved accuracy in distribution power flow analysis. Oversizing or undersizing the system can negatively impact its economic viability [39] [40] [41].

1.7.2 Energy management strategies for hybrid systems

Effective management of energy is critical for hybrid systems to enhance the efficiency and utilization of various energy storage sources, optimizing their performance. Several energy management strategies, including online strategy, adaptive fuzzy logic control strategy, grey wolf optimization technique, Pontryagin's minimum principle, and model predictive control , are used to improve fuel consumption, the lifespan of hybrid sources, battery operating conditions, and power flow coordination among system components. The selection of a suitable energy management strategy is crucial in providing an optimal solution for designing and operating hybrid energy systems. Hybrid energy systems are considered the most viable solution to address the stochastic nature of renewable energy resources . The HOMER Pro software is used to optimize hybrid energy systems, while the exponential smoothing method is used to forecast future load peak values based on historical data. The proposed strategies are validated through simulation and experimental studies to enhance hydrogen consumption, reduce greenhouse gas emissions, and achieve cost-effective solutions [42] [41].

1.7.3 Importance of load matching and balancing in hybrid systems

Load matching and balancing play a critical role in hybrid systems by ensuring that the energy generated by various sources meets the energy demand of the system. Hybrid systems employ a combination of different renewable energy sources such as wind, solar, and hydrogen fuel cells to form an optimal and reliable power supply. Due to the use of different sources, the production profiles become intermittent and stochastic, while load profiles vary over time. Hence, load matching and balancing are essential to minimize the gap between the production and consumption curves. The Energy Management Strategy is a crucial component of hybrid systems as it coordinates the power flow among various components, taking into account power demand and other constraints. To fully comprehend the system design, Energy Management Strategy optimization and hybrid system design must be treated as a single entity. Different control strategies such as Model Predictive Control ,fuzzy logic control, and frequency-selective predictive current controller can enhance load balancing and compensate for reactive power and harmonics [12, 17] .

1.8 Economic and environmental analysis of hybrid systems

1.8.1 Economic evaluation methods for hybrid systems

There are several methods for evaluating the economic feasibility of hybrid systems, including techno-economic analysis, optimization, and modeling and simulation (M&S). Techno-economic analysis involves assessing the cost of energy, net present cost, and greenhouse gas emissions to evaluate the economic feasibility of a hybrid system. Optimization methods aim to identify the optimal configuration of a hybrid system that minimizes the net present cost or levelized cost of energy while satisfying energy demand. Modeling and simulation methods are utilized to analyze the performance of a hybrid system under different operating conditions and predict energy output and load demand. The incorporation of load prediction methods, such as the exponential smoothing method, can enhance the accuracy of the load forecast and optimize the design of the hybrid system [42] [1].

1.8.2 Environmental impact assessment of hybrid systems

The environmental impact assessment of hybrid systems involves a comprehensive evaluation of the environmental impact of the system throughout its life cycle. This assessment encompasses various parameters, including greenhouse gas emissions, energy consumption, and resource depletion, and can be conducted using life cycle analysis techniques that consider the environmental impact from raw material extraction to waste disposal. The primary objective of this assessment is to identify areas where the system can be improved to reduce its environmental impact and facilitate the selection of the most environmentally friendly hybrid system configuration. The complexity of the system and the scarcity of environmental data can pose challenges in conducting the assessment. Nonetheless, it is essential to perform this assessment to ensure the sustainability of the hybrid system and to prevent significant environmental harm [43].

1.8.3 Case studies of hybrid systems in different applications and settings :

Various case studies have explored the use of hybrid systems in different applications and settings. One study proposes a novel definition of non-deterministic hybrid systems and aims to investigate maps between all relevant dynamic systems simultaneously. Another study presents a control scheme for designing appropriate controllers for hybrid systems, which considers the switching behaviors of the system and its subsystems to achieve overall stabilization effectively. Furthermore, a third study examines the linear hybrid system with constant coefficients that is unresolved with respect to the derivative of the continuous component of the unknown function. This study establishes necessary and sufficient conditions for R-controllability (i.e., controllability in the reachable set) of the hybrid system [3].

1.9 Conclusion

In conclusion, the design of hybrid energy systems is a complex process that involves considering various components and factors. In this chapter, we have discussed the components of hybrid energy systems, including photovoltaic and wind power systems, as well as the importance of load estimation. We have also introduced methods for sizing hybrid systems, including classical and artificial intelligence approaches. Furthermore, we have highlighted the importance of economic and environmental analysis of hybrid systems, which is essential in evaluating the feasibility and sustainability of such systems. Overall, the integration of renewable energy sources through hybrid systems is a promising solution for addressing the challenges of energy security, environmental sustainability, and economic development. Further research and development of hybrid systems are needed to optimize their performance and achieve a transition towards a more sustainable energy future.

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Chapter 2

Mathematical description of hybrid system components

2.1 Introduction

In this chapter, we present a methodology for designing and optimizing hybrid systems using genetic algorithms (GAs). GAs are a type of evolutionary algorithm that mimic the natural selection and mutation process to find optimal solutions to complex problems. By using GAs, we can effectively explore the design space and find the best combination of components for a given hybrid system, taking into account different constraints and objectives. The chapter is organized as follows. In the first part, we provide an overview of the different components of the hybrid energy system, including photovoltaic panels, wind turbines, and batteries, and their influence on the system performance. We then proceed to the modeling of the overall system. The purpose of modeling is to express the technical processes of the system in mathematical form, allowing us to study and optimize the behavior of the different parameters while respecting the given constraints. The modeling of the photovoltaic-wind-battery hybrid energy system is essential to establish a direct relationship between the energy produced by the system and the energy demand of the load. Finally, we discuss the use of genetic algorithms for optimizing the hybrid system design, and demonstrate their effectiveness through numerical simulations.

2.2 Modeling of the photovoltaic generator :

The PV generator is characterized as a non-linear device, and its behavior is determined by the I-V characteristics and the equivalent circuit. Numerous mathematical models have been developed to accurately depict the performance of PV systems [1]. Designing a photovoltaic system involves selecting the optimal number of PV modules that can directly convert sunlight into DC power. A PV module is typically a collection of PV cells. The power output of each PV module at a given hour can be determined using the following formula [2]:

$$p_{PV}(t) = \eta_{pv} A_{pv} G_i(t) \tag{2.1}$$

where A_{pv} represents the area in m^2 of the PV module, $G_i(t)$ the solar irradiation in kW/m^2 at hour t and η_{pv} the efficiency of the PV module. The total power produced by the PV system can be calculated by multiplying the number of PV modules (N_{pv}) by the power of one PV module:

$$P_{PV}(t) = N_{pv} p_{PV}(t) \tag{2.2}$$

The photovoltaic generator in this scenario is assumed to be controlled by an MPPT algorithm, which enables it to track and reach the maximum power point it can achieve. This control system manages both the photovoltaic generator and the static converter to ensure that the load receives maximum power output at any given moment. The complexity of the MPPT algorithm employed varies depending on the implementation and the duty cycle of the converter used [3].Additionally, energy losses within the photovoltaic system are assumed to be negligible.The instantaneous efficiency of the generator can be expressed using the following equation [4] :

$$\eta_{gpv} = \eta_r \eta_{cp} \left[1 - \beta_t (T_c - T_r)\right] \tag{2.3}$$

The equation relates the efficiency of a photovoltaic (PV) generator to several factors. The reference efficiency of the PV generator is denoted by η_r, while $\eta_{\eta pc}$ represents the efficiency of the power tracking equipment. If a perfect maximum power point tracker is utilized, $\eta_{\eta pc}$ is equal to 1. The temperature of the PV cell (T_c) is also taken into account, along with the reference temperature of the PV cell (T_r), and β, which is the temperature coefficient of efficiency. The temperature coefficient of efficiency (β) ranges from 0.004 to 0.006 per $°C$ [5].The temperature of the photovoltaic cell can also be expressed using the energy balance proposed by Duffie et al. This equation is given as follows [6]:

$$T_c = T_a + G_t. \left(\frac{NOCT - 20}{800}\right) \tag{2.4}$$

The equation includes parameters such as T_a, $NOCT$, η_{cp}, G_t, and β_t, which are specific to the type of photovoltaic module being used and are provided by the module manufacturer. T_a refers to the ambient temperature in Celsius, while $NOCT$ is the nominal operating temperature of the cells. $NOCT$ is the temperature that a cell would reach when in operation and open circuit under average conditions, including a solar irradiation of $800, W/m^2$, an ambient temperature of $20°C$, spectral distribution $AM = 1.5$, and wind speed equal to or greater than $1, m/s$ [7]. G_t represents the solar irradiation, which denotes the amount of solar energy incident on the photovoltaic module's surface. The solar irradiation is typically measured in units of watts per square meter (W/m^2). The parameters C_p, β_t, and $NOCT$ are used to determine the temperature coefficient, which is unique to each photovoltaic module

2.3 Wind turbine modeling:

As the wind speed increases beyond the cut-in velocity (V_{ci}), the power produced by the generator is proportional to the cube of the wind speed. Once the speed exceeds the rated velocity (V_r)), the power produced by the generator remains constant and equals the rated power (P_r). If the wind speed exceeds the cut-out value (V_{co}), the generator stops operating to protect itself, resulting in zero power output. Mathematically, the power generated by each wind turbine (P_{WT}) at time t can be expressed as follows [2]:

$$p_{WT} = \begin{cases} 0 & V(t) < V_{\text{ci}} \text{ or } V(t) > V_{\text{co}} \\ P_r \cdot \dfrac{V^3(t) - V_{ci}^3}{V_r^3 - V_{ci}^3} & V_{ci} < V(t) < V_r \\ P_r & V_r \leq V(t) \leq V_{co} \end{cases} \tag{2.5}$$

