Cape Peninsula
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PLANNING AND OPTIMIZATION OF THE RENEWABLE-ENERGY-BASED MICRO-GRID FOR RURAL ELECTRIFICATION.

by

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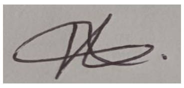
DECLARATION

I, Nteka Maletsie Mojela, declare that the contents of this dissertation represent my own unaided work, and that the dissertation has not previously been submitted for academic examination towards any qualification. Furthermore, it represents my own opinions and not necessarily those of the Cape Peninsula University of Technology.



Signed **Date 15/02/2026**

ABSTRACT

Microgrid systems are a sustainable, technically feasible alternative to grid extension, and for off-grid, energy-impoverished communities, rural electrification serves as an equity-in-energy access reduction effort and a means to evolve supply reliability to ensure greater renewable penetration. This dissertation evaluates planning, modelling, and optimization for microgrid-based rural electrification as a reliable, cost-effective approach compared to traditional grid extension methods.

Through an expansive review of contemporary literature, the increasingly feasible and applicable advancements support microgrids within modern power systems as a means of reducing operational costs, minimizing technical losses, and accommodating shifting energy needs. The microgrid set up for this dissertation is constructed on realistic operational definitions, empirically established cost functions, and anticipated technical considerations for distributed energy resources, solar systems, wind turbines, and battery storage. The general goal of the study is to present operational cost functions for each energy component, using relevant cost-of-operations realities to better inform microgrid-based rural electrification planning. Thus, this dissertation develops a microgrid-based rural electrification approach and assesses the impacts of various established optimization methodologies within a renewable-driven microgrid context. Furthermore, new methodologies emerge; one offers an innovative Dynamic Arithmetic Optimization Algorithm, assessed for microgrid energy management using expected information gain from MATLAB simulations for empirical validation. Scheduling alternative approaches emerge through the development and subsequent validation of Linear Programming and Grey Wolf Optimization.

The Dynamic Arithmetic Optimization Algorithm (DAOA) is employed to minimize the microgrid’s total operating cost by intelligently coordinating renewable power generation, battery charging and discharging, and interaction. Its dynamic arithmetic operators enable the algorithm to respond flexibly to fluctuating resource availability, resulting in more adaptive search patterns than classical AOA and other metaheuristics. Through this implementation, the study evaluates DAOA's performance relative to LP and GWO, providing insights into the algorithm’s dispatch behaviour, cost efficiency, and suitability for renewable-energy-based microgrid applications. By comparing DAOA, LP, and GWO under the same system configurations and constraints, the study provides a clear assessment of each method’s cost-effectiveness, stability, and suitability for microgrid management. The case studies presented are implemented and simulated in MATLAB using the DAOA-based optimization framework. According to the simulation results, a fully integrated microgrid yielded the lowest cost of \$5,467.56, demonstrating the economic benefits of integrating diverse renewable energy resources with energy storage. The moderate cost for the wind-grid configuration is $6148.10. The highest cost is recorded for the PV-battery configuration at $15411.41, due to solar intermittency and storage capacity limitations. Therefore, the study verifies the efficacy of the DAOA technique for solving microgrid dispatch problems and indicates that resource diversification is a key enabler of cost-efficient, flexible microgrid operation.

Dynamic Arithmetic Optimization Algorithms, Linear Programming, and Grey Wolf Optimization are assessed against each other under varying load requirements and renewable generation profiles to better understand their performance. Ultimately, all three algorithms performed successfully, resulting in reduced overall energy costs, improved reliability, and enhanced renewable penetration. Therefore, the results of this dissertation support the microgrid-based rural electrification approach as a feasible, economically viable means of transforming rural access to electrical power.

Keywords: Microgrid; Rural electrification; Distributed energy resources (DERs); Renewable integration; Energy management system; Linear programming (LP); Grey wolf optimization (GWO); Dynamic Arithmetic Optimization Algorithm (DAOA)..

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DEDICATION

For (Letsie & Napo Mojela)

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ABBREVIATIONS AND ACRONYMS

Abbreviation/Acronym

ABC	Artificial Bee Colony
AC	Alternating Current
ACO	Ant Colony Optimization
BESS	Battery Energy Storage System
CdTe	Cadmium Telluride
CHP	Combining Heat and Power
CMS	Charging Management System
CO_2	Carbon Dioxide
CP	Convex Programming
C-Si	Crystaline Slilicon
DC	Direct Current
DAOA	Dynamic Arithmetic Optimization Algorithm
DE	Differential Evolution
DERs	Distributed Energy Resources
DG	Distributed Generator
DGUs	Distributed Generation Units
DoD	Depth of Charge
DP	Dynamic Programming
EIA	Energy Information Administration
EMBs	Electric Motorcycle Batteries
EMS	Energy Management Systems
EOL	End of Life
EPBT	Energy Pay Back Time
ESS	Energy Storage System
EVs	Electric Vehicles
GA	Genetic Algorithm
GHG	Green House Gas
GWCSO	GWO- Cuckoo Search Optimization
GWO	Grey Wolf Optimization
HOMER	Hybrid Optimization Model for Electric Renewable
ICE	Internal Combustion Engine
IEA	International Energy Agency
IP	Integer Programming
LAN	Local Area Network
LCA	Life Cycle Assessment
LCOE	Levelized Cost of Energy
LP	Linear Programming
MATLAB	Matrix Laboratory
MG	Microgrid
MHP	Mini- Hydro-Power
MILP	Mixed- Integer Linear Programming
NLP	Non-Linear Programming
NPC	Net Present Cost
NO	Nitrogen oxide

PCC	Point of Common Coupling
PSO	Particle Swarm Optimization
PV	Photovoltaic
QP	Quadratic Programming
RE	Renewable Energy
RET-screen	Renewable energy and Energy-efficiency Technology Screen.
RNNs	Recurrent Neural Networks
SA	Simulated Annealing
SGs	Smart Grids
SHS	Solar Home System
SoC	State of Charge
SOH	State of Health
SO_2	Sulphur Dioxide
WSP	Wind and Solar Power
WT	Wind Turbine
V2G	Vehicle -to- Grid
V2H	Vehicle -to- Home

GLOSSARY

Term	
Administration	A range of activities connected with organizing and supervising the way that an organization or institution functions.
Algorithm	A step-by-step procedure for solving a problem or accomplishing some end, especially by a computer
Battery Storage	A large-scale rechargeable battery for later use, typically from renewable sources such as solar and wind.
Classical Optimization	Mathematical techniques for finding the best solution to a problem by minimizing or maximizing an objective function, typically using differential calculus.
Constraint	Something that limits or controls what can be done.
Conventional Fuel	Traditional, non-renewable energy sources such as oil have been extracted using well-established methods for a long time.
Demand Side Management.	A strategy used by utilities to influence customer energy consumption by encouraging them to reduce or shift their electricity use, especially during peak hours.
Distribution	A final stage of the electricity grid, delivering electricity from local substations to homes and businesses through a network of poles, underground cables, and transformers.
Dynamic	A branch of classical mechanics that studies the effects of forces on motion.
Economic Dispatch	A process of determining the optimal power output of each available generating unit to meet the total system demand at the minimum possible cost.
Electricity Bill	A statement from the utility company detailing energy consumption, charges, and payment information.
Electric Vehicle	A vehicle that can be powered by an electric motor that draws electricity from a battery and is capable of being charged from an external source.
Energy Consumption	Amount of energy used by a process, building, or entity, measured by transforming energy from one form to another, not the complete disappearance.
Energy Dispatch	Maintaining a balance between energy supply and demand to avoid any disruption to the service provided to customers.
Energy Management System	A set of hardware and software tools that monitors, controls, and optimizes energy generation, storage, and consumption.
Generation	The process of generating electric power from sources of primary energy, such as thermal, wind, solar, and chemical energy.
Global Warning	The unusually rapid increase in Earth's surface temperature over the past century is primarily due to the greenhouse gases released by fossil fuel emissions.
Greenhouse Gas	A gas in the Earth's atmosphere that traps heat, causing a warming effect known as the greenhouse effect.
Heuristic Optimization	A problem-solving technique that uses shortcuts or rules of thumb to find a good but not necessarily the absolute best solution quickly.
Hybrid Source	Multiple resources, a combination of generation, storage, and/or flexible load-sharing, a common point of interconnection, and operated as a single integrated resource.

