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List of abbreviations

ACO	Ant Colony Optimization
AHA	Artificial Hummingbird Algorithm
BESS	Battery Energy Storage Systems
CAPEX	Capital Expenditure
CC	Cycle Charging
CHP	Combined Heat and Power
COE	Cost Of Energy
DE	Differential Evolution
DERs	Distributed Energy Resources
DG	Diesel Generator
DSM	Demand Side Management
EMS	Energy Management Systems
ESS	Energy Storage System
FC	Fuel Cell
GA	Genetic Algorithms
GAMS	General Algebraic Modeling System
GWO	Grey Wolf Optimizer
HBA	Honey Badger Algorithm
HHO	Harris Hawks Optimization
HOMER	Hybrid Optimization of Multiple Energy Resources
HSA	Harmony Search Algorithm
ICA	Imperialist Competitive Algorithm
IEEE	Institute of Electrical and Electronics Engineers
ISSA	Improved SSA
ISSAHF	Improved Salp Swarm Algorithm with Harris Hawk Foraging
LC	Load Controller
LCOE	Levelized Cost of Energy
LF	Load Following
LOLP	Loss of Load Probability
LP	Linear Programming
LPSP	Loss of Power Supply Probability
MAE	Mean Absolute Error
MARO	Modified Artificial Rabbit Optimizer
MCSA	Modified Capuchin Search Algorithm
MFO	Moth flame optimization. A ()
MILP	Mixed-Integer Linear
MINLP	Nonlinear Programming
MT	Microturbine
NLP	Nonlinear Programming
NOCT	Normal Operating Cell Temperature
NOx	Nitrogen Oxide
NPC	Net Present Cost
OPEX	Operational Expenditure

PCC	Grid Interface and Point of Common Coupling
PENREE	National Renewable Energy and Energy Efficiency Program
PID	Proportional-Integral-Derivative
PSO	Particle Swarm Optimization
PV	Photovoltaic
RE	Relative Error
RES	Renewable Energy Sources
RF	Renewable Fraction
RMSE	Root Mean Square Error
SAIDI	System Average Interruption Duration Index
SD	Standard Deviation
SI	Swarm Intelligence
SOC	State Of Charge
SSA	Salp Swarm Algorithm
TID	Tilt-Integral-Derivative
TLBO	Teaching Learning-Based Optimizer
TOU	Time-Of-Use
WSSA	Weighted Salp Swarm Algorithm
WT	Wind Turbine

Introduction

The 21st century has witnessed a significant shift in global energy systems, driven by the urgent necessity to mitigate the environmental impacts of traditional power sources and transition towards sustainable alternatives [1]. This transition demands a decisive shift from massive, carbon-intensive power systems toward more flexible, intelligent, and decentralized energy architectures. A central challenge in this evolution is the secure and efficient integration of variable renewable energy sources (RES), such as solar and wind power, into existing electrical infrastructures without disturbing grid stability or economic viability [2]. Traditional distribution networks, historically designed for unidirectional power flow, are increasingly inadequate for managing the bidirectional energy flows and inherent intermittency associated with high-RES penetration [3].

In this context, microgrids have emerged as a pivotal technological framework for modern power systems [4]. Defined as localized clusters of distributed energy resources (DERs), energy storage systems (ESS), and controllable loads capable of operating in both grid-connected and autonomous (standalone) modes, microgrids offer a pathway to enhanced resilience, improved power quality, and greater renewable energy integration [5], [6]**.** However, the operational benefits of microgrids introduce significant complexity and challenges. The core challenge lies in the continuous optimization of heterogeneous, intermittently available resources to meet dynamic demand while satisfying a multitude of technical, economic, and environmental constraints under uncertainty [7], [8].

Addressing this challenge requires effective Energy Management Systems (EMS) built on sophisticated optimization frameworks that can coordinate multi-objective decision-making [9]. While classical deterministic optimization methods provide a solid foundation for microgrids energy planning and optimal operation, they often struggle with the non-linear, and stochastic nature of real-world microgrid scheduling problems, particularly when unit commitment and profound uncertainty are involved [10]. Consequently, metaheuristic optimization techniques, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have gained prominence for their flexibility and robustness in exploring complex search spaces [11]. Nevertheless, a common limitation of standalone metaheuristics is their difficulty in maintaining an optimal balance between global exploration and local exploitation, which can lead to premature convergence or excessive computational cost [12]. This gap underscores

the need for enhanced algorithmic strategies that effectively combine complementary search mechanisms to improve performance.

The imperative for such advanced solutions is particularly acute in regions undergoing significant energy transitions, such as Algeria. As a developing country with substantial and growing energy demand, Algeria's electricity mix remains overwhelmingly dependent on fossil fuels, primarily natural gas, which accounts for more than 97% of electricity generation [13]**.** This dependency presents considerable economic and environmental vulnerabilities. Conversely, Algeria possesses exceptional renewable energy potential, including world-class solar irradiation and significant wind resources. National strategies such as the National Renewable Energy and Energy Efficiency Program (PENREE) aim to reach a renewable electricity share of 27% by 2030 [14], [15]. However, progress has remained limited due to infrastructural, financial, and regulatory barriers.

Microgrids, coupled with advanced EMS, represent a highly promising path to accelerate Algeria's energy transition. They offer a scalable model for integrating local renewable resources, enhancing energy security in remote areas, and reducing reliance on centralized fossil-fuel generation. Realizing this potential, however, requires optimization tools capable of handling the specific complexities and uncertainties of such systems within the national context.

Motivated by these intertwined global challenges and national opportunities, this doctoral dissertation addresses the challenges of optimal planning and energy management in low voltage microgrids. The research proposes a novel hybrid metaheuristic optimization strategy designed to improve convergence behaviour, robustness, and solution quality for complex microgrid scheduling problems. The work is grounded in a rigorous mathematical formulation that accurately models the technical and economic dynamics of a typical low voltage microgrid system.

To address this objective systematically, the dissertation is organized into four coherent chapters that progressively develop the research framework from fundamental concepts to advanced methodological contributions and empirical validation. ***Chapter I*** establishes the essential background by presenting the fundamental concepts, architectures, and components of microgrids, along with a critical review of hierarchical control strategies and state-of-art of energy management and optimization techniques. ***Chapter II*** provides a comprehensive techno-economic optimization of microgrids, using Hybrid Optimization of Multiple Energy Resources Pro (HOMER Pro) as a widely used optimization tool. It details the underlying

methodology, defines key performance indicators, and apply this framework to evaluate the viability of a grid-connected urban microgrid, establishing a foundational approach for similar studies through the considered case. ***Chapter III*** constitutes the core methodological contribution by introducing the proposed Improved Salp Swarm Algorithm with a Harris Hawk Foraging optimizer (ISSAHF), preceded by an overview of relevant metaheuristic optimizers and a rigorous formulation of the microgrid energy management problem including the objective function and related constraints. ***Chapter IV*** is devoted to the presentation and discussion of simulation results, where the performance of the proposed algorithm is evaluated against benchmark techniques in terms of statistical robustness, solution quality, and computational efficiency, supported by comprehensive sensitivity analysis. Finally, the dissertation ***concludes*** with main findings that highlights the scientific contributions, and outlines perspectives for future research.

We report on the application of a new hybrid metaheuristic technique that uses the Harris Hawk optimizer and the Improved Salp Swarm algorithm (ISSA) for optimal energy planning in a low-voltage microgrid where the aim is to reduce the operating costs (generation and emission treatment costs). To the best of the authors' knowledge, this is the first hybrid approach for microgrid energy planning.

The main research contributions of this thesis are the following:

- The metaheuristic Salp Swarm algorithm SSA was improved by introducing the *multi-leader concept* and the *best leader-following strategy.*
- The improved SSA is combined with the Harris Hawks Optimization (HHO) to enhance more global search ability.
- The battery power limits and state of charge (SOC) were seriously taken into consideration.
- The effectiveness and robustness of the proposed method were assessed through: comparison, statistical study as well as sensitivity analysis.

CHAPTER I

Background and Literature Review on Microgrids

Chapter I : Background and Literature Review on Microgrids

I.1 Introduction

The rapid transformation of modern power systems, driven by increasing energy demand, decarbonization goals, and the proliferation of renewable energy technologies, has highlighted the limitations of conventional centralized electricity networks. Traditional power systems were historically designed for unidirectional power flow, from large-scale generation units toward passive end-users. However, this paradigm has proven inadequate for emerging challenges such as grid congestion, integration of RES, the need for enhanced resilience face of natural disasters, and the increasing electrification of remote or underserved regions. In this evolving context, microgrids have emerged as a promising technological and operational solution capable of addressing these issues while supporting the transition toward a decentralized, flexible, and resilient energy landscape.

Microgrids integrate distributed energy resources (DERs), including photovoltaic (PV) systems, wind turbines (WT), energy storage devices, and controllable loads, within a localized electrical network that can operate either connected to the main grid or autonomously. These systems enhance energy security, improve reliability, and enable the effective integration of renewable resources at local scale. Furthermore, advancements in power electronics, communication systems, and hierarchical control architectures have significantly increased the sophistication and performance of modern microgrids, enabling real-time optimization, intelligent energy management, and coordination among heterogeneous energy assets [16].

Academic and industrial interest in microgrids has grown substantially over the last decade, with applications ranging from campus and institutional microgrids to rural electrification, industrial energy management, military installations, and smart city infrastructures. Microgrids are now widely recognized as a foundational element of future smart grids and distributed energy systems, enabling greater system flexibility, improved power quality, and enhanced resilience against disturbances and extreme events [17].

This chapter provides a detailed review of the fundamental principles of microgrids, their technical characteristics, and their role within modern energy systems, with emphasis on their challenges and the optimization approaches required for efficient energy planning and management.

I.2 Microgrid Concept and Definition

One of the most widely cited formal definitions is provided by the U.S. Department of Energy, which defines a microgrid as "a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island mode"[18]. Similarly, the Institute of Electrical and Electronics Engineers (IEEE) Standard 2030.7–2017 specifies operational and control requirements for microgrid controllers, reinforcing the view of a microgrid as a coordinated system capable of autonomous operation and seamless transition between modes [19]

From a functional perspective, microgrids can serve multiple objectives [20]:

- **Reliability enhancement**, ensuring continuity of supply during outages through islanded operation.
- **Renewable energy integration**, mitigating variability through local optimization and storage.
- **Energy cost reduction**, via optimized dispatch and peak-shaving strategies.
- **Environmental benefits**, through reduced greenhouse gas emissions and higher energy efficiency.
- **Support for remote or underserved regions**, particularly in rural electrification or off-grid applications.

In summary, a microgrid can be defined as a localized, flexible, and intelligent energy system designed to enhance reliability, promote renewable energy integration, and support efficient energy management through advanced control and communication technologies. This foundational concept forms the basis for the detailed exploration of microgrid components, classification, benefits, challenges, and optimization strategies in the subsequent sections of this chapter.

A typical microgrid that contains several parts is presented in Figure I.1

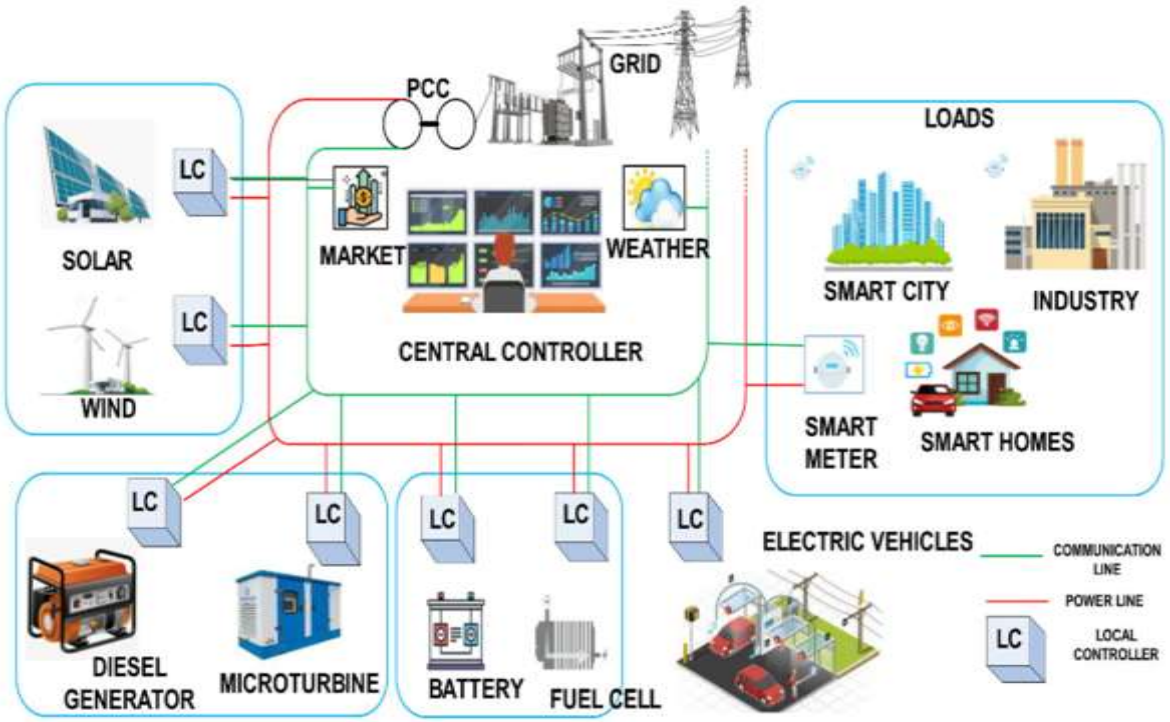


Figure I-1: Typical microgrid system [21]

I.3 Components and Architecture of Microgrids

A microgrid is a complex energy system whose performance and reliability critically depend on the integration, coordination, and control of multiple interconnected components. Understanding the architecture and constituent elements is essential for the effective design, operation, and optimization of microgrids. The primary components include DERs, ESS, power electronics and converters, load infrastructure, control and communication networks. These components interact within a well-defined electrical boundary to enable both grid-connected and islanded operation.

I.3.1 Distributed Energy Resources (DERs)

Distributed energy resources are the generation units within a microgrid, typically small to medium-scale, decentralized, and located close to the point of consumption. DERs include renewable sources such as PV systems, WT, biomass generators, and fuel cells (FC), as well as conventional units like microturbines and diesel generators (DG) [4], [22], [23]. Renewable DERs introduce variability and intermittency, which necessitate advanced energy management and storage strategies. Conventional DERs provide dispatchable power and act as backup sources during islanded operation. The integration of DERs enables reduced transmission

losses, local voltage support, and enhanced energy autonomy, forming the foundation of a microgrid's operational flexibility. DERs technologies are presented as follows [4], [22], [23] :

I.3.1.1 Solar photovoltaic (PV)

Solar PV generator produces electrical energy from the sunlight using semiconductor materials that convert sunlight directly into electricity. Photovoltaic generators are one of the most common renewable distributed generation technologies, providing clean and sustainable energy for residential, commercial, and microgrid applications. Their output depends on solar radiation and weather conditions, often complemented by energy storage systems.

I.3.1.2 Wind turbine

Wind turbine is a renewable energy resource that generates electricity by converting the kinetic energy of wind into mechanical power, which drives a generator. Wind turbines can be installed onshore or offshore and are frequently used in small-scale microgrids as well as large distributed generation networks. Their performance depends on wind speed and site selection, making careful planning essential.

I.3.1.3 Fuel cell

A fuel cell is an electrochemical device that generate DC electrical energy converting the chemical energy from various types of chemicals like hydrogen, methanol, phosphoric acid, molten carbonate, etc. Fuel cells are environmentally friendly since no nitrogen oxide (NOx) is produced, and because there are no moving parts, no noise or wear and tear are involved in the cells' operation.

I.3.1.4 Diesel generator

The diesel generator (DG) set is widely used as an alternative backup supply power in microgrids. DG fuel consumption depends on generator size and on connected load to which generator supplies the power. It is used as backup or standalone power sources, especially in areas with limited grid access. While they provide reliable and controllable electricity, their operation emits greenhouse gases, so they are often paired with renewable sources in hybrid systems.

I.3.1.5 Microturbine

Microturbines are compact gas turbines that generate electricity by burning natural gas or liquid fuels. They are known for their small footprint, modularity, and ability to operate continuously or on-demand. Microturbines are suitable for distributed generation in commercial buildings, industrial facilities, or combined heat and power (CHP) systems.

I.3.2 Power Electronics and Converters

Power electronics are essential for interfacing DERs and ESSs with the microgrid, providing voltage and frequency regulation, bidirectional energy flow, and power quality control. Key converter types include [24]:

- **DC/AC inverters**: Convert DC from PV systems or batteries into AC compatible loads and the main grid.
- **AC/DC rectifiers**: Convert AC from conventional generators to DC for storage or DC loads.
- **DC/DC converters**: Enable voltage regulation for battery systems or PV arrays.
- **Bidirectional converters**: Allow two-way power flow between ESSs and the microgrid.

Advanced control strategies, such as droop control, virtual inertia, and voltage source/load-following modes, are implemented through these converters to maintain stable operation during dynamic conditions.

I.3.3 Energy Storage Systems (ESS)

Energy Storage Systems are the critical enablers of microgrid flexibility and resilience, decoupling generation from consumption in time. They perform multiple vital functions [25]:

- **Energy Arbitrage:** Storing excess renewable generation for use during periods of high demand or low generation.
- **Power Quality and Stability:** Providing fast frequency response and voltage support by injecting/absorbing real and reactive power almost instantaneously.
- **Seamless Mode Transition:** Ensuring uninterrupted power during the switch from grid-connected to islanded mode.
- **Peak Shaving:** Reducing power draw from the grid during expensive peak periods.

Technologies range from high-power, fast-responding devices like supercapacitors and flywheels (suited for stability services) to high-energy density solutions like lithium-ion and flow batteries (suited for energy time-shifting). The optimal ESS technology and sizing are determined by the required discharge duration, power rating, cycling needs, and cost [25]

I.3.4 Loads

Loads in a microgrid environment exhibit substantial diversity in terms of criticality, controllability, and temporal behaviour. They are typically categorized into [26]:

- **Critical loads**, which must remain energized during faults or islanding events (e.g., medical equipment, data centers).
- **Controllable loads**, which can be shifted or modulated without significantly compromising performance (e.g., HVAC systems, industrial processes).
- **Flexible loads**, capable of participating in demand response or load-shaping programs.

Accurate load modelling is fundamental for energy management optimization, storage sizing, and system reliability assessment. Models may range from aggregated deterministic demand curves to stochastic, high-resolution profiles that incorporate behavioural and environmental uncertainties.

Contemporary microgrids increasingly adopt smart load management strategies, leveraging automation, demand response algorithms, and real-time monitoring, to adjust consumption in response to renewable variability, grid constraints, or dynamic pricing signals. This enhances operational efficiency, reduces peak demand, and improves renewable energy utilization.

I.3.5 Grid Interface and Point of Common Coupling (PCC)

The grid interface defines the connection between the microgrid and the main utility network through the Point of Common Coupling (PCC). This interface ensures safe and reliable synchronisation, protection coordination, and energy exchange under diverse operating scenarios.

Key functionalities include [27]:

- **Synchronization and protection mechanisms,** enabling seamless transitions between grid-connected and islanded modes.
- **Voltage and frequency support**, particularly when the microgrid contributes ancillary services to the upstream grid.
- **Export/import control**, allowing the microgrid to operate as a net energy consumer or producer depending on economic and operational criteria.
- **Fault detection and isolation**, ensuring that disturbances do not propagate across the PCC.

The design of the grid interface plays a critical role in ensuring resilience, interoperability, and compliance with grid codes, especially in systems with high penetration of inverter-based DERs.

I.3.6 Control and Communication Infrastructure

It represents the nervous system that overlays the physical components, implementing a hierarchical control architecture essential for reliable microgrid operation. This hierarchy is commonly structured into three primary levels [27] [28]:

- **Primary Control:** This is a local, decentralized, and fast-acting layer (typically operating in milliseconds). Implemented within the power electronic converters themselves (e.g., using droop control), its objective is instantaneous power sharing among parallel sources and the maintenance of basic voltage and frequency stability during load changes or generation shifts. It requires no communication between units.
- **Secondary Control:** Operating on a timescale of seconds to minutes, this layer compensates for the steady-state voltage and frequency deviations introduced by the primary control. It can be implemented in a centralized manner, where a central controller calculates correction setpoints based on global measurements and sends them to individual units, or in a distributed manner using consensus algorithms. A key function of this layer in grid-connected mode is to regulate the power exchange at the Point of Common Coupling (PCC)[27].
- **Tertiary Control / Economic Dispatch:** This is the highest control level, functioning on a timescale of minutes to hours. It is inherently centralized and is the core of the Energy Management System (EMS). Based on forecasts (load, renewable generation, electricity prices), cost functions, and system constraints, the EMS solves an optimization problem to determine the most economical or efficient schedule for all dispatchable Distributed Energy Resources (DERs) and Energy Storage Systems (ESS). It sends setpoints (e.g., power output commands) to the secondary control layer.

I.4 Microgrid Classification

Microgrids exhibit significant diversity in their design, purpose, and operation. To systematically study and deploy them, a clear classification framework is essential. This framework typically categorizes microgrids based on three principal dimensions: electrical architecture, application scenario and location, and primary operational mode. This taxonomy helps in understanding their technical requirements, control complexities, and optimal use cases. A comprehensive overview of this classification is presented in Table I.1.

Table I-1: Taxonomy of Microgrid Classifications [29]

Classification Basis	Type	Key Characteristics	Typical Applications
Architecture & Sources	DC Microgrid	DC generation/storage; reduced conversion stages; high efficiency for DC loads.	Data centers, telecom shelters, EV charging hubs, offices with solid-state lighting.
	AC Microgrid	Aligns with standard AC distribution, easier integration with legacy grid.	Campus energy systems, industrial plants, most urban and community grids.
	Hybrid AC/DC Microgrid	Integrates both AC and DC sub-grids via interlinking converters; maximizes source/load compatibility.	Systems with diverse DC and AC resources/loads (e.g., renewables, storage, industrial motors).
Scenario & Location	Commercial/ Industrial	Focus on reliability, power quality, and demand charge reduction.	Office buildings, supermarkets, factories, hospitals.
	Residential	Aims for self-consumption, bill reduction, and backup power.	Single homes, housing complexes, apartment blocks.
	Community/ Campus	Shared resources for collective benefit; larger scale.	Neighborhoods, universities, military bases.
	Remote/Island	Off-grid necessity; 100% renewable penetration goals.	Isolated villages, islands, mining operations.
	Virtual (VPP)	Non-physical aggregation of distributed assets for grid services.	Portfolio of residential PV/Storage, dispatchable demand.
Operation Mode	Grid-Connected	Interacts with main grid for import/export; must respect grid codes.	Majority of urban and commercial MGs.
	Stand-Alone (Islanded)	Must independently maintain voltage/frequency stability.	Remote systems, critical infrastructure backup.

I.5 Benefits and Importance of Microgrids

Microgrids provide numerous advantages that make them a key component in modern energy systems. Their importance arises from the ability to enhance system reliability, facilitate renewable energy integration, improve energy efficiency, and support energy security. Microgrids also offer socio-economic benefits, particularly in remote and rural areas, while providing ancillary services to the main grid [30]. In Figure I-2 are summarized benefits and Importance of Microgrids.

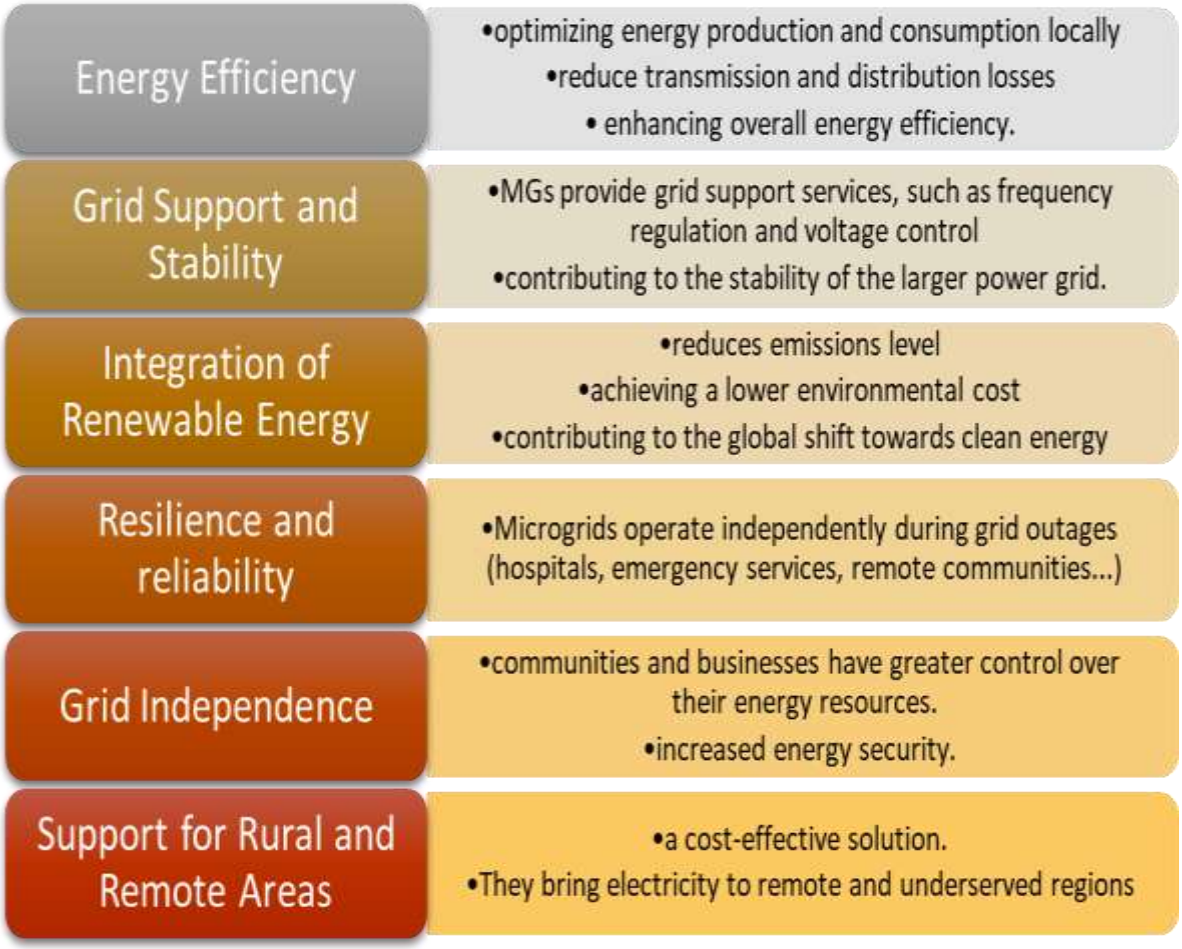


Figure I-2 Benefits and Importance of Microgrids

I.6 Challenges in Microgrid Energy Management

Despite their numerous benefits, microgrids face significant challenges in energy management due to the integration of diverse distributed energy resources, variable loads, and the need for coordination with the main grid [21]. Efficient energy management is critical for maintaining reliability, optimizing operational costs, and achieving environmental and technical objectives. In Figure I-3 are summarized the main Microgrid challenges.

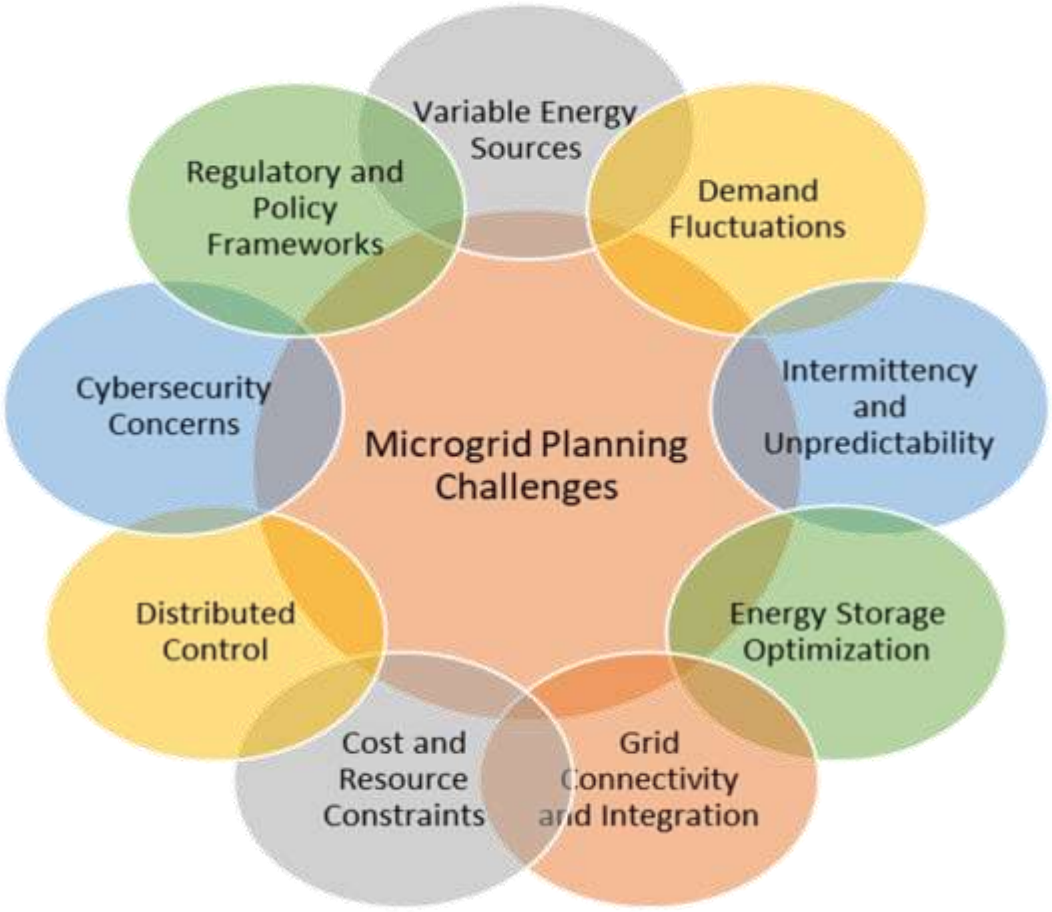


Figure I-3: Microgrids main challenges

I.7 Microgrid Energy Planning and Management

Energy planning and management in microgrids is critical to ensure reliable, cost-effective, and sustainable operation. It involves coordinating generation, storage, and load to meet technical, economic, and environmental objectives. Effective energy management requires a combination of forecasting, hierarchical control, optimization algorithms, and real-time decision-making.