The overall amount of power produced by the wind turbines at hour t, $P_{WT}(t)$, is determined by the product of the number of wind turbines N_{WT} and the power generated by each individual wind turbine $p_{WT}(t)$. This equation provides a way to estimate the total power output of the wind farm at any given time based on the number of wind turbines in operation and the power generated by each turbine. By summing the power output over time, we can also calculate the total energy generated by the wind farm [2]:

$$P_{WT} = N_{WT} p_{WT} \tag{2.6}$$

2.4 Battery bank modeling:

Battery systems, particularly deep-cycle lead-acid types, are frequently utilized for energy storage in hybrid systems. To achieve optimal sizing of the battery, it is imperative to conduct a comprehensive investigation of the charge and discharge requirements. [2] The state of charge (SOC) of a battery bank at a given time (t) is dependent on the previous state of charge ($SOC(t-1)$) and the amount of energy depletion or accumulation from the previous time interval ($t-1$) to the current time (t). [2]

1. If $P_g(t) = P_{pv}(t) + P_{WT}(t) \geqslant \dfrac{P_l}{\eta_{inv}}$ When the generated renewable power is sufficient The expression illustrates how the state of charge (SOC) of a battery in a renewable energy system can be calculated based on the excess generated power that is stored during the charging state. Specifically, SOC is determined by the previous state of charge ($SOC(t-1)$), the amount of energy accumulated during the current time interval (t), and the battery's capacity. This expression serves as a crucial tool for monitoring and regulating battery charging to ensure optimal performance and longevity, and is expressed as follows [2]:

$$SOC(t) = SOC(t-1) + \frac{\left(P_g(t) - \dfrac{P_l(t)}{\eta_{inv}}\right) \times \eta_{bc}}{1000 \times N_b \times C_b} \tag{2.7}$$

   The equation for determining the state of charge (SOC) of a battery bank in a renewable energy system involves several variables. These include the inverter efficiency (η_{inv}) and the charging efficiency of batteries (η_{bc}), as well as the nominal capacity of a single battery (C_b) measured in kilowatt-hours, the total number of batteries in the bank (N_b), and the hourly self-discharge rate (δ). Together, these variables allow for the accurate calculation of SOC, which is essential for proper battery management and system performance optimization.

2. If $P_g(t) < \dfrac{P_l}{\eta_{inv}}$ In situations where the renewable power generated is not enough to meet the load demand, the energy stored in the batteries is utilized to make up for the shortfall. This occurs when the batteries are in the discharge state, and the state of charge (SOC(t)) of the battery is calculated accordingly. SOC(t) is determined based on the previous state of charge (SOC(t-1)), the amount of energy discharged from the battery during the current time interval (t), and the battery capacity. This expression is vital for monitoring and regulating battery discharge and optimizing system performance. Therefore, SOC(t) can be expressed as follows [2]:

$$SOC(t) = SOC(t-1) - \frac{\left(\dfrac{P_l(t)}{\eta_{inv}} - P_g(t)\right) \times \eta_{bd}}{1000 \times N_b \times C_b} \tag{2.8}$$

   η_{bd} denotes the discharging efficiency of batteries. In order to prolong the lifespan of batteries, it is essential to avoid over-discharging them. To achieve this, $SOC(t)$ must be subjected to specific constraints at any given time t. These constraints are put in place to ensure that the state of charge of the battery remains within a safe range and prevent excessive discharge. Some examples of the constraints that can be imposed on $SOC(t)$ include the minimum state of charge (SOC_{min}), which represents the minimum acceptable battery capacity, and the maximum depth of discharge (DOD_{max}), which defines the maximum amount of energy that can be discharged from the battery before it becomes unsafe. By adhering to these constraints, battery life can be extended, and overall system performance can be optimized [1].

2.5 Modeling DC/AC converter

The power generated by the photovoltaic (PV) modules and wind turbines needs to be converted from direct current (DC) to alternating current (AC) because the power consumed by the loads is in AC form. The output power of the inverter, which performs the DC-AC conversion, is determined using this equation [19]:

$$P_{\text{inv-AC}} = (P_{\text{fc-inv}} \cdot P_{\text{ren-inv}})_{\text{inv}} \tag{2.9}$$

where $P_{\text{fc-inv}}$ represents the output power from the fuel cell ,$P_{\text{ren-inv}}$ represents the output power produced from renewable energy sources,and represents the assumed constant efficiency of the inverter [19]. An FC is a device employed to convert chemical energy to electrical DC energy using an electrolyzer [19].

2.6 Genetic algorithms

2.6.1 Generalities

Genetic algorithms (GAs) are stochastic optimization algorithms based on the mechanisms of natural selection and genetics. Their operation is extremely simple. We start with a population of potential solutions (chromosomes) that are initially arbitrarily chosen. We evaluate their relative performance (fitness). Based on these performances, we create a new population of potential solutions using simple evolutionary operators: selection, crossover, and mutation. We repeat this cycle until a satisfactory solution is found [8, 9].

The use of genetic algorithms in the context of hybrid systems is particularly advantageous because it allows for the optimization of multiple variables and constraints simultaneously. By using genetic algorithms, it is possible to find solutions that are not only optimal but also robust, meaning that they are able to perform well under different conditions and with varying parameters. Furthermore, the ability to handle large amounts of data and complex relationships between variables makes genetic algorithms a powerful tool for modeling and optimization in hybrid systems.

2.6.2 Properties of genetic algorithm

Among the properties of genetic algorithms, we can mention:

- Genetic algorithms use parameter encoding, rather than the parameters themselves.
- Genetic algorithms work on a population of points, rather than a single point.
- Genetic algorithms only use the values of the studied function, not its derivative or other auxiliary knowledge.
- Genetic algorithms use probabilistic transition rules, rather than deterministic ones. The simplicity of their mechanisms, the ease of their implementation, and their effectiveness even for complex problems have led to an increasing number of works in different fields [10].

2.6.3 Basic mechanisms of genetic algorithms

Genetic algorithms utilize several fundamental mechanisms such as individuals/chromosomes/sequences, genes, populations, generations, parents, environment, and fitness function to efficiently search for optimal solutions to complex problems. An individual is a potential solution defined by a set of parameters called genes, while the population is a collection of individuals or points in the search space. A generation is a population at a given time, and a parent is an individual chosen as a basis for creating another in the next generation. The environment refers to the search space, while the fitness function is the function that the algorithm seeks to optimize, either by maximizing or minimizing it [11] [12]. In genetic algorithms, crossover and mutation are two genetic operators used to create new solutions from existing ones. Crossover involves combining two parent solutions to create a new offspring solution. This is done by randomly selecting a point in the parent sequences and exchanging the genetic information from that point onwards to create two offspring solutions. On the other hand, mutation involves randomly changing one or more genes in an individual's sequence to create a new solution. These operators are used in combination with selection to create a new population of solutions, which is then evaluated using the fitness function. By utilizing these basic mechanisms, genetic algorithms can efficiently search for optimal solutions to complex problems [11–13]. The different phases of genetic algorithms, which are as follows [12, 13]:

- Initialization: an initial population of N chromosomes is randomly generated.
- Evaluation: each chromosome is decoded and evaluated.
- Selection: a new population of N chromosomes is created by using an appropriate selection method.
- Reproduction: there is a possibility of crossover and mutation within the new population.
- Return to the evaluation phase until the algorithm terminates.

2.6.4 A standard genetic algorithm

A standard genetic algorithm involves encoding optimization problem parameters into a string and simulating the evolution of a population of individuals until a termination criterion is met. The process starts with generating an initial population of solutions randomly. At each generation, individuals are selected based on their fitness, which is evaluated by an objective function, and crossover and mutation operators are applied to create a new population. This process is repeated until the termination criterion is reached, which is usually a maximum number of desired generations. The algorithm begins by generating an initial population, evaluating the fitness function of all individuals, selecting individuals for reproduction, generating offspring by applying genetic operators, placing the offspring in a new population, and repeating the process until the termination criterion is met. This is known as a generational genetic algorithm because the offspring generated replace the entire population of parent individuals [15].

2.6.5 Model for optimizing system size

The modeling process of any optimization problem involves several steps, including identifying decision variables, defining an objective function, and setting constraints. For the purpose of an optimization design study, we explain these three components and how they are connected in detail in the following subsections. By explicitly defining these components, we can create a comprehensive optimization model that helps determine the best solution to a given problem [2]

2.6.6 Decision variables

In the context of this optimal size study, a decision variable represents a quantity that the decision maker can control, the optimal value of which is determined by the optimization process.