Institution	An organization, society, or corporation having a public purpose, as a school, church, bank, or hospital.
Integration	A process of combining different systems, applications, or technologies into a cohesive whole that works together seamlessly.
Interconnection	The process of connecting power grids, either within a country or between countries, to improve the stability, security, and efficiency of the power supply.
Linearization	A method of approximating a nonlinear function with a linear one at a specific point, effectively replacing the function.
Model	A usable knowledge base based on the representation of the essential aspects of an existing system
Method	The procedures and techniques characteristics orderly arrangement of parts or steps to accomplish an end
Microgrids	A localized, self-sufficient power grid that can operate independently from the primary electric grid or in a grid-connected mode.
Network	The apparatus, equipment, plant, and buildings used to convey, and control the conveyance of, electricity to customers (whether wholesale or retail), excluding any connection assets.
Optimization	An action of making the best or most effective use of a situation or resource.
Photovoltaic	Technology and research focus on using solar cells to convert solar energy directly into electricity by employing semiconductors with photovoltaic properties.
Procurement	The process of buying goods and services enables an organization to operate its supply chains profitably and ethically.
Programming Language	A formal language comprising a set of instructions used to produce various kinds of output.
Power Flow	A numerical analysis of electrical flow in an interconnected power system, aiming to optimize energy delivery to grid buses and enhance the operation levels of the electrical network.
Power Grid	A system of high-tension cables by which electrical power is distributed throughout a region's power grid or power system.
Power system	A network includes the point where power is generated, the transmission network, and the distribution network. A system of high-tension cable by which electrical power is distributed throughout a region
Renewable Curtailment	Intentional reduction of electricity generation from renewable energy sources, such as solar and wind, is done to prevent grid instability when supply exceeds demand, or the grid cannot handle the power.
Renewable Energy	Power generated from natural resources that replenish faster than consumption, such as solar, wind, hydropower, geothermal, and biomass.
Rural Electrification	A process of bringing electricity to rural and remote areas, which involves technical, economic, and social actions to extend or reinforce the national grid.
Renewable Intermittency	Inability of renewable energy sources, such as solar and wind, to deliver consistent power output due to daily cycles and unpredictable weather, which can lead to lulls in energy production.
Simulation	An imitative representation of a process or system that could exist in the real world.
Stability	The quality or attribute of being steadfast, reliable, and balanced power system

Supply	An electrical device that offers electric power to an electrical load.
Sustainable Energy	A form of energy that can be maintained long-term without depleting resources or negatively impacting the environment for future generations.
Tariff	A pricing structure that determines the payment for electricity usage.
Technology	Application of scientific knowledge for practical purposes or applications.
Techno-Economic	A method of analysis that combines technical and economic factors to evaluate the performance, feasibility, and competitiveness of a project, process, or technology.
Telecommunications	A means of electronic transmission of information in the form of voice telephone calls, data, text, images, or video over a distance.
Transient	A sudden, brief increase in current or voltage in a circuit that can damage sensitive components and instruments
Transmission System	A part of an electrical grid that handles the bulk movement of electricity from generation stations to local distribution networks, typically over long distances.
Turbine	A rotating machine which converts the kinetic energy of a moving fluid, such as steam, gas, or water, into mechanical power to drive a generator.
Utility	An organization supplying the community with electricity, gas, water, or sewerage.

CHAPTER 1
INTRODUCTION

1.1 Introduction

Despite growing interest in renewable energy systems, there is still a gap in research on energy management strategies specifically designed for rural electrification. Most studies focus on technical or economic aspects in isolation, without considering how cost, reliability, renewable integration, and local socio-economic impacts interact. This study addresses that gap by developing a mathematical model for an energy management system that accounts for operational energy costs, the likelihood of power shortages, the share of renewable energy, and the employment opportunities created. By bringing these facts together, the model offers a practical and holistic approach to planning rural systems that are efficient, reliable, and socially and economically beneficial. In addition, the microgrid control system development using DAOA, LP, and GWO aims to minimize energy costs, reduce the probability of power supply shortages, maximize the renewable fraction, and maximize the employment fraction. The general observation that conventional fuels are depletable, the worldwide climate change issues, and the constant supply required from the source require power stability for continuous flow operations. Renewable energy offers a viable alternative to traditional energy systems, thus improving energy security and reducing the emission of poisonous gases into the atmosphere. (Giallanza et al 2018; Al-Sharafi et al 2016)

Implementation of the Energy Management Systems (EMS) that collect energy measurement data from the field and make it available to consumers through graphics simulation, online monitoring tools, and energy quality analysers to enable the energy resources management. The energy management system is a system of computer-aided tools used by operators of electric utility grids to monitor, control, and optimize the performance of the generation or transmission system. In addition, it can be applied in small-scale systems such as microgrids.

An energy management system in commercial spaces involves steps to reduce electrical energy consumption costs, but without compromising the quality of work. Our world is already fraught with rising energy demands. As per the data available, the total energy consumption of the world is expected to increase by 48% before 2040, says a report published by the US Energy Information Administration (EIA) (https://urjanet.com/blog/top-5-tips-successful-energy-management).

Sustainable development and power provision to communities have become bottlenecks due to ongoing population growth worldwide. Industrialization and technological advances lead to changes in land use and greenhouse gas emissions as the population grows rapidly (Al-Sharafi et al., 2016; Ghorbani et al., 2018). This atmospheric pollution has harmed the ecosystem.

Thus, it causes an extra challenge to the power grid. Most developing countries face a supply-demand gap due to these challenges. (Yon et al, 2021; Fathima and Palanisamy. 2015).

Furthermore, a large part of the population in rural areas of developing countries is not connected to the national grid because of the high investment costs associated with low population density. Most householders are unable to afford their energy bills (Thamae, 2018). Limitations, challenging ambitions, and the uncertainty of renewable energy production make micro-grids a drawback; therefore, the analysis of feasibility and techno-economic aspects must be urgently considered. Additionally, factors including the Identification of Energy Consumption Sources, utility bill data collection, meter data analysis, identification of opportunities to save on costs, as well as tracking the progress (Jouma et al 2024)

Implementing an energy management system (EMS) in a building to efficiently use energy sources can reduce energy consumption costs and improve return on investment. Therefore, efficient energy use is the solution to this ever-rising global energy demand. (Ghorbani et al 2018) Recognizing that contrary to the ongoing belief, the energy management process applies not only to large buildings and industrial facilities but also to even small living units, such as domestic use. Therefore, it is high time to implement the process at home immediately, ensuring that electrical appliances are turned off when not in use to save on electricity bills.

Energy management is the proactive, organized, and systematic coordination of procurement, conversion, distribution, and use of energy to meet the requirements, taking into account environmental and economic objectives.

1.2 Awareness of the problem

The literature review reveals that, as long as the proper optimization technique, such as GWO and DAOA, is used, the successful dispatch of the hybrid renewable energy microgrid is achievable. For example, DAOA, LP, and GWO have been successfully applied to the microgrid cost minimization problem. However, no peer-reviewed literature directly examines the effectiveness of each approach relative to the other within the microgrid problem definition and operational constraints. The literature that champions LP is applied to more general linear or mixed-integer linear problems (Shufian and Mohammad, 2022; Babu et al 2025), while the literature that supports GWO tends to be focused on non-linear problems with a means of multi-modal optimization (Aljribi and Yusupov, 2024; Tukkee et al, 2024; Jasim et al, 2022). The literature supporting DAOA is very limited; this gap is addressed by this study.

However, a contemporary microgrid system operates on a set of linear and non-linear factors - storage and renewable intermittency, demand/inflexibility - that complicate how the methods may be applicable or perform.

Similarly, independent research champions cost-cutting, speed of execution, and robustness, but until an effective means of demonstrating which technique best suits the purposes can be established based on a fair, controlled metric comparison, no correlation can be established. Thus, determining the DAOA, LP, and GWO comparison relative to the microgrid cost minimization problem will allow other researchers and system operators to value their results in real-world applications and support better options for sustainable, cost-effective systems. Therefore, a further study into the linearization of the existing optimization algorithm is required.

1.2.1 Problem statement

The problem of rural electrification is the inability to achieve consistent, reliable access to cheaper, green electricity, as long as all available resources, grid-tied PV, wind, and Battery, are used to their optimal potential to reduce costs and increase renewable use, thereby fostering socio-economic benefits.

1.3 Research aim and objectives

1.3.1 Aim

This study aims to develop a micro-grid-based Dynamic Arithmetic Optimization Algorithm, Linear Programming, and Grey Wolf Optimization algorithm for planning and operation, where energy management involves efficient utilization of energy through appropriate energy-saving measures to achieve desired results, and proper use and planned storage for eventual use. The developed algorithms are validated on standard microgrid test systems using MATLAB simulation.

1.4 Objectives

To achieve utility network improvements via microgrid-based rural electrification, this study seeks the following objectives to facilitate adequate planning for the integration's implementation:

- To conduct a literature review on the microgrid systems.
- To investigate the effects of the existing Optimization methods, including renewable energy penetrations.
- Mathematical formulation of the microgrid system, including the PV, wind, and battery renewable energy sources and their cost functions.
- Develop the Dynamic Arithmetic Optimization Algorithm (DAOA) optimization methods for micro-grid energy management systems
- Develop the Linear Programming (LP) optimization methods for micro-grid energy management systems.
- Develop the Grey Wolf Optimization (GWO) methods for microgrid energy management systems.

- Develop MATLAB software programs for the DAOA, LP, and GWO optimization methods for the microgrid system.
- To test the developed optimization methods for the microgrid system for the considered use case studies.

1.5 Hypothesis

H1: A microgrid-based rural electrification system is validated with LP, DAOA, and GWO innovative optimization solutions, which will be better in terms of cost of energy, supply quality, and reliability, and renewable energy share than conventional rural electrification systems.

Supporting Hypotheses

H_2: Multi-objective optimization algorithms for microgrid energy management lower the levelized cost of energy and increase reliability.

H_3: Optimization of DERs (distributed energy resources) is beneficial to system performance with low technical losses and increased energy re-utilization.

H_4: An optimized microgrid with renewable energy resources (solar, wind, battery) has a higher share of renewable energy compared to a conventional share in a rural energy portfolio.

1.6 Delimitation of the research

This study is bounded by several deliberate choices made by the researcher to define the scope and focus of the investigation. The delimitations include:

- **Geographic and System Scope:** The study focuses on a specific rural community or region, and the results are therefore limited to the characteristics, resource availability, and energy demand patterns of that location. Findings may not fully generalize to all rural areas with different socio-economic or environmental conditions.
- **Types of Microgrid Configurations:** The study performed focuses on small microgrid configurations with selected distributed energy resources (i.e., solar PV, wind, and storage). Other possibilities of larger hydro constructs, a hybrid AC/DC microgrid, or a grid-tied mini-utility are not relevant.
- **Exclusion of Optimization Methods:** The study performed focuses on selected optimization methods (DAOA, LP, and GWOs). More complex hybrid or machine-learning-based control methods are not assessed.
- **Operates Under Conditions and Assumptions:** This study only operates under conventional microgrid conditions. Should additional extreme cases of natural disasters, attacks, infrastructure weaknesses, market fuel shortages, or greater or lesser certainty about microgrid reliance on the grid for resiliency arise, these factors are outside the scope of this assessment.