I.7.1 Microgrid Energy Planning Levels and Process

Energy planning and management in microgrids works in three complementary levels and layers, each serving its purpose while supporting the others.

1. **Strategic planning:** Long-term decisions regarding the sizing, placement, and technology selection of DERs, storage, and communication infrastructure [31].
2. **Tactical planning:** Medium-term scheduling of resources, maintenance, and integration of demand response programs [32].

3. **Operational planning:** Short-term control and dispatch to balance supply and demand in real-time, considering variability of renewable energy sources and load fluctuations [8].

The energy planning process in a microgrid involves the following stages as summarized in Figure I-4 [33]:

1. Data Collection and Analysis: Gathering data on load profiles, weather patterns, and resource availability.
2. System Design: Selecting appropriate DERs and storage components based on energy requirements and technical constraints.
3. Optimization Modeling: Formulating objective functions and constraints for optimization.
4. Simulation and Evaluation: Running optimization algorithms to generate scenarios and evaluate performance metrics.
5. Implementation and Testing: Deploying the system and validating performance through real-time operation.

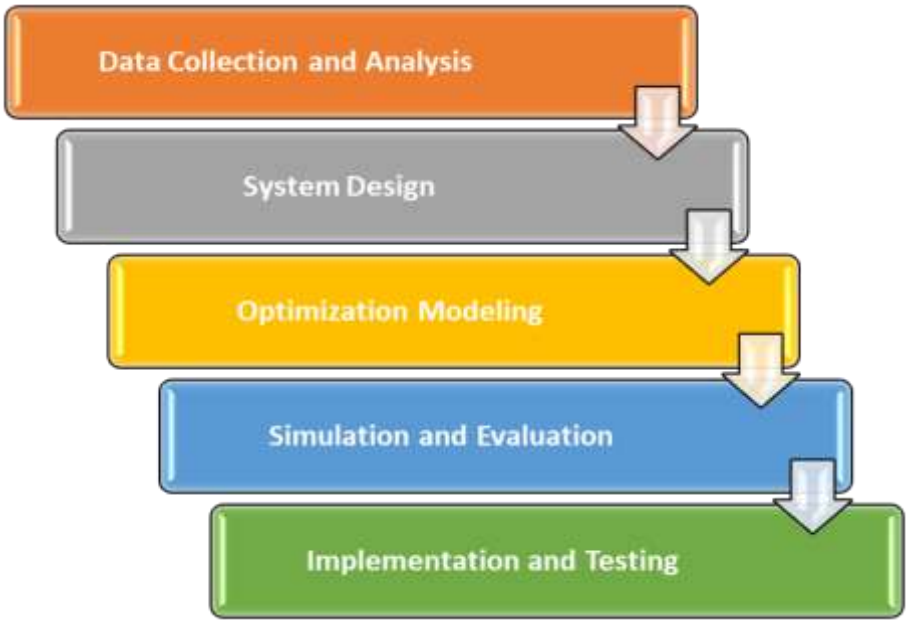


Figure I-4: Microgrid energy planning process

I.7.2 Classification of Energy Management Approaches

Energy management approaches can be categorized based on control strategy, optimization method, and time horizon:

1. **Rule-based/heuristic approaches:** Simple strategies using predefined rules for dispatch and storage control. They are computationally efficient but suboptimal under varying conditions [34].

2. **Optimization-based approaches:** Use mathematical programming (linear, nonlinear, mixed-integer) to determine the optimal dispatch of DERs and storage [35].
3. **Intelligent and predictive approaches:** Incorporate forecasting, machine learning, and real-time optimization to adapt to uncertain renewable generation and load variations [36].
4. **Decentralized and distributed approaches:** Use local controllers and peer-to-peer coordination to manage resources without relying on a central controller, enhancing scalability and resilience [37].

I.7.3 Optimization Criteria and Performance Metrics

Effective energy management in microgrids often involves optimization to balance technical, economic, and environmental objectives. Optimization requires defining appropriate criteria and performance metrics to evaluate the system's efficiency, reliability, and sustainability. These criteria can be categorized into economic, technical, environmental, social/political, and multi-objective considerations.

I.7.3.1 Economic Criteria

Economic performance metrics are central to microgrid operation and planning. They include:

- **Operational costs:** Fuel consumption, maintenance, and labour [38].
- **Net Present Cost (NPC):** The total cost of a system over its entire life, discounted to today's value, including installation, fuel, maintenance, and subtracting any revenue/salvage value [39].
- **Capital expenditure (CAPEX) and operational expenditure (OPEX):** Costs associated with DERs, energy storage, and control infrastructure [40].
- **Levelized Cost of Energy (LCOE):** Average cost per unit of electricity generated, considering capital, operation, and maintenance [41].(Shen et al. 2020).
- **Revenue from energy trading:** Participation in local electricity markets or demand response programs [42].

Economic criteria ensure that microgrids operate in a financially sustainable manner while minimizing cost to stakeholders.

I.7.3.2 Technical Criteria

Technical metrics focus on the reliability, stability, and efficiency of the microgrid:

- **Voltage and frequency stability:** Maintaining power quality within prescribed limits [43].
- **Reliability indices:** Loss of Load Probability (LOLP), System Average Interruption Duration Index (SAIDI) [44].

- **Power losses and efficiency:** Minimization of distribution and conversion losses [45].
- **Renewable energy utilization:** Maximizing the share of energy supplied by renewable sources calculated by the Renewable Fraction (RF) index [46].

I.7.3.3 Environmental Criteria

Environmental criteria assess the sustainability and ecological impact of microgrid operation:

- **Carbon dioxide and greenhouse gas emissions** [47].
- **Pollutant reduction** from replacing conventional fossil-fuelled generation [48].
- **Renewable energy penetration level** to minimize environmental impact [49].

I.7.3.4 Social and Political Criteria

Social and political criteria ensure that microgrid projects contribute to societal welfare and policy objectives, especially in rural or underserved regions:

- **Energy access and equity:** Providing reliable electricity to remote communities [13].
- **Job creation and local development:** Supporting local employment through microgrid deployment and maintenance [50].
- **Regulatory compliance and policy incentives:** Alignment with national energy policies and incentives for renewable integration [51].

I.7.3.5 Multi-Objective Optimization

Most microgrid energy management problems are multi-objective, requiring trade-offs between economic, technical, environmental, and social criteria [52], [53]. Multi-objective optimization techniques, such as Pareto-based approaches, weighted sum methods, or evolutionary algorithms, provide efficient solutions that balance conflicting objectives [53].
In Table I-2 is listed and summarized the optimisation criteria and corresponding performance metrics.

Table I-2: Summary of optimization criteria and corresponding performance metrics

Criterion Category	Metrics	Objective
Economic	NPC, LCOE, CAPEX, OPEX, revenue	Minimize costs, maximize revenue
Technical	Voltage/frequency stability, losses, reliability indices	Maximize reliability and efficiency
Environmental	GHG emissions, renewable penetration	Minimize environmental impact
Social/Political	Energy access, job creation, regulatory compliance	Maximize societal benefit
Multi-Objective	Weighted combination or Pareto front	Balance conflicting objectives

I.8 Computational Optimization Techniques

Optimization techniques are essential for efficient microgrid energy management, enabling the system to achieve multiple objectives while handling uncertainties in generation, load, and market conditions. Computational optimization approaches can be broadly classified into classical methods, stochastic methods, metaheuristic algorithms, and software-based solutions.

I.8.1 Classical Optimization Methods

Classical methods provide exact solutions for convex problems but may be computationally expensive or infeasible for large-scale or highly nonlinear microgrid systems. They rely on mathematical programming techniques with well-defined objective functions and constraints:

- **Linear Programming (LP):** Suitable for problems with linear objectives and constraints, often used for economic dispatch and load scheduling [54].
- **Nonlinear Programming (NLP):** Handles nonlinear relationships in power flow, storage dynamics, and generation costs [55].
- **Mixed-Integer Linear/Nonlinear Programming (MILP/MINLP):** Incorporates binary or integer decision variables, useful for unit commitment, DER on/off decisions, and storage allocation [56].

I.8.2 Stochastic Optimization Methods

Stochastic optimization incorporates uncertainty in renewable generation and load demand. These methods are particularly effective for planning and operational decision-making under uncertainty. :

- **Scenario-based stochastic programming:** Uses multiple scenarios to model variations in solar, wind, or load profiles [57].
- **Chance-constrained programming:** Ensures constraints are satisfied with a specified probability under uncertainty [58].
- **Robust optimization:** Seeks solutions that are feasible under worst-case variations, enhancing microgrid reliability [59].

I.8.3 Metaheuristic Optimization Algorithms

Metaheuristic algorithms have gained significant popularity for microgrid optimization due to their ability to provide flexible, adaptive, and near-optimal solutions for complex and multi-objective problems. Common metaheuristic approaches include:

- **Genetic Algorithms (GA):** Mimic natural selection to optimize multi-objective functions [60].
- **Particle Swarm Optimization (PSO):** Inspired by swarm behaviour for efficient exploration of solution space [61].
- **Ant Colony Optimization (ACO):** Used for routing and scheduling optimization problems [62].
- **Hybrid Algorithms:** Associate different methods to combine advantages of both [63].

I.8.4 Software Tools

Several software platforms and tools support microgrid optimization and simulation:

- **MATLAB/Simulink:** Offers toolboxes for modelling, simulation, and optimization of microgrids [64].
- **GAMS (General Algebraic Modelling System):** Used for LP, NLP, and stochastic optimization of energy systems [65].
- **HOMER:** Specialized in microgrid design, economic analysis, and optimization [66].
- **OpenDSS:** Distribution system simulator for performance assessment and optimization [67].

Table I-3: Summary of computational optimization techniques for microgrids

Method Type	Key Techniques	Advantages	Limitations
Classical	LP, NLP, MILP	Exact solutions for convex problems	Computationally heavy for large-scale/nonlinear problems
Stochastic	Scenario-based, chance-constrained, robust	Handles uncertainty, risk-aware	Requires scenario generation, may be complex
Metaheuristic	GA, PSO, ACO, Hybrid	Flexible, handles multi-objective and non-convex problems	No guarantee of global optimum, parameter tuning needed
Software Tools	MATLAB, GAMS, HOMER, OpenDSS	Integrated modeling, simulation, and optimization	Licensing cost, learning curve

I.9 Conclusion

This chapter provides a foundational framework and a comprehensive overview of microgrids emphasising progression from a specialized idea to decentralized, resilient, and sustainable electrical networks by integrating renewable sources. It presents their fundamental concepts including, main components comprising different distributed sources resources (solar PV, wind, fuel cells, microturbines, generators), energy storage systems, power electronic converters, and hierarchical control systems working in coordination. Their role in modern energy systems, and the challenges associated with their optimal planning and operation. It reviews and establishes a variety of existing computational optimization approach and tools, including classical (deterministic), stochastic, and metaheuristic approaches, that have been employed to address multiple objectives in energy management for microgrids that includes: economic, technical, reliability and environmental objectives. The next chapter, provides comprehensive overview of HOMER Pro methodology and capabilities. It details a practical application of HOMER Pro software for the sizing and techno-economic feasibility and viability analysis of a microgrid case study.

CHAPTER II

Techno-economic assessment of microgrids using Homer Pro

Chapter II : Techno-economic Assessment of Microgrids Using Homer Pro

II.1 Introduction

Microgrids containing clean and renewable energy sources have been traditionally considered as a cost-effective alternative for energy generation in remote areas, since they are more economically viable than grid extensions [68]. Nowadays, their integration in urban areas has become a key requirement to improve the reliability of the existing utility grid and to solve emissions and climate change issues [16].

A techno-economic assessment is essential to evaluate the technical performance, ensuring microgrids reliability, resilience and the economic feasibility, accounting for capital expenditures, operational costs, and potential revenues [69]. Furthermore, Environmental considerations, such as CO_2 emissions and renewable energy contribution, are increasingly critical in the context of global decarbonization goals [70].

Optimization techniques and simulation tools have become indispensable in microgrid analysis. These tools combine hourly simulations of energy flows with economic modelling, enabling systematic exploration of multiple design options under variable load, resource, and cost scenarios. Among these, HOMER (Hybrid Optimization of Multiple Energy Resources) has emerged as a benchmark platform in both academic research and industrial practices, providing detailed simulation, optimization, and sensitivity analysis capabilities [71].

This chapter aims to present a comprehensive framework for the techno-economic optimization of microgrids using HOMER Pro. It details the underlying methodology, defines key performance indicators, and evaluates the viability of a typical urban microgrid.

II.2 Related works

HOMER Pro has been extensively explored and used in diverse techno-economic feasibility in microgrid research and applications. The majority of research studies in this area has focused on optimal sizing and configuration to minimize the NPC and the COE ensuring a multi-objective optimization balancing cost, reliability, and environmental impact. Table II-1 summarizes recent pivotal studies that their outcomes is typically techno-economic feasibility, optimal sizing, environmental impact, and specific configurations of microgrids.

Table II-1: Recent studies using Homer Pro for different techno-economic purposes

Reference	Location	Techno-economic objectives	Key findings
Furat Dawood et al.,2020 [72]	North-West of Australia	Minimize LCOE, optimize storage, stand-alone microgrid	cost-effective: hybrid Hydrogen/battery, 100% renewable, Remote
Budes et al., 2020 [73]	Colombia	Minimize NPC, LCOE, and emissions	PV-wind hybrid, NPC, low CO2, optimal for grid support
Fatin Ishraque et al., 2021 [74]	Bangladesh	Minimize NPC, LCOE, CO2, compare dispatch strategies.	Load Following: NPC, LCOE, CO2; Combined Dispatch worst
Bhatt et al., 2022 [75]	Thailand	Minimize NPC, LCOE, compare battery types, Second-life batteries	reduce NPC and LCOE by 36% and 35%.
Al Afif et al., 2023 [76]	Jordan	Feasibility, optimal sizing, climate resilience	Hybrid system robust to climate, optimal sizing for resilience
Yazdani et al., 2023 [77]	Iran	Multi-objective optimization (NPC, LPSP, CO2), Pareto analysis.	Dominant configuration: PV/FC/Electrolyzer/Htank/Battery/Inverter/20%Grid
Araoye et al., 2024 [78]	Nigeria	Minimize TNPC, COE, unmet load	Biogas/diesel hybrid: COE, 0% unmet load, biogas key for affordability.
Yadav et al., 2024 [79]	India	Minimize NPC, COE, optimize storage	Multi-storage Hybrid configuration: lowest NPC, and COE.
Bahamida et al.,2025 [80]	Algeria	techno-economic and environmental criteria. off-grid and on-grid hybrid systems	NPC, LPSP, CO_2 emissions, The best-performing design: renewables, storage, and grid power.

II.3 Overview of Homer Pro

HOMER (Hybrid Optimization of Multiple Energy Resources) was Originally developed by the U.S. National Renewable Energy Laboratory (NREL) to facilitate the design of hybrid renewable energy. The software has undergone continuous development, validation, and enhancement over more than two decades. It is now commercialized as HOMER Pro and represents the commercial version with enhanced features, expanded component libraries, and professional support [81]. Among available tools, HOMER is a powerful simulation tool for design, techno-economic analysis, feasibility studies and optimization of microgrids.

HOMER simulates real-world performance and delivers a realistic optimized design of DERs and microgrids. It integrates time-series simulations, optimization and financial metrics such as NPC, LCOE, and payback periods. It performs an exhaustive search optimization across discrete system component sizes and dispatch strategies and helps a deep understanding about cost-effective solutions. HOMER remains a reliable platform for both research studies and industrial microgrid projects for preliminary feasibility assessments, comparative analyses, and sensitivity studies [17], [49], [71]

II.3.1 Homer Methodology

HOMER Pro's analytical strength lies in its integrated three-step process: simulation, optimization, and sensitivity analysis [39] as detailed in Figure II-1.

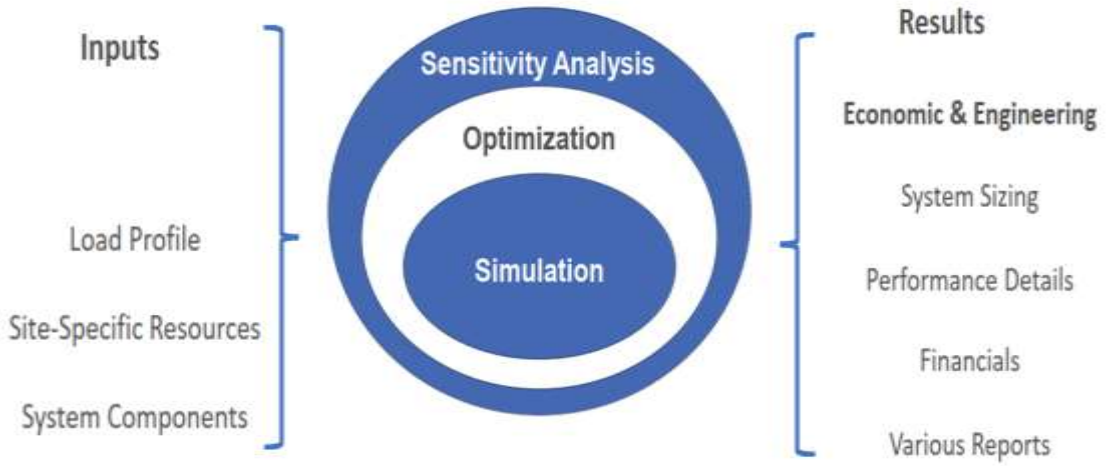


Figure II-1: Homer Pro methodology framework

II.3.1.1 Simulation Engine

The simulation engine calculates hourly energy balances across all components of a microgrid at each hour *t*:

$$\mathrm{E_{Load}}(t) = \mathrm{E_{PV}}(t) + \mathrm{E_{wind}}(t) + \mathrm{E_{DG}}(t) + \Delta\mathrm{E_{Storage}}(t) + \mathrm{E_{Grid}}(t) \quad \text{(II.1)}$$

where $E_{load}(t)$ is the demand at hour t, $E_{PV}(t)$ and $E_{Wind}(t)$ are the generation from renewable sources, $E_{Diesel}(t)$ the DG energy, and $\Delta E_{Storage}(t)$ the change in storage energy.
The simulation identifies energy deficits, surpluses, and evaluates component utilization over the project lifetime [69]. Users can input hourly load profiles, seasonal renewable resource data, and operational constraints to mimic real-world scenarios.

II.3.1.2 Optimization Engine

HOMER performs an exhaustive search optimization across discrete system component sizes and dispatch strategies. Each configuration is evaluated based on:

- **Net Present Cost (NPC)**: primary ranking criterion.
- **Levelized Cost of Energy (LCOE)**: secondary criterion.
- **Renewable fraction (RF), unmet load, emissions**: additional criteria

The optimization engine outputs the feasible set of system configurations and identifies the least-cost system while satisfying technical constraints.

II.3.1.3 Sensitivity Analysis

HOMER allows parametric sensitivity analysis by varying input parameters such as (Diesel fuel price, PV and battery costs, Load variation, Renewable resource availability…)

This approach evaluates robustness of the optimal solution and identifies trade-offs between cost, reliability, and renewable integration [82]. Sensitivity analysis helps decision-makers understand the impact of uncertainties and plan for scenarios such as fuel price spikes or demand variations.

II.3.2 Fundamentals of Techno-Economic Analysis

Techno-economic analysis of microgrids relies on three primary categories of indicators: technical performance, economic performance, and environmental impact. These indicators are defined and quantified to enable systematic evaluation of alternative configurations and to support design optimization [83]. Key indicators include [39]:

Table II-2: Key performance indicators of modelling

Technical Indicators		
Renewable Fraction (RF) (%)	$RF = \frac{\sum_{t=1}^{T} E_{renewable}(t)}{\sum_{t=1}^{T} E_{load}(t)}$ (II.2)	$E_{renewable}(t)$: Produced renewable energy. $E_{load}(t)$: Energy demand.
Loss of Power Supply Probability (LPSP) (kWh)	$LPSP = \frac{\sum_{t=1}^{T} E_{deficit}(t)}{\sum_{t=1}^{T} E_{load}(t)}$ (II.3)	$E_{deficit}(t)$: unmet load demand. Not used in this study
System Autonomy (h)	$\text{System Autonomy} = \frac{E_{storage,max}}{\text{Average Load}}$ (II.4)	$E_{storage,max}$: The maximum stored energy
Economic Indicators		
Net Present Cost (NPC) ($)	$NPC = \frac{C_{ann-tot}}{CRF(i,N)}$ (II.5) $C_{ann-tot} = \sum_{t=0}^{N}(C_{cap}(t) + C_{rep}(t) + C_{O\&M}(t) + C_{fuel} - R_{rev}(t))$ (II.6) $CRF = \frac{i(1+i)^N}{(1+i)^N-1}$ (II.7)	$C_{ann-tot}$: Total annualized cost CRF: Capital recovery factor C_{cap}: capital cost C_{rep}: replacement cost $C_{O\&M}$: operation & maintenance cost C_{fuel} : fuel cost R_{rev}: revenue from energy sales i: Real interest rate N: project lifetime in years
Levelized Cost of Energy (LCOE) ($/kWh)	$LCOE = \frac{NPC.i(1+i)^N}{(1+i)^N-1} \times \frac{1}{E_{served}}$ (II.8)	E_{served}: Electrical energy supplied to the load
Payback Period (PB) (yr)	$PB = \text{Year when } \sum R_{rev}(t) \geq \sum C_{initial}(t)$ (II.9)	$R_{rev}(t)$: Cumulative revenues $C_{initial}$:Initial investments
Environmental Indicators		
CO_2 Emissions (%)	$E_{CO_2} = \sum_{t=1}^{T} F_{fuel}(t).E\,F_{CO_2}$ (II.10)	$F_{fuel}(t)$: Fuel consumption EF_{CO_2} Emission factor

II.3.3 Microgrid Component Modelling in HOMER

HOMER provides a modular and physics-based representation of all major microgrid components. Each element, load, generation, storage, and power electronics, is modelled both technically and economically, ensuring consistency during the annual simulation and optimization processes. This section details the formulation used for each component class and highlights typical parameter ranges adopted in techno-economic assessments [39], [84], [85]:

a. ***Load Modelling***

The electrical load is represented as an 8760-hour demand profile, which may be imported from measurements or synthesized using daily and seasonal variability patterns. The total load at hour *t* is expressed as:

$$L(t)=L_{avg}(t)(1+\delta_{day}(t)+\delta_{season}(t)) \quad \text{(II.11)}$$

where:

- $L_{avg}(t)$: baseline hourly demand,
- $\delta_{day}(t)$: intraday variation factor (±20–40% typical),
- $\delta season(t)$: seasonal variation (0–50% depending on climate).

The unmet load fraction, used as a reliability criterion, is computed as:

$$f_{unmet} = \frac{\sum_t L_{unmet}(t)}{\sum_t L(t)} \quad \text{(II.12)}$$

b. ***PV System Modelling***

PV output is expressed as:

$$P_{PV}(t) = P_{rated}\, f_{derate}\, \frac{G(t)}{G_{STC}} [1 + \gamma(T_{cell}(t) - 25)] \quad \text{(II.13)}$$

where:

- f_{derate}: derating factor (75-90 % typical),
- G_{STC} = 1000 W/m², under Standard Testing Conditions.
- γ: temperature coefficient (–0.25 to –0.45 %/°C).

Cell temperature is estimated using the following model:

$$T_{cell}(t) = T_{amb}(t) + \frac{NOCT-20}{800} G_{STC}(t) \quad \text{(II.14)}$$

Orientation options include south-facing, east-west, or tracking configurations.

c. ***Wind Turbine Modelling***

Wind turbine output is obtained directly from manufacturer power curves. A simplified analytical representation is:

$$P_{WT}(v) = \begin{cases} 0, & v < v_{ci} \\ P_{rated}\left(\frac{v - v_{ci}}{v_r - v_{ci}}\right), & v_{ci} \leq v < v_r \\ P_{rated}, & v_r \leq v < v_{co} \\ 0, & v \geq v_{co} \end{cases} \quad \text{(II.15)}$$

with:

- cut-in speed v_{ci}=3–4 m/s,
- rated speed v_r=10–12 m/s,
- cut-out speed v_{co}=20–25 m/s

HOMER interpolates power curves hourly and accounts for air-density correction using:

$$P_\rho = P_{\rho_0}\left(\frac{\rho}{1.225}\right) \quad \text{(II.16)}$$

d. ***Energy Storage Modelling***

Storage is modelled via state-of-charge (SOC) dynamics:

$$SOC(t+1) = SOC(t) + \frac{\eta_{ch} P_{ch}(t)\Delta t - P_{dis}(t)\Delta t/\eta_{dis}}{E_{nom}} \quad \text{(II.17)}$$

e. ***Diesel Generator***

Diesel generator output is governed by its fuel consumption curve:

$$F(P) = aP + bP_{rated} \quad \text{(II.18)}$$

where:

- a: variable consumption coefficient (0.2–0.3 L/kWh),
- b: fixed consumption (0.05–0.1 L/kWh).

f. Dispatch Strategies

Dispatch strategies include:

- **Load Following (LF):** generator meets only unmet load; charging by excess renewable.
- **Cycle Charging (CC):** generator operates near rated power and charges the battery.
- **Advanced Dispatch:** minimizes cost with probabilistic forecasting.

g. ***Grid Modelling***

The grid is modelled as a source that can supply power to the load or absorb excess generation, subject to a maximum import and export power limit the user specifies. HOMER supports:

- **time-of-use (TOU) pricing**,
- **demand charges**,
- **net metering or feed-in tariffs**,
- **grid outages** modelled via a stochastic availability variable.

Grid availability can be defined as:

$$A_{grid} = \frac{1-SAIDI}{8760} \quad \text{(II.19)}$$

where SAIDI is the average annual outage duration (1–500 h/year depending on region).

h. Power Electronics and System Coupling

Inverters and converters determine AC/DC coupling:

Maximum AC load tracking and DC bus voltage limits are enforced hourly [85]

In a typical AC-coupled microgrid:

$$P_{AC}(t) = \eta_{inv} P_{DC}(t) \quad \text{(II.20)}$$

while for DC-coupled systems:

$$P_{DC}(t) = \eta_{rec} P_{AC}(t) \quad \text{(II.21)}$$

II.4 Case study

Through a detailed case study, a real-world microgrid scenario is examined, analysing different configurations and scenarios to assess their performance under varying conditions [71]. The present case study deals with the optimization, and the techno-economic viability of the rooftop microgrid located in the urban region of Bou-Ismail (Tipaza, Algeria) using HOMER Pro software. The microgrid is designed to meet electrical needs of a typical research laboratory selected as a pilot small-scale case study. A comprehensive simulation results of different configurations of the microgrid based on the analysis of the three criteria, including: reliability, cost-effectiveness, and environmental sustainability, has been conducted. The present work analyses the operational strategy and the power flow control between system components including PV, wind, DG, BESS which work together to supply power to the selected load, enhancing reliability and resilience while reducing dependence on traditional utility grid.

II.4.1 Optimization Process by Homer

the flowchart of the process followed by Homer to realize the techno-economic analysis, is represented in Figure II-2.