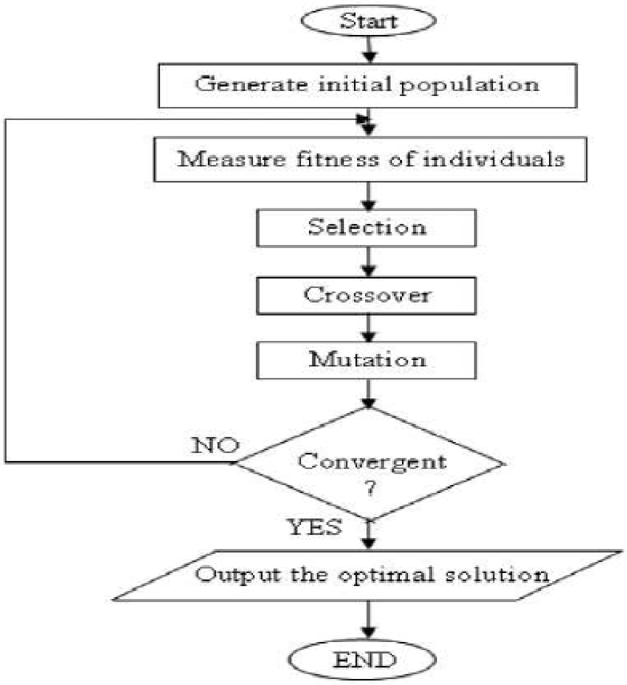

Figure 2.1: Flow-chart of the genetic algorithm (GA) [14]

Specifically, we identify three decision variables that are critical to solving the optimization problem. They are as follows [2]:

- N_{PV} : number of PV modules.
- N_{WT} : number of wind turbines.
- N_{bat}: number of batteries.

2.6.7 Objective function

In the context of optimization, an objective function is a mathematical representation that describes the goal of optimization in terms of decision variables. The goal of this optimal design study is to minimize the total cost of the proposed Hybrid Renewable Energy System (HRES). The total annual cost (TAC) of the system is considered as the objective function of the optimization problem, defined as follows [2]:

$$\text{Minimize TAC}(N_{PV}, N_{WT}, N_{BAT}) = C_i + C_m + C_r \tag{2.10}$$

where C_i, C_m, C_r are respectively the installation cost, maintenance cost, and replacement cost. The costs of PV modules, wind turbines, batteries, and other essential components are included in the installation cost (C_i). It is computed using the number of PV modules (N_{PV}), wind turbines (N_{WT}), and batteries (N_{BAT}), as well as the unit prices of each component [16].

$$C_i = N_{PV}C_{i,PV} + N_{WT}C_{i,WT} + N_{BAT}C_{i,BAT} \tag{2.11}$$

where $C_{i,PV}$, $C_{i,WT}$ and $C_{i,BAT}$ represent respectively the installation cost of one unit of PV module, wind turbine and battery. The maintenance cost (C_m) is expressed as a percentage of the initial cost of each component, and this percentage is applicable for a duration of one year. [16] :

$$C_m = (N_{PV}M_{PV}C_{i,PV} + N_{WT}M_{WT}C_{m,WT} + N_{BAT}M_{BAT}C_{i,BAT})L_{SYS} \tag{2.12}$$

where M_{PV}, M_{WT} and M_{BAT} represent respectively the annual maintenance percentage of PV module, wind turbine and battery. Every component within the system has a specific lifespan (L) and needs to be replaced at regular intervals during the operation of the hybrid system. The cost associated with the replacement, also known as the replacement cost (CR), is provided as follows [2]:

$$C_r = N_{PV} C_{i,PV} \frac{L_{SYS} - L_{PV}}{L_{PV}} + N_{WT} C_{i,WT} \frac{L_{SYS} - L_{WT}}{L_{WT}} + N_{BAT} C_{i,BAT} \frac{L_{SYS} - L_{BAT}}{L_{BAT}} \quad (2.13)$$

where L_{SYS}, L_{PV}, L_{WT} and L_{BAT} are respectively the lifespan of system, PV module, wind turbine and battery.

2.6.8 Constraints

Constraints are important in the optimization process because they define the boundaries and restrictions within which the decision variables of a problem must function. These restrictions define the circumstances and requirements that will direct the search for the best solution. In this study, we identified three types of restrictions that are critical to the formulation of our problem. Let us investigate each category and the constraint expressions that encompass these requirements [17] :

- Variable type constraints, defined by equation:

$$N_k = \text{Integer}, k \in \{PV, WT, BAT\}$$

- Bound constraints, defined by Equation :

$$0 \leqslant N_k \leqslant N_{k,Max}, k \in \{PV, WT, BAT\}$$

  where $N_{k,Max}$ is the maximum available number of component k.

- The equation defines the constraint of reliability [2] :

$$\text{LPSP} \leqslant \text{LPSP desired}$$

The loss of power supply probability, denoted as $LPSP$, is defined for a specific period T in the following manner [16]:

$$LPSP = \frac{\sum_{t=1}^{T} LPS(t)}{\sum_{t=1}^{T} P_l(t)} \quad (2.14)$$

with

$$LPS(t) = P_l(t) - [P_g(t) + \{SOC(t-1) - (1 - DOD)\} \times 1000 \times C_b \times \eta_{inv}], \quad (2.15)$$

LPSP desired, the maximum allowable value of $LPSP$ and $\sum_{t=1}^{T} P_l(t)$ the total energy required by the load during the operating period T [16] [2].

2.6.9 Simulation and optimization process

In this study, a simulation of a Hybrid Renewable Energy System (HRES) was performed using MATLAB. The genetic algorithm was employed to determine the optimal system layout, considering constraints and factors. A flowchart was used (see figure 2.2) to visualize the genetic algorithm's step-by-step process, showcasing how it evolved potential solutions through genetic operators. By incorporating the flowchart, a deeper understanding of the genetic algorithm's mechanisms in identifying the optimal HRES configuration was achieved, enhancing system performance and efficiency. [2]

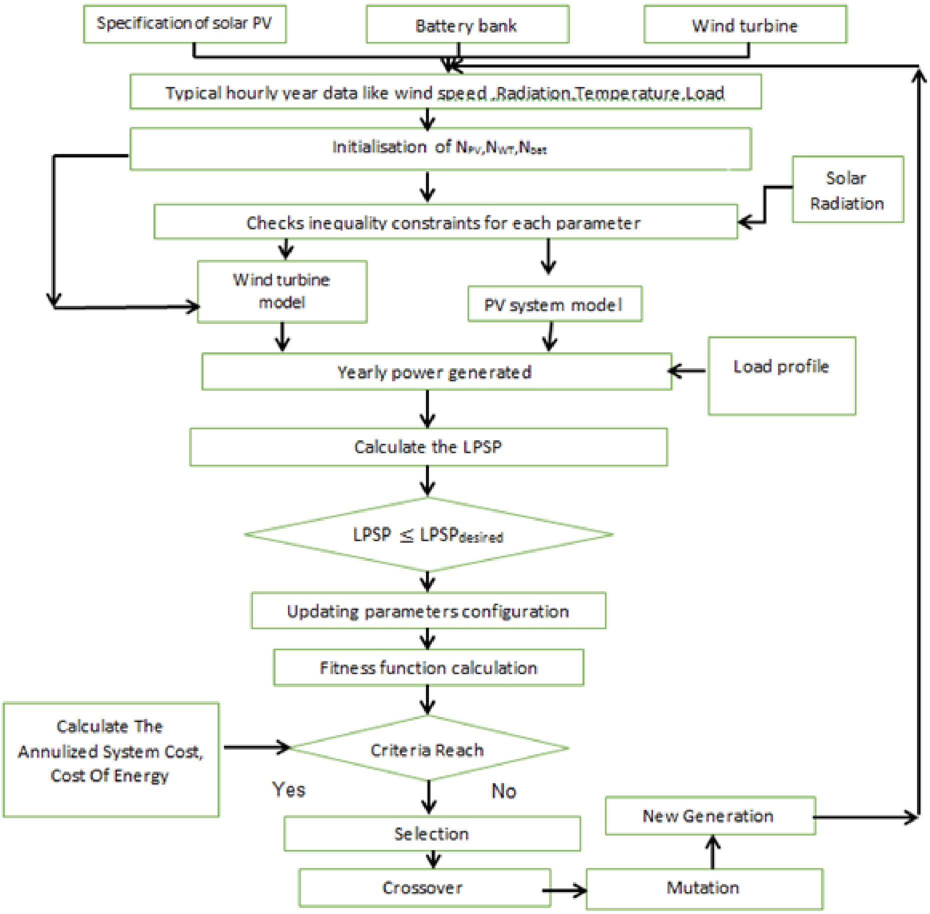

Figure 2.2: Flowchart of the optimization process using a genetic algorithm [18].

This flowchart is an invaluable tool for visualizing the GA process and improves our understanding of the optimization process involved in determining the optimal configuration of HRES. By using this systematic approach, researchers and practitioners can gain insight into the GA decision-making process and the overall performance of the designed HRES.

2.7 Conclusion

In summary, this chapter lays the groundwork for a hybrid renewable energy system (HRES) by developing models of photovoltaic generators, wind turbines, and battery packs. The integration of genetic algorithm realizes the optimization of the system scale. These modeling and optimization techniques provide a solid foundation for the subsequent chapters, in which an optimized HRES configuration is implemented and thoroughly examined to evaluate its performance, efficiency, and feasibility in real-world applications.

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Chapter 3

Results and discussion

3.1 Introduction

In this chapter, we present a comprehensive analysis of hybrid PV/wind/batteries systems using genetic algorithms. The objective is to optimize system configurations and minimize costs while ensuring reliable power supply. The study focuses on three distinct sites: Tlemcen, Adrar, and Tenes, each characterized by unique environmental conditions and energy requirements. By employing genetic algorithms, we aim to determine the optimal combinations of PV panels, wind turbines, and batteries that maximize energy generation and minimize costs.
This analysis provides valuable insights into the design and operation of hybrid energy systems, contributing to the development of sustainable and economically viable solutions.