- **Economic Feasibility Study:** The economic feasibility study focuses on energy payment reductions and appropriate economic findings. No other economic considerations, such as financing arrangements, tariff creation, regulatory assessment, or forecasting, are within the scope of this study.
- **Simulation Software and Applications:** The systems modeling and optimization occur within the MATLAB simulation application. No simulation results are cross-referenced through any other application, such as Python.

1.6.1 Assumptions

- **Linearity:** The objective and constraints are linear. The objective function and constraints of any mathematical model are linear, meaning they are linear equations. This means that all relative values are precise, meaning the analysis and results are precise relative to the analysis's parameters.
- **Additivity:** The contributions to the objective and constraints are additive. Contributions to the objective function and the constraints of any mathematical model are additive, meaning they exist independently but can be combined to yield a cumulative effect. This means that everything is linear in this investigation, making it easier to determine contributions and distinguish between effects.
- **Well-behaved objective function:** The cost function is well-behaved and considered appropriate for iterative heuristic improvements even if no derivatives are required (Ibrahim et al., 2025).
- **Proper constraint treatment:** Boundary checks and feasibility restoring techniques can always keep solutions inside the unbounded values (Ibrahim et al., 2025).
- **Stable dynamic values:** The adaptive exploration–exploitation parameters of DAOA are assumed stable over iterations (Abualigah et al., 2025).
- **Realistic Energy Demand:** The load profile data obtained for this research will be utilized to anticipate future needs.
- **Resource Availability:** The used solar irradiance and wind speed data within the model are assumed to be consistent and accurate for long-term mean results relative to the location.
- **Technology Performance Stability:** All generation, storage, and distribution technologies are assumed to perform at their rated efficiencies throughout the project lifespan.

- **Economic and Tariff Stability:** Energy pricing, tariff structures, and economic factors (e.g., inflation and the discount rate) are assumed to remain stable over the modelling horizon.
- **Optimal Control Feasibility**: It is assumed that the microgrid's control and management system can technically implement and maintain the optimization strategy used in the study.
- **Social Hierarchy:** The wolf pack is divided into four levels: alpha (α), beta (β), delta (δ), and omega (ω), where α, β, δ, and ω represent the best three candidates' solutions, which guide the rest of the population ω in the optimization (Mirjalili et al 2014).
- **Prey position Unknown:** Since the prey's exact position (global optimum) is unknown, GWO assumes that the best approximation can be obtained from the positions of the α, β, and δ wolves, which collectively guide the search. (Jain et al., 2023;Pradhan et al 2016).
- **Mathematics Encircling:** The DAOA encircling behaviour is modelled through adaptive coefficient vectors (A and C), which control the step size and direction towards prey, enabling the algorithm to transition between global exploration and local exploitation (Jain et al 2023).

1.7 Motivation for the project development

A microgrid is a small electricity grid that produces, distributes, and consumes electricity. Microgrids can be independent from the primary grid or connected to it. They can be large enough to serve an entire island, but small-scale microgrids serving a single campus or industrial facility also exist. From sustainability to economics, microgrids offer benefits for many businesses. Therefore, a planned, optimal microgrid-based rural electrification is a crucial solution to current electricity demand (Kamal et al., 2022).

Three factors have made microgrids an increasingly popular option within the power generation ecosystem.

1. First, the trend of deregulation that energy markets have experienced in many countries has resulted in options and opportunities for electricity consumers. In the past, the owners of local generation resources may have faced steep administrative requirements. In many cases, interconnecting these resources to the primary grid would not have been allowed at all. Moreover, the electricity tariff structure provided no incentive for consumers to invest in such resources. Today's regulatory environment is far more favourable to owning and operating non-utility assets

(Yuksel, 2021). The contribution of this research is to promote access to energy in rural areas, which are complex and expensive to connect to the grid.

2. Second, wind turbines, solar panels, and energy storage systems have become far more affordable than they were in the past. In the case of solar panels, their prices have dropped off a cliff, decreasing by almost 10% over the past 15 years.
3. Third, advances in intelligent grid management software, control systems, power electronics, and other electrical components have made it possible to build, operate, and maintain a small-scale grid without a large staff, and with a degree of flexibility not possible on a large-scale grid. (Yuksel, 2021). Thus, enabling the research to contribute to an affordable, clean energy supply for rural electrification.
4. Investigate the novel optimization algorithms ADAO, LP, and GWO for microgrid energy management and cost optimization for a grid-tied PV-wind-battery storage system to provide cheap operating cost in comparison with other methods.
5. Finally, as a result, microgrids are within reach of many companies and institutions that want to benefit economically from operating their own generation, or to be more sustainable by using renewable resources, or have a more reliable and resilient system than a grid-only supply (Yuksel, 2021). This research promotes job creation in rural areas.

1.8 Research methodology

1.8.1 Literature review

- Literature review study of microgrid system.
- Literature review on microgrid for Rural Electrification.
- Literature review study of optimization methods used in microgrid systems.

1.8.2 Mathematical Formulation

Mathematical formulation of the microgrid system, including the renewable energy sources and their cost functions.

1.8.3 Development of the Optimization Methods

- Develop the Dynamic Arithmetic Optimization Algorithm (DAOA) optimization methods for micro-grid energy management systems.

- Develop the Linear Programming (LP) optimization methods for micro-grid energy management systems.
- Develop the Grey Wolf Optimization (GWO) methods for microgrid energy management systems.

1.8.4 Software development & Validation

- Develop MATLAB software programs for the DAOA, LP, and GWO optimization methods for the microgrid system.

- To test the developed optimization methods for the standard microgrid test systems for the considered case studies.
- The most applied algorithms include DAOA, LP, and GWO. DAOA, LP, and GWO are used in the thesis to illustrate the pivotal role of optimization in renewable-energy-based microgrids in power systems.

1.9 Contribution of the Thesis

This thesis focuses on microgrid implementation for rural electrification using renewable sources and, in addition, proposes improvements to the optimal solution, applicable to academics and system operators for enhanced decision-making and sustainable development. The optimized renewable-energy-based hybrid system developed utilizing DAOA, LP, and GWO methods provides a feasible approach to the power system operation, planning, design, and control.

The thesis contributions can be concisely outlined as follows:

- Through literature review investigations on microgrid systems, optimization methods, and economic analysis of the microgrid system.
- Developed a DAOA optimization method for the microgrid system utilizing renewable energy sources.
- Developed LP optimization method for the microgrid system utilizing renewable energy sources.
- Developed GWO optimization method for the microgrid system.
- Developed Software programs for DAOA, LP, and GWO optimization methods.
- Comparison of the performances of DAOA, LP, and GWO algorithms for standard microgrid test systems.

1.10 The organization of the Thesis

This research thesis has been structured as follows:

- Chapter 1 presents the aim and objective of the research in the thesis. It determines the hypothesis, assumptions, problem statement, research methodology, project motivation, and the thesis's contribution to power systems.
- Chapter 2 presents the literature review of the optimization techniques and renewable energy-based microgrid systems. The review compares the most commonly used optimization techniques in microgrid system models, and the software used in the literature from 2009 to 2025. The research has examined the applications and backgrounds of the various optimization methods used in previous studies.

- Chapter 3 describes the application of the Dynamic Arithmetic Optimization Algorithm technique to the hybrid microgrid system.
- Chapter 4 describes the application of the Linear Programming optimization algorithm to the hybrid microgrid system.
- Chapter 5 constitutes the application of the Grey Wolf optimization algorithm to the hybrid microgrid system.
- Finally, Chapter 6 presents the overall conclusions and the recommendations for future research activities in this field of study

.

1.11 Conclusions

In conclusion, the research aims to develop approaches, optimization algorithms, and techniques for a renewable-energy-based microgrid. The study has emphasized that, recently, a renewable-based hybrid microgrid is the solution for modern power systems. On the other hand, this initiative has to be optimized to minimize operational costs. The Thesis research work has consequently developed DAOA, LP, and GWO, an optimal hybrid renewable energy microgrid system. Chapter 2 presents a literature review of microgrid systems and optimization methods for renewable-energy-based microgrids for rural electrification.

CHAPTER 2

REVIEW OF PLANNING AND OPTIMIZATION OF THE RENEWABLE-ENERGY-BASED MICRO-GRID FOR RURAL ELECTRIFICATION

2.1 Introduction

A microgrid is a local energy system component that can store and distribute energy to facilities within the network. Microgrids may be composed of several resources, also called Distributed Energy Resources (DERs). Commonly used DERs for power generation include solar photovoltaics (PV), wind turbines, and power generators. Energy Storage System (ESS), intelligent controls, and management software are other components of the power system that provide additional functionality to the microgrid (Kamal et al., 2022). Microgrids can also be connected to the centralized grid or completely off-grid and self-sustaining (Chen et al., 2022). Given the clear need for continuous, reliable power, healthcare facilities are well-suited to grid-connected microgrids. Remote mining sites that require substantial energy can be ideal applications for off-grid microgrids (Sharip et al., 2020).