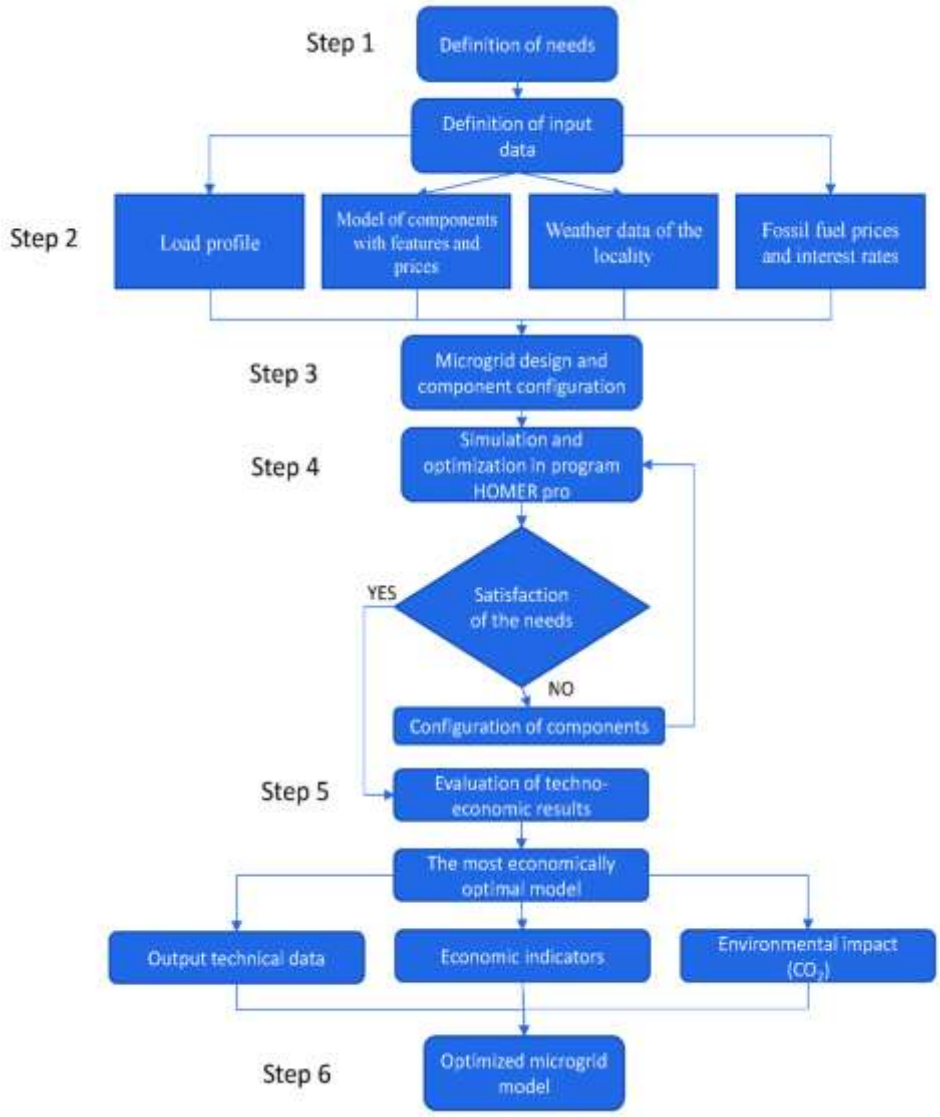


Figure II-2: flowchart of optimization framework in Homer Pro

II.4.2 Input Data and Assumptions

II.4.2.1 Study Area Selection

This study presents the optimization and techno-economic analysis of an urban microgrid located in Tipaza- Algeria the region of Bou-Ismaïl (Latitude 36.64, Longitude 2.69). The microgrid is designed to meet the electrical needs of a typical academic rooftop laboratory (Figure II-3), selected as the primary installation site for renewable energy components, and integration challenges that reflect real urban deployment conditions.



Figure II-3 : The studied microgrid localization

II.4.2.2 Renewable Energy Resources Availability

II.4.2.2.1 Solar

Bou Ismaïl, located on Algeria's northern Mediterranean coastline, benefits from a solar climate that is highly conducive to photovoltaic electricity generation. Regional assessments consistently report strong solar irradiation in the coastal zone, with annual global horizontal irradiance typically reaching around 1,700 kWh/m², equivalent to an average of 4.7–5.0 kWh/m²/day. These values align with broader national studies showing that much of Algeria receives 5–7 kWh/m²/day, reflecting the country's position within one of the world's most solar-rich regions.

II.4.2.2.2 Wind

Wind measurements in the study area indicate a moderate but usable wind resource. Monthly average wind speeds generally fall between 4.2 m/s and 6.8 m/s at the standard reference height of 10 meters above ground level.

The region tends to experience stronger winds during the winter and spring seasons, which provides a natural complement to solar generation since these periods coincide with lower solar irradiation. Daily wind patterns also follow typical coastal behaviour, with speeds increasing during the afternoon and evening as a result of land-sea temperature differences.

Figure II-4 presents solar irradiance and wind speed available on the selected site.

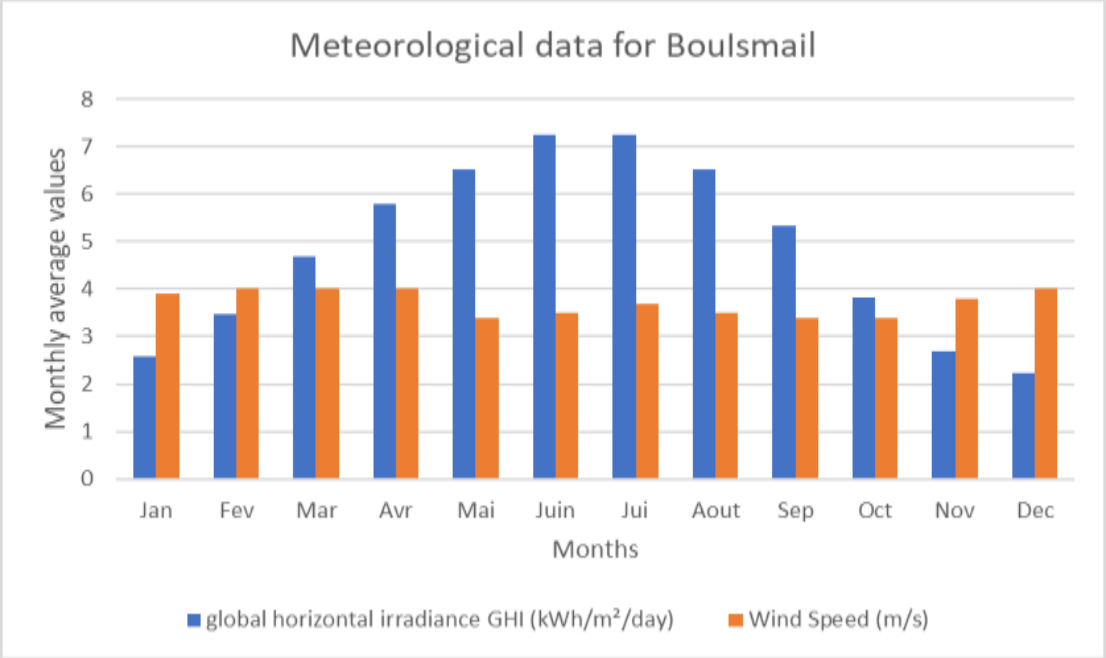


Figure II-4: Meteorological data for the selected site

II.4.2.3 Load Profile Characterization

In this study, the average daily energy consumed by the selected area is estimated at 17 kWh/day (65000kWh/yr) with 3.3 kW peak demand, corresponding to a daily consumption where the maximum demand occurs during working hours in the laboratory selected as a case study (daytime from 9 to 17), with no considered seasonal variations (a moderate load demand). Figure II-5 presents the hourly variations of the typical daily load demand to be met while the monthly load demand profile generated by Homer Pro is presented in Figure II-6.

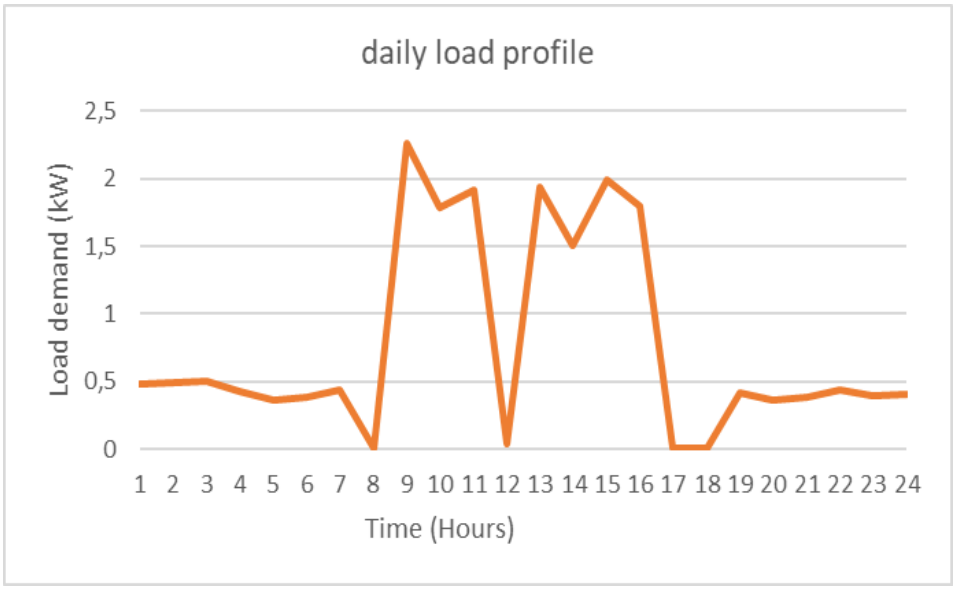


Figure II-5: Hourly variation of the selected demand profile

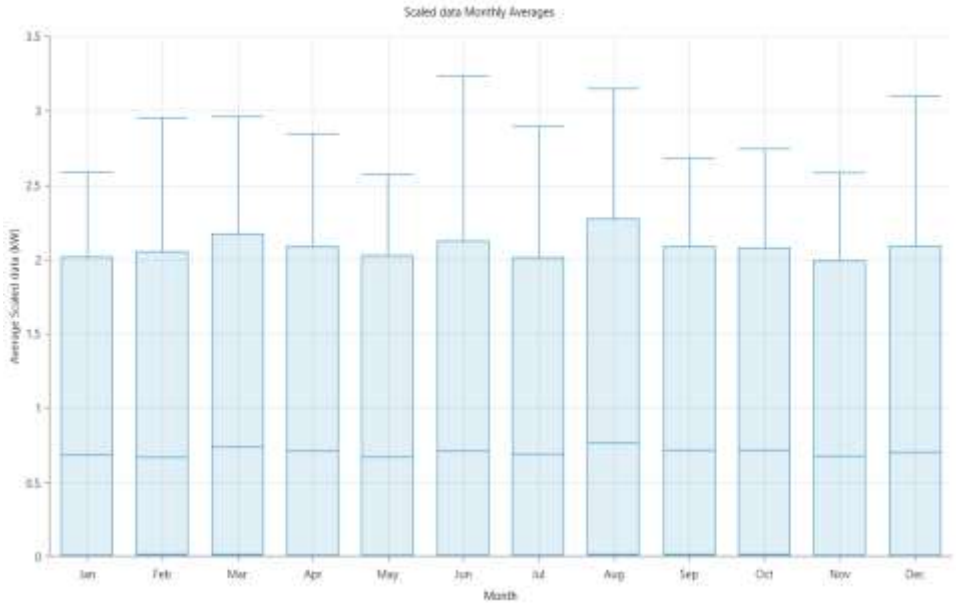


Figure II-6: Average Monthly load demand over a year period.

II.4.2.4 System Architecture and simulation parameters

The microgrid architecture is shown in Figure II-7. The adopted DC coupled system (DC Bus 48 V) provides a simple battery integration, a simple PV-battery-load path, a conversion from PV (DC/DC) and wind generators (AC/DC) to the battery. The AC output of DG is supplying the AC load and injected into the DC Bus through an (AC/DC) power converter to charge the batter bank.

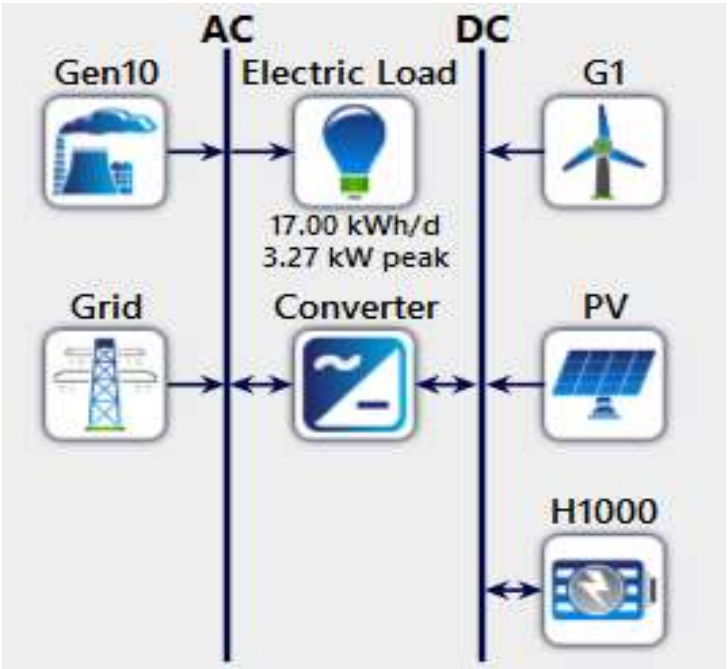


Figure II-7: microgrid topology.

Table II-3 summarizes the parameters values used in this simulation.

Table II-3: Parameters values used in this simulation

Component	Parameter	Value	Unit
Global economic parameters	Discount Rate Inflation Rate Project lifetime	6 3 25	% % Years
Photovoltaic PV	Capacity Lifetime Capital cost Replacement cost O&M cost Derating factor	0-6 25 1000-2000 850-1500 100 77	kW Year $/kWc $/kWc $/yr %
Wind	Capacity Lifetime Capital cost Replacement cost O&M cost	1 10 7500 5000 10	kW Year $/kWc $/kWc $/yr
Diesel generator DG	Capacity Lifetime Capital cost Replacement cost O&M cost	10 20000 4000 4000 0.4	kW Hours $ $ $/op.hour
Battery	Capacity Lifetime Capital cost Replacement cost O&M cost	Optimized by Homer 10 1500 1200 50	kW Year $/kWc $/kWc $/yr
Grid	Purchase capacity Sale capacity Purchase price sellback	4000 0 0.043 0	kW/yr kW/yr $/kWh $/kWh

II.4.3 Constraints and Requirements

To ensure that the simulated microgrid configurations are technically and economically viable, and aligned with sustainability objectives, specific operational constraints and performance requirements are enforced within the HOMER Pro optimization framework, to switch from a standard simulation and optimization to a constrained optimization making the

obtained configurations more practical and realistic than unconstrained and theorical optimum solutions. These parameters act as critical filters, eliminating any configuration that fails to meet all established standards for reliability, efficiency, and renewable integration.

The following key constraints were applied to guide the search for an optimal system. We focus on technical (hard) constraint while other economic and environmental constraints and requirements are considered as simulation parameters.

Table II-4: Hard constraints applied in the present case study

Constraints	**Value**	**Objective**
Maximum Capacity shortage	0 % (unmet load=0%)	100% reliability required
Generator Operation	Minimum Load: 30% of rated capacity	Efficiency and maintenance
Renewable Integration	Minimum RF ≥ 50%	Sustainability target
Battery Management	(SOC) Limits: 30% - 80%	Lifetime preservation
Operating reserve	10%	Reliability margin
No Charging Battery Grid Sales from Battery Max sellback to grid	0 kW 0 kW 0 kW	Energy self-sufficiency Prevent inefficient grid-to-Battery flows No feed-in allowed

II.4.4 Simulation Results and Optimization

In this study, we first consider a microgrid including PV and wind sources, Battery storage, a diesel generator, in order to obtain a comprehensive understanding of the full system behaviour (Figure II-7).

Applying a set of constraints as presented in the table below (Table II-4), and conducting extensive simulations, the obtained results shed light on the performance and feasibility of three microgrid configurations that reflect realistic optimization, presented in detailed at the next section.

II.4.5 Optimal Sizing Results

The optimal sizing of the obtained configurations defined by the power rate of each element in the hole combined system and other technical parameters are depicted in Table II-5.

Table II-5: Sizing and power rate of components

Rated capacity	**PV/Wind/Batt/Grid**	**PV/Wind/DG/Batt**	**PV/wind/Batt**
PV (kW)	2	3	6
Wind (kW)	1	1	1
DG (kW)	0	10	0
Batteries (1000Ah)	24	24	24
Grid (kW)	2	0	0
Converters (kW)	1,5	3	3,58
RF (%)	79,2	96,6	100
Dispatch	CC	LF	CC
Battery autonomy (hr)	56,7	56,7	56,7

Configuration 1: PV/Wind/Batt/Grid, it is a grid-connected microgrid combining (2 kW) photovoltaic PV generator, (1 kW) wind turbine and (24) batteries with connection to the conventional grid (2 kW as peak load). The grid acts as backup source (no electricity sells are allowable).

Configuration 2: PV/Wind/Batt/DG, it is about a diesel backup microgrid that reveals the combination of PV (3 kW), wind (1 kW), diesel generators (10 kW) and (24) batteries.

Configuration 3: PV/Wind/Batt, it is a stand-alone (autonomous) renewable microgrid relying on only renewable energy sources and batteries with no external support (DG, Grid). In this case, generation (6 kW from PV) and battery capacities are generally oversized compared to other configurations containing backup support.

Renewable Fraction (RF) is an important key parameter that ensure the sustainability target by integrating the renewable penetration in the microgrid to meet the load demand. It indicates how much the energy demand is met by renewable energy sources. Figure II-8, presents the variation of renewable fraction of the obtained configurations.

The hourly contribution extracted from PV, wind, DG sources and grid imports to meet the load demand for each configuration is illustrated in figure II-9.

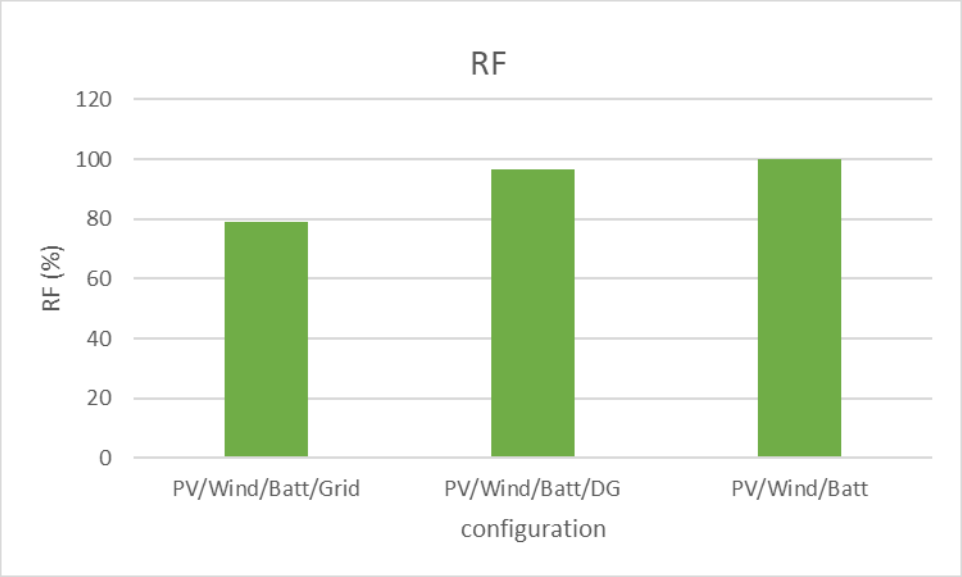


Figure II-8: Renewable fraction variation for optimal configurations

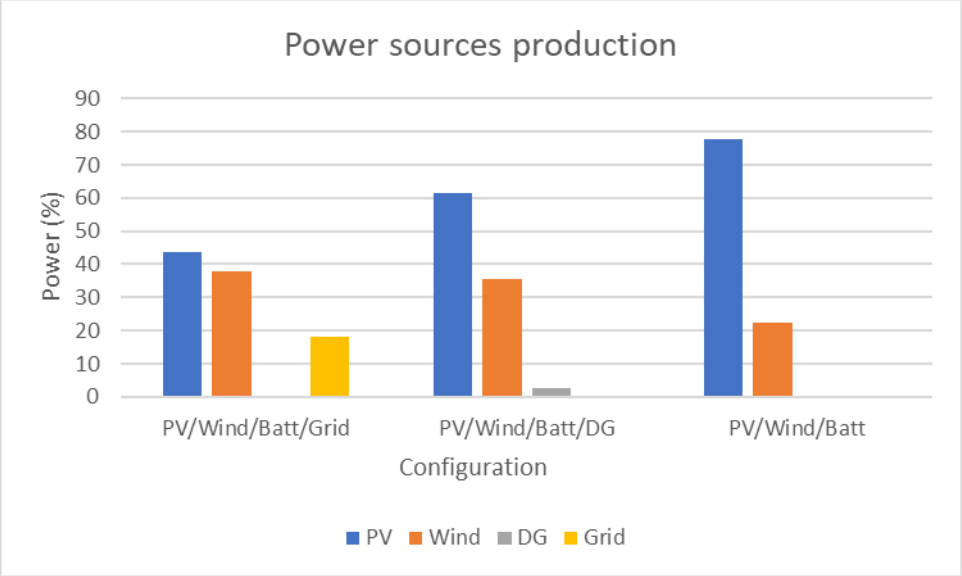
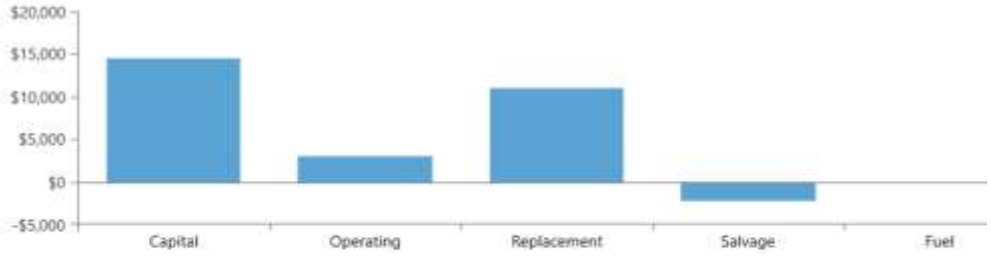


Figure II-9: Power sources production for optimal configurations

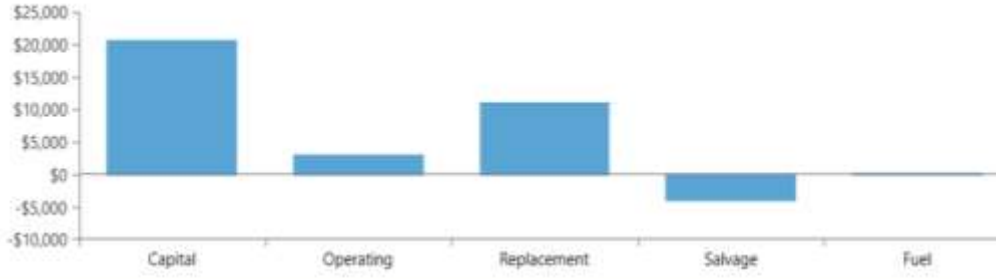
II.4.6 Economic Performance

The economic results presented by cost type for each case are given in the following figures (Figure II.10: a, b, c)



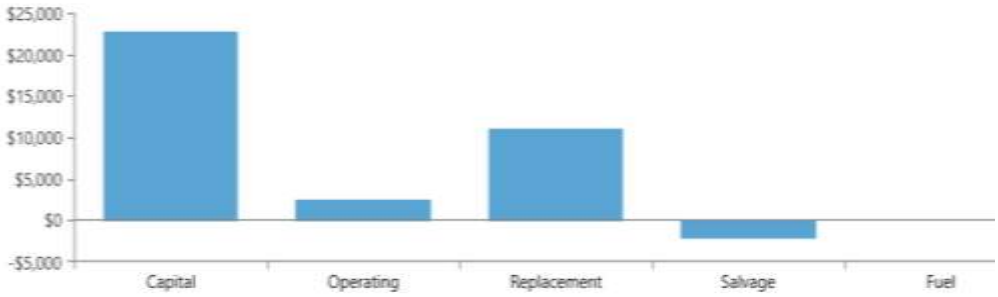
Component	Capital ($)	Replacement ($)	O&M ($)	Fuel ($)	Salvage ($)	Total ($)
Generic 1 kW	$7,500.00	$6,567.95	$175.84	$0.00	-$1,219.62	$13,024.17
Grid	$0.00	$0.00	$975.28	$0.00	$0.00	$975.28
Hoppecke 10 OPzS 1000	$3,000.00	$4,628.47	$1,758.39	$0.00	-$1,024.48	$8,362.38
PV	$4,000.00	$0.00	$0.00	$0.00	$0.00	$4,000.00
System Converter	$171.88	$0.00	$302.22	$0.00	$0.00	$474.10
System	$14,671.88	$11,196.42	$3,211.73	$0.00	-$2,244.10	$26,835.93

a) Case 1: PV/Wind/Batt/Grid



Component	Capital ($)	Replacement ($)	O&M ($)	Fuel ($)	Salvage ($)	Total ($)
Generic 1 kW	$7,500.00	$6,567.95	$175.84	$0.00	-$1,219.62	$13,024.17
Generic 10kW Fixed Capacity Genset	$4,000.00	$0.00	$492.35	$329.38	-$1,780.64	$3,041.09
Hoppecke 10 OPzS 1000	$3,000.00	$4,628.47	$1,758.39	$0.00	-$1,024.48	$8,362.38
PV	$6,000.00	$0.00	$0.00	$0.00	$0.00	$6,000.00
System Converter	$427.08	$0.00	$750.98	$0.00	$0.00	$1,178.06
System	$20,927.08	$11,196.42	$3,177.56	$329.38	-$4,024.74	$31,605.71

b) Case 2: PV/Wind/Batt/DG



Component	Capital ($)	Replacement ($)	O&M ($)	Fuel ($)	Salvage ($)	Total ($)
Generic 1 kW	$7,500.00	$6,567.95	$175.84	$0.00	-$1,219.62	$13,024.17
Hoppecke 10 OPzS 1000	$3,000.00	$4,628.47	$1,758.39	$0.00	-$1,024.48	$8,362.38
PV	$12,000.00	$0.00	$0.00	$0.00	$0.00	$12,000.00
System Converter	$416.67	$0.00	$732.66	$0.00	$0.00	$1,149.33
System	$22,916.67	$11,196.42	$2,666.89	$0.00	-$2,244.10	$34,535.88

c) Case 3: PV/Wind/Batt

Figure II-10: Economic outcomes

The key performance indicators extracted from the obtained results for the three configurations are summarized in the following table II-6.

The NPC is the main metric used in ranking the obtained configurations. As it is showed in figure II-11, the grid connected (PV/wind/Batt/Grid) offers the best economic configuration with the least NPC cost, followed by the diesel backup configuration, and finally the stand-alone renewable configuration.

Table II-6: Configurations Economics

Configuration	PV/wind/Batt/Grid	PV/Wind/Batt/DG	PV/Wind/Batt
NPC ($)	26835,93	31605,71	34535,88
COE ($)	0,245957	0,289673	0,316537
Operation cost ($/yr)	691,7722	607,2952	660,787
Initial capital cost ($)	14671,88	20927,08	22916,67

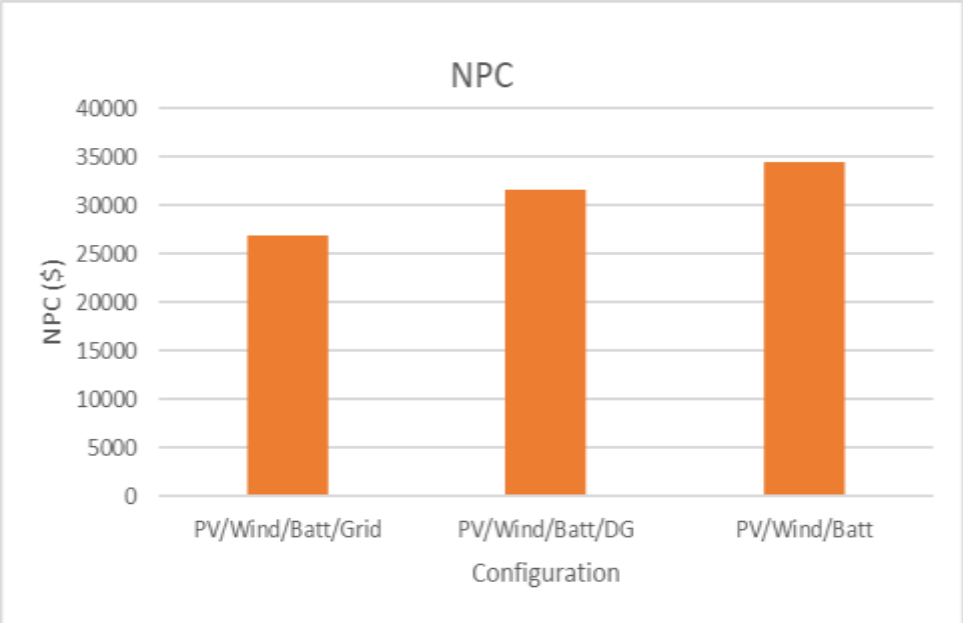


Figure II-11: NPC variation for optimal configurations

II.4.7 Environmental Performance

The annual CO_2 emissions associated with diesel fuel consumption and grid electricity, is one of the typical indicators that facilitates a clear evaluation of environmental performance of the candidate configuration. Table II-7 summarizes the annual CO_2 emissions and fuel use.