3.2 Weather data and load profile

We have included the geographical data of all three sites, namely Tlemcen, Adrar, and Tenes, in table (3.1)

Site	Longitude	Latitude	Altitude(m)	Slope (optimum)	Azimuth (optimum)
Tlemcen	-1.315	34.896	684	33	19
Adrar	-1.358	26.489	334	28	28
Tenes	1.290	36.468	167	34	15

Table 3.1: Geographic data for selected sites [1, 2].

The sizing study of the hybrid system involved analyzing meteorological data collected for one year (365 days) from January 1, 2005, to December 31, 2005, at the selected sites [1, 2]. Figure (3.1) presents the hourly variations of solar irradiance (measured in W/m^2) at three distinct sites: Tlemcen, Tenes, and Adrar.

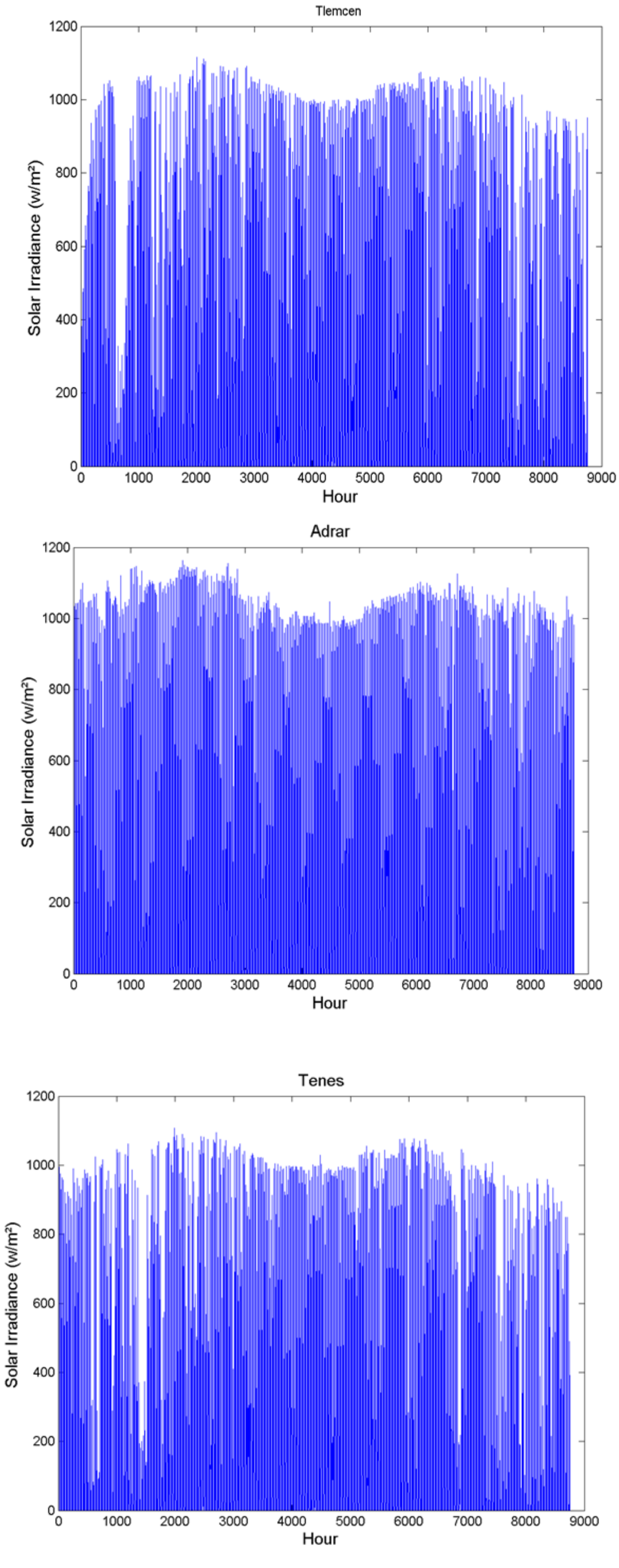

Figure 3.1: Profiles of solar irradiance on the three selected sites: Tlemcen , Adrar and Tenes for one year (January 1, 2005 – December 31, 2005) [1, 2]

Similarly, figure (3.2) displays the hourly variations of ambient temperature (measured in C) specifically for Tlemcen, Tenes, and Adrar.

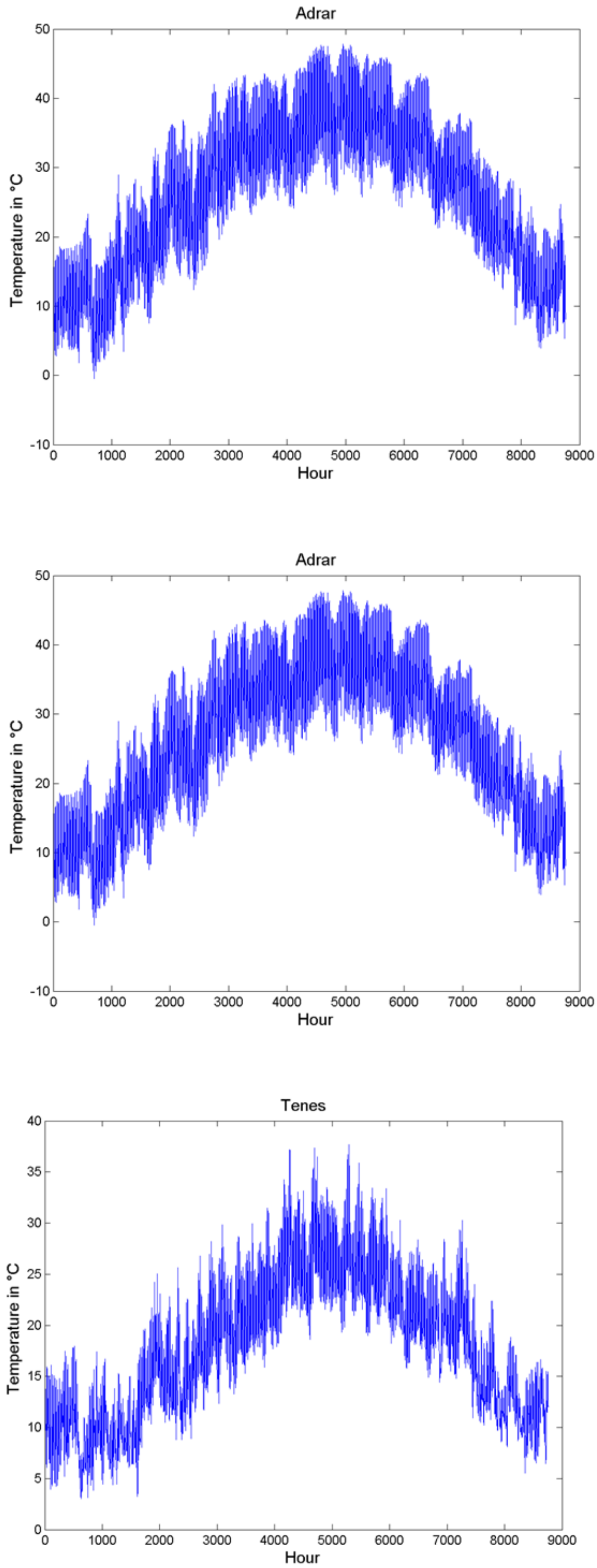

Figure 3.2: Profiles of ambient temperature on the three selected sites: Tlemcen , Adrar and Tenes for one year (January 1, 2005 – December 31, 2005 [1, 2].

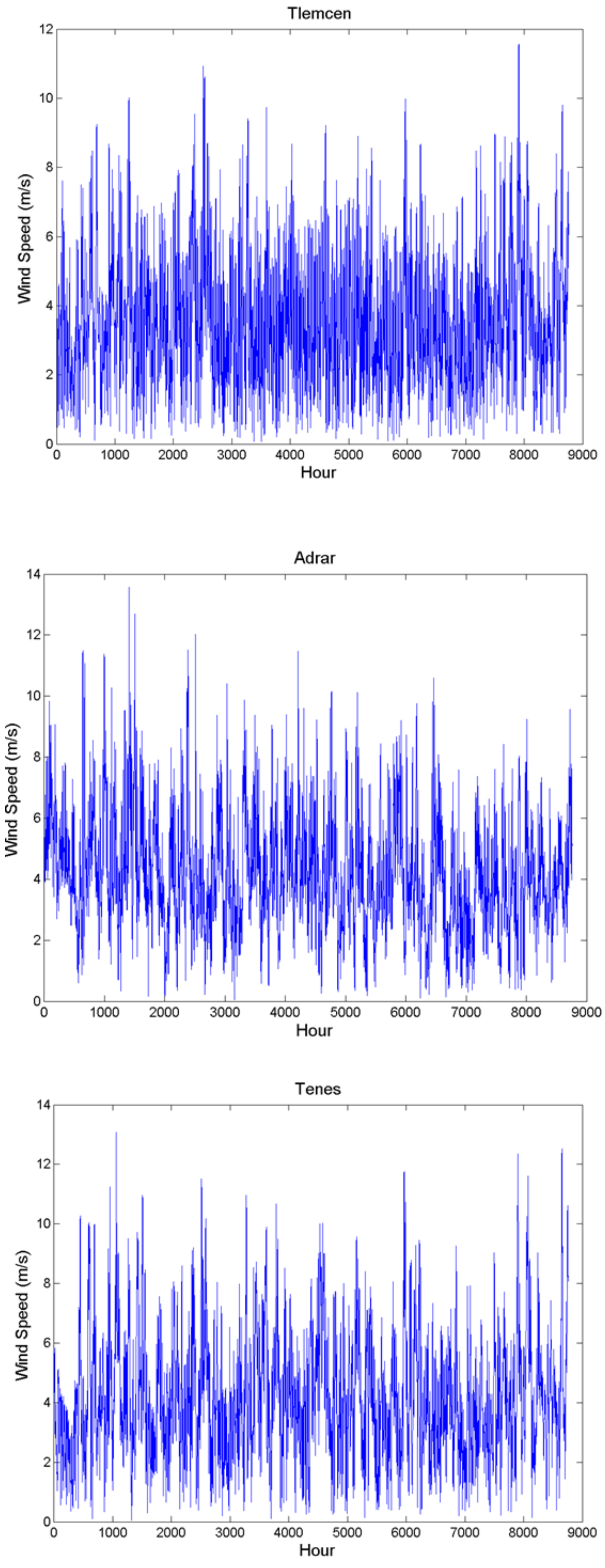

Figure 3.3: Profiles of The wind speed on the three selected sites: Tlemcen , Adrar and Tenes for one year (January 1, 2005 – December 31, 2005) [1, 2].