Furthermore, (Möller and Krauter, 2022) stated that there is a need for alternative technologies to satisfy the world's energy demand, with the focus being shifted to environmentally friendly technologies due to the rapid increase in global warming (Valencia-Díaz., 2025) issues caused by the emission of greenhouse gases into the atmosphere from burning oil, gas, and coal. Renewable Energy Sources are considered an assurance approach for closing the gap between supply and demand.

This study investigates previous studies on the operation optimization of microgrid systems in three aspects: (1) Microgrid system; (2) microgrid for rural electrification; (3) optimization methods used in Microgrids. In addition, this study provides a bibliometric analysis of previous work on optimizing microgrid operation. This work makes several contributions. First, this is a comprehensive review focused on optimizing microgrid operation. Second, the optimization method is discussed across various aspects, including Microgrid Design and Configuration, Grid Interconnection and Market Participation, Coordinated Demand Response, and Economic Dispatch. Lastly, this work provides a literature review of both classical and heuristic optimization algorithms used in microgrids. Figure 2.1 expresses the structure diagram for the literature review conducted in this work, while Figure 2.2 shows the comparison of the number of publications against the year of publication.

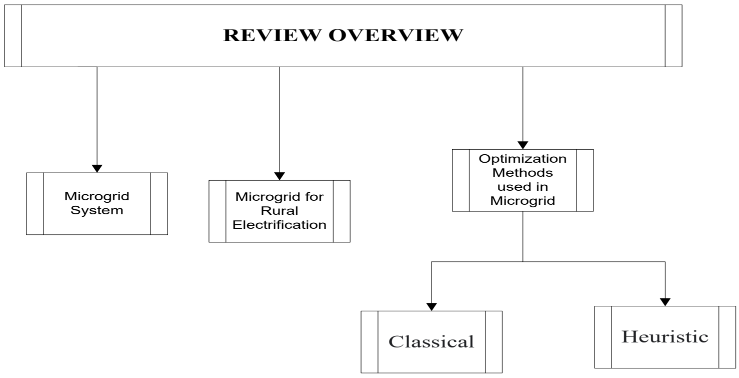

Figure 2. 1: Structure Diagram for Literature Overview

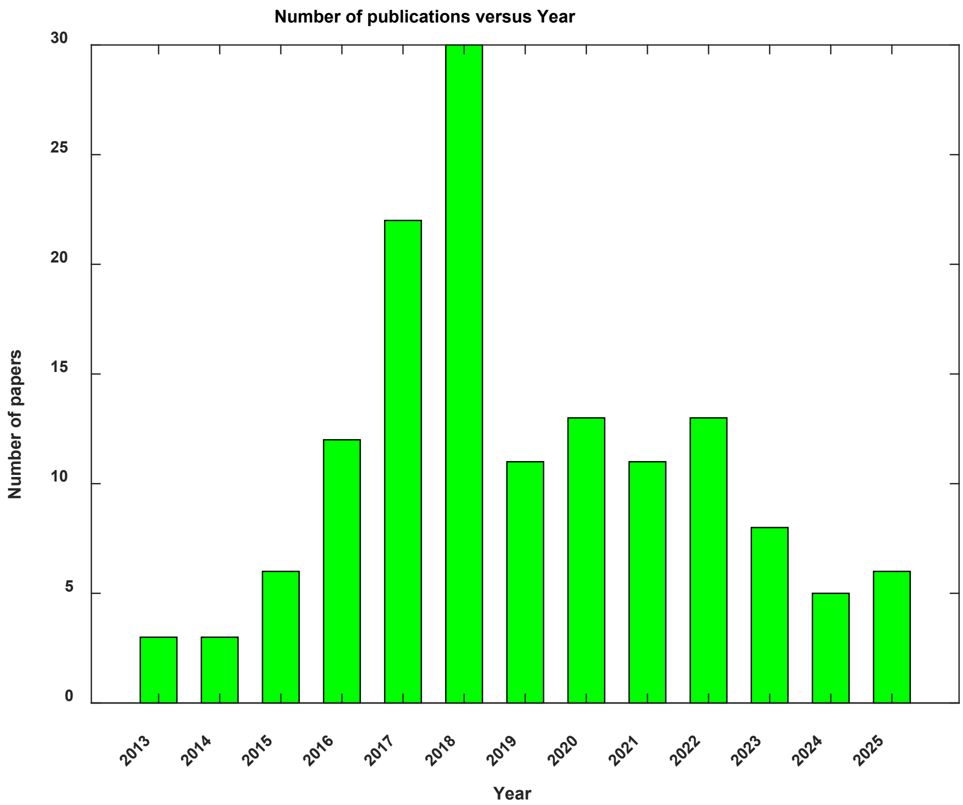

Figure 2. 2: Comparison of the number of publications versus the year of microgrid systems for Rural Electrification

2.2 LITERATURE REVIEW

2.2.1 Microgrid systems

The use of microgrids is being extensively researched as a feasible means to tackle challenges of rural electrification and remote areas. Microgrids deliver the most viable means to integrate RESs into the grid, enabling clean energy for the African continent. Research indicates that microgrid-based rural electrification requires substantial investigation, incorporating both technological and socio-economic aspects into an appropriate design for the specific area. (Liu et al., 2020; Nsengimana et al., 2022; Ahmed, Ali et D'Angola, 2024).

Appropriate implementation methodologies for microgrids in rural electrification have been actively investigated worldwide. Thus, aid in reducing carbon emissions and in seeking options to the current means of power system operation. Microgrids enable the full integration of distributed and renewable energy resources. Therefore, lowering the prices of low-carbon technologies creates a future that permits a large share of renewable energy and supports job creation in electricity access. (Liu et al., 2020; Bhanja et al 2020; Nsengimana. et al., 2022).

Moreover, the ability of microgrids to operate in off-grid and on-grid modes enables many possibilities, including reliable transmission during transient and steady-state grid operation following disturbances caused by accidents or natural disasters. (Liu et al., 2020; Bhanja et al., 2020) Microgrids also improve electricity availability by enabling them to operate independently of the primary power grid. In addition, microgrids in remote areas can be integrated into the primary grid once the primary grid has reached a suitable level of expansion, offering an excellent opportunity to foster rural electrification. They also improve productivity and security through lighting, use of clean energy for cooking, improve telecommunications for rural areas, and community development, such as improved irrigation methods for agriculture, as well as the provision of basic services dependent on electricity. (Liu et al., 2020; Bhanja et al. ,2020).

The demand for microgrid systems for rural electrification is currently high in developing countries. The majority of researchers emphasised that rapid urbanisation among residents, as well as technological advances over the past decade, have ominously driven a rise in energy demand across the biosphere. Moreover, the modern power grid is transitioning from a conventional, centralized generation configuration to a more distributed, decentralized one. To attain this transition, decentralized energy sources and loads must be smoothly integrated into an off-grid configuration. Recognition of one such tactic is termed ‘‘Microgrid. Microgrids are a clean, efficient, and economical way to integrate renewable energy sources and loads into the primary grid.

Various islands and rural areas are suffering a massive gap between power demand and supply. Remote electrical systems require the shipment of diesel, fuel oil, or other liquid fuels over long distances. Unsurprisingly, this can become very expensive. Some industries also seek to manufacture their own fuel on-site using renewable electricity. Rural electrification is feasible and reliable through microgrid systems (Nsengimana et al., 2022). The rate of consumer willingness towards RE-based microgrid solutions shows greater support for their implementation in rural areas (Bhanja et al., 2020).

Their study specified that microgrid systems typically consist of loads, DERs, a master controller, smart switches, protective devices, and communication, control, and automation systems. Microgrids Distributed Generation Units (DGUs) are classified as dispatchable or non-dispatchable. Dispatchable units are well-ordered by the microgrid master and are focused on technical constraints, while non-dispatchable units are uncontrollable. Solar and wind are considered non-dispatchable units due to their unpredictable and irregular output power. An Energy Storage System (ESS) synchronizes with DGUs to ensure sufficient microgrid generation (Bhanja et al., 2020). Moreover, ESSs are utilised to store energy from low-priced hours and supply it back to the microgrid during high market prices. Islanding applications in microgrids are possible via ESSs. The purpose of smart switches and protective devices is to control the connection between DERs and loads. Islanding from the grid is performed using special switches at the Point of Common Coupling (PCC). Automation systems are also in place to ensure stability, effectiveness, and reliability across microgrid components (Lambert and Hassani, 2023). Figure 2.3 depicts a typical structural design of microgrids (Bhanja et al, 2020).

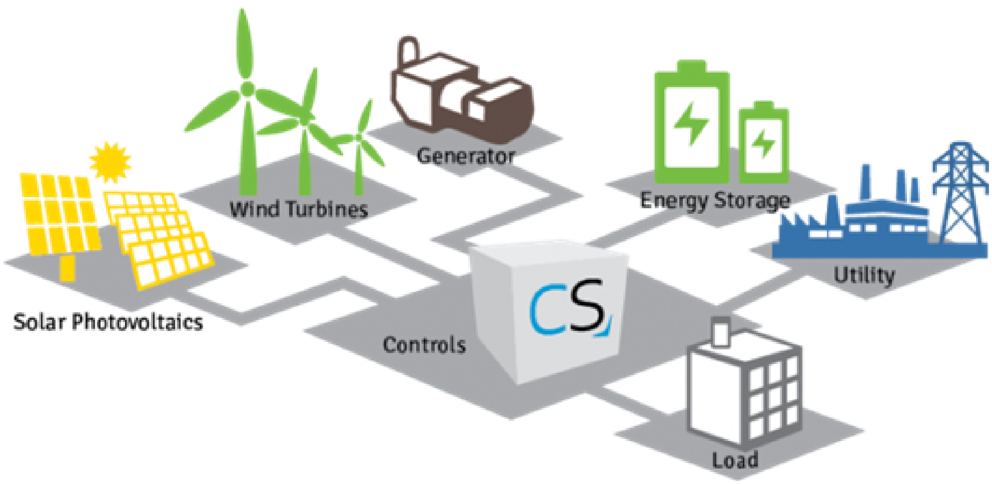

Figure 2. 3: A typical structural design of microgrids
(Bhanja et al, 2020)

(Kumar et al 2018) proposed a novel and straightforward framework for designing a rural sustainable microgrid for developing nations (Kumar et al 2018). Their work involves a simple, effective method for techno-financial analysis of an energy system. The case study results supported social and environmental issues. Therefore, they must be included in the design of microgrids for rural electrification. Most of the researchers, such as (Ireland, Hughes, and Merven 2017; Kumar et al 2017; Namaganda-Kiyimba and Mutale, 2018; Xu and Chowdhary, 2013; Doorsamy, Cronje, and Lakag-Doorsamy, 2015; Olomiyesan and Oyedum, 2024), emphasized that for a successful implementation of microgrid for rural electrification, an in-depth tactic must include social as well as environmental issues.