Table II-7: The annual CO_2 emissions and fuel use

Configuration	PV/Wind/Batt/Grid	PV/Wind/DG/Batt	PV/wind/Batt
CO_2 (kg/yr)	815	245	0
Fuel consumption (L/yr)	0	93.7	0

II.4.8 Hourly Simulation Findings

In order to understand the optimal configurations operation in practice, the hourly simulations are examined for a typical week in November characterized by fluctuation in renewable generation and load patterns which is suitable for examining the microgrid operation in challenging operation conditions, since it is a moderated month from transitional season (Mars-May, September-November). Figure II-12 presents the load demand profile selected during a week in November.

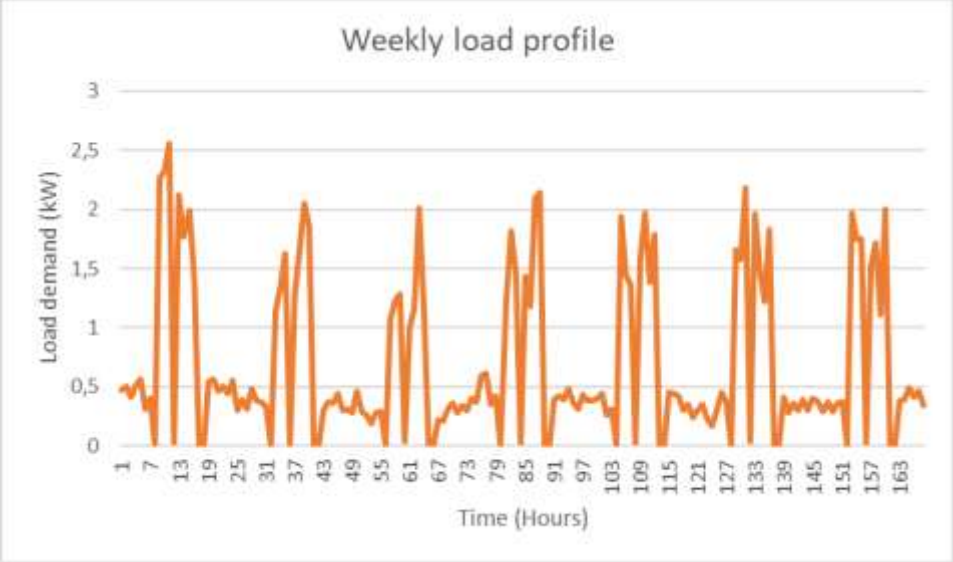


Figure II-12: Load demand profile during a week in November.

In figure II-13, the hourly PV output for the three configurations is presented, showing that the stand-alone microgrid generates the highest amount of PV power to cover the full demand without external backup (oversized). The diesel backup microgrid produces less PV power because the load demand deficit can be supported by the DG. The grid-connected microgrid generates the smallest PV capacity, since the load demand can be economically supplied by the conventional grid.

Figure II-14, shows that the produced wind power is limited to 1 kW for all configurations (to limit wind problems and respect the urban structure). The wind power compensates and completes the PV production to meet the load demand in each hour of

operation. Supported by the battery to fill any gap, the diesel generator and the grid are called as backup sources.

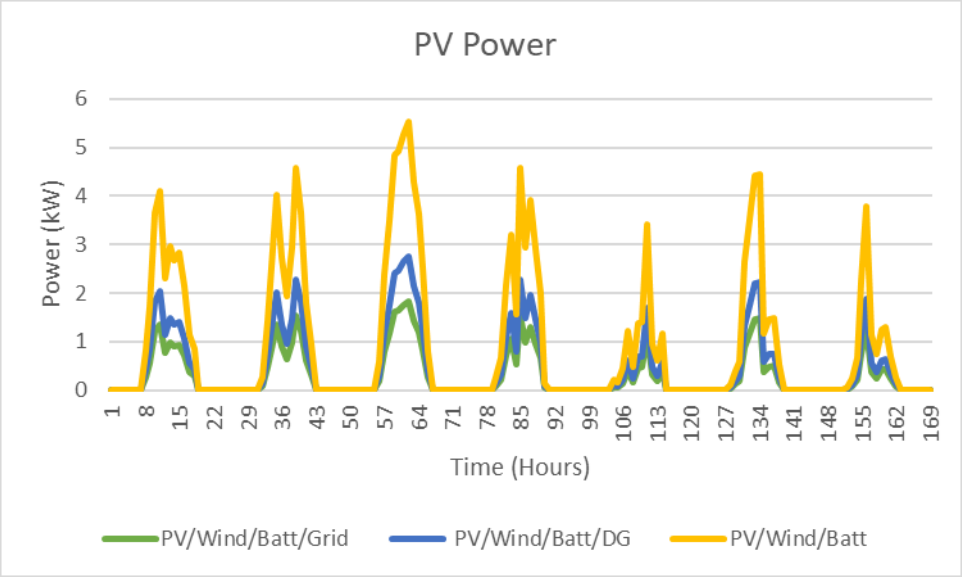


Figure II-13: Produced PV power.

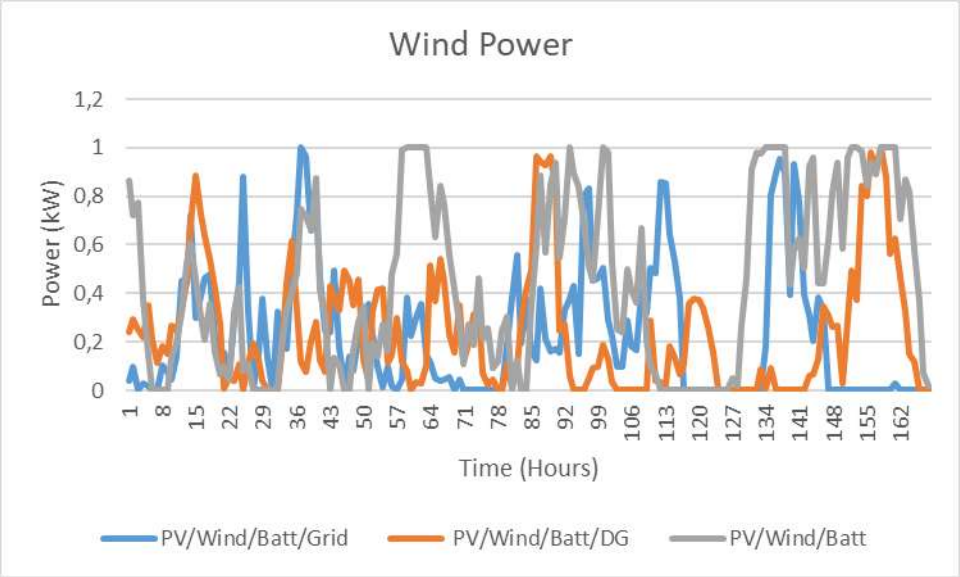


Figure II-14: Produced Wind Power.

In grid-connected configuration, the grid purchase power profile during the selected week is presented in Figure II-15. It shows that the power imports occur when the generated power from PV and wind is low and the battery is discharged. For the rest of time, it remains low (0.6 kW) which confirms that the grid id used as supplementary source and not a continuous supplier.

The same trend is observed for the diesel generator which is turned on for few hours in the week as an emergency unit when necessary to maintain reliability (Figure II-16). The DG

output power for one day of the selected week is presented in Figure II-17, to confirms that the DG does not run continuously but during certain hours (70 hrs/yr calculated by Homer Pro). It is also clearly remarked that the DG operates at around a mean output power of 3 kW even though it is rated at 10 kW, this is because of the applied constraint in Table II-4 (30% of its rated capacity).

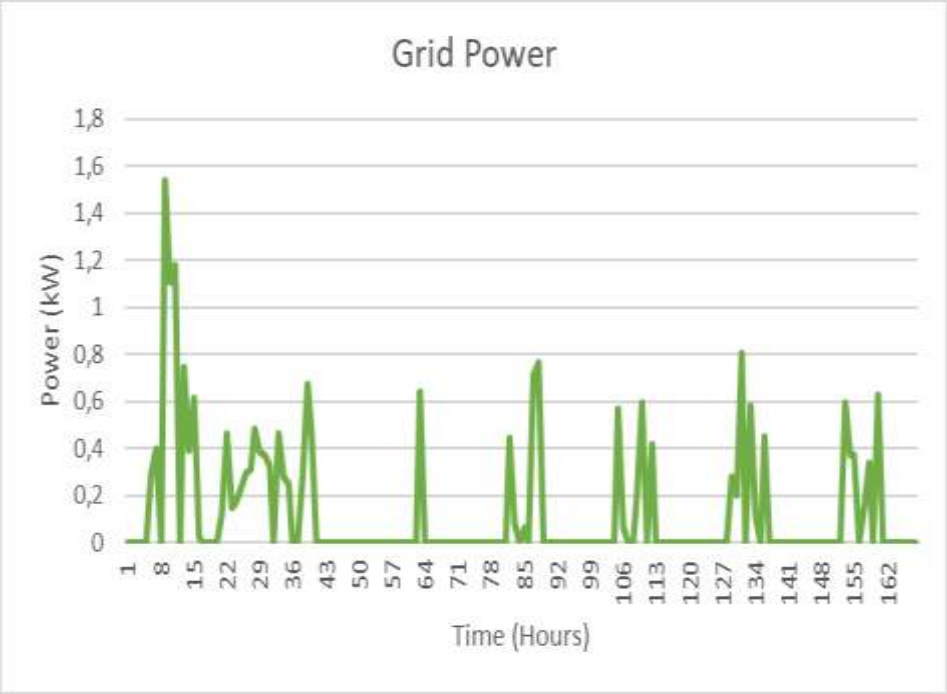


Figure II-15: Grid purchase power profile.

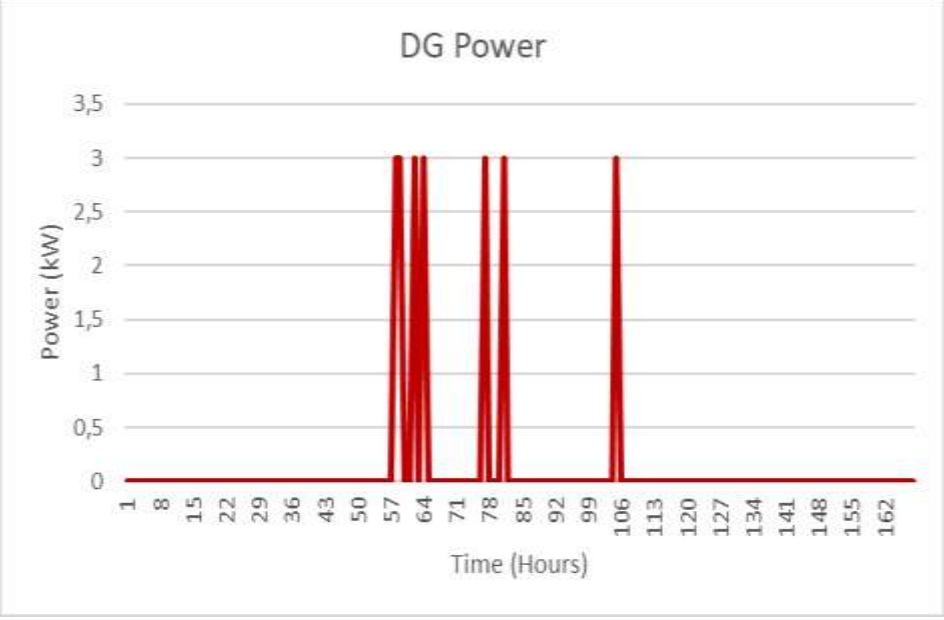


Figure II-16: DG output power for one week.

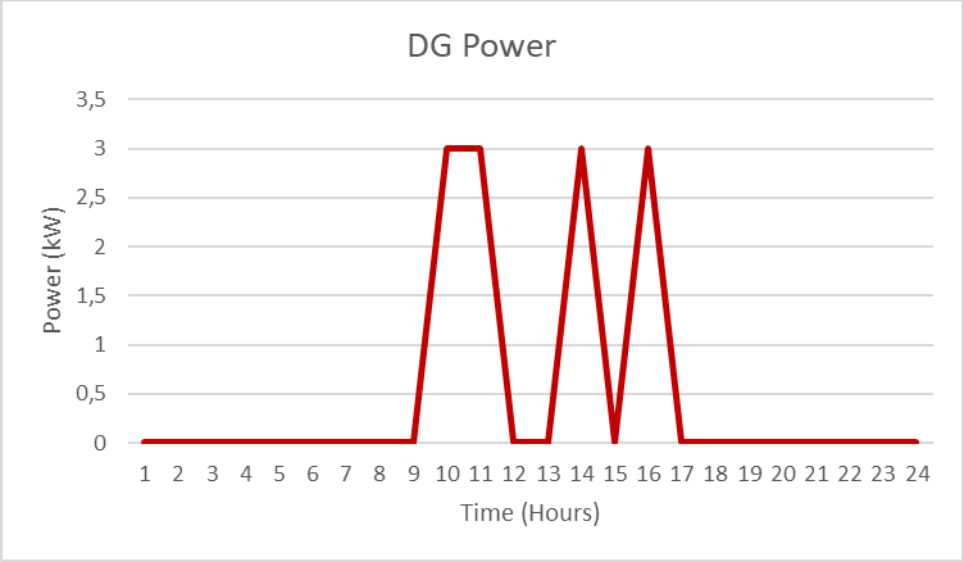


Figure II-17: DG output power for one day.

A comparison based on the variation of state of the charge (SOC) of the battery storage system for the three obtained optimal configurations is presented in Figure II-18.
It can be noted that the battery SOC profile during the simulation period (week) describes the operational behaviour of the three optimal configurations:

- In the grid connected case (PV/Wind/Batt/Grid), the SOC stays relatively low (30-60) %, indicating that the battery is moderately cycled and less stressed. This emphasis the crucial role of the grid in balancing the other resources (PV and Wind) and preventing the battery from rapid degradation.

- When the DG replaced the grid, shows more favourable SOC profile and comfortable range during the selected period (40-80) % , the battery is used actively in healthier operation since the load demand is ensured by DG with PV and Wind sources.

- In the case where the system totally relies on PV and wind generated powers and storage to meet the load demand without any backup (DG, Grid), PV and wind sources are sized higher than the other configurations (over dimensioned, PV in this case: 6kW). Consequently, the SOC stays most of the time in its higher levels to guarantee reliability in the absence of any external backup. This point justifies also the noticed high excess of electricity related to this configuration (Table II-4).

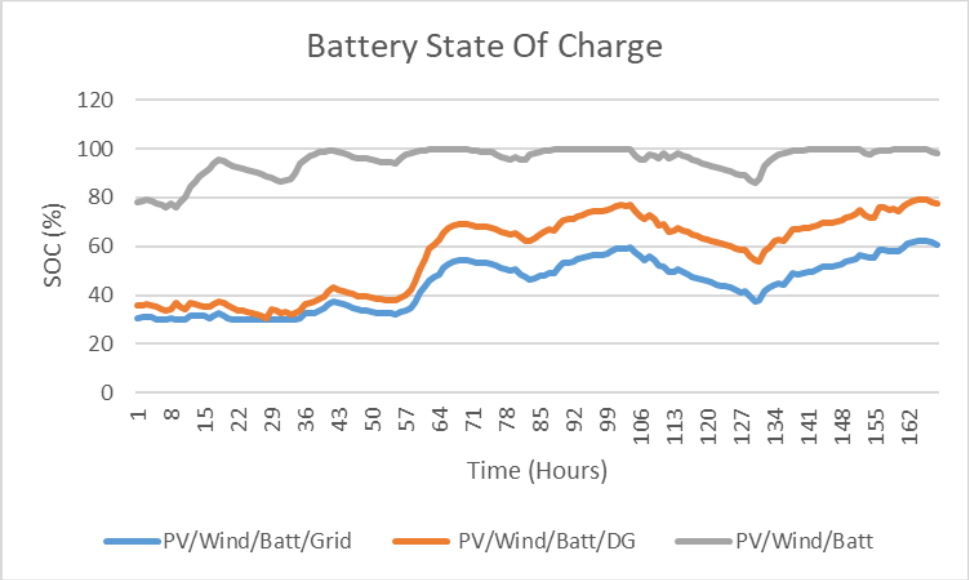


Figure II-18: SOC variation in one week.

The final selection among the configurations, that seems all feasible, depends on specific project goals, budget constraints, and environmental priorities.

The grid-connected configuration is best economic findings with least-cost and high renewable fraction: the presence of the grid, where the tariff of the purchased electricity from the nation utility grid is subsidized, makes the grid-connected microgrid the best balances cost, reliability, and sustainability for the specific coastal and urban microgrid.

Furthermore, the diesel backup microgrid remains a strong candidate for supplying critical loads during low renewable production and unexpected disturbances in the system.

The stand-alone configuration offers higher renewable fraction RF and lowest CO_2 emissions, maximize sustainability but requires high NPC, high excess of electricity, and stressed battery operation.

II.4.9 Sensitivity Analysis

To assess the robustness of the optimal microgrid configuration, the grid-connected one (PV/Wind/Batt/Grid), a sensitivity analysis is carried out. Sensitivity analysis on selected set of parameters (renewable sources availability, rate discount, fuel price, load demand…) helps to understand how the variation of these parameters around their best estimated values impacts the key system metrics such as: NPC (LCOE), renewable fraction RF.

This analysis focuses on in variations of the following parameters and each parameter was varied within a realistic band of approximately ±15-20% around its base value [86]:

- Electric scaled average load demand variations (15,17,20 kWh/day) to anticipate its reduction and future increase.

- Resources availability: solar scaled average: (4, 4.85, 5.3 kWh/m²/day), wind scaled average: (4.5, 5.23, 6 m/s)
- Grid tariff variation to evaluate the impact of the progressive unsubsidized of the purchased electricity from the nation grid (0.043, 0.05, 0.06 $/kWh).
- Discount rate variation (6, 8,10 %) to assess the impact of capital or financing conditions.
- The results are presented using optimization spider plot, which shows the individual impact of each selected parameter on the NPC "the main economic indicator" and optimization surface plot, that illustrates the combined effect of two parameters.

Figure II-19, shows the spider plot and indicates that NPC is most sensitive to discount rate and load variations, while it is moderate for the other parameters

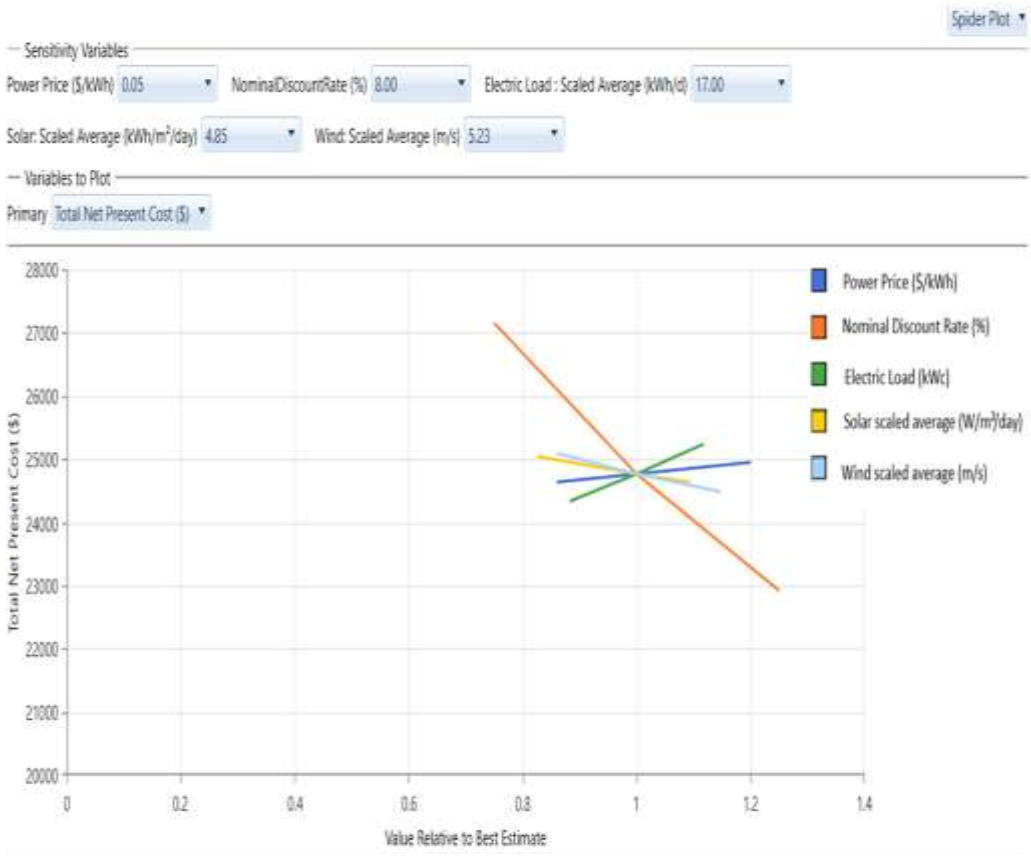


Figure II-19: Optimization Spider plot for NPC variations

Figure II-20, shows the surface plot of NPC as function of both grid power price and nominal discount. It is noticed that NPC decreases when the discount rate increases for lower load values. However, the variation remains moderate over the range of the study. The optimal configuration is economically robust.

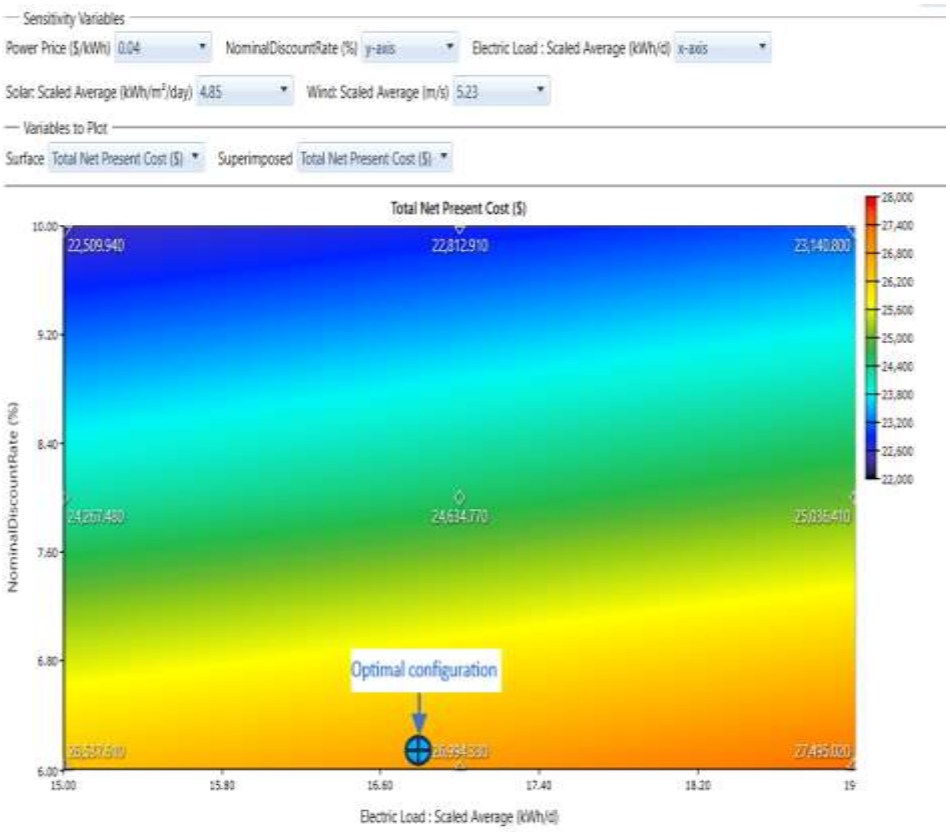


Figure II-20 Optimization Surface plot for NPC variations.

II.5 Conclusion

This chapter has provided a comprehensive techno-economic assessment of microgrids using Homer Pro. Technical evaluation involves ensuring the reliability and stability of the power supply, managing the integration of multiple DERs, and optimizing the power flow within the microgrid. Economic analysis focuses on the cost-effectiveness of the microgrid, considering the net present cost (NPC). Environmental assessment considers the reduction of greenhouse gas emissions and the promotion of sustainable energy practices.

The analysis was performed in order to decide which optimization is beneficial to cover the energy consumption taking into account the meteorological resources available in the city of Bou-Ismaïl (Tipaza-Algeria). Comparing the optimization results of the (PV/Wind/Batt/ Grid), (PV/Wind/Batteries/DG) and (PV/Wind/Batt) systems, shows that the grid connected microgrid is the cost-effective in terms of NPC even it produces the highest amount emissions. The other configurations remain candidates feasible and capable solutions to meet the energy needs with varying degrees of economic and environmental benefit.

CHAPTER III

Metaheuristic Optimization Algorithms in Microgrid Energy Management

Chapter III : Metaheuristic Optimization Algorithms in Microgrid Energy Management

III.1 Introduction

Microgrid operation scheduling, often formulated as an economic load dispatch problem, involves managing multiple distributed energy resources while ensuring reliable and cost-effective power supply. Microgrid optimization problems are inherently nonlinear, multi-objective, constrained, and frequently affected by uncertainties in load demand and renewable energy generation. Classical optimization methods struggle to handle these complexities, motivating the adoption of metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE)[61], [87], [88], [89], [90].Click or tap here to enter text. Metaheuristics constitute a class of optimization algorithms capable of addressing complex, nonlinear, and multimodal problems by efficiently approximating near-optimal solutions without necessarily guaranteeing global optimality [87]. Unlike conventional optimization techniques that rely on problem linearization, gradient information, or derivative calculations, metaheuristics employ heuristic search strategies to explore and exploit the search space effectively [89]. These algorithms have demonstrated robustness and flexibility across diverse fields, including engineering design, optimization, and strategic planning [11], [91].

In the context of microgrid management, metaheuristic optimization techniques play a critical role in enhancing energy security and integrating distributed energy resources [92], [93]. They provide effective solutions to challenges arising from the intermittent nature of renewable energy sources while improving power quality [94], [95]. Metaheuristic approaches are inspired by various natural and social phenomena, including biological behaviours, physics, chemistry, and human decision-making, offering a diverse set of tools to address microgrid optimization problems [96], [97], [98], [99], [100], [101], [102], [103].

This chapter presents an overview of some of nature inspired algorithms most widely used for microgrid energy management, with emphasize on the proposed hybrid Improved Salp Swarm Algorithm (SSA) with Harris Hawks Foraging: “ISSAHF”.

III.2 Mathematical Problem Formulation for Microgrid Energy Management

The microgrid optimization problem can be expressed as:

$$P_{ref}^{t} = \underset{P}{argmin}\{C(P^{t})\}, t \in [1,24] \quad \text{(III.1)}$$

where $P^t = \left[P_1^t, ..., P_{NG}^t\right]^T$ is the hourly powers vector from/to DERs.

$C_p(P^t)$concerns the operating costs of the MG, mainly including generation costs, and emission treatment costs, in addition to other costs. Hence, the MG optimization problem can be treated as either a single or multi-objective optimization framework. In this work, the objective function is formulated as a single-objective optimization problem that combines generation costs and emission treatment costs, which can be expressed as follows:

$$C\left(P^t\right) = C_g\left(P^t\right) + C_e\left(P^t\right),\ \mathrm{t} \in [1,24] \tag{III.2}$$

$C_g\left(P^t\right)$is the generation cost function including the fuel cost, operation and maintenance cost, depreciation cost, and the cost of electricity sold or bought to/from the utility grid expressed as follows:

$$C_g\left(P^t\right) = C_{fc}\left(P^t\right) + C_{om}\left(P^t\right) + C_{dc}\left(P^t\right) + C_{grid}\left(P^t\right) \tag{III.3}$$

Where $C_{fc}\left(P^t\right), C_{om}\left(P^t\right), C_{dc}\left(P^t\right), C_{grid}\left(P^t\right)$ represent the fuel cost (fc), the operation and maintenance (O&M) cost, depreciation cost (dc), and grid cost, expressed respectively by the following equations:

$$C_{fc}\left(P^t\right) = B_{fc}^t P^t \tag{III.4}$$

$$C_{om}\left(P^t\right) = B_{om}^t P^t \tag{III.5}$$

$$C_{dc}\left(P^t\right) = B_{dc}^t P^t \tag{III.6}$$

$$C_{grid}\left(P^t\right) = B_{grid}^t P^t \tag{III.7}$$

where B_{fc}^t, B_{om}^t , B_{dc}^t, B_{grid}^t are the vectorized hourly bids related to fuel, O&M, dc, and grid respectively.