Furthermore, Figure (3.3) showcases the hourly variations of wind speed at a 10-meter height above ground level for all three sites. Additionally, Figure (3.4) depicts the daily electrical load profile, which remains consistent across all three sites. This load profile represents the electricity consumption pattern of an administrative unit located in the Tlemcen region of Algeria, primarily influenced by daytime electricity usage and nighttime requirements for irrigation and lighting [3].

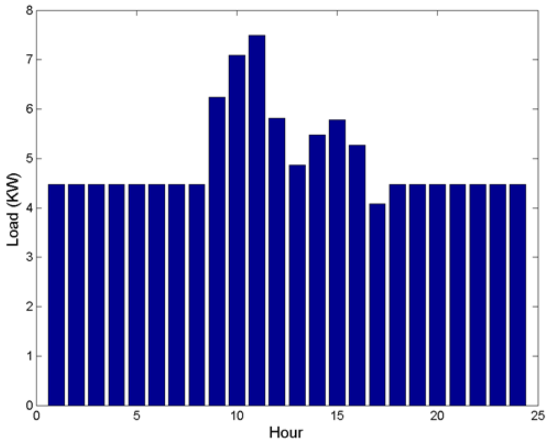

Figure 3.4: Load profile to be supplied with energy [3].

Based on the observed data, it can be concluded that the significant peak in consumption between 9:00 a.m. and 4:00 p.m., with the highest demand occurring around 11:00 a.m., coincides with the period of maximum environmental conditions in Adrar. This correlation suggests a potential relationship between energy demand and the availability of solar energy, temperature, and wind speed.
Furthermore, the distinct patterns in solar irradiance, temperature, and wind speed indicate that Adrar, compared to Tlemcen and Tenes, experiences more extreme environmental conditions. The higher temperatures, stronger winds, and greater levels of solar irradiance in Adrar highlight the region's unique characteristics and potential for renewable energy generation.

These findings contribute to the understanding of energy consumption and environmental factors, emphasizing the importance of considering local conditions when designing and optimizing energy systems. By harnessing the abundant solar resources, capitalizing on favorable wind conditions, and accounting for temperature variations, Adrar has the potential to become a prime location for renewable energy projects and further enhance its energy sustainability.

3.3 Technical and economical specifications of the hybrid system

3.3.1 Photovoltaic panel selection

Table 3.2 provides a comprehensive overview of the solar modules used in this study. It contains basic information about the particular solar module used, including its technical specifications and performance characteristics.

Model	rec TwinPeak 2 Series
Open Circuit Voltage V_{OC}(V)	39.0
Short Circuit Current I_{SC} (A)	9.65
Panel Efficiency (%) η_r	17.7
Nominal Power Voltage V_{MPP} (V)	32.2
Nominal Power Current I_{MPP} (A)	9.14
Nominal Power P_{MPP} (Wp)	295
Nominal operating cell temperature (NOCT)(C)	44.6
Price per unit(€)	142
Standard temperature(C)	25
Standard Radiance (W/m^2)	1000
Area (m^2)	1.67
power conditioning efficiency η_{cp}	1.0
efficiency coefficient per degree Celsius (β_t)	0.005
Annual maintenance percentage(%)	1
Lifetime(year)	25

Table 3.2: The characteristics of the photovoltaic panel [4].

3.3.2 Wind turbine selection

Table 3.3 briefly summarizes the wind turbine specifications used in this study. It contains necessary details such as model number, rated voltage, starting wind speed, wind speed rating, survival wind speed, rated power and unit price.

Model	elege-1000
Rated voltage (V)	24
Start-up wind speed (m/s)	2
Rated wind speed (m/s)	12
Survival wind speed (m/s)	45
Rated power (W)	1000
Price per unit (€)	150
Annual maintenance percentage(%)	3
Lifetime(year)	25

Table 3.3: The characteristics of the Wind Turbine [5].

3.3.3 Battery selection

Table 3.4 presents a comprehensive overview of the batteries utilized in this study, encompassing crucial information such as their capacity (Ah), battery voltage (V), and price per unit (€).

Model	Batterie VICTRON étanche Gel 12V / 220Ah
Capacity (Ah)	220
Battery voltage (V)	12
Price per unit (€)	605
Annual maintenance percentage (%)	0
Lifetime(year)	7

Table 3.4: Characteristics of the used battery [6].

3.4 Results and discussion

Our research focuses on the use of genetic algorithms (GA) to optimize system performance, with a particular focus on the effects of population size. Genetic algorithm provides an efficient method for solving complex optimization problems by simulating the process of natural selection and evolution. In this study, we wanted to examine the impact of population size changes within the GA framework on two key metrics: execution time and total system cost. To ensure statistical robustness, we run the GA algorithm three times for each population size. Furthermore, we introduce a constraint called Loss of Power Probability (LPSP), which is set to 1 % to ensure system reliability. We tested population sizes ranging from 10 to 100 people, with increments of 10 people per step. The table below summarizes the findings

population	Execution time (s)	Generation	Cost(€)	Mean of execution time(s)
10	14.0105 13.9663 14.3564	51 51 52	49146.3276 45057.3822 43863.4368	14.1111
20	27.1984 26.9259 27.1087	51 51 51	42965.4095 43020.9368 43127.9095	27.0777
30	40.3768 40.519 40.506	51 51 51	42965.9095 43767.3822 43020.9368	40.4673
40	53.4423 53.3999 53.4246	51 51 51	42965.9095 42965.9095 42965.9095	53.4223
50	66.5565 66.5385 66.6829	51 51 51	42965.9095 43020.9368 42965.9095	66.5926
60	79.6672 80.1125 79.8421	51 51 51	42965.9095 42965.9095 42965.9095	79.8739
70	92.9219 92.9559 93.6687	51 51 51	42965.9095 43028.4368 42965.9095	93.1822
80	106.1759 106.1017 106.5502	51 51 51	42965.9095 43020.9365 42965.9095	106.2759
90	119.714 119.3996 119.0816	51 51 51	42965.9095 42965.9095 42965.9095	119.3984
100	132.2117 132.7427 132.288	51 51 51	42965.9095 42965.9095 42965.9095	132.4141

Table 3.5: Impact of Population Size on Execution Time and Total System Cost in Genetic Algorithm Optimization for Tlemcen site.

Having shown a table summarizing the results, we can now delve a little deeper into the relationship between population size and execution time. To illustrate this relationship, we plot a graph of execution time as a function of population size (Figure (3.5). By graphically representing the data obtained from our study, we aim to visualize how different population sizes affect the execution time of our system.

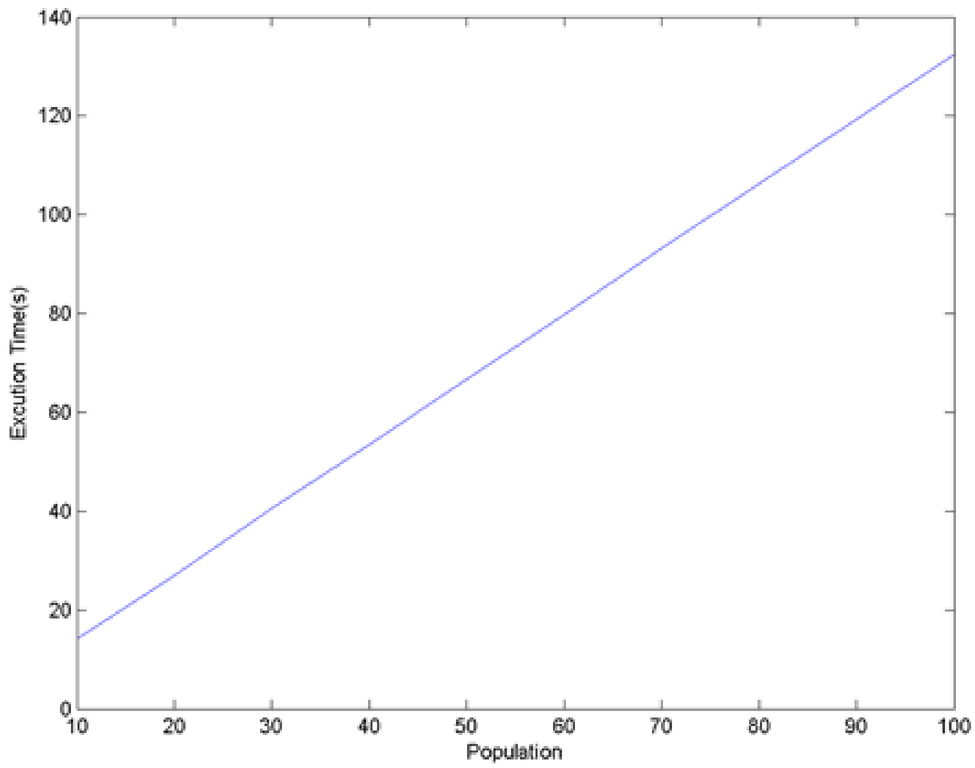

Figure 3.5: Variation of Execution Time with Population Size for Tlemcen site.