Advancement and operation of renewable energy, which can be defined as the clean energy including wind energy, solar energy, water energy, biomass energy, geothermal energy, tidal current and other non-fossil energy, has progressively turn out to be the merely approach to guarantee social sustainable development in relations to energy challenges (Ishaq et al., 2022; Sami et al., 2021; Cao et al., 2016).

In this lexicon, many developing countries are taking action to advance energy efficiency and plan and develop renewable energy dynamically (Ishaq et al., 2022; Sami et al., 2021; Gao et al., 2023). Figure 2.4 depicts the classification of microgrid systems by mode of operation, type, source, scenario, and size. Furthermore, under the sources category, renewables are generated from solar, wind, mini hydro, biomass, and, lastly, hybrid systems. Various researchers used a hybrid system in which the solar system is the common factor. Table 2.1 presents a comparison of microgrids for rural electrification in the literature from 2015 to 2025.

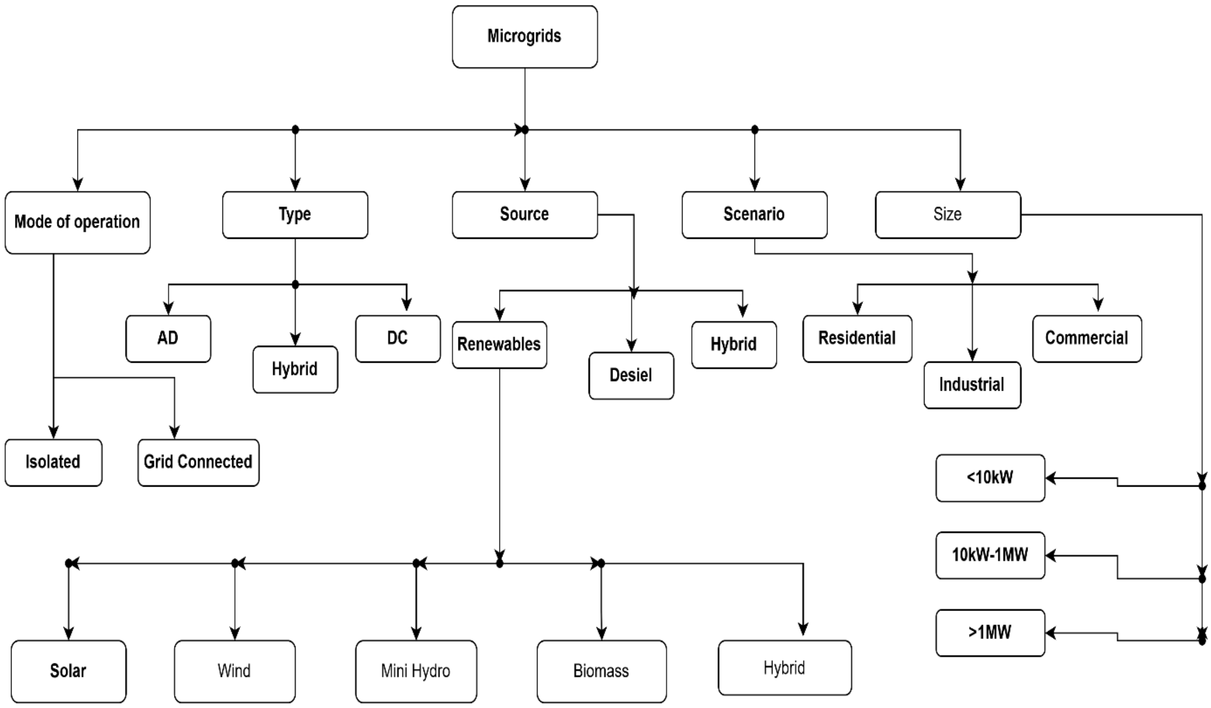

Figure 2. 4: Typical layout of categorization of microgrid systems
(Eluri and Naik,2021)

Table 2. 1: Review comparison for Microgrid systems.

Authors	Year	Resource type	Objectives	Results	Country
Nsengimana.C et al	2022	PV and Battery	-Rural household power access. -Poverty reduction.	-Levelized cost of energy. -Least cost of energy.	Rwanda
El.Bidairi et al	2020	PV, Wind, Tidal current, and diesel generator	-Minimum fuel consumption. -Less greenhouse gas emissions. -Maximizing renewable fraction.	-Developed a multi-objective method. -Minimized dependency on fossil fuels.	Australia
Al-Addous et al	2017	PV	-Develop a temperature control with PV system cooling.	-Developed off-grid PV with a cooling system. -Better efficiency.	Jordan
Ghafoor and Munir	2015	PV	-Implementation of the off-grid PV electrification system	- PV decreased cost. -More cost-competitive. -Proper design, feasibility, viability, as well as financing.	Pakistan
Veldhuis and Reinders	2015	PV	-Develop an off-grid hybrid PV system	-better performance than electricity generation with diesel.	Indonesia
Agbonaye et al	2020	PV	-Develop an optimization method for designing off-grid PV for residential.	-Cost-effective operating system.	United Kingdom.
Abebe.A, Pushparaghava and Godefage. Edemealem	2018	PV, wind and battery	-Enable optimal power provision and feasibility to design a microgrid.	- Improved power quality, reliability and minimum loss by integrating.	Ethiopia
Mothilal.S.B and, Pilai.G	2018	PV	-Develop an optimal PV microgrid.	-Improved design procedures.	United Kingdom.
Kumar et al	2018	PV, Diesel generator, hydro, wind and battery.	-Determine a suitable size of the microgrid. -Reduction of net present costs.	Developed a real-time solution for the design of a sustainable microgrid.	India
Idoniboyeobu D C.; Braide S L.and Franklin F C	2019	PV, Diesel generator, and battery.	-Develop an optimal microgrid system.	- PV has 100% renewable penetration. -No greenhouse gas emissions.	Nigeria
Kamal, Ashraf.I and, Fernandez	2022	PV, wind, diesel generator, and battery.	-Investigate microgrid performance. -Conduct feasibility and techno-economic analysis of a proposed microgrid. -Sizing of components and sensitivity analysis of energy costs.	-Decreased energy costs. -Increased renewable fraction. -More effective solutions for the electrification of the rural population are obtained.	India
Rwegasira, Kondoro, Kelati et al	2018	PV	-Design an intelligent DC microgrid that can satisfy the energy demands of small communities.	-Efficient, reliable, autonomous, and self-sustaining microgrid.	Tanzania
Moller, M.C and Krauter, S.	2022	PV, hybrid energy system	-Present a verified hybrid energy system model created in Simulink.	-Developed a model in Simulink that evaluates realistic solutions. - Applicable to give profound suggestions for the sizing of the energy system.	Germany

				-Both profitability and lifetime analyses are possible.	
Olomiyesan BM, and Oyedum OD	2024	Hybrid PV-wind-diesel system	-Design an optimal hybrid PV-wind-diesel system for rural electrification.	-boost the social, educational, and economic activities in the villages. -Improve education, healthcare delivery and enhancement of local businesses.	Nigeria
Aljribi A., and Yusupov Z	2023	-PV-Diesel Generator-Battery hybrid system	-To minimize overall cost of the microgrid operation.	- The cost of the overall system is optimized effectively, and load sharing is done effectively	Turkey
Babu, K., Chakraborty, P. and Pal, M	2025	-PV and BESS	-Demand Response Optimization. -Implementation of an advanced load classification and management strategy that differentiates between critical, flexible, and curtailable loads while maintaining system stability	-peak load reduction of 10% -energy cost savings ranging from 13.1% to 38.0%. -The results validate the framework's effectiveness in managing diverse operational challenges while maintaining system stability and economic efficiency.	Hyderabad India
Shahzad, S.; Abbasi, M.A.; Ali, H.; Iqbal, M.; Munir, R.; and Kilic, H	2023	-Solar, wind, diesel generator, microturbine, BESS, Fuel cell, EVs, smart cities, smart homes, and smart meters.	-To review possibilities, challenges, and future opportunities of Microgrids	-Highlighted the numerous advantages of microgrids, including enhanced energy resilience, increased renewable energy integration, improved energy efficiency, and the empowerment of local communities.	Pakistan
Safder, M.U.; Sanjari, M.J.; Hamza, A.; Garmabdari, R.; Hossain, M.A. and Lu, J	2023	-Wind power, solar power, combined heat power, small hydro power, tidal power, geothermal power, and wave power, batteries and hydrogen fuel cell	-Enhancing Microgrid Stability and Energy Management: Techniques, Challenges, and Future Directions.	-provides an overview of the state of the field and proposes potential areas of future research for Microgrids.	Australia
Juan Carlos León Gómez, Susana Estefany De León Aldaco and Jesus Aguayo Alquicira	2023	A comparison is made between different energy sources	-With improvements in the research and development of solar and wind technologies, the cost of renewable energy sources is expected to decrease in contrast to the annual increase in the cost of conventional energy resources. - The inclusion of artificial intelligence in energy management is expected to improve further the performance of the hybrid system in the near future	The analysis highlighted the following point: -The most used architecture is the isolated hybrid network. -The most commonly used generation source configuration was PV-WECS-BESS-DG, as they have shown the best reliability and cost–benefit. - The most used storage sources were lead acid and Li-ion batteries. -The most used auxiliary generation source was diesel generators. -The energy analysis commonly employed the LPSP indicator, while	Mexico