The main pollutants considered in this work are CO_2, SO_2, NO_x [93]. To model the emitted pollutants treatment cost, let us denote T_j the treatment cost vector for each pollutant and Y_j the jth pollutant quantity vector emitted from all DGs and grid. The emission treatment cost function $C_e\left(P^t\right)$can be expressed as follows [104]:

$$C_e\left(P^t\right) = \sum_j \left(T_j Y_j\right) P^t,\ \mathrm{t} \in [1,24] \tag{III.8}$$

III.2.1 Production and consumption balance

The algebraic sum of powers flowing from all DERs, the grid, and the batteries should sum up to the load power[95]. This can be stated as follows:

$$\sum_{i=1}^{n} P_i^t = P_{load}^t, \ t \in [1,24] \tag{III.9}$$

III.2.2 Capacity limits for DERs and grid

All the DERs and the grid are constrained by their maximum powers to meet the power demand [95], this is expressed by the following two inequalities:

$$P_{DG_i,\min}^t \le P_{DG_i}^t \le P_{DG_i,\max}^t \tag{III.10}$$

$$P_{grid,\min}^t \le P_{grid}^t \le P_{gird,\max}^t \tag{III.11}$$

III.2.3 Battery constraints

The sourced or drained power from the battery generally depends on the battery capacity boundaries and on the battery state of charge [95]. They are defined as follows:

$$P_{b,\min}^t \le P_b^t \le P_{b,\min}^t \tag{III.12}$$

$$SOC^{t+1} = SOC^t + \frac{\delta t \times \eta_{ch} \times P_{ch}^t}{E_{nom}} - \frac{\delta t \times \eta_{dis} \times P_{dis}^t}{E_{nom}} \tag{III.13}$$

where P^t_{ch} and P^{di}_{dis} are the charging and discharging power flows respectively, η_{ch} and η_{dis} are respectively the charging and discharging efficiencies of the battery, E_{nom} is nominal energy of the battery, and t the sampling time. In order the increase battery lifespan, the battery SOC must be maintained within the allowable limits [11] as follows:

$$SOC_{\min} \le SOC^t \le SOC_{\max} \tag{III.14}$$

This work aims to minimize the cost function (III.2) subject to the equality and inequality constraints (III.9)-(III.12), and (III.14) using a hybrid metaheuristic optimization technique that combines the Harris Hawk Optimizer (HHO) and the Salp Swarm Algorithm (SSA) [103]. The following section offers a brief overview of metaheuristic algorithms mostly applied to solve such a problem

III.3 Metaheuristic Optimization Techniques Applied for Microgrid Optimization

III.3.1 Definition and Fundamental Principles

Metaheuristic methods represent a class of intelligent optimization techniques. They are inspired by natural processes, such as biological evolution or collective intelligence of swarms and colonies [105]. These techniques are designed to find approximate solutions to complex optimization problems. They incorporate random exploration to escape local minima, while focusing on local search to move over optimum solutions. They use iterative process to update candidates' solutions, store and reuse information from previous search steps [87].

III.3.2 Algorithm Classification Taxonomy

Metaheuristics are broadly classified into five principal categories, illustrated in Figure III-1:

1. **Evolutionary Algorithms (EA)**: Inspired by biological evolution mechanisms GA, DE) [88], [90].
2. **Swarm Intelligence (SI)**: Model collective behaviour of social organisms (e.g., PSO, SSA) [61], [91].
3. **Physics-Based Algorithms**: Mimic physical laws and phenomena (e.g., Simulated Annealing) [89].
4. **Human-Based Algorithms**: Emulate human activities and interactions (e.g., Harmony Search) [87].
5. **Other Bio-Inspired Algorithms**: Derived from diverse natural behaviours (e.g., GWO, HBA, HHO) [11], [92].

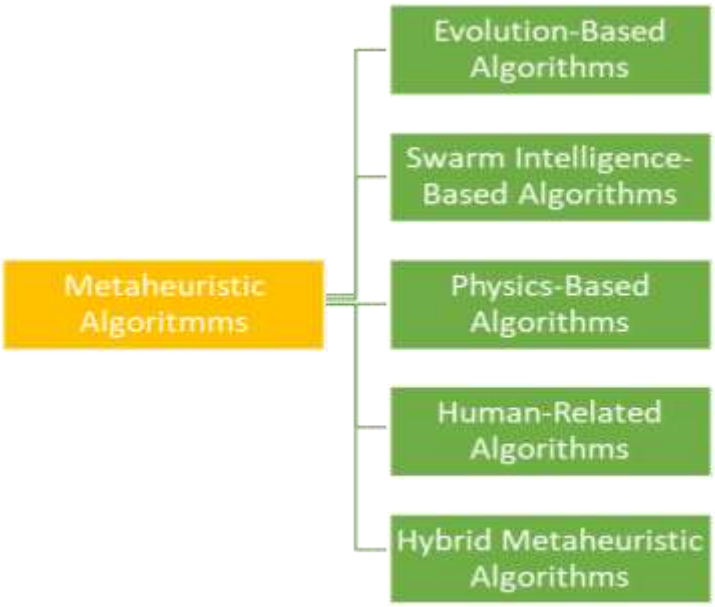


Figure III-1: Taxonomy of Metaheuristic Algorithms

III.4 Metaheuristic algorithm families in microgrid optimization

This subsection, focuses on a general description of swarm intelligent-based and evolutionary algorithms.

III.4.1 Swarm intelligence algorithms

Swarm intelligent algorithms are inspired by the collective of many interacted agents (individuals), which follow local rules and environments. They now play an important role for solving complex problems. PSO is among the most commonly used for solving to microgrids-related problems [106].

III.4.1.1 Particle Swarm Optimization (PSO)

Inspired by bird flocking social behaviour, PSO iteratively improves candidate solutions (particles) that adjust trajectories based on personal and swarm-best experiences [61]. Its computational efficiency and simple implementation have made it prevalent in MG applications including economic dispatch and optimal power flow [96]. However, PSO suffers from premature convergence in multimodal landscapes and limited local search capability. PSO is mainly defined by two co-dependent parameters particle position and velocity. Figure III-2 illustrates the moving of each particle updating its velocity based on the computed value of individuals and global best solutions and its position, which is updated itself using the newly

updated velocity. The simplified flowchart that describes the principal steps of the PSO Algorithm is presented in Figure III-3.

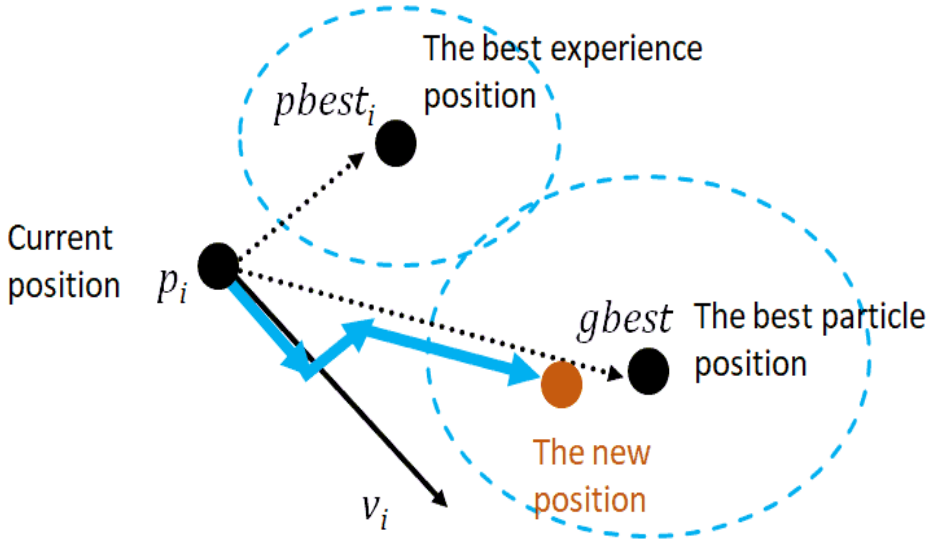


Figure III-2: Particles update in PSO algorithm.

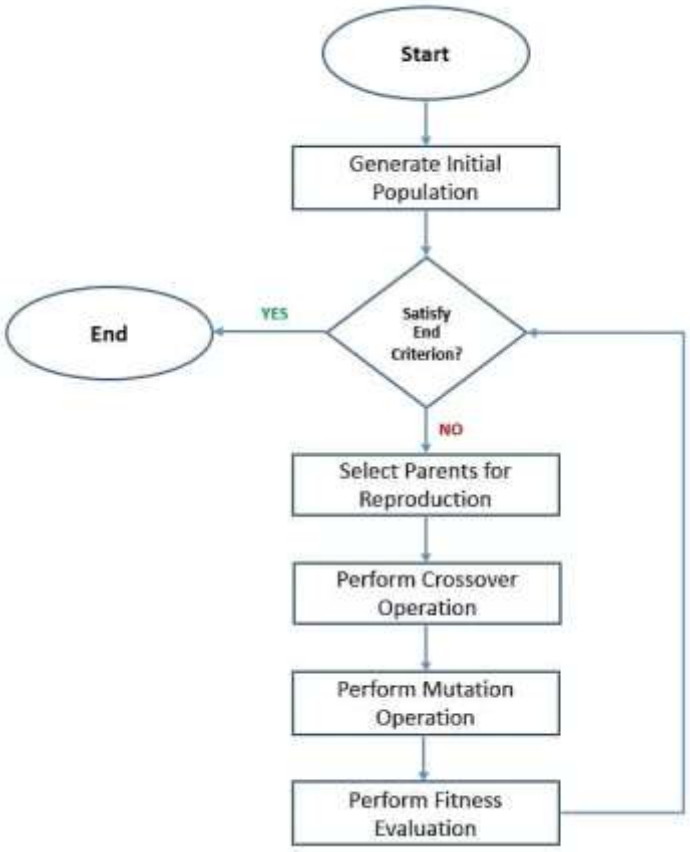


Figure III-3 : PSO Algorithm Flowchart [107]

III.4.2 Evolutionary Algorithms (EA)

Evolutionary algorithms are inspired by biological evolution, where the candidate solutions evolve over many iterations and through parent selection, recombination (crossover),

mutation and survivor selection [108]. GA and DE are among the most well-known and widely used Evolutionary Algorithms.

III.4.2.1 Genetic Algorithm (GA)

Genetic Algorithm (GA) is a bio-inspired metaheuristic founded on the principles of heredity and population genetics [88]. Candidate solutions are represented as chromosomes, which evolve over generations through genetic operators (such as selection, crossover, and mutation). This iterative evolutionary process enables the progressive improvement of solutions toward optimality as shown in Figure III-4.

GA has been extensively applied in engineering optimization, including microgrid management for tasks, such as reducing power losses in electrical networks, unit commitment, and network reconfiguration [97]. Its robustness and ability to handle mixed-integer and combinatorial problems make it particularly suitable for complex microgrid optimization challenges. However, GA is computationally intensive and sensitive to parameter settings, which can affect convergence and solution.

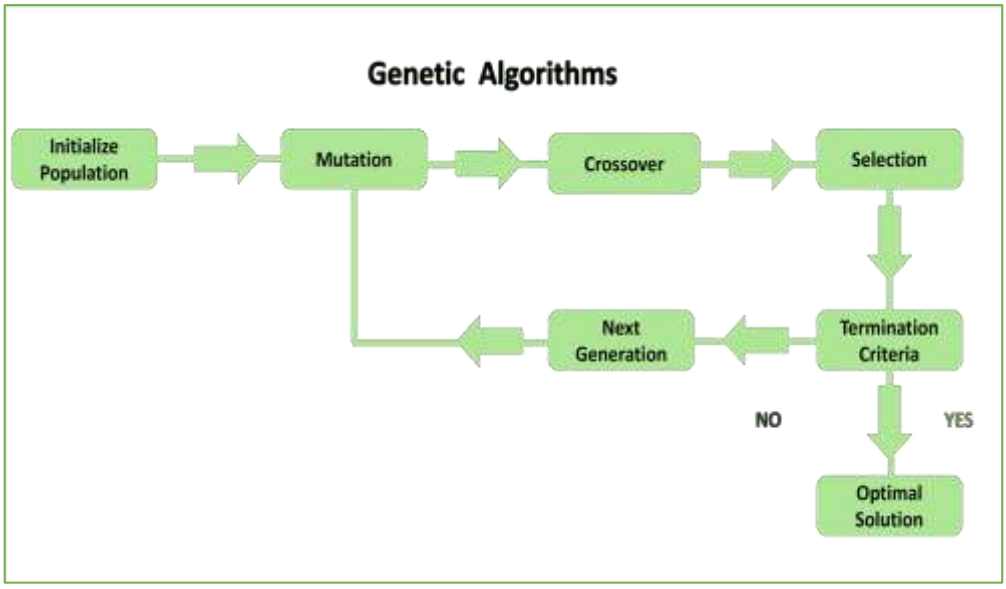


Figure III-4: Workflow of Genetic Algorithm (GA)[107]

III.4.2.2 Differential Evolution (DE)

Differential Evolution (DE) is a population-based stochastic optimization technique that generates new candidate solutions by combining scaled differences between randomly selected individuals from the population [90]. It has four main steps: Initialisation, mutation, crossover and selection (Figure III.5). Crossover and mutation represent the exploration phase, while parents and survivor selection ensure the exploration.DE is especially effective in global search and has been successfully applied to microgrid optimization problems, including power

flow optimization, power quality enhancement, and optimal scheduling of distributed energy resources [98]. Its simplicity, robustness, and strong exploration capability make it a widely used evolutionary optimizer. Nevertheless, its performance depends on careful parameter tuning, and convergence may be slow for highly complex or high-dimensional problems.

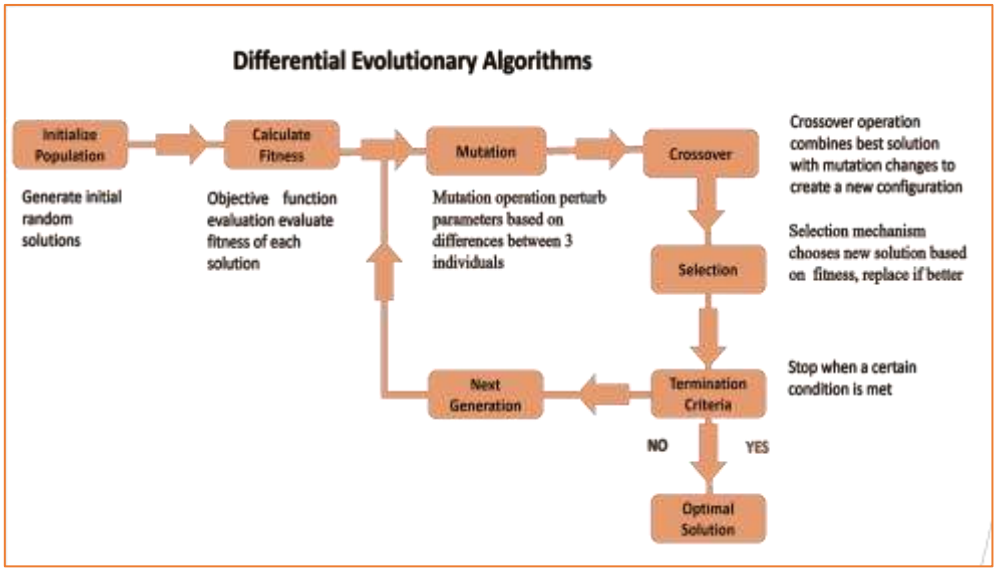


Figure III-5: Workflow of the Differential Evolution (DE) Algorithm [107]

III.4.3 Recent Bio-Inspired Algorithms

Metaheuristic optimization techniques have known a continuous discovery of new nature-inspired and rapid evolution, that aim to improve solution quality and to address modern engineering challenges. Among the widely used methods for microgrid optimization problems, the following algorithms are selected in this work.

III.4.3.1 Grey Wolf Optimizer (GWO)

Grey Wolf Optimizer (GWO) is among new bio-inspired metaheuristics that simulate the social hierarchy and cooperative hunting behaviour that employs searching for the prey, encircling it, and attacking of grey wolves [109]. Grey wolves can be categorized to four groups:

- The first group is the leader, which is called alphas (α) and considers the best one as well as responsible for taking decisions regarding organization of the group specially during attacking a prey. All other group's members must obey and follow the instructions of group leader;
- The second group is called beta (β), which monitors the remaining wolves of group and ensures that they obey and follow orders.

- The third group is the delta (δ) wolves, They have several functions in the group such as attacking, monitoring, and paying attention to sick wolves.
- The other wolves are called omegas (ω), and they must obey and follow the α, β, and δ wolves.

The mathematical model that defines the hunting strategy is based on the positions of α, β, and δ wolves which encircle and attack the prey while the ω wolves follow the leaders. By leveraging this hierarchical structure, GWO effectively balances exploration (global search) and exploitation (local refinement).

GWO algorithm has demonstrated competitive performance in solving complex optimization problems, but can exhibit slow convergence when applied to high-dimensional or highly nonlinear problems [11], [110].

Figure III-6, illustrates the position-updating strategy of wolves (search agents) hunting together in a pack.

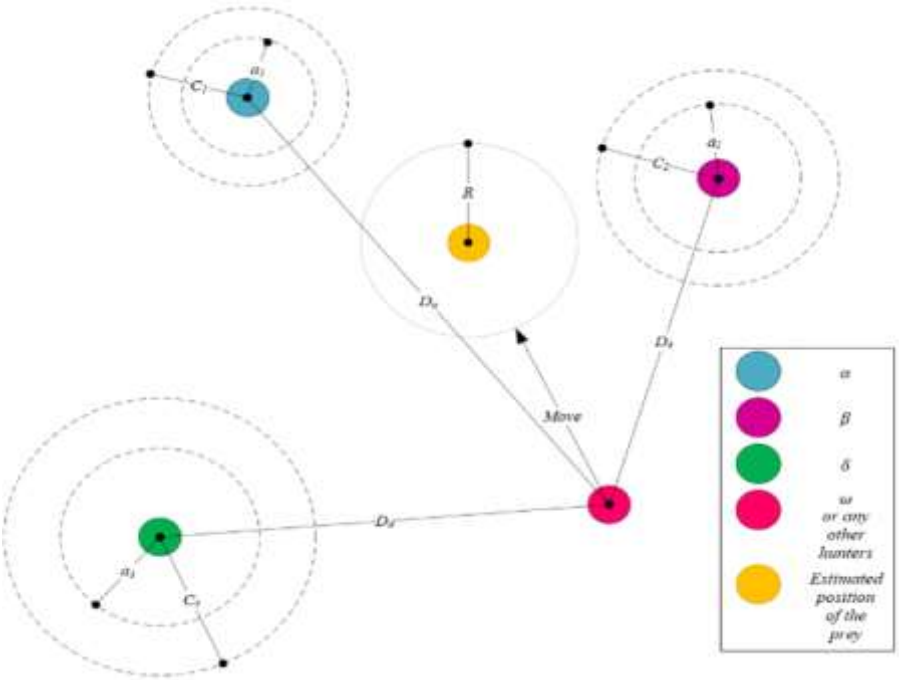


Figure III-6: Strategy of updating position in GWO [109]

The main steps of the GWO algorithm implementation are presented in detail in the following flowchart of Figure III-7.

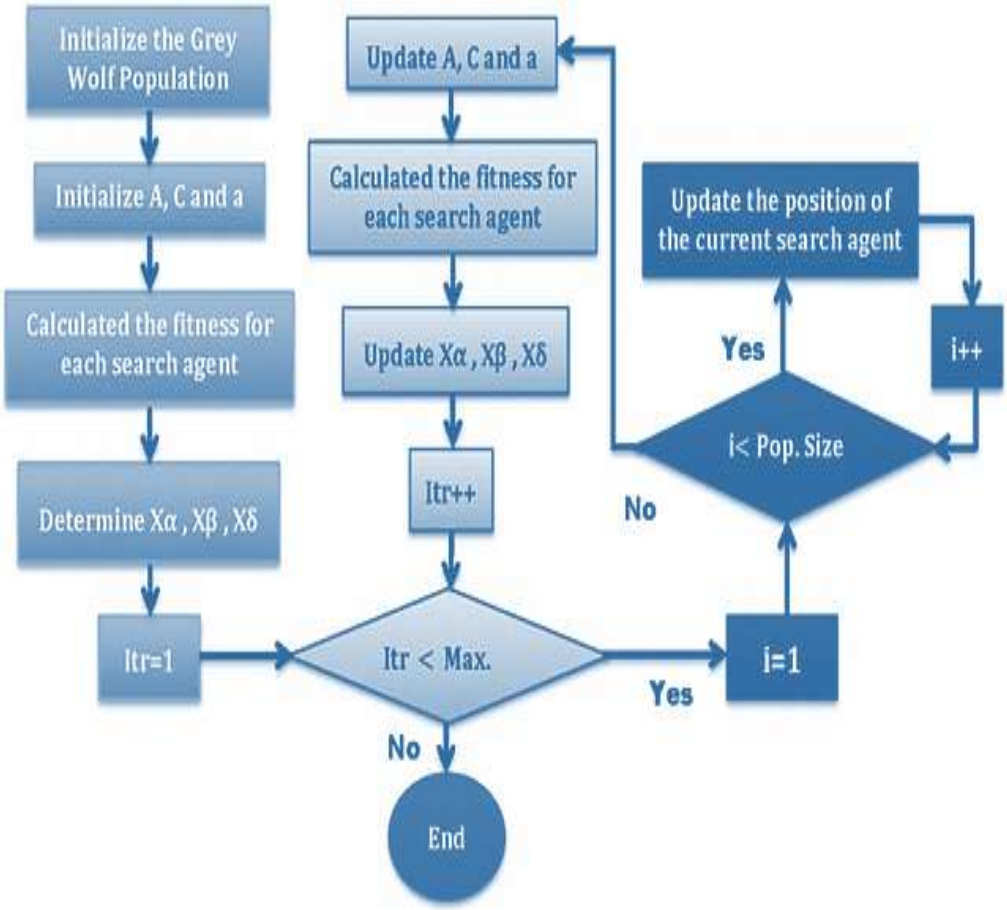


Figure III-7: Flowchart of GWO implementation [111]

III.4.3.2 Salp Swarm Algorithm (SSA)

[112]This nature-inspired optimization method mimics the chain behaviour of salps swarming while searching for food in deep oceans, employing leader-follower hierarchy for solution space exploration (Figure III-8).

This algorithm, like other metaheuristics, is designed with exploration and exploitation phases and its simplicity, minimal parameter requirements, and direct updating mechanism which facilitate its implementation.

The flowchart presented in Figure III-9, summarizes the key procedure of the SSA mechanism: from population initialization, evaluation, to updating the position of salps iteratively and termination. Nevertheless, SSA demonstrates imbalanced exploration-exploitation phases with tendency toward solution stagnation [91], [100].



Figure III-8: Leader and Followers' Mechanism in the Salp Chain [113]

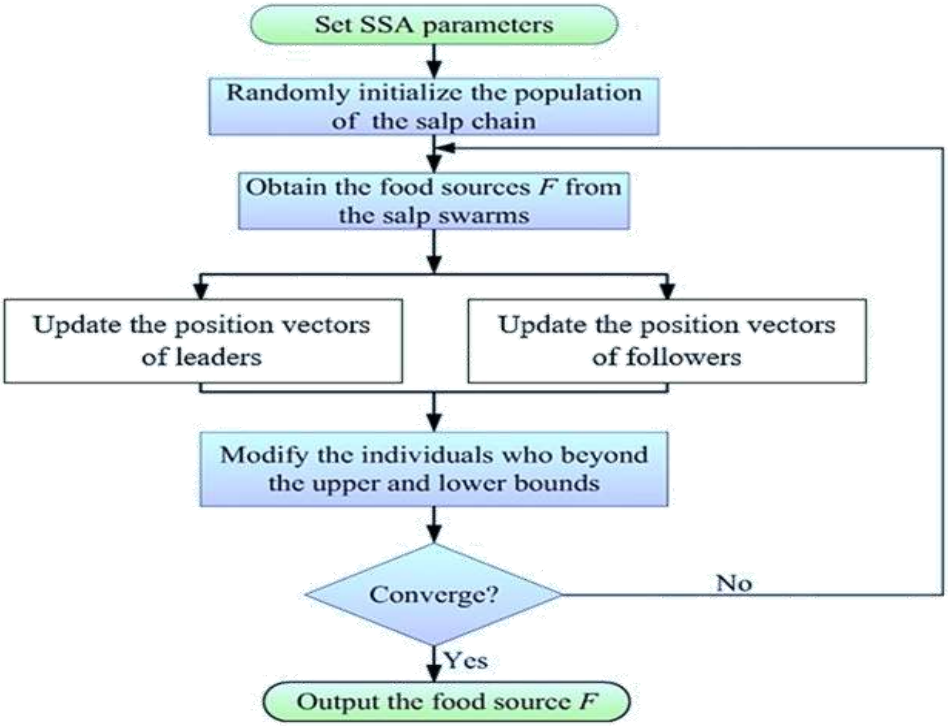


Figure III-9 : Flowchart of Salp Swarm Algorithm [114].

III.4.3.3 Harris Hawks Optimizer (HHO)

Harris Hawks Optimizer (HHO) is a novel evolutionary optimization algorithm that draws inspirations from the cooperative behaviours and hunting styles of predatory birds [115]. This smart strategy involves hawks collaborating to pounce on their prey from various directions, aiming to catch it off guard with a "surprise pounce". Harris hawks are capable of demonstrating a diverse range of chasing patterns, adapting them according to the dynamic nature of scenarios and the escaping patterns of their prey. The optimization algorithm effectively emulates the social intelligence of Harris Hawks by mathematically simulating these dynamic patterns and behaviours.

Figure III-10 illustrates the search phases of the HHO algorithm: exploration, transition, and exploitation phases with soft/hard besiege mechanisms [92]. [92], [100]

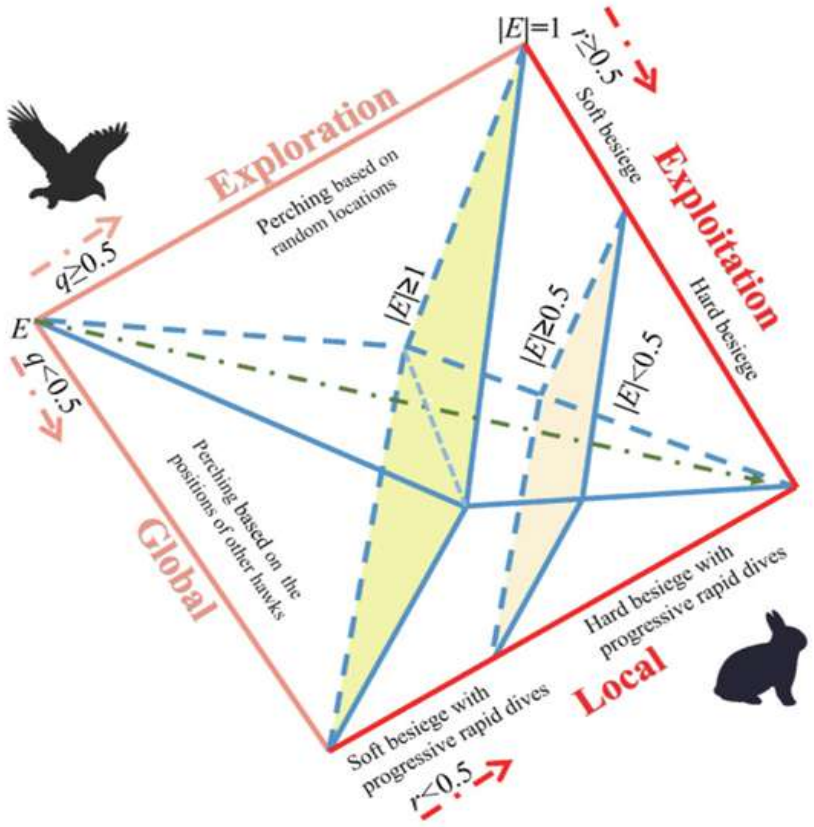


Figure III-10 : Harris Hawk workflow- Transition from exploration to exploitation [116]

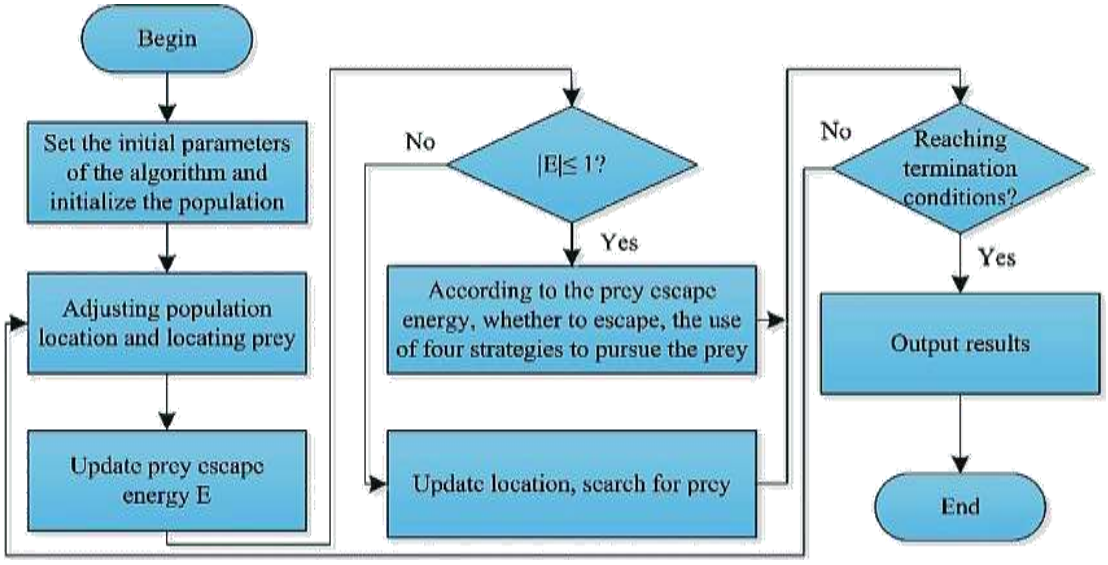


Figure III-11 : Flowchart of Harris Hawks Optimization algorithm [117].