The results from the graph (Figure 3.5) and table (Table 3.5) show that increasing the population size in genetic algorithm optimization results in longer execution durations. This can be attributable to a variety of things. To begin with, a bigger population size necessitates examining a greater number of candidate solutions in each generation, increasing processing complexity. Because the program must evaluate and manage more individuals during the evolutionary process, each iteration takes longer to finish. Secondly, a larger population allows for a more thorough study of the solution space, potentially leading to superior solutions. This investigation, however, comes at the expense of greater computational time because more evaluations and iterations are necessary to evaluate a bigger pool of candidate solutions. Finally, when population sizes increase, the interactions between individuals, such as crossover, mutation, and selection, grow more complicated, incurring additional computational overhead. As a result, these factors contribute to the observed rise in execution time as population size climbs. For each population size, we ran the algorithm three times. From the table, it is clear that smaller population sizes can yield inconsistent results, whereas larger population sizes tend to produce more consistent outcomes at the expense of longer execution times. This finding highlights the trade-off between result consistency and computational efficiency when adjusting the population size in the genetic algorithm optimization. In continuation of the study, an examination of the impact of Loss of Power Supply Probability (LPSP) on the system configuration in the genetic algorithm optimization was conducted. The LPSP was varied within two different ranges: from 0% to 1% with increments of 0.1%, and from 0.1% to 5% with increments of 1%. The objective was to determine the optimal number of photovoltaic panels, wind turbines, and batteries for a cost-minimized hybrid energy system design. The findings are presented in Table 3.6, which summarizes the system configuration based on the LPSP ranges

Desired LPSP(%)	Cost (€)	N_{PV}	N_{WT}	N_{BAT}
0	43553.4368	43	5	16
0.1	43545.9368	40	7	16
0.2	43490.4095	43	13	15
0.3	43375.9368	42	5	16
0.4	43397.9095	41	14	15
0.5	43312.9095	42	13	15
0.6	43227.9095	43	12	15
0.7	43198.4368	41	5	16
0.8	43113.4368	42	4	16
0.9	43050.4095	42	12	15
1	42965.4095	43	11	15
2	42440.4095	43	9	15
3	41822.9095	41	8	15
4	41297.9095	41	6	15
5	40709.8822	41	12	14

Table 3.6: System Configuration Based on Loss of Power Supply Probability (LPSP) Ranges in Genetic Algorithm Optimization for Tlemcen site.

After analyzing the table, which presents the cost values achieved under different LPSP constraints, a Genetic Algorithm (GA) with a population size of 100 was employed to further investigate the optimization of a hybrid energy system's cost while satisfying the LPSP constraint. The LPSP acts as a reliability criterion, ensuring that the system maintains an acceptable level of power supply loss probability.
Building upon the findings from the table, a graph (Figure 3.6) was constructed to visually depict the relationship between the cost and the varying LPSP values. This graph will provide a clearer understanding of the trade-off between system cost and reliability, allowing for more informed decision-making in determining the optimal LPSP level for the hybrid energy system.

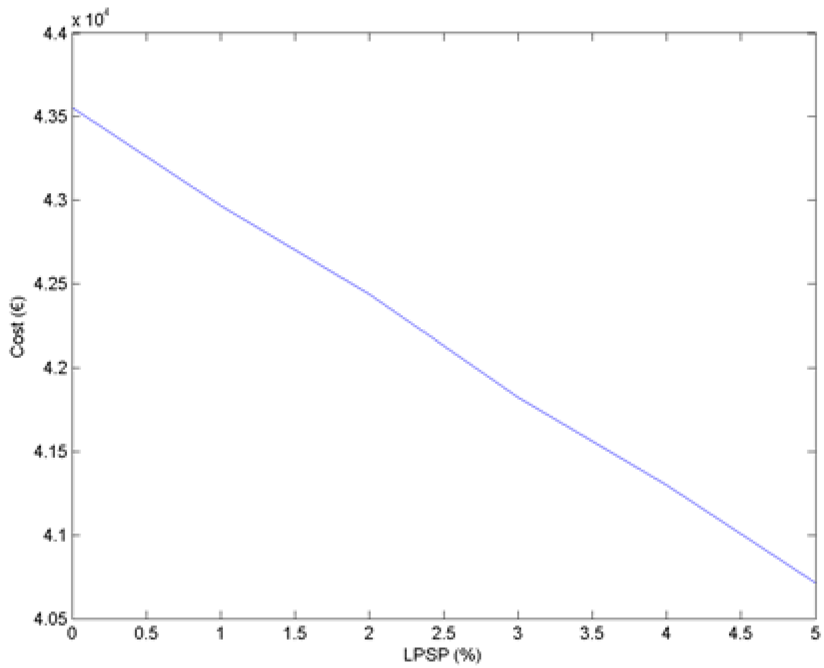

Figure 3.6: Cost Variation with Loss of Power Supply Probability (LPSP).

The graph (Figure 3.6) and table (Table 3.6) presented in this study elucidate the relationship between the Loss of Power Supply Probability (LPSP) and the cost of a hybrid energy system , as optimized through a Genetic Algorithm (GA) with a population size of 100. The findings reveal a compelling trend whereby an increase in LPSP corresponds to a notable decrease in system cost. This dynamic can be attributed to the delicate balance between system reliability and cost optimization. As the LPSP threshold is relaxed, allowing for a higher tolerance of power supply loss, cost reductions become feasible through the utilization of less expensive components or less sophisticated technologies. Consequently, the optimized design of the hybrid energy system strikes a delicate balance between ensuring an acceptable level of reliability and minimizing costs.
In Table 3.7, we conducted a series of simulations where we fixed the number of photovoltaic panels (N_{PV}) while allowing the Genetic Algorithm (GA) to determine the optimal number of wind turbines (N_{WT}) and batteries (N_{BAT}) for a hybrid energy system. Our objective was to find the configurations that minimize the overall cost while maintaining a Loss of Power Supply Probability (LPSP) value of 1%. Throughout these simulations, we used a population size of 100 in the GA to ensure robust optimization. By varying the N_{PV} values from 0 to 50, we were able to observe how the GA algorithm adapts and finds the optimal combinations of N_{WT} and N_{BAT} for each N_{PV} setting.

N_{PV}	N_{WT}	N_{BAT}	Cost (€)
0	45	19	52910.0187
5	34	19	50910.0187
10	31	18	48846.9914
15	29	17	47046.4641
20	19	17	45308.9641
25	20	16	44295.9368
30	14	16	43608.4368
35	9	16	43183.4368
40	5	16	43020.9368
45	10	15	43057.9095
50	7	15	43157.9095

Table 3.7: Optimization Results for Hybrid Energy System Configuration with Varying fixed N_{PV}.

In order to understand the relationship between the number of wind turbines (N_{WT}), the N_{PV} values, and the associated costs, a line graph (Figure 3.7) was constructed. The graph depicts the N_{PV} and N_{WT} values on the y-axis, while the cost is represented on the x-axis. This arrangement enables a visual analysis of how variations in N_{WT} and N_{PV} values correspond to changes in the cost of the hybrid energy system.
The line graph (Figure 3.7) presented in this analysis offers valuable insights into the relationship between cost, the number of wind turbines (N_{WT}), and the number of photovoltaic panels (N_{PV}) in a hybrid energy system. It reveals a clear trend where decreasing costs coincide with a reduction in the number of wind turbines and an increase in the number of photovoltaic panels. This trend suggests that as costs decrease, it becomes more economically viable to rely more on photovoltaic panels rather than wind turbines due to their relatively lower installation and maintenance expenses. The graph also emphasizes the trade-off between N_{WT} and N_{PV}, where reducing the number of wind turbines allows for a greater allocation of resources towards photovoltaic panels. This trade-off enables decision-makers to optimize costs while still meeting the

required energy output. By identifying the optimal combinations of N_{WT} and N_{PV} that result in lower costs, this analysis offers valuable insights for making informed decisions in configuring hybrid energy systems.