				the economic analysis mainly utilized the NPC and COE indicators. -The most used optimization algorithms were PSO and GA. -The most used software for optimization is HOMER.	
Khosravani, A.; Safaei, E.; Reynolds, M.; Kelly, K.E.; Powell, K.M.	2023	PV-WECS-BESS-DG	-To investigate techno-techno-economic feasibility of hybrid renewable energy systems	-The fraction of renewable energy in each system increases. -Hybrid renewable energy systems can be designed with LCOEs equivalent to existing averages with renewable fractions of 83%, 82%, 91%, and 78% for Western NY, San Diego, Milwaukee, and Texas, respectively.	USA
Muleta, N.; and Badar, A.Q.	2023	PV-WECS-BESS	-Designing an optimal MG model for rural electrification with different renewable energy resources.	-An optimal combination of RES and battery packs is found with the objectives of reliability, economics, and low GHG emissions.	India
Akkur, M.S., Singh, S., Iqbal, M.A. and Kaur, S.,	2023	-Solar PV, wind power, Hydropower, Bio-power, and Geothermal	-To promote increased awareness of the technical, financial, and ecological aspects of these sectors -To offer practical suggestions for achieving sustainable development and resilience in the setting of shifting power landscapes.	-Microgrids powered by sources of clean power need to be maintained, monitored, and professionally operated constantly, and obtaining specialist technical abilities can be difficult in distant or rural locations, which might result in problems with operations. - There are chances of technical difficulties and inefficiency in the framework. -The installation of reliable fallback generators, including technologies for storing energy, is needed.	India
González-Niño, M.E.; Sierra-Herrera, O.H.; Pineda-Muñoz, W.A.; Muñoz-Galeano, N.; López, and Lezama, J.M.	2025	A comparison is made between different energy sources	-To contribute to the development of sustainable and efficient energy systems. -To explore key trends and emerging technologies in microgrid energy management.	-Microgrids promote sustainable energy systems through the integration of renewable energy sources and advanced management strategies.	Colombia
Lu, W.-M., and Le, T.-T	2025	A comparison is made between different energy sources	-To identify intellectual structures, thematic clusters, and research trajectories in microgrids.	-provide actionable insights for researchers, policymakers, and industry leaders by highlighting technological maturity, real-world applications, and strategic implications for energy transition.	Taiwan

Liu L, Zhang S, Zhang H, Zhang Z, and Liu Y	2024	Wind-solar-storage systems	-To improve the global search and local search capability of the microgrid scheduling problem. -To solve the microgrid optimal scheduling model.	-The optimal scheduling scheme obtained based on an Improved Sparrow Algorithm (ISA) improves the daily operating total revenue and the system operation stability of the microgrid.	China
Li, Q.; Dong, X.; Yan, M.; Cheng, Z.; Wang, Y	2023	Hybrid Wind–Solar–Energy Storage AC/DC Microgrid System.	-To solve the impulse current and voltage generated during the switching between a grid-connected state and an off-grid state. -To introduce an improved pre-synchronization control strategy based on BP neural networks	-The results of this work can be generalized to the grid-connected and off-grid transition control strategies suitable for more complex AC–DC hybrid microgrids, which are being explored by the authors for further research. However, there are still some problems that need further research.	China
Suriya Ponnambalam and M.K. Ilampoornan	2025	- Solar, wind, and biomass	-To evaluate the policy and socio-economic impacts of smart grids integrated with renewable energy in enhancing energy access, economic development, social inclusion, and environmental sustainability.	-It incorporates a case study analysis of real-world smart grid implementations across five countries –India. Kenya, Bangladesh, Rwanda, and Nepal. highlighting practical outcomes and challenges. Studies are systematically mapped to the United Nations Sustainable Development Goals (SDGs).	India

Shoaib Ahmed, Amjad Ali 2 and Antonio D'Angola	2024	PV, Solar Thermal, Biomass Gasification, Geothermal, Min-hydro, wind, and Ocean Energy.	-To mitigate climate change - To reduce GHG emissions, fostering local economic development, enhancing energy resilience and security, - To promoting social cohesion and community empowerment	- Introducing supportive and encouraging policies and regulations specifically for the development of Renewable Energy Communities (RECs), -Update grid codes and regulations to accommodate the integration of RESs at the community level. -Utilize community engagement strategies in the initial stages of project development. -Policymakers must invest in the design of real REC systems as prototypes, making high-resolution time-dependent (for example, on an hourly basis) simulations to show for any country the economic, environmental, and social benefits to boost REC development and increase public acceptance in the community.	Italy
Jouma et al.,	2024	PV, Wind Turbine, and grid.	-To investigate the short-term operation (24-hour) of MG that copes with vital contingencies associated with selling and procuring energy with the main grid, considering the environmental cost. Outstandingly, -To minimise daily operation costs -To engage the consumers by smart meters.	-The proposed research engaged the consumers through smart meters to apply demand-side DSM, while the previous studies largely focused on supply-side management. -improved the system performance from the economic and environmental perspectives.	
Lobos-Cornejo.S et al.,	2025	-Wind generation, (BESSs), and distribution static synchronous compensators (D-STATCOMs).	-To minimize operational costs, including grid electricity purchases (grid-connected mode), diesel generation costs (islanded mode), and maintenance expenses of distributed energy resources while ensuring voltage limits, maximum line currents, and power balance.	-GWO achieved the lowest operational costs (USD 3299.39 in grid-connected mode and USD 11,367.76 in islanded mode), the highest solution stability (0.19% standard deviation), and superior voltage regulation. -GWO with Successive Approximations provides the best trade-off between cost efficiency, system stability, and computational performance, making it an optimal approach for	Colombia

				microgrid energy management.	
Huynh, et al	2024	-PV, Diesel Generator, BESS, supercapacitor energy storage system.	-To minimize the total annual cost.	GWO is better than other meta-heuristic algorithms in terms of efficiency, convergence, fewer control parameters, flexibility, and parallelism.	Not specified.
Chen. B et al.,	2025	ESS, PV, Diesel Generator, and Wind turbine.	-To optimize microgrid performance under uncertainty. - To dynamically balance supply and demand.	The findings underscore the framework's ability to adapt to diverse stakeholder objectives and highlight its potential to revolutionize demand-side energy management, fostering efficient and sustainable microgrid operations.	

2.2.2 Review discussion on microgrid system

In reference to Table 2.1, the literature indicates that the PV resource is the most applicable across all research conducted between 2015 and 2025. Moreover, most of us operate in an off-grid mode, and India is considered the country most interested in microgrid planning. The basic objectives from all the publications are almost the same, namely;

- Cost reduction.
- Renewable energy fraction increase
- Job creation and
- Minimal greenhouse emissions.

Therefore, this field of study has a gap for young, emerging researchers to develop new and advanced ideas to address the global energy demand crisis. In this regard, optimal microgrids are indeed achievable.

2.2.3 Off-grid Microgrid System for Rural Electrification

Developing countries such as Rwanda adopted affordable solar systems early on and considered government support and incentives to make rural electrification more affordable (Nsengimana et al., 2022). Traditional power systems pose challenges such as substantial power losses in both transmission and distribution systems, poor power quality and reliability, and, ultimately, environmental impacts. These challenges can be addressed by implementing low-cost microgrids to improve power quality and reliability, and to minimize power losses by integrating and optimizing a variety of renewable energy sources (Abebe, et al., 2018; Olomiyesan and Oyedum, 2024).

(Bhagavathy and Pillai 2018) confirmed that most rural villages in some countries still lack electrification. Only an off grid microgrid based on renewables is the potential solution. Additionally, (Diego et al 2017) stated that microgrid-based rural electrification enhances economic and social welfare for communities through benefits such as healthcare clinics, power supply, access to technology, improved household tasks, and improved water quality. Nonetheless, due to low population density and low electricity demand, the cost of transitioning the existing network to an isolated community can be much higher than that of a microgrid-based electrification system.

Another study by (Mekonnen and Sarwat, 2017) found that approximately 600 million people in Africa lack access to electricity. Access to energy is considered one of the primary causes contributing to the disparity between developed and developing countries.

(Bhandari et al.,2020) used a PV system to assess microgrid-based rural electrification, indicating that reductions of 80% in monthly expenses, as well as broader access to electricity, might be achieved by combining collaborative consumption with appropriate policies and regulations and community ownership. (Nsengimana et al, 2022) designed a standalone photovoltaic microgrid to provide an affordable long-term solution for rural electrification. Research determined that the grid-sharing load-demand model microgrid is a green energy solution for middle- and low-class rural households in Rwanda. In addition, the article notes that only 12% of rural households are connected to the grid, so off-grid PV microgrids are highly recommended for essential energy demand (Nsengimana et al 2022).