III.4.3.4 Honey Badger Algorithm (HBA)

Honey Badger Algorithm (HBA) is a recently developed metaheuristic inspired by the intelligent foraging behaviour of honey badgers [118]. It simulates their digging phase and honey-finding phase strategies through dynamic search patterns that balance exploration and exploitation based on honey odour intensity and distance. The ability to maintain population diversity throughout the search process allows HBA to effectively navigate complex landscapes with numerous local optima, making it well-suited for solving challenging optimization problems as used for microgrid scheduling and energy management [119]. The schematic illustration and the flowchart of the HBA search strategy are presented in Figure III-12 and in Figure III-13 respectively [120].

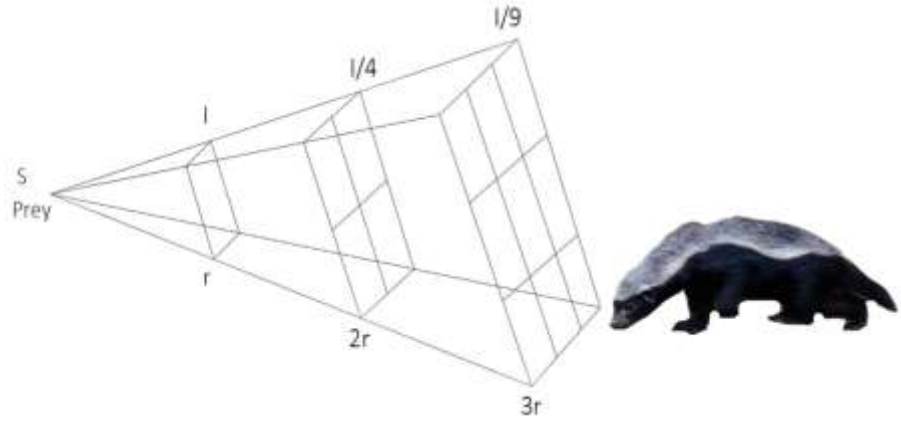


Figure III-12: HBA search mechanism "honey odour intensity and position"

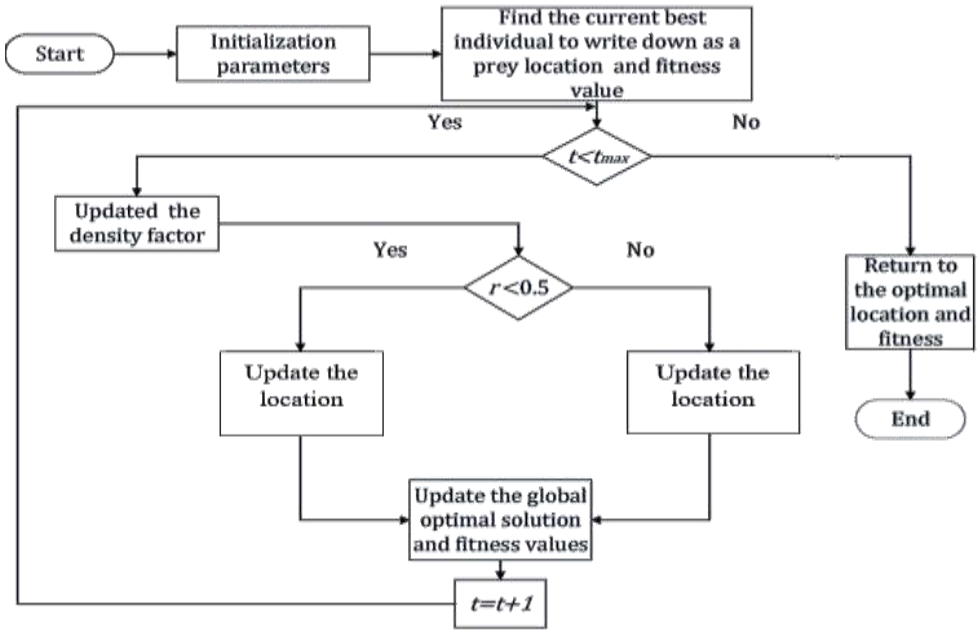


Figure III-13: Flowchart of HBA optimization.

III.5 Proposed Hybrid Metaheuristic: Improved SSA with Harris Hawks Foraging Strategy (ISSAHF)

While standalone metaheuristic algorithms such as the Salp Swarm Algorithm (SSA) are effective for many problems, they can suffer from limitations like slow convergence or premature stagnation in complex, multi-modal search spaces.

This work proposes a hybrid Improved Salp Swarm Algorithm with Harris Hawks Foraging strategy (ISSAHF) [121]. This algorithm synergistically integrates the directional, chain-based search of SSA with the adaptive, dynamic exploitation tactics of the Harris Hawks Optimizer (HHO) to enhance overall optimization performance [91], [92], [121].

III.5.1 Mathematical Overview of Base Algorithms

In this section, the mathematical modelling of the proposed algorithm ISSAH is introduced in details, as well as the mathematical formulation of each constituent algorithm SSA and HHO algorithm.

III.5.1.1 Salp Swarm Algorithm (SSA)

The iterative nature of SSA involves the continual generation and evolution of random individuals (salps) within the defined problem space. During each iteration, all salps update their location vectors, with a designated leader salp advancing towards a food source (*F*) (the best-known solution), while the other followers align their movements with the rest of the salps [91], [99]. Within the SSA, the search agents (which is denoted as P to refer to powers) consists of N agents with d-dimensions; the leader position is updated using the following equation [102]:

$$P_j^1 = \begin{cases} F_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 \geq 0.5 \\ F_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 < 0.5 \end{cases} \quad \text{(III.15)}$$

P_j^1 denotes the leader's location and F_j is the position vector of food source in the jth dimension, ub_j and lb_j are the upper and the lower limits of jth dimension, c_2, c_3 are random values in [0, 1], and c_1 is the main key parameter of the SSA, given by:

$$c_1 = 2e^{-(4iter/\max_iter)^2} \quad \text{(III.16)}$$

where $iter$ and $\max_iter$ denote the number of iterations and the maximum number of iterations respectively. This parameter decreases over iterations. As a result, it can effectively

prioritize diversification during the initial stages and the intensification in the last steps of optimization. The followers' position is updated as follows [102]:

$$P_j^i = \frac{\left(P_j^i + P_j^1\right)}{2} \tag{III.17}$$

where P_j^i is the ith follower's position and P_j^1 is the leader's position in the jth dimension.

III.5.1.2 Harris Hawks Optimizer (HHO)

The HHO algorithm includes three characteristic phases: exploration phase, transformation from exploration to exploitation, followed by the exploitation phase [115], [118][115].

a. *Exploration Phase*

Hawks perch randomly and search for prey using two distinct search strategies as given in the following equation:

$$P_{new} = \begin{cases} P_{rnd} - r_1 \left| P_{rnd} - 2r_2 P \right| & \text{q} \geq 0.5 \\ P_{rabbit} - P_m - r_3 \left(lb + r_4 \left(ub - lb \right) \right) & \text{q}<0.5 \end{cases} \tag{III.18}$$

where P_{new} and P are the Harris hawk positions in iteration $t+1$ and t respectively. P_{rabbit} and P_{rnd} represent the prey position in the iteration t and randomly selected Harris hawk in the current population. The values of r, r_1, r_2, r_3, q are randomly generated and, ub and lb represent respectively the upper and lower boundaries. P_m is the mean position of the Harris Hawks given by:

$$P_m = \frac{1}{N} \sum_{i=1}^{n} P_i \tag{III.19}$$

where P_i indicates the location of each hawk in the current iteration t and N denotes the total number of Hawks.

b. *Transition from Exploration to Exploitation*

This shift is controlled by the prey's escaping energy, E, which decreases over iterations [92], [103]:

$$E = 2E_{init} \left(1 - \frac{iter}{\max_iter} \right) \tag{III.20}$$

where E is the escaping energy of the prey, $\max_iter$ is the maximum number of iterations, and E_{init} signifies its initial energy. The transformation from exploration to exploitation is stated as follows:

- For $|E \geq 1|$, the HHO is in exploratory mode within the global space.

- For $|E \le 1|$, the HHO transitions to an exploitative mode within predetermined promising zones.

c. *Exploitation Phase*

This phase defines the attacking pattern of the hawks to prevent the escaping of prey. Four besiege strategies are employed based on the energy E and a chance r of prey escape:

- ***Soft besiege****:* In this situation $r \ge 0.5$ & $|E| \ge 0.5$, as the prey still has enough energy, the Harris hawks try to exhaust it before they attack. The position of the Harris hawk in the $(t+1)^{th}$ iteration is calculated as follows:

$$P_{new} = (P_{rabbit} - P) - E|J \times P_{rabbit} - P| \quad \text{(III.21)}$$

where $J = 2(1 - r_5)$ denotes the jump strength of the rabbit generated randomly during the escape process, and r_5 represents a randomly generated number between 0 and 1.

- ***Hard besiege****:* at this stage $r \ge 0.5$ & $|E| < 0.5$, the prey having depleted all its energy. The current positions are then updated based on the following equation:

$$P_{new} = P_{rabbit} - E|P_{rabbit} - P| \quad \text{(III.22)}$$

- ***Soft besiege with progressive rapid dives*****:** When $|E| \ge 0.5$ & $r < 0.5$, it implies that the prey's energy might be adequate for escape. Therefore, a softer besiege is needed for a sudden attack. the Hawks employ the concept of Levy flight LF and perform a soft besiege for progressive rapid dives using the following formula:

$$P_{new} = \begin{cases} P_y \ \ if \ \ F(P_y) < F(P) \\ P_z \ \ if \ \ F(P_z) < F(P) \end{cases} \quad \text{(III.23)}$$

where P_y & P_z are respectively given by

$$P_y = P_{rabbit} - E|J \times P_{rabbit} - P| \quad \text{(III.24)}$$

$$P_z = P_y + R \times Levy(D) \quad \text{(III.25)}$$

where D and R are the problem dimension and a random 1xd vector respectively, $Levy(D)$ is the levy flight formula for parameter $\beta = 1.5$ and random coefficients *u* and *v* which is given by:

$$Levy(D) = 0.01 \times \frac{u}{|v|^{\frac{1}{1.5}}} \left(\frac{2\Gamma(2.5) \times \sin\left(\frac{1.5\pi}{2}\right)}{\Gamma\left(\frac{5}{4}\right) \times 3 \times 2^{\left(\frac{1}{2}\right)}} \right)^{2/3} \quad \text{(III.26)}$$

- ***Hard besiege with progressive rapid dives:*** Here, $r < 0.5$ & $|E| < 0.5$, The prey is tired and lacks enough energy to escape. Therefore, the Hawks can employ the hard siege behaviour and the position is updated as follows;

$$P_{new} = \begin{cases} P_y \ \ if \ \ F(P_y) < F(P) \\ P_z \ \ if \ \ F(P_z) < F(P) \end{cases} \tag{III.27}$$

In this equation, the quantities Y and Z are respectively provided as follows:

$$P_y = P_{rabbit} - E|J \times P_{rabbit} - P_m| \tag{III.28}$$

$$P_z = P_y + R \times Levy(D) \tag{III.29}$$

where P_m is the mean position given in (III.19).

III.5.1.3 Key Modifications to the Standard SSA:

The ISSAHF introduces three strategic enhancements to the standard SSA framework:

1. Multi-Leader Strategy:

It has been shown through benchmarking that the leader search strategy provides more search ability as it is directly related to the food location. Therefore, the top *m* fittest salps are designated as leaders in the modified SSA to prevent over-reliance on a single guide and enhance global exploration and create multiple search trajectories [91]. Followers track the best leader, enabling intensive exploitation around the current best while maintaining swarm diversity — balancing convergence with diversity preservation. Hence, (III.15) is updated as follow:

$$P_i^j = \begin{cases} F_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 \geq 0.5 \\ F_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 < 0.5 \end{cases}, \qquad i = 1 : N_{leaders} \tag{III.30}$$

where $N_{leaders}$ is the number of leaders within the salps population, the other parameters are the same in (III.15).

2. Enhanced follower update rules

This modification is related to the followers update rules. The followers (remaining population members) adjust their position by following the best leader location according to equation (III.17). this allows an intensive exploration around the best solution while keeping some diversity in the swarm.

3. Hybrid Follower Update with HHO Dynamics

HHO predation strategies in the SSA. To expand the performance of the four HHO predation strategies, the energy of escaping E is improved to provide a nonlinear decrease in this energy which allows a more global search ability. The linear escape energy in the HHO given in (III.20) is reformulated by adding an exponential form as follows [121].

$$E = 2E_{init}\left(2 \times rand \times e^{-\left(\delta \times \frac{iter}{iter_\max}\right)}\right) \tag{III.31}$$

where the parameters are taken from equation (III.20), the initial energy of the prey E_{init} is a random number in [-1,1], δ represents the attenuation parameter indicating the rate of decline of prey energy. In Summary, the ISSAHF algorithm is implemented according to the following three steps:

- **Step 1:** Initialize the population size of the Salps (**nSalps)** and define the number of iterations (**nIter)**.

- **Step 2:** Initialize the population location of Salps (**Salps.Location**), and then compute the fitness value for each salp (**Salps.Cost**). Based on a sorting process, the leaders and the followers are identified.

- **Step 3:** Update leaders and followers. The leaders move according to equation (III.30), while the followers move based on their escaping energy given in (III.31)

- **Step 4:** Calculate the nonlinear energy escape E:

  - When $|E| > 1$, the followers update their locations according the SSA original formula (III.17) with respect to the best leader.

  - When $|E| \leq 1$, the followers will update their location according to the four Harris Hawk foraging strategies described in equations (III.21), (III.22), (III.23), and (III.27) respectively, based on a random chance r. This allows for a more nuanced and intensive local search.

- **Step 5:** Termination: Repeat step 3 until a stopping criterion (e.g., max iterations) is met. Return the best solution found [91], [92], [103].

The flowchart illustrating the proposed ISSAHF strategy is provided in Figure III-14.

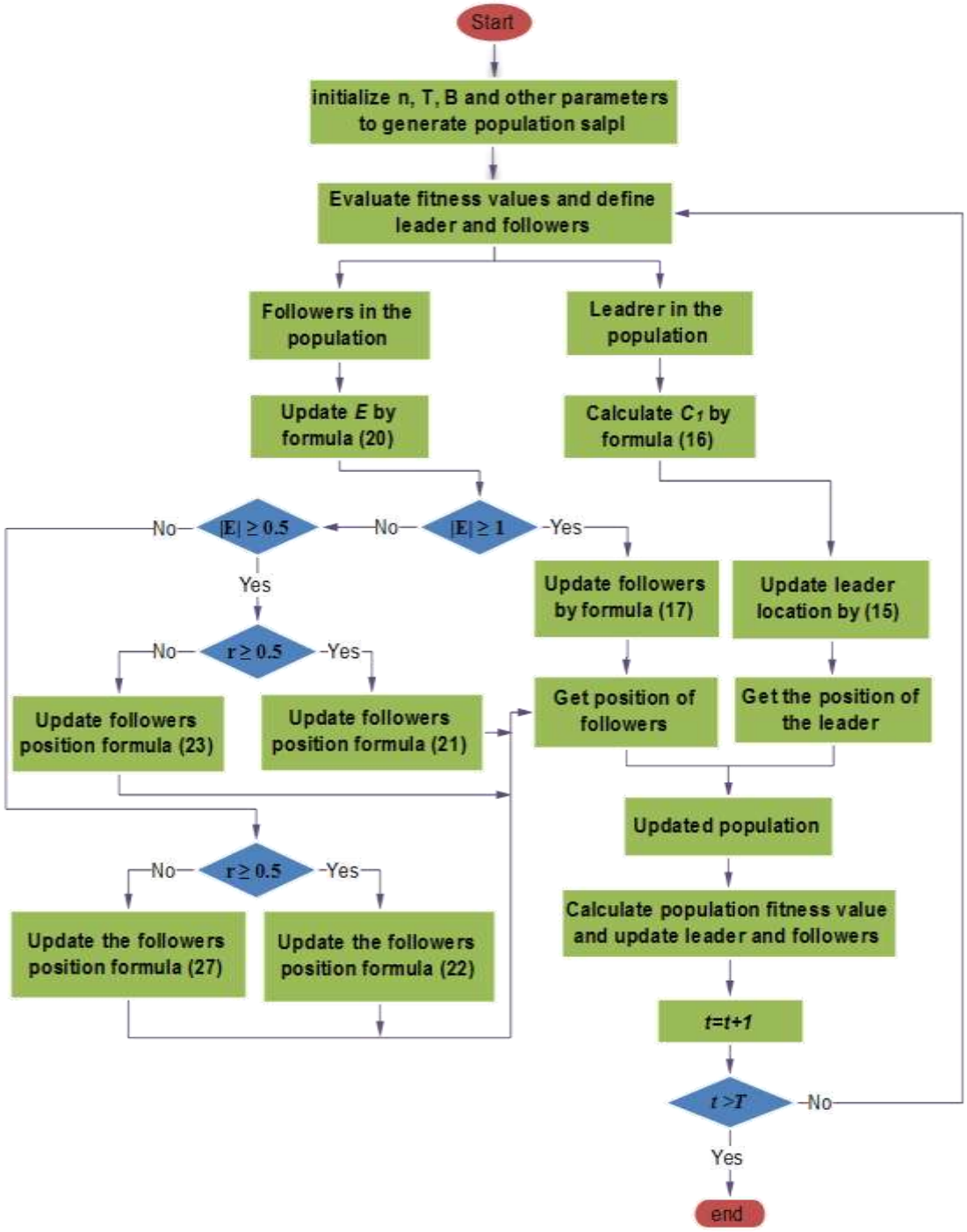


Figure III-14: Flowchart of the proposed ISSAHF algorithm approach

III.6 Comparative Analysis and Performance Evaluation of Metaheuristic Techniques

Selecting the most suitable metaheuristic algorithm for microgrid optimization is critical to achieve optimal cost minimization, system reliability, and computational efficiency [96], [97]. A rigorous comparative analysis is essential to navigate this selection problem, as no single algorithm universally outperforms all others across every problem class.

Despite their diverse inspirations, metaheuristic algorithms generally follow a mostly common iterative workflow [122], including initialization, fitness evaluation, solution update, and termination, as illustrated in a generalized flowchart (see Figure III-15).

These algorithms generate a population of candidate solutions as it is the case in Evolutionary and swarm-based methods. A selection step focuses on the good solutions, exploiting the best information. The procedure iterates until a stopping condition is met and updating and checking the population again. Search moves (such as mutation, crossover…) help the algorithm to explore new parts in the space solution. Other details are specific for each single algorithm as described in previous sections.

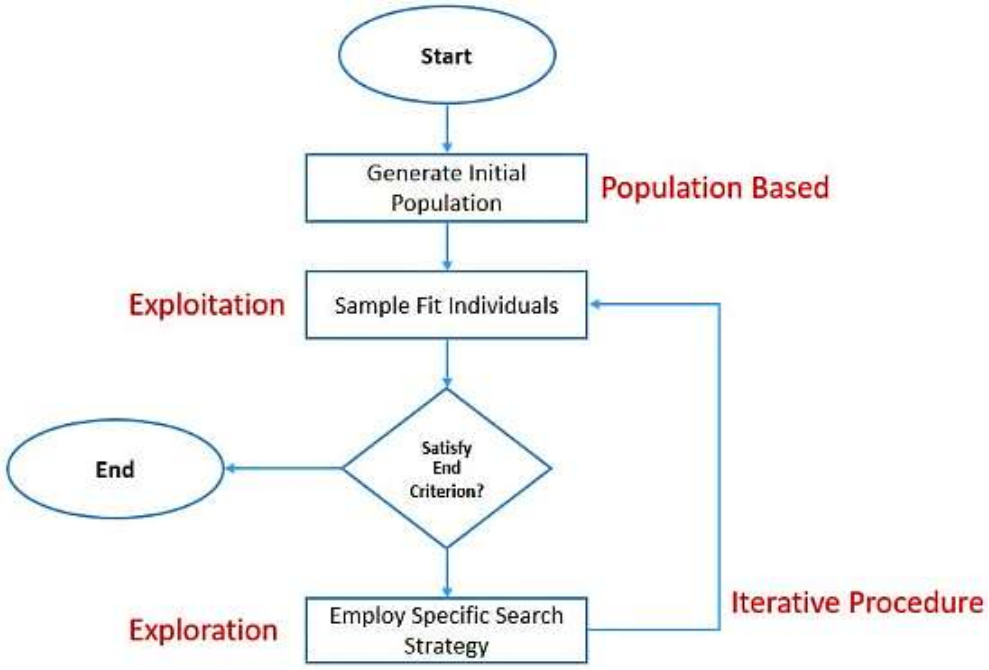


Figure III-15: Common high-level flowchart of metaheuristic optimization techniques

To objectively compare algorithm performance and validate the reliability of proposed methods like ISSAHF, researchers employ a suite of standard statistical metrics. These metrics, calculated over multiple independent runs, provide insights into solution quality, consistency, and convergence behaviour, including [123], [124], [125] :

- **Solution Quality:** Best (Min), Worst, Mean, and Median of the final objective function value.
- **Convergence & Stability:** Standard Deviation (SD) of results, indicating algorithm reliability.
- **Accuracy Metrics:** Relative Error (RE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) when a known optimum or a superior benchmark exists.

Table III-1 provides a structured comparison of the key algorithms discussed in this thesis, highlighting their main advantages and inherent limitations relevant to microgrid energy management problems [126], [127].

Table III-1: Comparative analysis of metaheuristic algorithms for microgrid optimization

Algorithm	Main features	Limitations
GA (Genetic Algorithm) [128]	Well-established, strong global search ability, suitable for discrete and mixed-integer problems, and easy to adapt to microgrid optimization	Convergence can be slow, sensitive to parameter settings (population, crossover, mutation), may get stuck in local optima
DE (Differential Evolution) [129]	Robust global search for continuous variables, widely used in hybrid optimization schemes	Convergence may be slow; requires careful tuning of mutation and crossover parameters
PSO (Particle Swarm Optimization) [130]	Very simple and easy to implement; fast convergence on small- to medium-size problems	Tends to get trapped in local optima; performance degrades on large or highly constrained problems.
GWO (Grey Wolf Optimizer) [131]	Naturally balances exploration and exploitation, it has shown good performance on nonlinear and multi modal problems	Can converge early in high dimensions problems, often needs adjustment of control parameter or hybridization
SSA (Salp Swarm Algorithm) [132]	Compact, easy to code with few parameters, structured leader–follower search pattern to balance diversification and intensification	Risk of premature convergence and weaker performance on complex or high dimensional problems few applications to practical microgrids studies
HHO (Harris Hawks Optimizer) [133]	Strong adaptive behaviour with exploration and exploitation search strategies, suitable for nonlinear and constrained optimization problems	May converge slowly or trapped to local optima if parameters are not well chosen. its efficiency varies with the problem scale and complexity
HBA (Honey Badger Algorithm) [134]	Dynamic strategies, maintain diversity, good exploration – exploitation balance, attractive for multimodal problems	Relatively new, with limited benchmarks, performance and cost depend strongly on parameter choice
ISSAHF (Proposed) [135]	Hybrid and improved design intended to enhance both global and local search and reduce trapping in local minima	Higher computational cost and more parameters; still needs validation on large, real microgrids

III.7 Application Trends and Current Research Focus in Microgrid Optimization

The application of metaheuristic algorithms extends across the entire lifecycle and operational spectrum of microgrids. Their primary value lies in handling the high-dimensional, nonlinear, and often discrete-continuous mixed nature of real-world optimization problems where traditional methods falter. Current research and application trends are prominently focused on the following key domains [127], [136]:

- **Optimal Sizing and Planning:** This is a fundamental, design-phase application where metaheuristics determine the optimal nominal capacity and technology mix of various components-such as photovoltaic arrays, wind turbines, battery energy storage systems, and backup diesel generators, to minimize total lifecycle cost (capital and operational) while meeting reliability criteria (e.g., Loss of Power Supply Probability, LPSP). The problem often involves long-term weather data and probabilistic load profiles, making metaheuristics ideal for navigating this complex, multi-year design space [93], [96], [98], [99], [102], [104].
- **Energy Management Systems (EMS):** This is the core operational application, as formulated in Section III.2. Metaheuristics solve both day-ahead scheduling (deterministic or stochastic) and real-time or rolling-horizon dispatch problems. They are particularly adept at managing the trade-offs between conflicting objectives, such as minimizing operational cost versus reducing carbon emissions, or maximizing self-consumption of renewable energy versus minimizing battery degradation. Advanced applications include participation in energy markets and ancillary services [96], [97], [110].
- **Control System Tuning and Optimization:** Beyond power scheduling, metaheuristics optimize the parameters of lower-level control systems. This includes tuning the gains of Proportional-Integral-Derivative (PID) controllers for voltage and frequency regulation, optimizing the droop coefficients in hierarchical control schemes, and calibrating the settings of inverter-based resources to ensure stable islanded and grid-connected operation under disturbance [96], [97].
- **Resiliency Enhancement and Anomaly Detection:** With increasing emphasis on grid resilience, metaheuristics are used to optimize strategies for intentional islanding, survivability during extreme events, and subsequent reconnection to the main grid. Furthermore, they are applied in anomaly detection frameworks to identify and diagnose faults, cyber-attacks, or equipment failures by optimizing detection thresholds and pattern

recognition models, thereby enhancing the microgrid's security and self-healing capabilities [100], [101], [103]

These trends underscore the transition of metaheuristics from purely academic solvers to integral components in the computational toolkit for designing and operating smarter, more efficient, and robust modern microgrids.

III.8 Conclusion

Metaheuristic algorithms provide indispensable tools for addressing the complex, nonlinear optimization challenges inherent in modern microgrid energy management. While standalone algorithms like PSO, GA, and GWO have demonstrated efficacy, they are not without limitations, such as convergence speed issues and susceptibility to local optima. Hybrid approaches, such as the proposed ISSAHF, aim to synergize the strengths of different algorithms to create more robust and efficient solvers. By integrating the multi-leader exploration of SSA with the adaptive exploitation tactics of HHO, the ISSAHF algorithm is proposed as a powerful method for microgrid optimization. In the following chapter, this hybrid algorithm will be implemented to solve the 24-hour energy management problem for a case-study microgrid, with its performance benchmarked against established metaheuristics.

CHAPTER IV

A Hybrid Metaheuristic for Microgrid Energy Planning and Management

Chapter IV : A Hybrid Metaheuristic for Microgrid Energy Planning and Management

IV.1 Introduction

The optimal planning and scheduling of microgrids is the key findings behind minimized operating cost, achieved through the implementation of an efficient energy management strategy which combines economic performances, sustainability and reliability.

In this chapter a technique based on an improved multi-leader Salp Swarm Algorithm that uses an elite leader following strategy combined with Harris Hawks Foraging (ISSAHF), is proposed as a novel hybrid bio-inspired optimization strategy for energy planning in microgrids

IV.2 Related works

Metaheuristic techniques, inspired by natural phenomena and evolutionary processes, offer more flexible and adaptive approach for solving optimization problems. They leverage population-based search strategies, allowing the exploration of diverse solution spaces and robust adaptation to changing conditions. They can be employed to optimize the operational schedule of microgrid components, balancing the trade-off between conflicting objectives like cost minimization and environmental impacts. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE) are among the widely explored metaheuristic techniques in optimizing microgrid operation and energy planning [137], [138], [139], [140], [141].

A grey wolf optimizer was used for optimal microgrid planning in islanded [142] and grid-connected modes [143]. A quantum teaching learning-based optimizer (TLBO) was used for optimal energy planning in MGs [144]. A Honey Badger Algorithm (HBA) was proposed in [145]. Moth Flame Optimization (MFO) was proposed for the optimization of a standalone rural microgrid in [146]. An artificial Hummingbird Algorithm (AHA) has been applied to solve the allocation problem of renewable DGs under uncertainty conditions in [147]. In [148], a Modified Artificial Rabbit Optimizer (MARO) is applied to resolve the stochastic energy management in a smart MG. A modified Capuchin Search Algorithm (MCapSA) was proposed in [149] to solve the optimization problem for a multi-microgrid system with stochastic load demand.