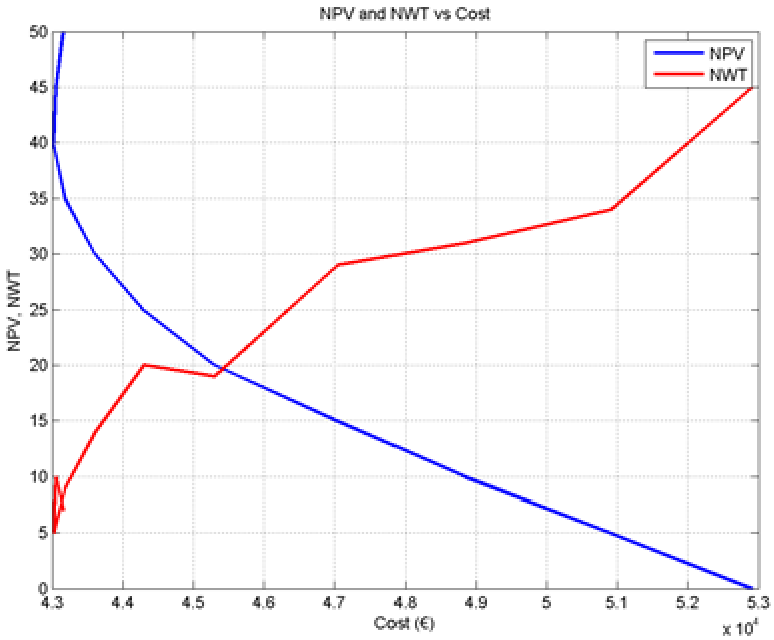

Figure 3.7: Optimization of Hybrid Energy System Configuration: Cost Analysis and Trade-offs between Wind Turbines and Photovoltaic Panels.

The line graph (Figure 3.7) presented in this analysis offers valuable insights into the relationship between cost, the number of wind turbines (N_{WT}), and the number of photovoltaic panels (N_{PV}) in a hybrid energy system. It reveals a clear trend where decreasing costs coincide with a reduction in the number of wind turbines and an increase in the number of photovoltaic panels. This trend suggests that as costs decrease, it becomes more economically viable to rely more on photovoltaic panels rather than wind turbines due to their relatively lower installation and maintenance expenses. The graph also emphasizes the trade-off between N_{WT} and N_{PV}, where reducing the number of wind turbines allows for a greater allocation of resources towards photovoltaic panels. This trade-off enables decision-makers to optimize costs while still meeting the required energy output. By identifying the optimal combinations of N_{WT} and N_{PV} that result in lower costs, this analysis offers valuable insights for making informed decisions in configuring hybrid energy systems.
Through the analysis presented in Table 3.8, we conducted a series of simulations focusing on optimizing the configuration of a hybrid energy system. Specifically, we kept the number of wind turbines (N_{WT}) fixed while utilizing the Genetic Algorithm (GA) to determine the optimal values for the number of photovoltaic panels (N_{PV}) and batteries (N_{BAT}). Our primary objective was to minimize the overall cost of the system while maintaining a Loss of Power Supply Probability (LPSP) value of 1%. To ensure robust optimization, we employed a population size of 100 in the GA. By systematically varying the N_{WT} values from 0 to 18, with an increment of 2, we were able to observe how the GA algorithm adapted and identified the optimal combinations of N_{PV} and N_{BAT} for each N_{WT} setting.

N_{WT}	N_{PV}	N_{BAT}	Cost (€)
0	45	17	44758.9641
2	45	16	43120.9368
4	42	16	43113.4368
6	39	16	43105.9368
8	48	15	43065.4095
10	45	15	43057.9095
12	42	15	43050.4095
14	40	15	43220.4095
16	37	15	43212.9095
18	35	15	43382.9095

Table 3.8: Optimization Results for Hybrid Energy System Configuration with Varying fixed NWT Values.

In this analysis , we examine the relationship between the number of wind turbines (N_{WT}) and the associated cost in a hybrid energy system. The objective is to understand how changes in the number of wind turbines impact the overall cost of the system.

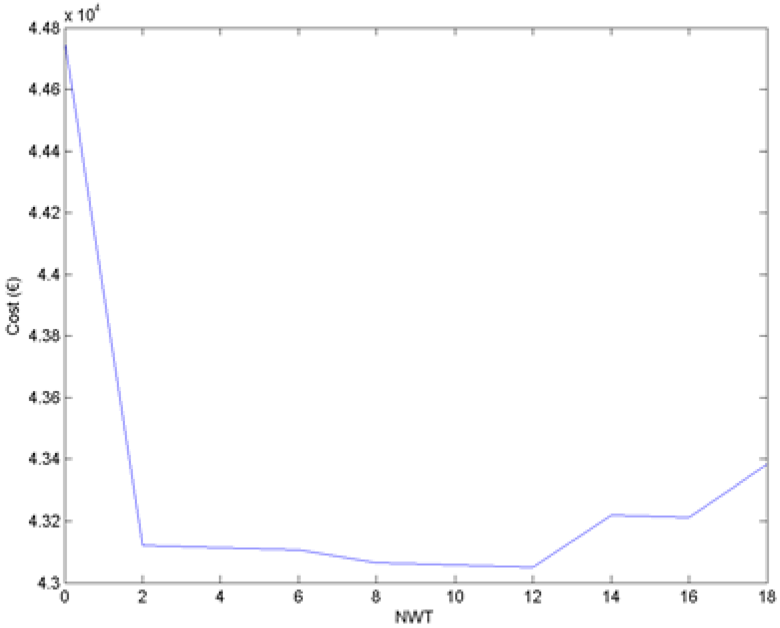

Figure 3.8: Cost Variation with Number of Wind Turbines in a Hybrid Energy System.

The line graph (Figure 3.8) depicting the relationship between the number of wind turbines (N_{WT}) and the associated cost provides valuable insights into the cost dynamics of a hybrid energy system. The graph reveals an initial decrease in cost as N_{WT} increases, indicating the cost-effectiveness of integrating wind turbines. This decline can be attributed to the increased energy production from wind turbines, reducing the reliance on more expensive energy sources. However, the cost trend eventually shows a slight upward trend, indicating diminishing cost benefits. This suggests that the additional expenses incurred in installing, maintaining, and operating extra wind turbines outweigh the potential savings. Moreover, the cost variation becomes minimal once a certain N_{WT} threshold is reached, suggesting that further increases in N_{WT} have limited impact on the overall cost. The graph underscores the significance of optimizing the N_{WT} configuration to achieve cost-effectiveness in hybrid energy systems. It highlights the need for decision-makers to carefully balance the number of wind turbines with associated costs to ensure the efficient and economically viable operation of the hybrid energy system.

In this study, we utilized the Genetic Algorithm (GA) with a population size of 100 to optimize the cost of a hybrid PV/wind/batteries system across three sites: Tlemcen, Adrar, and Tenes. By analyzing the convergence of the cost as a function of generation in Figure 3.9, we observed the effectiveness of the GA algorithm in minimizing overall cost while considering the generation capacities of each site. With a focus on cost-performance trade-offs, our analysis demonstrated the potential for cost optimization in hybrid energy systems using the GA approach, while ensuring a Loss of Power Supply Probability (LPSP) of 0.

On the other hand, Tenes shows a slightly higher optimal cost of 40624.3549. Although still relatively competitive, it suggests that additional considerations, such as site-specific factors and technological adaptations, may be necessary to further optimize the cost efficiency of the system in this location. These factors could include wind resource availability, solar irradiance levels, and energy consumption patterns specific to Tenes. By analyzing these factors and making necessary adjustments, such as selecting more efficient turbine models or fine-tuning the system configuration, it may be possible to achieve greater cost optimization in Tenes.

In contrast, Tlemcen exhibits the highest optimal cost at 43553.4368, indicating potential challenges in achieving cost optimization in this particular location. This might be attributed to various factors, such as lower renewable energy resources, higher energy demands, or less favorable weather conditions. To overcome these challenges, alternative strategies could be explored, such as incorporating energy storage technologies to enhance system efficiency or considering grid integration options to supplement the renewable energy supply. These findings underscore the significance of site-specific considerations in the design and configuration of hybrid energy systems to ensure maximum cost-effectiveness.

Overall, the variations in optimal costs observed among Adrar, Tenes, and Tlemcen highlight the importance of tailoring renewable energy solutions to the specific characteristics and conditions of each location. By conducting thorough assessments of local resources, energy demands, and environmental factors, it becomes possible to identify the most effective approaches and technologies for achieving cost optimization and sustainable energy generation in different regions.