In addition, a study by Abebe et al. (2018) investigated optimal power supply and microgrid feasibility using solar, wind, and battery storage for Ethiopia, improving power quality and reliability while minimizing power loss. Furthermore, Aklin et al., 2015 investigated quantifying solar microgrids on rural regions experiencing extreme energy poverty. Energy poverty was ultimately resolved for this vulnerable group (Aklin et al,2015). This study was highlighted as the first systematic investigation of socio-economic outcomes of decentralized renewable energy systems. Finally, (Olomiyesan and Oyedum, 2024) assessed an optimal off-grid hybrid power system to meet the electric load of a hypothetical rural community of 100 houses in Kaduna and Katsina States of northwestern Nigeria at the minimum energy cost. The highlights of their study emphasized improved education, social, and economic activities in the rural areas of Nigeria.

(Bhagavathy and Pillai 2018) introduced an improved design procedure for PV microgrids for the rural electrification of two remote villages. This was a potential way forward for the electrification of isolated remote villages in developing countries. The approach was used to identify the optimal location of the central PV source in rural microgrids. (Diego et al 2017) presented a methodology for planning and designing a microgrid for the rural electrification of remote off-grid areas. Variables such as location, RE resource availability, equipment costs, initial budget, operation and maintenance costs, and equipment replacement costs were strongly considered in their study.

Additionally, the design enables sizing technological solutions and community involvement. It is also considered a future research study for stages of implementation. (Parimalram, 2015) described the design and validation of a community-scale DC microgrid architecture that can integrate RES by utilizing a distributed control scheme. The discussed system was designed to address the technical and economic problems of electrifying evolving regions. Their limit cost of electricity was supposed to be no more than $ 0.40 per kWh for a period of 15 years. (Yemeserach and Arif 2017) presented a detailed review of ongoing RE-supported technologies for rural electrification in sub-Saharan Africa. Energy poverty issues and the development of off-grid microgrids were also discussed. Eventually, the impact of future off-grid renewable technology, the status, and challenges of rural electrification were also included in their research scope.

(Christina, et al., 2018) reviewed the conditions of DC microgrids, which make them an attractive option for local energy communities in developing countries. Applications of DC microgrids were also discussed in detail in order to develop reliable DC microgrids in rural areas. (Nawab et al, 2022) proposed an off-grid solar-biogas microgrid for rural communities in Pakistan. Economic analysis and simulation of the system were performed by using RET-Screen and HOMER, respectively, to obtain the research outcomes. As a result, the system meets the cooking and power needs of 900 individual residences, each with 100 homes.

Moreover, the system provided fixed-period electricity to productive buildings and free electricity to community buildings. This research is considered techno-economically viable based on the payback period and the internal rate of return (Nawab et al 2022). (Idoniboyeobu et al., 2019) used a standalone diesel generator in remote areas of Nigeria. Integration of the RE system with a view to determining an optimal system design, primarily technical and economical, was considered. Their research used a range of scenarios, including PV systems, diesel generators, PV-battery systems, and PV-diesel hybrid systems. According to the research outcomes, the PV Battery system has 100% renewable penetration and no emissions, making it the most environmentally friendly of the systems. A diesel generator was considered to have a greater greenhouse effect and contribute to global warming.

In (Kumar et al 2016), the development of a green and hybrid microgrid for rural electrification in relation to the availability of local resources and local demands. This has improved living standards because the project's main benefits include community health, education, information exchange, income generation, and women's empowerment. Nevertheless, appropriate regulatory policies and guidelines must be in place to support the project's long-term lifecycle.

2.2.4 Review discussion on Off-grid Microgrid Systems for Rural Electrification

A literature review on microgrids for rural electrification by various researchers, engineers, and scientists emphasized the importance of integrating social and environmental considerations into the planning, design, and implementation of microgrid-based rural electrification. Most researchers identified solar PV as the most affordable solution for most African nations, compared to other RE sources. Table 2.2 summarizes the literature on microgrids for rural electrification from 2009 to 2025.

In conclusion, the rapid escalation of microgrid-based rural electrification underscores the need for an advanced framework for planning and designing sustainable microgrids. The literature shows that suitable microgrids must be environmentally friendly, cost-effective, and economically viable, and they must provide social and health benefits. Again, most microgrids operate in off-grid mode. In this field of study, an analysis of the challenges and opportunities for improving grid resiliency was also conducted. Minimizing greenhouse gas emissions and maximizing the renewable fraction were considered. Moreover, site selection and improvements in grid efficiency are also discussed in the literature. The year 2018 was very busy with publications, and most researchers used PV and hybrid systems as their resources.

Table 2. 2: Review comparison of the off-grid microgrid system for Rural Electrification.

Year	Author	Resource used	Outcomes
2009	Wang et al	3-kW MHP system with two self-excited induction generators Water resources	Financially viable. Increasing reliability.
2010	[Balijepalli et al]	Not mentioned	Better renewable fraction
2011	[Deichmann et al], [Guenter et al]	Solar photovoltaic systems	-Improved development within the country. -Essential economic development.
2012	[Cronje W. A, Hofsajer I. W, Shuma-Iwisi M., and Braid J. I], [Lukuyu J.], [Prasad. et al],	Scalable microgrid, WT-DG hybrid microgrid,	-Measurement and control subsystems required for the stable, smooth, uninterrupted operation of the MG, as major hurdles for implementation. -Analyze the reliability of the MG system as demand grew over a period of time.
2013	[Xu, and Chowdhury S.], [Orajaka I. B]	Not mentioned	
2014	[Jaffery S.M.I., Khan M., Ali L., Khan H. A., Mufti R. A., Khan A., Khan N., Jaffery S. M], [Pegueroles-Queralt et al]	off-grid solar electricity,	-Framework for designing a sustainable microgrid. -Implementation of acceptable and sustainable energy development projects.
2015	[Doorsamy, Cronje, and Lakay-Doorsamy], [Pendieu Kwaye M., Bendfeld J. N. and Anglani], [Giraneza M. and Kahn M. T. E], [Ghafoor and Munir],[Veldhuis and Reinders], [Madduri.P.A] , [Parhizi S., Ltfi H., Khodaei A. and Bahramirad S.], [A.Hina Fathima, and K. Palanisamy],[Zaheeruddin; Manas, Munish]	WT-based microgrid, IL VDV, Solar, wind, and biomass with battery.	Re-emphasized the importance of a thorough approach to design and implementation.

2016	[Loomba P., Asgotraa S., and Podmore R.], [Buque C. and Chowdhury S.], [Louie H., Goldsmith G., Dauenhauer P., Almeida R. H], [Backes M., Idehen I. Panumpabi P., Yardley T.], [Opiyo. N], [Khan J., Arsalan M. H.],	DC microgrid, PV MGs and distributed generation, DERs (PV, WT, Aand, GS)	-Analyse the challenges and opportunities for improvement of grid resiliency in Mozambique. -Off-grid data acquisition and monitoring. -Economic, social, and health benefits to rural impoverished communities.
2017	[Ireland G., Hughes A., and Merven B.], [Kumar, Sah, Deng et al], [Ogunnubi O., Ajala O., and Idehen I], [Hamza M., Shehroz M., Fazal S., Nasir M. and Khan H. A], [Nasir, Khan, Hussain et al], [Nwulu N.], [Lai C. S and McCulloch M. D] [Onai K. and Ojo O.], [Arega.T, Tadesse.T,], [Dugoua. E, Liu.R, and Urpelainen. J], [Kabir.E, Kim.K.H and Szulejko. J.E], [Harrison.K et al], [Al-Addous et al], [Diego Jimenez. J], [Yemeserach.M and ArifI.S], [Rezkallah M., Chandra A., Singh B., and Singh S.], [Kumar and Kaur]	DC microgrid, CHP, solar PV, battery powered hybrid MG, solar PV and ESS, a vehicle-to-grid (V2G) technology	-Framework for designing a sustainable microgrid -Bidirectional power flow and distributed voltage droop control. -Cost-effective system. - Ensure that grid voltage and frequency are kept within acceptable limits of operation.
2018	[Kumar, Singh, Deng et al], [Namaganda-Kiyimba J. and Mutale J.], [Soltowski B., Bowes J., Strachan S., Anaya-Lara O. L.], [Rwegasira, Kondoro, Kelati et al.], [Patel and Chowdhury], [Hamatwi E, Nyirenda C.N and Davidson I. E], [Otieno B, Williams N. J. and McSharry P.],[Otieno F, Williams N. and McSharry P] [Adetunji K. E, Akinlabi O. A and Joseph M.K], [Williams N. J, Jaramillo P., Campbell K., Musanga B., Lyons-Galante I.], [Otieno, Williams and McSharry], [Avrin A., Yu H. and Kammen D.M], [Ntanos.S et al], [Quak, E], [Stadler.M], [Graber. S et al], [Melhem.F.Y], [El-Bidairi et al], [Abebe.A, Psuhparaghavan.A, and Gedefaye.E], [Mothilal B.S.and Pillai G.], [Christina.P, Vasilis.K and Nikos.H], [Giallanza et al], [Leboli. Z. Thamae], [Ghorbani et al]	Solar Home Systems (SHS), DC microgrid, MHP system, PV, WT, DG AND Battery Bank, Tidal current, Diesel generator, Hybrid wind – PV battery system	-Techno-financial analysis. -Development in the community - Sustain the community during intermittent utility grid outages, while incorporating high efficiency, low-cost, and minimal emissions. - Assist in site selection and design process for deploying MGs. - increasing reliability.
2019	[Nigam. A, Kaur.I, and Sharmo K.K], [Güney,], [Shakya et al], [Mancuso, M.V., Campana, P.E. and Yan, J., 2019], [Priyadarshana et al], [Idoniboyeobu., Braide.and Franklin.], [Memeti, S., Pllana, S., Binotto, A., Kołodziej, J. and Brandic, I. et al], [Mohd.R. M. Sharip, Ahmed M.A. Haidar, and Aaron C. Jimel], [Wang. X et al]	Not mentioned	-Low carbon emission. -Reducing the cost of electrical power.
2020	[Bhandari.R, Sessa. V, Adamou.R], [Entele.B.R], [Meles], [Soudan and Darya], [Liu et al], [Kumar et al], [Maqbool. U et al]	PV system	Incorporating high efficiency, low-cost, and minimal emissions.
2021	[Raya-Armenta et al], [Essayeh. C et al], [Yon et al], [Meliani et al], [Yuksel], [Younes, et al]	Not mentioned	-Increasing energy efficiency.
2022	[Nyong-Bassey], [Md Mustafa kamal, Imtiaz Ashraf, &Eugene Fernandez], [Nsengimana et al], [Möller, and Krauter], [Cho and Valenzuela]	PV	-The results show the efficacy of the group sharing load demand model design to provide green energy solutions to the mid-and low-income rural population in Rwanda.
2023	[Lambert and Hassani],	Diesel generators	-Reduced fuel consumption by 4.3 % when compared to the actual dispatch during those 2 days.