Salp Swarm Algorithm (SSA) have attracted the attention in the field of optimal energy planning in MGs, numerous implementations of both original and enhanced versions have been proposed in the literature. In [150], [151], the SSA was employed in energy management and capacity planning for MGs with multiple renewable energy sources. In [152], a weighted Salp Swarm Algorithm (WSSA) was used to minimize the total operating cost of a microgrid with constraints. An improved SSA (ISSA) was proposed in [153] to address optimal power flow issues of grid-connected MG. A Harris Hawk Optimizer (HHO) was implemented for optimal energy planning in MGs [154]. [155] proposed a HHO-based Tilt-Integral-Derivative (TID) controller to manage the power flow within the microgrid and maintain system stability, addressing the intermittent nature of renewable energy sources and the dynamics of the interconnected system.

To harness the strengths of both classical and metaheuristic optimization techniques, hybrid approaches have gained prominence. These approaches integrate either classical methods or metaheuristic methods with other search algorithms to add more exploitation capability to the basic algorithm. This hybridization aims to leverage the complementary strengths of different algorithms, offering a versatile and robust framework to address the challenges inherent in microgrid optimization [156], [157]. In this regard, numerous hybrid search techniques have been employed for microgrid optimization. [158] proposed a neighbour based differential evolution technique for microgrid planning optimization, The same authors have proposed a microgrid management system with demand response (DR) program using a novel intelligent algorithm called Hybrid CSAJAYA [159] . In [160], hybrid harmony search algorithm (HSA) incorporating (DE) was used for addressing one-day-ahead scheduling problem within a MG. In [161], Grey Wolf Optimizer (GWO) was combined with Cuckoo Search Algorithm (CSA) for optimal sizing and energy management in a MG. In [162], a novel hybrid technique combining PSO and ICA (Imperialist Competitive algorithm) is proposed to optimize the scheduling of a grid-connected system and minimize daily operational costs while handling uncertainties (load and renewable variability). Recently, hybrid GA-PSO have gained significant traction in energy management optimization in smart grids and microgrids [163]. A novel hybrid GA-PSO and TLBO was developed to minimize power losses in smart grids [164]. GA-PSO hybrid metaheuristic approach is introduced for demand side management (DSM) in smart grids, optimizing peak reduction via flexible load shifting [165].

Many modified and improved variants of SSA have been introduced recently in the literature. Despite the plethora of research works in the field of MG energy planning, a critical

review of these works such as [166], [167], [168], [169] shows that the optimization problem was tackled by keeping hard boundaries for the battery limits. This led the search algorithm to fall into infeasible solutions, more precisely, the battery keeps charging/discharging for the next hours within its maximum capacity without considering the fact that it is already fully charged/discharged.

In this chapter, the typical low-voltage microgrid (MG) configuration incorporates various renewable energy sources such as photovoltaic generator (PV), wind turbine (WT), diesel engine (DG), microturbine (MT), fuel cell (FC), and energy storage system (ESS), is considered. The MG is seamlessly connected with the utility grid and can operate in both grid-connected and off-grid modes. The MG central controller (MGCC) controls the energy flow in the MG. Within this framework, the micro-source controller (MC) and load controller (LC) play pivotal roles in maintaining power balance. This is achieved by issuing optimal generation set points obtained from the (MGCC).

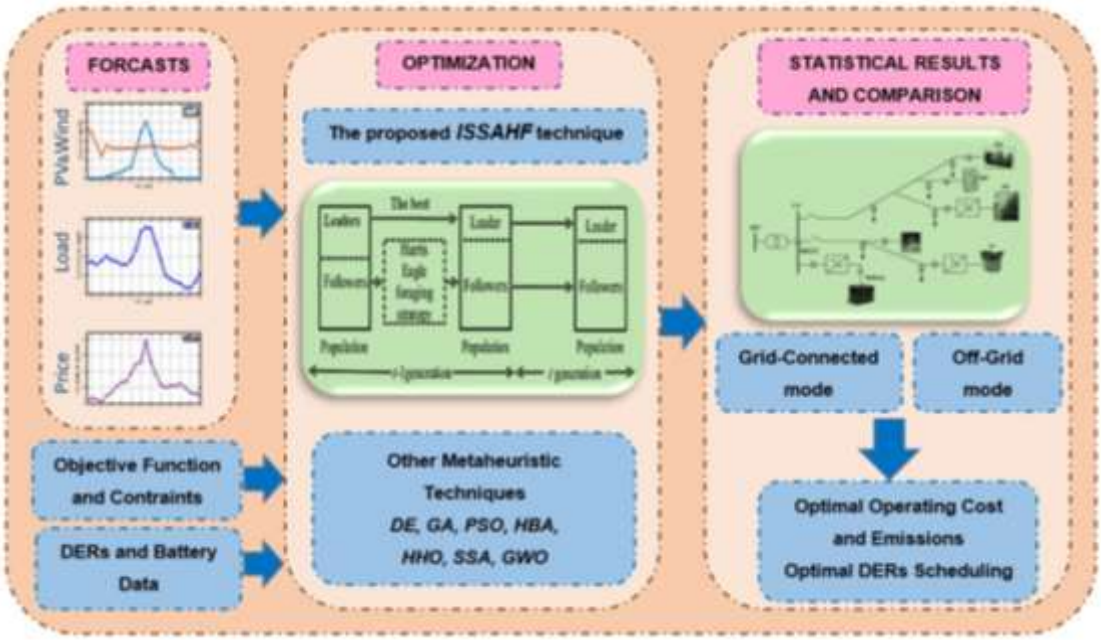


Figure IV-1: Optimization framework for the MG energy planning and management strategy

This study aims to minimize the overall generation and emission costs by issuing optimal one-hour-ahead reference powers to local controllers from/to different distributed energy resources (DERs) and storage systems. The inputs to the problem are the predictions of utility price, hourly load profile, PV, and Wind generations. Figure IV-1 illustrates the overall outlines of the MG optimal planning strategy; the range of the hour index t is 1 to 24h.

This work aims to minimize the cost function (III.2) described in details in section III.2, subject to the equality and inequality constraints (III.9), (III.10), (III.11), (III.12), and (III.14) using a

proposed hybrid metaheuristic optimization technique that combines the Harris Hawk Optimizer (HHO) and the Improved Salp Swarm Algorithm (ISSA).

IV.3 Simulation results and discussion

IV.3.1 Input simulation data

IV.3.1.1 Technical and economical parameters

The allowable power limits for the MG subsystems are summarized in Table IV.1. The remaining simulation parameters were taken from relevant literature [156] [166]. The price characteristics for DERs resources are displayed in Table IV -2, the emission characteristics for DERs are summarized in Table IV.3, and CO_2 treatment cost is 0.027 € /kg, for SO_2 it is 1.93 € /kg, and for NOx it is about 8.185 € /kg. The architecture typically involves a combination of specialized hardware and software optimizations, as well as techniques such as quantization, compression, and pruning, to reduce the size and complexity of the models and improve their efficiency.

Table IV-1: Allowable power limits for different (DERs) in the microgrid

DERs	PV	WT	MT	DG	FC	Battery	Grid
Min power (kW)	0	0	0	0	0	-30	-30
Max power (kW)	30	30	30	100	30	30	80

Table IV-2: Price characteristics for (DERs) in the microgrid

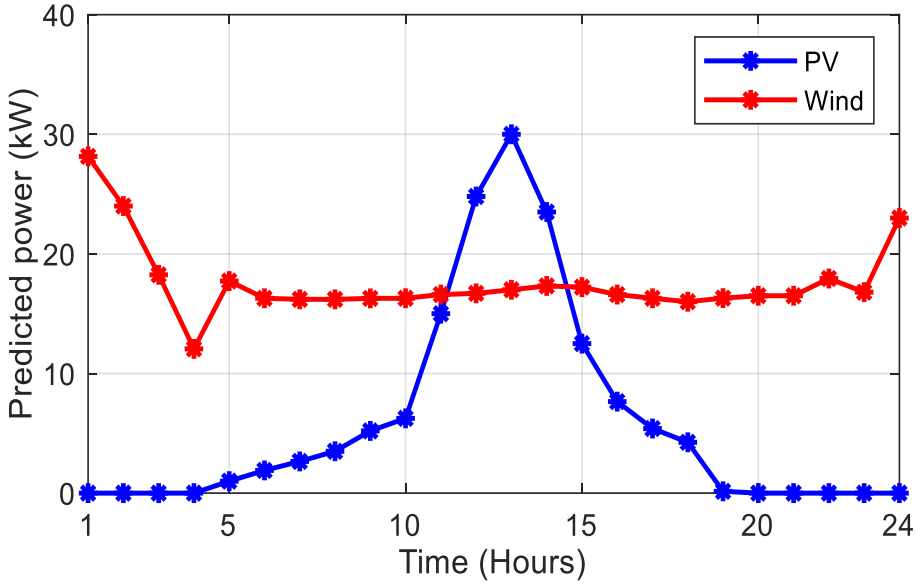
DERs	PV	WT	MT	DG	FC
In.cost (€/kW)	8.6450	2.9055	1.6978	6,5273	5.5575
Y_{OM} (€/kWh)	0.0012	0.0038	0.0084	0,0345	0.0038
Y_{FC}(€/kWh)	0	0	0.0903	0,1545	0.0268

Table IV-3: Emission characteristics for (DERs) in the microgrid

DERs	PV	WT	MT	DG	FC	Grid
CO2 (g/kW)	0	0	724	1978	489	889
SO2 (g/kW)	0	0	0.0036	0.718	0.003	1.8
NOx (g/kW)	0	0	0.2	29.87	0.01	1.6

IV.3.1.2 Forecast input profiles

Accurate load forecasting plays a pivotal role in energy management. The predicted power generation from the renewable energy sources throughout a typical day is presented in Figure IV-2. The total power requirement for the microgrid over a 24-hours period is 2002,6 kW, as illustrated in Figure IV-3. The predicted grid electricity price varies depending on the hourly power demand is shown in Figure IV-4.



. Figure IV-2: Hourly predicted PV and wind powers

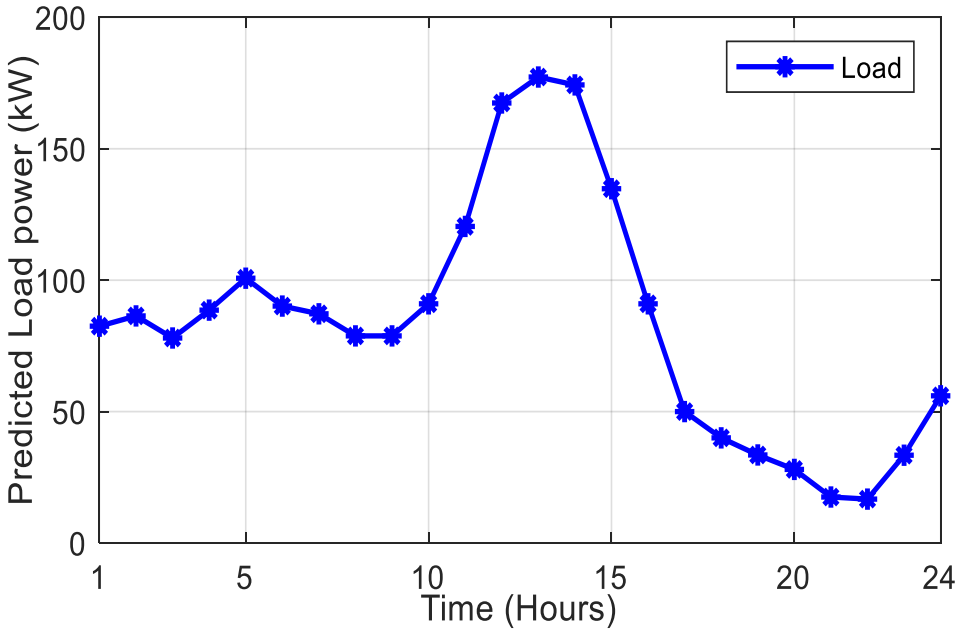


Figure IV-3: Hourly predicted load profile

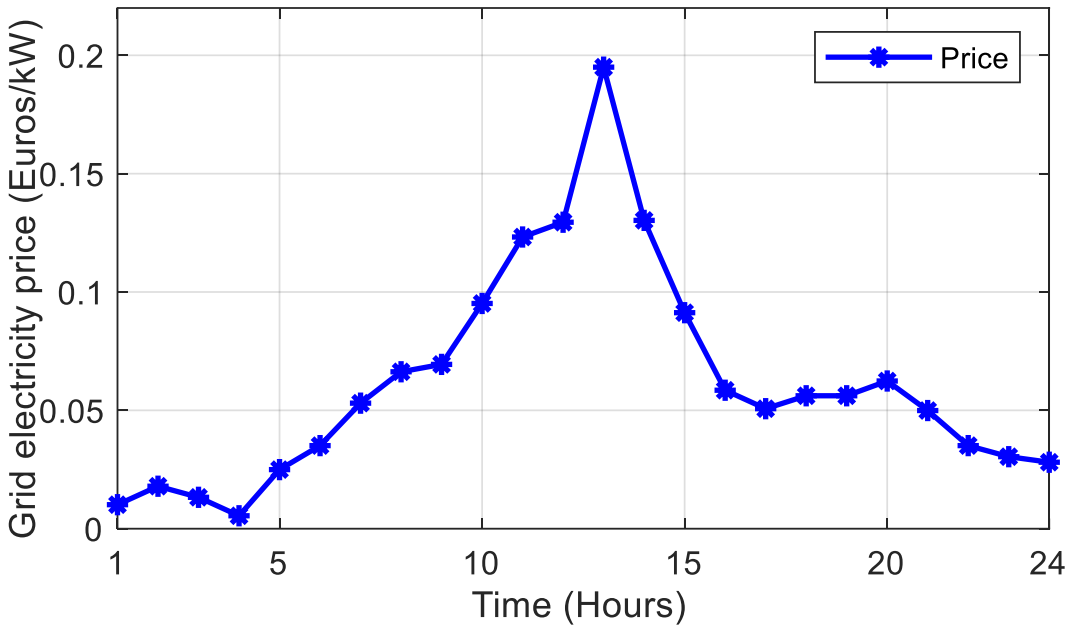


Figure IV-4: Hourly predicted grid electricity price

IV.3.2 Results and comparative study

The proposed ISSAHF optimizer is tested considering the off-grid and the grid-connected operating modes. The program was run for 1000 iterations using a population size of 120. The initial battery SOC is assumed 50%. To prevent the battery from overcharging or undercharging, we set the allowable limits of the state of charge as SOC_{max}=80%, and SOC_{min}=30%.

The results are presented for two cases (off-grid and grid-connected operating modes). The hourly power references from renewable energy sources are shown in Figure IV-5 and Figure IV-6 for the off-grid and the grid-connected mode respectively. It is noticed that the power profiles are almost similar, and when referring to predicted PV and Wind powers shown in Figure IV -2, the renewables were utilized at their corresponding maximum powers.

The hourly power references for different traditional generators are shown in Figure IV -7 for the off-grid mode and in Figure IV-8 for the grid-connected mode. The comparison between the two figures indicates that in the off-grid mode, the Diesel generator (DG), drains a considerable amount to compensate the power drawn from the grid in the second scenario.

The two other sources (FC and MT), have almost the same power reference, this is due to the fact that the diesel generator has less cost compared to other generators.

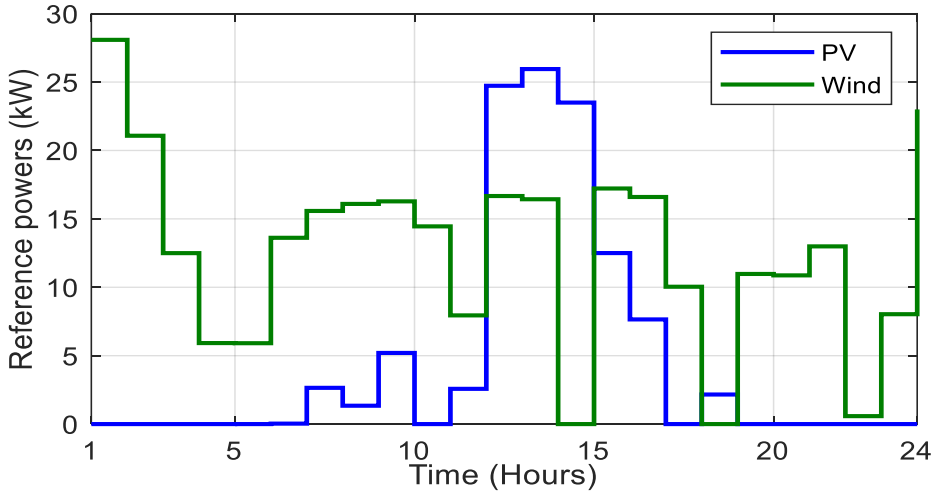


Figure IV-5: Hourly reference powers from renewables (Off-grid mode)

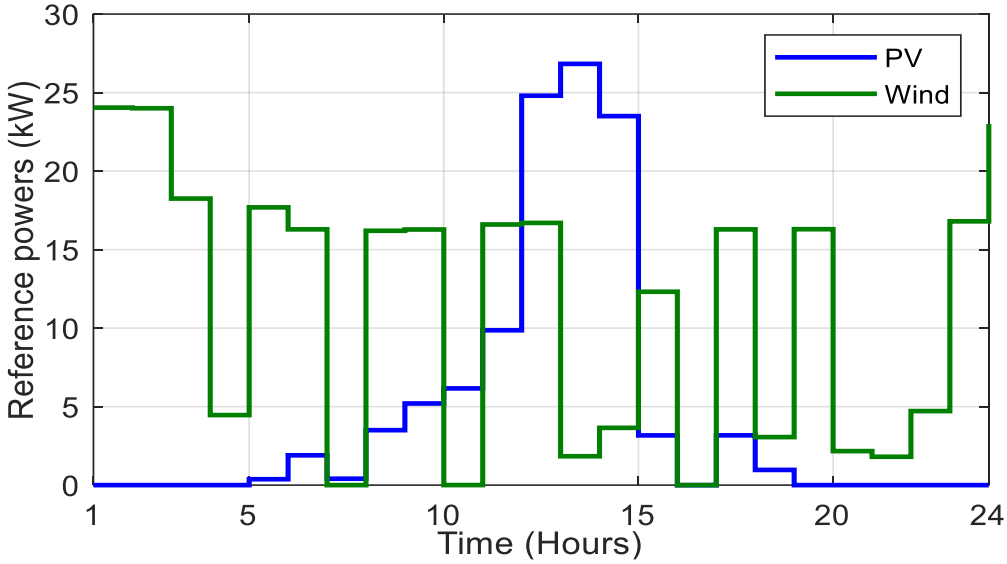


Figure IV-6: Hourly reference powers from renewables (Grid-connected mode)

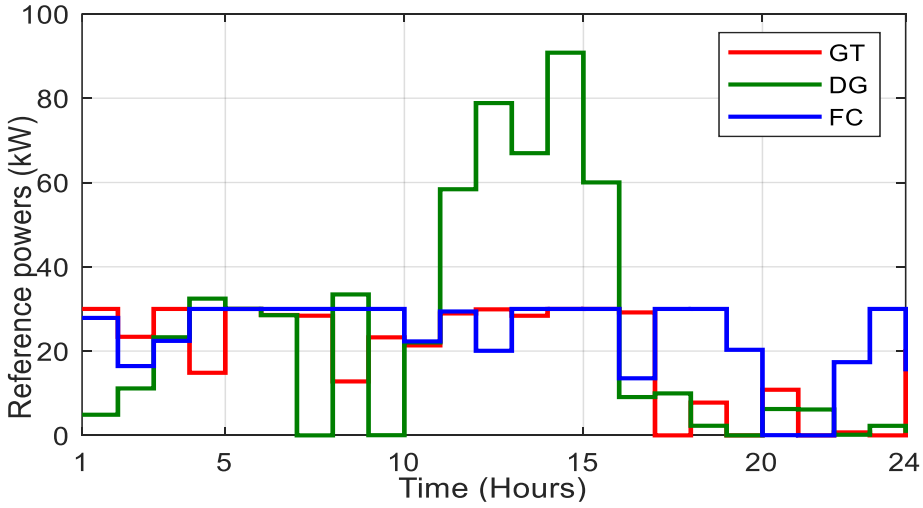


Figure IV-7: Hourly reference powers from distributed generators (Off-grid mode)

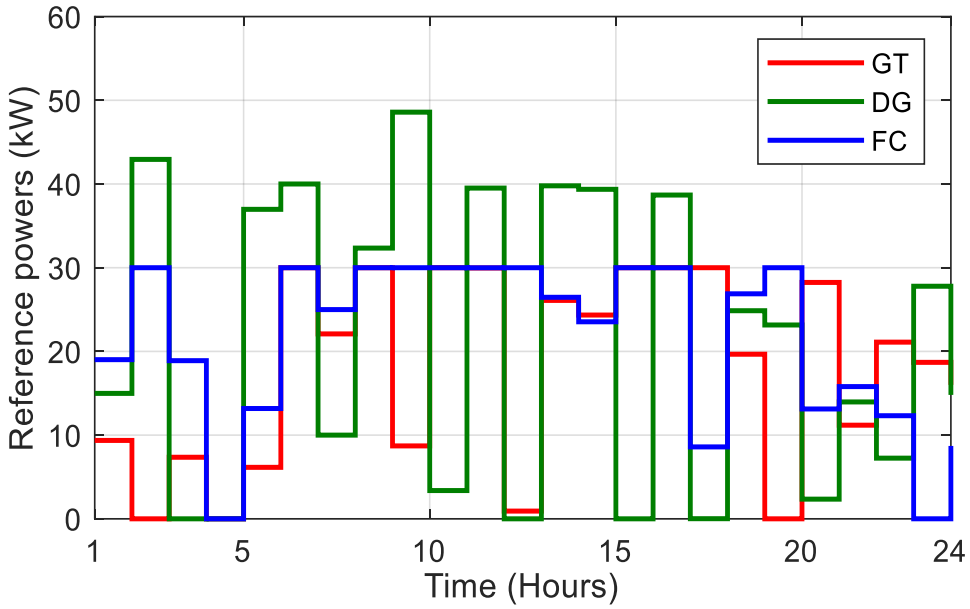


Figure IV-8: Hourly reference powers from distribution generators (Grid-connected mode).

For the battery storage system, the hourly power references are shown in Figure IV-3 for the off-grid mode and in Figure IV-10 for the grid-connected mode. More charge and discharge cycles are present in the off-grid mode to compensate for the energy demand. One peculiarity of this work is that the reference powers from the battery follow a realistic behaviour as opposed to many research papers [156], [166], [167], [169], where the fully discharged battery still provides power, which is contradictory.

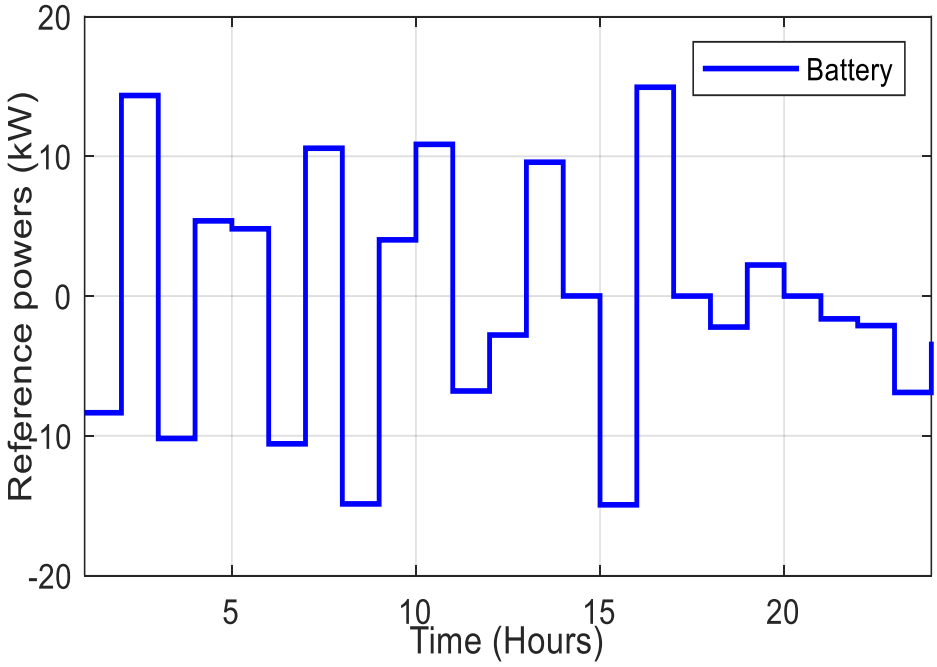


Figure IV-9: Hourly reference power for the battery (Off-grid mode)

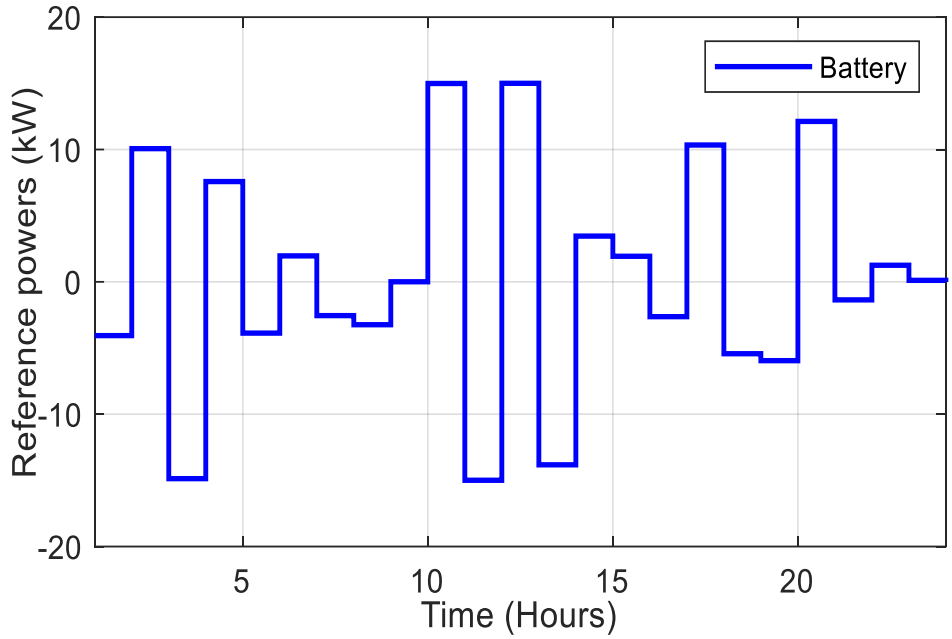


Figure IV-10: Hourly reference power for the battery (Grid-connected mode)

The battery state for charge for both modes is shown in Figure IV-11 and Figure IV-12 respectively. We can see that the SOC is indeed kept within the allowable bounds (SOC_{max}=80%, and SOC_{min}=30%), we see also that in off-grid mode, there are more charge/discharge cycles for the battery especially in hours corresponding to peak load.

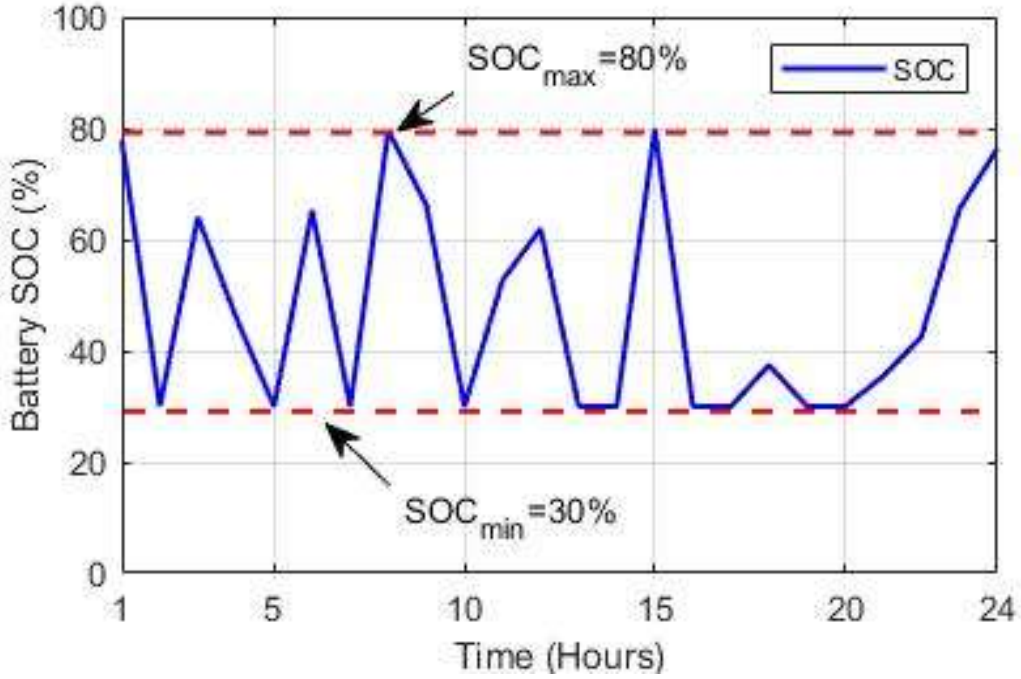


Figure IV-11: Hourly battery SOC (Off-grid mode)

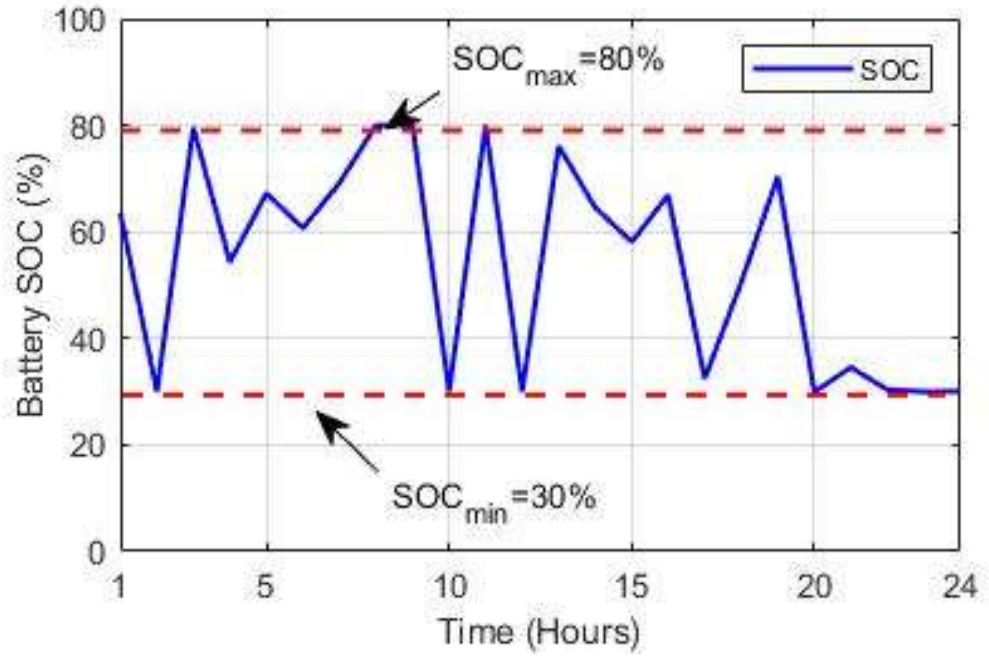


Figure IV-12: Hourly battery SOC (grid-connected mode)

The hourly power drawn or fed to the grid in the grid-connected mode is given in Figure IV-6, it can be seen that in the hours corresponding to load peaks, a significant amount of power was drawn from the grid, while in load valleys; the generated power is bought to the grid.