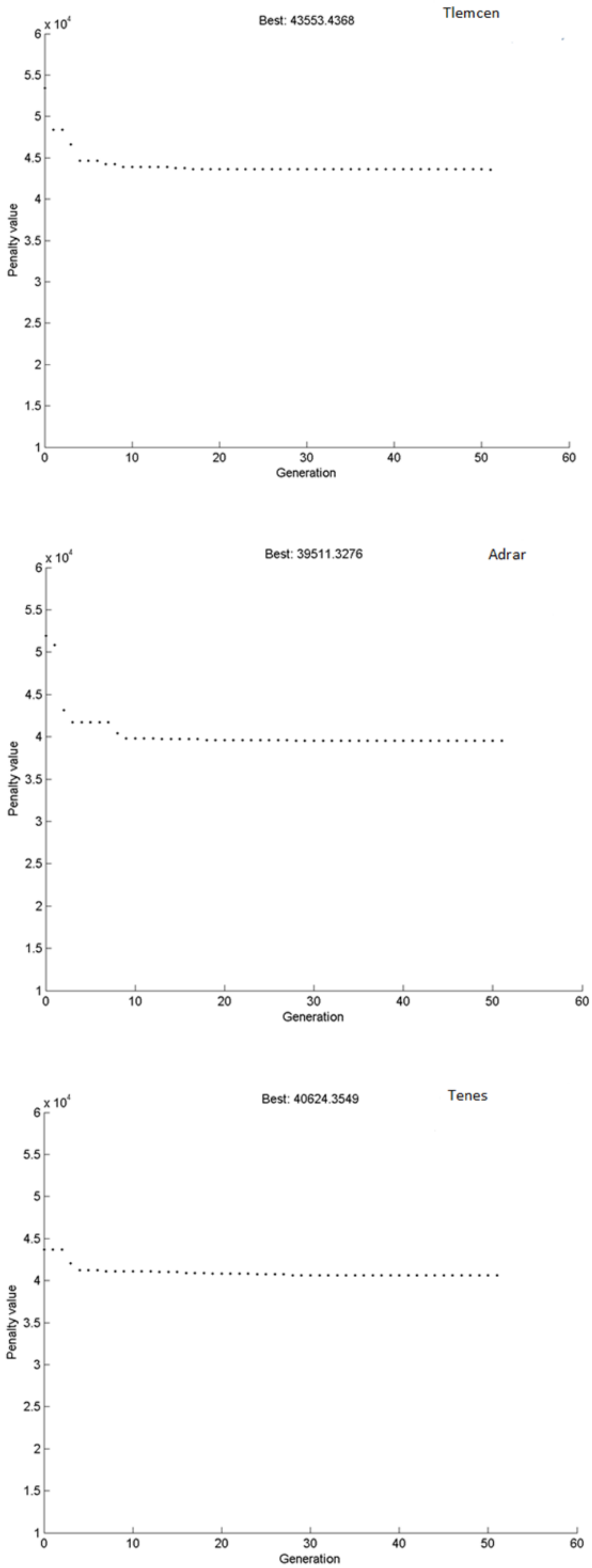

Figure 3.9: Profils de Cost convergence graph for the three sites :Tlemcen,Adrar,Tenes.

The graph (Figure 3.10) depicting the cost as a function of Loss of Power Supply Probability (LPSP) for the three sites, Adrar, Tenes, and Tlemcen, provides insights into the relationship between cost and system reliability.

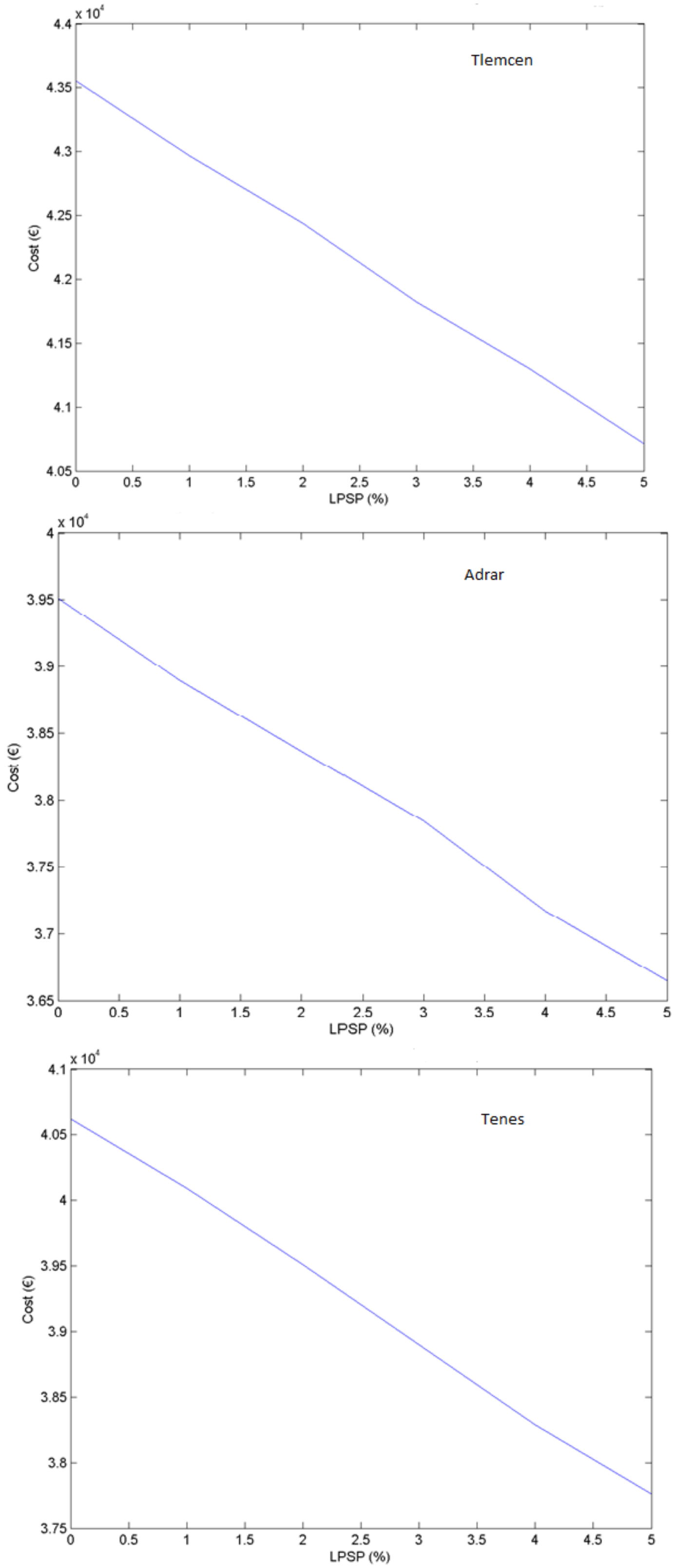

Figure 3.10: Exploring the Relationship between Cost and Loss of Power Supply Probability (LPSP) for Three Sites: Tlemcen, Adrar, and Tenes.

The cost convergence graphs for the three sites, Adrar, Tenes, and Tlemcen, provide valuable insights into the optimization of hybrid PV/wind/batteries systems. Analyzing the graphs (Figure 3.10), it is evident that Adrar exhibits the lowest optimal cost of 39511.3276, followed by Tenes with a cost of 40624.3549, and Tlemcen with the highest cost of 43553.4368. The observed differences in optimal costs can be attributed to a combination of site-specific factors and system characteristics.

The lower optimal cost in Adrar can be attributed to favorable natural resources, including ample sunlight and wind availability, leading to higher energy generation potential. This reduces the reliance on costlier energy sources and contributes to improved cost-effectiveness. Additionally, potential factors such as better infrastructure, access to lower-cost equipment, and favorable weather patterns in Adrar could further enhance cost optimization.

In the case of Tenes, the slightly higher optimal cost indicates that there may be some challenges related to natural resource availability or weather conditions, which impact energy generation efficiency. Limited access to lower-cost equipment or infrastructure limitations may also contribute to the increased cost.

Tlemcen exhibits the highest optimal cost among the three sites, suggesting that it faces additional challenges in achieving cost optimization. Factors such as lower sunlight or wind intensity, logistical hurdles, and increased costs associated with infrastructure development and equipment procurement contribute to the overall higher cost.

These findings underscore the importance of considering site-specific factors, including resource availability, weather conditions, infrastructure, and equipment accessibility, when designing hybrid energy systems. By accounting for these factors, decision-makers can better optimize the system configuration to achieve greater cost efficiency in each specific location. Such insights can inform the decision-making process and guide the development and implementation of hybrid PV/wind/batteries systems in real-world applications.

3.5 Conclusion

In this chapter, we conducted a comprehensive analysis of hybrid PV/wind/batteries systems using genetic algorithms. The study focused on three sites: Tlemcen, Adrar, and Tenes. The results provide valuable insights into the optimization process and cost implications of these systems. We explored the impact of population size on execution time and total system cost, highlighting the need for careful selection. The relationship between system configuration and Loss of Power Supply Probability (LPSP) was examined to ensure reliable performance while minimizing costs. Optimization results for fixed NPV and NWT values demonstrated trade-offs and cost implications. The cost variation with the number of wind turbines revealed the importance of finding the optimal balance. Overall, these findings contribute to the understanding of cost-effective and reliable hybrid energy systems, guiding decision-makers in the implementation of sustainable energy solutions.

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General conclusion

This thesis has focused on the optimization and performance evaluation of hybrid photovoltaic (PV)/wind/batteries systems using genetic algorithms (GA). Through extensive simulations and analysis, valuable insights have been obtained regarding the cost-effectiveness, reliability, and performance of these systems.

The research findings have demonstrated the potential of hybrid energy systems in addressing the intermittent nature of solar and wind energy sources. By integrating PV panels, wind turbines, and energy storage batteries, these systems can provide a reliable and sustainable power supply. The utilization of genetic algorithms has proven to be an effective approach in finding optimal system configurations that minimize costs while ensuring adequate power supply.

The results have practical implications for the design and implementation of hybrid PV/wind/ batteries systems. The findings highlight the importance of considering site-specific factors such as solar irradiance, wind speed, load demand, and storage capacity in system optimization. By carefully balancing these factors, decision-makers can achieve the desired cost-effectiveness and reliability of the system.

Furthermore, this research opens up avenues for further advancements in the field of hybrid energy systems. The study underscores the significance of ongoing research and development in optimization techniques and the integration of renewable energy sources. Future studies can build upon this work by exploring additional factors, improving algorithm efficiency, and considering emerging technologies to enhance the performance and feasibility of hybrid energy systems.

In conclusion, this thesis contributes to the body of knowledge in renewable energy systems, providing valuable insights into the optimization and performance evaluation of hybrid PV/wind/batteries systems. The research outcomes serve as a foundation for future studies and practical applications, supporting the global transition towards a more sustainable and environmentally friendly energy landscape. By harnessing the potential of hybrid energy systems, we can work towards a greener future and contribute to the achievement of global energy goals.