To further assess the effect of the grid integration on the reduction of the MG generation cost, Figure IV-14 shows the variation of the hourly cost of electricity for both off-grid and grid-connected modes. When computing the average values, for the off-grid the daily average cost of the electricity was found to be 28.3370 €, whereas in the grid-connected mode, it was 19.2676 €. The grid-connected operation mode is the most economical and reliable one because the grid participates in the power exchange (selling/buying) within the MG.

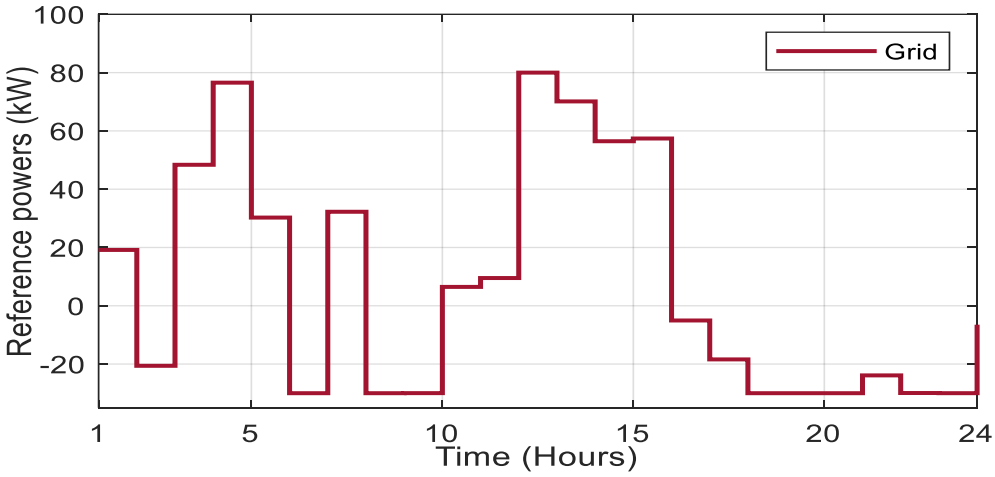


Figure IV-13: Hourly reference power from/to the grid

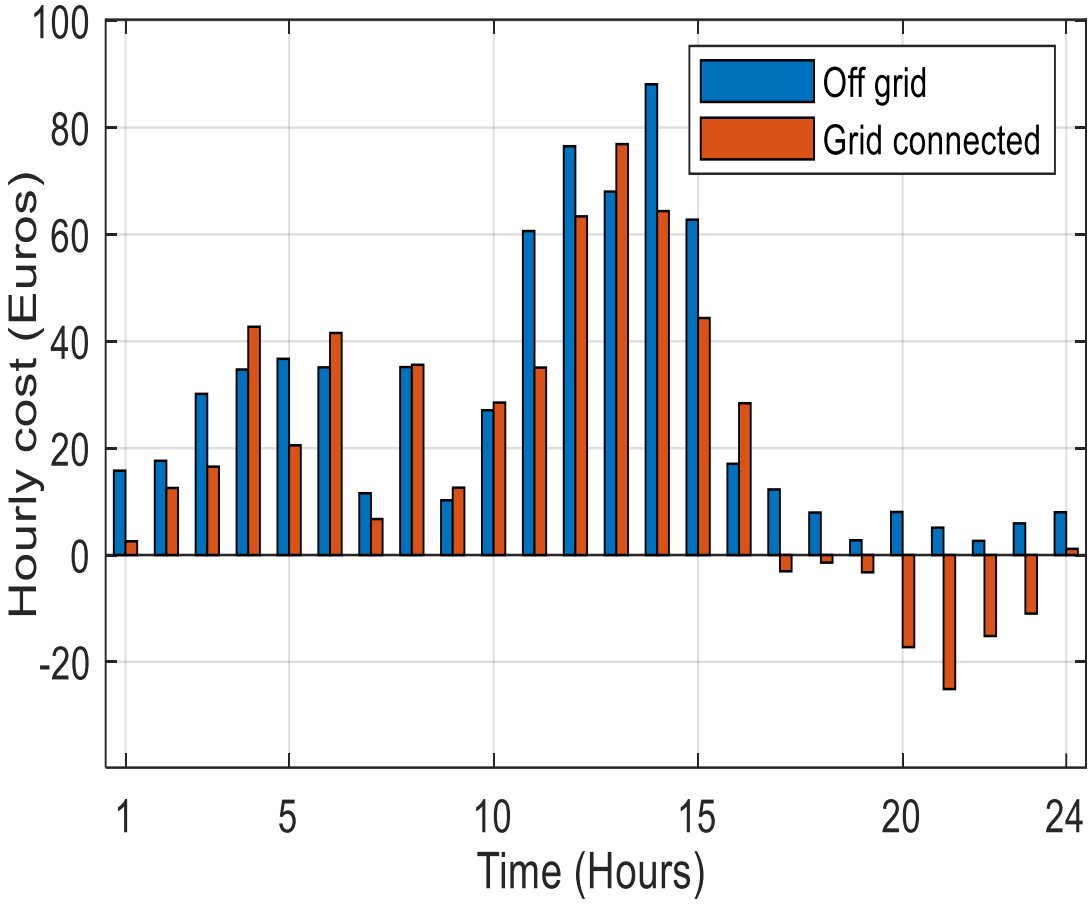


Figure IV-14: Hourly cost of electricity for Off-grid and Grid-connected modes

In order to position the present study with related studies, Table IV-4, shows a comparative study of the proposed strategy with other similar works published in the same period of the with similar technical and economic data in terms of the daily cost of electricity (€/kWh) for different configurations and optimization algorithms.

Upon initial examination, the results obtained for the current study are not the best among the cited results. However, it is important to note that this discrepancy is due to the search space in those approaches where the battery limits (discharge/charge) were not considered during the study, this enlarges the search space to include non-practically feasible or possible solutions. To confirm this, a careful examination of the results in these references can be done. In those papers, the battery continuously drains/charges at its full capacity for many consecutive hours, without considering whether it is already charged or discharged. In contrast, the present study meticulously. considers this aspect, this has shrunk the search space but provides only feasible solutions, which is a key contribution in this study. Note that the obtained results in this study were generated under the same conditions as those of the related works, allowing for a fair and accurate comparison.

Table IV-4: Comparative Study with similar works in terms of the daily cost of electricity

Reference	Configuration	Algorithm	Daily COE (€/kWh)
(Dey et al. 2023) [167]	PV/WT/DG/FC/MT/grid	CSAJAYA	0.0572
(Dey et al. 2023) [167]	PV/WT/DG/FC/MT	CSAJAYA	0.0643
(Raghav et al. 2021) [168]	PV/WT/ESS/FC/Grid	QTLBO	0.1434
(Fathy et al. 2023a) [169]	PV/WT/ESS/FC/Grid	HB	0.0648
(Li et al. 2021) [170]	PV/WT/ESS /FC/MT/Grid	GSA-PS	0.1647
Present work	PV/WT/ESS/DG/FC/MT	ISSAHF	0.3114
Present work	PV/WT/ESS/DG/FC/MT/grid	ISSAHF	0.2021

IV.3.3 Sensitivity analysis

To assess the effect of forecasting uncertainties or deviations on the optimal cost, a sensitivity analysis is carried out with respect to PV power, Wind power, load, and utility price, within confidence intervals of 5%. The sensitivity results are summarized in Figures IV-8, and Figure IV-9 for both grid-connected and off-grid scenarios respectively. The results show that the load variation has a large effect on the change of the optimal cost for the grid connected and the off-grid cases respectively. The variation of the PV and wind powers causes slight changes on the optimal case (less than 10%) proportionally for the grid-connected case and inversely for the off-grid case. In contrast, the change in the utility price has a proportional effect on the optimal price which is justifiable, since a large amount has been drawn from the grid it has relatively less mean cost compared to unitary operating cost.

Overall, the optimal cost is less sensitive to fluctuations in the PV and Wind power, but the variations in the load lead to large variations in the optimal cost, as the load is the main factor that determine the consumption.

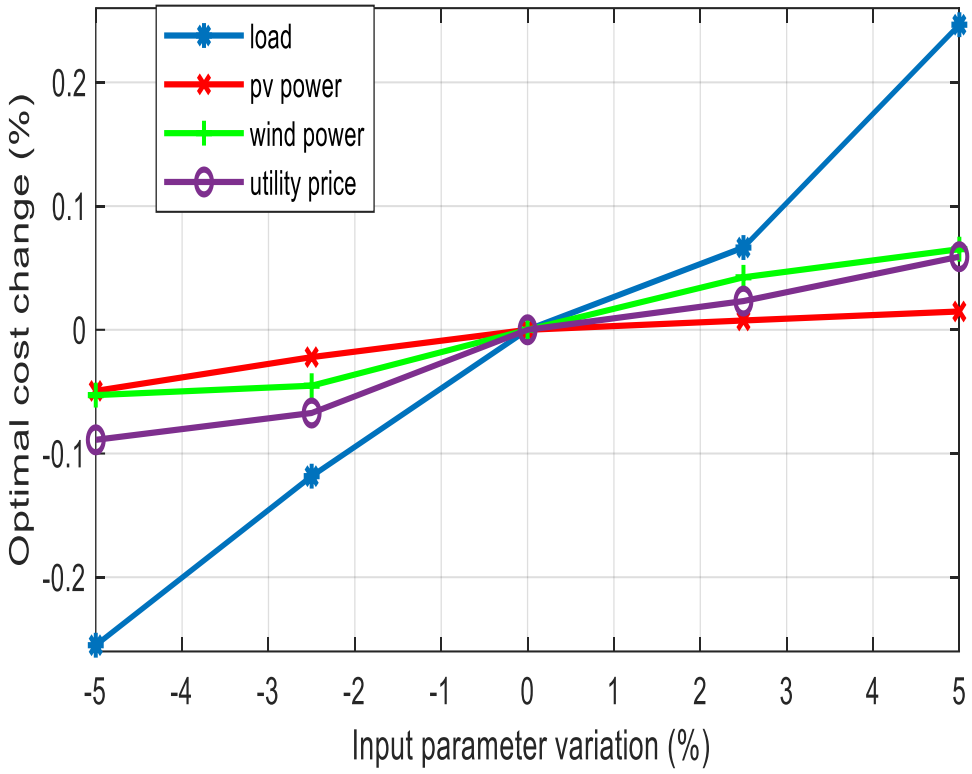


Figure IV-15: Sensitivity curves for the grid-connected mode

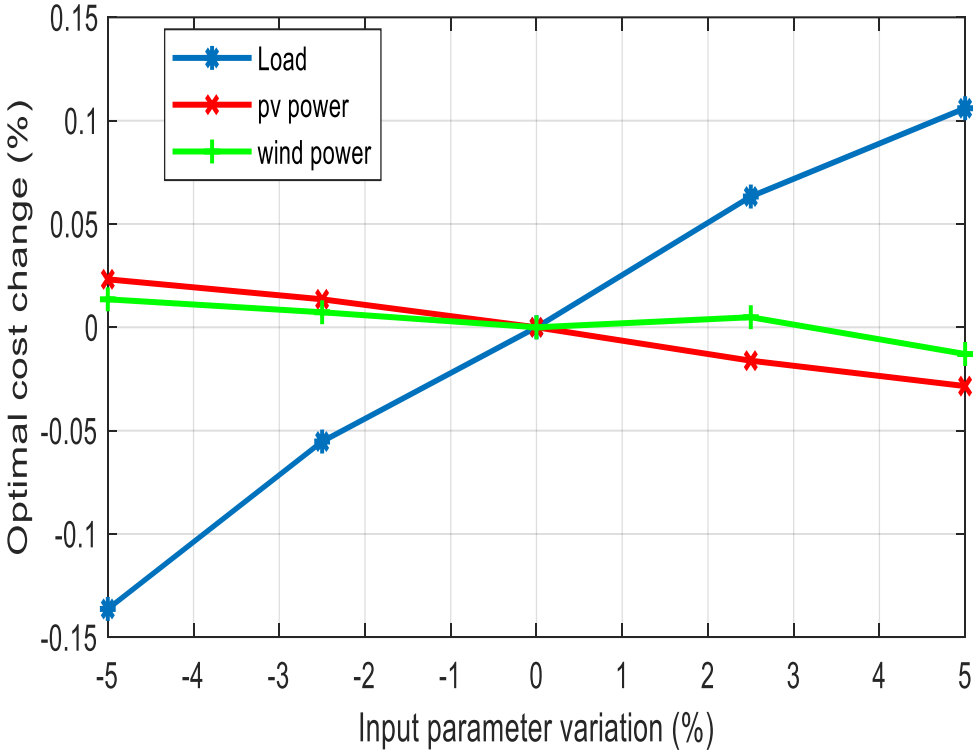


Figure IV-16: Sensitivity curves for the off-grid mode

IV.3.4 Statistical study

The robustness and the statistical behaviour of the optimization ISSAHF technique is accessed through a comparative statistical analysis among various optimization techniques (DE, GA, PSO, HBA, GWO, HHO, SSA, and ISSAHF).

The algorithm was run 30 runs, with a population size nSalps=120 and the same number of iterations nIter=1000.The parameters of different algorithms are summarized in Table IV-5 The statistical metrics used for comparison are minimum cost, median cost, mean cost, maximum cost, and standard deviation. These metrics provide more insight and information on how the proposed hybrid algorithm is performing among standalone algorithms and other applied optimization methods. Table IV 6 summarizes the obtained results in for the off-grid mode and in Table IV 7 for the grid-connected mode. From the results, the proposed method (ISSAHF) shows higher performance and allows finding the best results in terms of mean optimal cost for the (off-grid=623.5248 €, grid-connected=404.7475€), followed by the differential evolution (DE) with (off-grid=667.2141€, grid-connected=424.5841€) and the Salp Swarm Algorithm (SSA) with (off-grid=684.0561€, grid-connected=456.8171€).

In terms of robustness, measured by the standard deviation metric, the DE has the best standard deviation Std=17.024 €, followed by the proposed ISSAHF with Std=20.765 € and the SSA with 22.1376 €, for the off-grid mode. For the grid-connected mode, the DE comes first with Std=21.6316 €, then the proposed ISSAHF with Std=28.8771 €, then the SSA with Std=37.6899 €. Note that these results are relative to the number of runs (30), and the hyperparameters for each method (nIter, nSalps).

It can be also seen that the HHO, when applied alone provides the worst results among the eight strategies. This is due to the fact that the HHO has a tendency to stuck into local minima and it has poor convergence [171]. However, its combination with SSA has improved its search capability thanks to the four attack phases which provide more diversity.

In all examined methods, it has been observed that the involvement of the grid resulted in a reduction of the total and average generation costs. This makes the grid-connected mode a more cost-effective configuration compared to the off-grid mode.

In summary, the proposed ISSAHF optimization technique has demonstrated its competitiveness as an effective technique for optimal energy planning within MGs when compared to other off-the-shelf techniques. It has more capability to achieve global optimum and it is more robust.

Table IV-5: Parameters of optimization algorithms for Population Size N= 120, MaxIter= 1000

Method	Control parameters
DE	Crossover Ratio (CR) =0.2, Weight factor Wf=1.8
GA	Cross over probability (cp) = 1, mutation probability mp = 0.02, selection: Roulette weel
PSO	Inertia weight (w_1) = 1, inertia weight, damping (w_2) = 0.99, Acceleration Coefficients: C_1 = 2.0, C_2 = 2.0
GWO	No specific parameters.
HBA	Badgers ability to get food (beta) = 6, control parameter (c)= 2
HHO	No specific parameters.
SSA	No specific parameters.

Table IV-6: Statistical performance for off-grid mode (€)

Method	Mean	Median	Min	Max	Std
GA	848.4704	851.2427	810.7984	880.2071	19.4083
PSO	755.4208	754.6964	664.8345	806.1971	37.5585
DE	667.2141	666.6038	632.4642	711.2371	17.0241
GWO	730.8167	729.8274	635.2688	811.3497	40.2903
HBA	954.7602	946.4376	867.4887	1043.4506	47.2423
HHO	959.5747	966.9542	881.7831	1081.1091	35.6041
SSA	684.0561	687.5186	629.5487	731.9473	22.1376
ISSAHF	623.5248	621.9544	584.1015	669.7051	20.765

Table IV-7: Statistical performance for grid-connected mode (€)

Method	Mean	Median	Min	Max	Std
GA	714.0474	714.1886	678.2953	760.1168	18.657
PSO	565.1783	565.2674	510.9225	672.4604	34.2138
DE	424.5841	420.7959	392.3049	505.0811	21.6316
GWO	529.3936	533.282	429.99	604.4359	42.0674
HBA	752.3002	744.6791	634.4811	878.1544	45.3774
HHO	813.932	814.9977	727.6547	914.2983	37.6899
SSA	456.8171	454.0642	401.0338	523.5602	31.3733
ISSAHF	404.7475	407.6663	342.9625	493.3864	28.8771

IV.4 Conclusion

In this chapter, a hybrid ISAAHF algorithm solves the optimal energy management problem in a typical MG over a 24-hour period. The algorithm successfully guarantees the load satisfaction with an optimal cost while satisfying all the involved equality and inequality constraints. Besides, the battery was maintained within its allowable power and SOC (SOC_{max}=80% and SOC_{min}=30%) ranges. Compared to already used metaheuristic optimization approaches namely DE, PSO, GWO and SSA, HHO, HBA, the ISSAHF has been validated theoretically as a strong and effective optimization method, particularly suitable for addressing optimal energy planning challenges within Microgrids. The statistical analysis shows the proposed technique's superior performance with mean optimal costs of 623.52€ (off-grid) and 404.75€ (grid-connected), outperforming others (667.21€-959.57€ off-grid, 424.58€-813.93€ grid-connected). Its robustness is demonstrated with a standard deviation of 20.77€ (off-grid) and 28.88€ (grid-connected), better than the worst cases of 47.24€ and 45.38€, respectively. This is particularly beneficial in addressing the dynamic and complex nature of microgrid energy planning, where uncertainties and fluctuating conditions play a significant role.

General Conclusion

This thesis addresses optimal energy management challenges in microgrids, employing Homer Pro for techno-economic analysis and advanced metaheuristic optimization to deal with multi-objective trade-offs between economic viability, resilience and emission reduction. It outlines a structural progressive approach, from fundamental concepts and statistic simulation, to advances algorithm and dynamic optimization solutions.

Throughout this thesis, we provided a comprehension literature review of microgrids concepts, their classification, components, architecture and application areas. we discussed the energy planning and management of microgrids, by reviewing a variety of existing computational optimization approaches and available software tools, employed to address multiple objectives: economic, technical, reliability and environmental criteria.

Then we focused on applying Homer Pro to conduct a techno-economic assessment (sizing and dispatch baseline) of a representative pilot microgrid based on technical, economic and emission evaluation. Starting with a detailed methodology defining key performance indicators, and components modelling. Followed by providing a detailed sizing, simulation and sensitivity analysis curried out on realistic load profile, local renewable source and their economic assumptions. Then we provided a discussion and a detailed comparison of the obtained configurations to identify the cost-effective and reliable solution. Results showed that among three candidate configurations, the Grid-connected configuration was selected as cost-effective compared to diesel-based, and stand-alone microgrid configurations. the grid-connected microgrid exhibits the lowest NPC, while maintaining a significant renewable fraction even though it presents higher missions due to gird electricity imports. The subsidized electricity tariff of the national utility grid makes the grid-connected configuration the best compromise between cost, reliability, and sustainability for the specific coastal and urban microgrid. Nevertheless, other configurations remain feasible candidates and capable solutions to meet the energy needs with varying degrees of economic and environmental benefits.

We presented an overview of recent and modern metaheuristic techniques commonly applied in energy management problems, with focus on of the hybrid Improved Salp Swarm Algorithm with a Harris Hawks foraging (ISSAHF) algorithm, proposed for the first time to deal with mathematical formulation of the microgrid energy management problem.

Finally, we concluded with a comparison of the algorithms applied in this thesis, highlighting their principal advantages and inherent limitations relevant to microgrid energy management problems.

Last part of the work established the implementation of the proposed ISSAHF method derived from the previous part, applied to two operation scenarios: stand-alone and grid-connected integrating different DERs (PV/Wind/Battery/FC/MT). We presented the simulation data and the optimization techniques applied to solve the optimal energy management problem in a typical MG over a 24-hour period by the minimization of the operating costs while satisfying all system constraints. We also provided a detailed results for energy scheduling of the hourly references powers of all DERS, including comparison between the two operation scenarios.

Performance evaluation based on statistical comparison and sensitivity analysis was also discussed. The results demonstrates that the proposed algorithm successfully guarantees the load satisfaction with an optimal cost while satisfying all the involved equality and inequality constraints. Besides, the battery was maintained within its allowable powers and SOC ranges. Compared to already used metaheuristic optimization approaches namely DE, PSO, GWO and SSA, HHO, HBA, the hybrid ISSAHF has been validated theoretically as a strong and effective optimization method, particularly suitable for addressing optimal energy planning challenges within Microgrids operation modes.

In conclusion, energy planning in microgrids offers a promising approach for optimizing the operation and management of microgrid systems. Obtained results demonstrate that the grid-connected operation mode emerges as the optimal solution when grid access is available, validating Homer Pro findings.

Despite its contributions, the present work has some limitations related mainly to battery and demand side management, the prioritization of renewable resources, and the availability of hourly forecasts for renewables, load, and grid electricity prices.

As an outlook for this work, and as a valuable contribution to the field of swarm intelligence algorithms and optimization, future works could include:

- Improving the system's performance by exploring more advanced techniques and optimizing the system's architecture.
- The storage management could be considered separately, and the renewables utilization can be posterized.

- Add a forecasting block before the optimization block to provide hourly forecasts for load, prices, PV, and wind generations).
- Validate and compare the obtained results with off-the-shelf software tools (HOMER Pro, HOGA, HYBRID2) when feasible.
- Incorporating uncertainty modelling for renewable sources and load to improve robustness of optimization.
- The con of demand side management and flexible loads to reflect real loads and prioritize renewable use.
- Adopting a multi-objective optimization, considering economic, reliability and environment criteria simultaneously.

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ملخص

يعد التخطيط الأمثل للطاقة في الشبكات الصغيرة تحديًا رئيسيًا لضمان أنظمة إمداد طاقة مجدية اقتصاديًا ومستدامة وموثوقة للمجتمعات الحديثة. تتناول هذه الأطروحة المشكلة من خلال إطار شامل تقني واقتصادي قائم على التحسين. أولاً، يتم تحليل شبكة صغيرة الحجم تتألف من خلايا كهروضوئية وتوربينات رياح ومولدات ديزل ونظام تخزين الطاقة وذلك باستخدام برنامجHOMER pro، مع الأخذ في الاعتبار الطلب الواقعي على الحمل والموارد المتجددة المحلية. يحدد تقييم التكوينات المتعددة بناءً على الأداء التقني والتكلفة الاقتصادية والانبعاثات أن بنية الشبكة المتصلة بالطاقة الكهروضوئية/طاقة الرياح/البطاريات هي الحل الأكثر فعالية من حيث التكلفة والموثوقية. علاوة على ذلك، تم اقتراح نهج جديد للتحسين الهجين الميتاهيوريستي(ISSAHF) ، والذي يجمع بين خوارزمية Salp Swarm المحسنة وHarris Hawks Foraging، من أجل التخطيط الأمثل للطاقة لشبكة صغيرة أكبر وأكثر تعقيدًا ذات جهد منخفض مع مستوى عالٍ من دمج موارد الطاقة الموزعة. تُظهر نتائج المحاكاة، المدعومة بالتحليل الإحصائي وتحليل الحساسية، القدرة الفائقة على البحث وقوة الخوارزمية المقترحة مقارنة بالطرق الميتاهيوريستية التقليدية. توفر النتائج المتحصل عليها فهمًا شاملاً لتخطيط طاقة الشبكات الصغيرة عبر مستويات مختلفة من الأنظمة، وتُظهر أن العمل المتصل بالشبكة يُعد الحل الأمثل عند إمكانية الوصول إلى الشبكة، مما يؤكد صحة النتائج التي خلص إليها HOMER Pro.

كلمات مفتاحية: التخطيط الأمثل للطاقة، الشبكات الصغيرة، التحسين باستخدام الميتاهيوريستية، إطار تقني واقتصادي، موارد الطاقة الموزعة.

Résumé

La planification énergétique optimale des micro-réseaux représente un enjeu majeur pour garantir des systèmes énergétiques durables, fiables et économiquement viables. Cette thèse propose un cadre méthodologique intégrant une analyse technico-économique et des techniques d'optimisation avancées. Dans un premier temps, un micro-réseau de petite échelle composé de systèmes photovoltaïques, éoliens, d'un groupe électrogène diesel et d'un système de stockage est analysé à l'aide du logiciel HOMER Pro, en tenant compte d'une demande réaliste et de ressources renouvelables locales. L'évaluation multicritère des configurations étudiées met en évidence l'architecture PV/éolien/batterie connectée au réseau comme la solution la plus performante. Par ailleurs, une approche d'optimisation métaheuristique hybride innovante, combinant une version améliorée de l'algorithme Salp Swarm et la stratégie du Faucon de Harris (ISSAHF), est développée pour un micro-réseau basse tension plus complexe et fortement pénétré en ressources énergétiques distribuées. Les résultats de simulation, appuyés par des analyses statistiques et de sensibilité, démontrent la supériorité de l'algorithme proposé en termes de capacité de recherche et de robustesse par rapport aux méthodes métaheuristiques conventionnelles.et soulignent la pertinence du mode connecté au réseau lorsque celui-ci est disponible.

Mots clés : *planification énergétique optimale, micro-réseaux, analyse technico-économique, optimisation par métaheuristiques, ressources énergétiques distribuées.*

Abstract

Optimal energy planning in microgrids is a key challenge for ensuring economically viable, sustainable, and reliable energy supply systems for modern communities. The present thesis addresses the identified problem through a comprehensive techno-economic and optimization-based framework. First, a small-scale microgrid comprising photovoltaic, wind turbine (WT), diesel generator (DG), and energy storage system (ESS) is analyzed using HOMER Pro, considering realistic load demand and local renewable resources. The evaluation of multiple configurations based on technical performance, economic cost, and emissions identifies the PV/Wind/Battery grid-connected architecture as the most cost-effective and reliable solution. Furthermore, a novel hybrid metaheuristic optimization approach, combining an improved Salp Swarm Algorithm with Harris Hawks Foraging (ISSAHF), is proposed for optimal energy planning for a larger and more complex low-voltage microgrid with high integration level of distributed energy resources. Simulation results, supported by statistical and sensitivity analysis, demonstrate the superior search capability and robustness of the proposed algorithm compared to conventional metaheuristic methods. The findings give a comprehensive understanding of microgrid energy planning across different system scales, and demonstrates that the grid-connected operation mode emerges as the optimal solution when grid access is available, validating Homer Pro results.

Keywords: *optimal energy planning, microgrids, techno-economic framework, metaheuristic optimization, distributed energy resources.*