		Solar PV	-The performance of the model solved with CPLEX and Gurobi is adequate for real-time optimization in remote microgrids, and the economic gain of using a baseload strategy instead of a load sharing strategy is negligible compared to the increase in complexity in implementing this baseload strategy. -The approach helps to reduce uncertainty and increase flexibility to identify appropriate sites and strengthen indicators of sustainable development impacts of decentralized rural electrification.
2024	[Davoudkhani, I.F., Shayeghi, H., and Nabatalizadeh, J], [Hassan and Atia]	Wind turbines (WT), photovoltaic (PV), electric vehicles (EV), battery energy storage (BES), combined heat and power (CHP) systems, and thermal energy storage (TES). -Solar-wind-battery hybrid microgrid.	-Enhanced efficiency and performance. -Successfully provided electrical and thermal loads with minimized costs. -PSO algorithm achieved the best objective function value, -TSO algorithm achieved the minimum objective function value. -TSO being the most effective.
2025	[Valencia-Díaz, Toro, and Hincapié], [Jialin et al]	Diesel generator, voltage source converters, PV, Wind turbine, and BESS (PV-WT-HYD and Long duration Energy Storage (LDES)	-Reduces CO2 emissions of the diesel generators and the operational costs of the EWC nexus, highlighting the proposed approach's environmental and economic benefits. - The potential of LDES in OGMs with wind, photovoltaic, or a hybrid of both is analyzed. -Compared to SDES, LDES incurs lower system costs under all scenarios. -The PV-WT-Hydrogen microgrid has the lowest cost, reducing it by 46.61 %. -LDES performs better when paired with wind power in off-grid microgrids. -Northern, southeast coastal, and central China are ideal for PV-WT- Hydrogen OGMs.

2.3 Optimization methods used in Microgrid systems

Microgrid-based rural electrification requires efficient, economical generation units to respond to load demand and provide a continuous power supply under stable conditions at minimum production costs. Thus, it is referred to as economic dispatch. Various stochastic search algorithms have proved very efficient for solving complex power system problems. Planning and optimization of microgrids for rural electrification represent a breakthrough in addressing the growing imbalance between demand and power supply. The application of optimization techniques helps us achieve cost-effectiveness, reliability, efficiency, technological advancement, reduced greenhouse gas emissions, increased renewable fraction, improved job creation, and an environmentally friendly microgrid.

The distinct features of microgrids, such as the utilization of renewable energy resources and the elimination of power transmission requirements, made them an inevitable area of research in the power sector. An extensive analysis of the literature on optimization techniques for microgrid systems encapsulated by an Energy Management System (EMS) can be presented by grid type, microgrid operation mode, and the software/solvers used to solve EMS problems. According to the literature (Arunkumar et al., 2022), meta-heuristic methods are considered the most widely used optimization techniques. Their work also pointed out that the cost minimization objective is of interest in the literature.

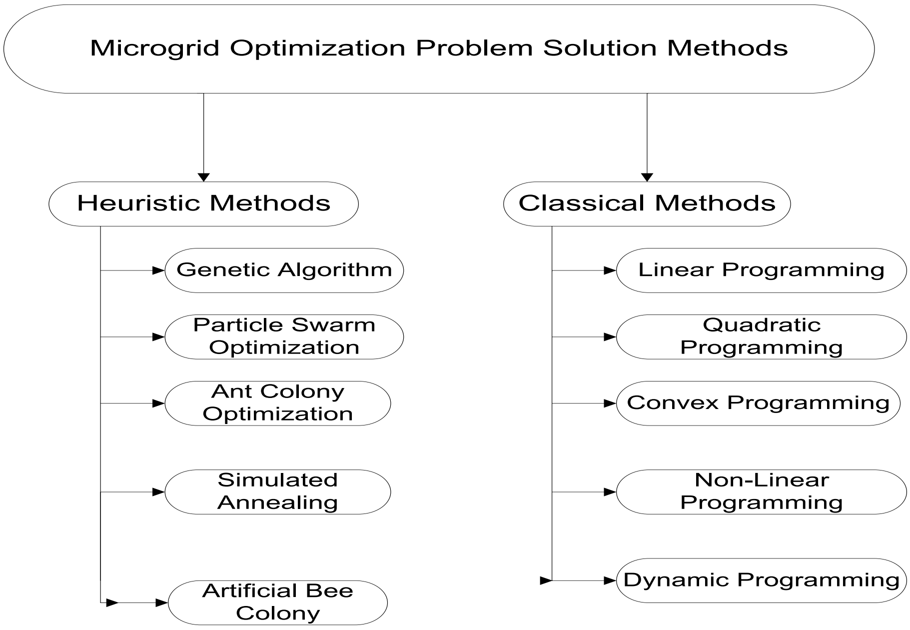

Figure 2. 5: Classification of the optimization methods

Optimization methods used in microgrid systems have become a crucial research topic recently. A well-planned rural electrification involves both classical and computer intelligence optimization techniques. According to the literature, optimal Microgrids are a promising option for addressing the current demand crisis driven by rapid population growth. Optimization applications enable microgrid control and energy management systems. (Tazi et al., 2019) stated that energy demand is expected to increase by 34% by 2030; therefore, the fundamentals for achieving a reliable and stable microgrid are as follows;

- Voltage/ current control.
- Active/reactive power balance.
- Size of the microgrid as well as technologies to be utilized.
- Types of RES to be integrated and their positions.
- Control strategies and communication protocols (Tazi et al., 2019)

2.3.1 Review of Classical Optimization Methods for Microgrid Applications

Classical optimization methods, on the other hand, are based on mathematical programming and involve formulating a mathematical model of the problem and then finding the optimal solution by solving the corresponding mathematical optimization problem. This study investigates six classical optimization methods applied to a microgrid, namely: Quadratic Programming, Convex Programming, Nonlinear Programming, Dynamic Programming, Integer Programming, and Linear Programming.

In their research (Duan et al., 2021), they proposed a classic two-stage robust optimization technique to address uncertainties in the microgrid system, including the power output of the renewable energy source and the power demand of loads. Nevertheless, the technique was considered the worst-case scenario, so an expected-scenario-oriented two-stage robust optimization was used to mitigate the drawbacks of the classic two-stage robust optimization. The outcomes of their work were effective, and the cleft analysis of the results was conducted, thereby improving the economic efficacy of the system (Duan et al., 2021).

2.3.2 Quadratic Programming (QP)

Quadratic Programming (QP) is a well-known optimization method and a typical approach to specific microgrid optimization challenges. QP formulations have been used for economic dispatch and unit commitment in microgrids (Yoon et al., 2020). For example, (Zhang et al., 2018) suggested a QP formulation for economic dispatch to minimize costs, load divergence, and system constraints. Furthermore, QP formulations have been used to model different sources' commitment and dispatch to meet load requirements, including renewable energy, storage, and conventional generators (Zhang et al., 2023; Choi et al., 2024).

QP formulations have also been applied for optimal control and voltage stability/regulation of microgrid networks. For example, Zhang et al. (2021) propose a

QP formulation for voltage-level dispatch, providing directional control over demand response and subsequent voltage and current changes that define microgrid systems with specific constraints, including power losses. (Xie et al., 2020) expand on this with a QP voltage regulation model for microgrids where constraint parameters include stability and quality factors (Sheng et al., 2022; Long et al., 2023) where voltage stability is maintained through optimized allocations/determinations of distributed energy resources, reactive power devices, and grid connection decisions (Shi et al., 2021; Ahmed et al., 2024).

Additionally, QP has been used for forecasting and optimization of microgrid storage (Kumtepeli et al., 2019), and QP methods have been proposed for energy storage-related optimization in microgrids. For example, Takano et al. (2021) provide a review of QP-based operation of energy storage, encompassing load trend patterns, renewable generation patterns, and energy storage limits that help define nominal charge/discharge patterns. Likewise, optimal charge/discharge patterns are assessed through QP methods with efficiency and cost as additional rational parameters (Kumtepeli et al., 2019).

Moreover, QP formulations have been established to assess uncertainty/stochasticity in microgrid systems. For example, (Li et al., 2019) present a QP model for optimal dispatch, and (Jin et al., 2018) expand upon this by incorporating uncertainty related to predictive capabilities for renewable generation and load demand. The authors assess probabilistic and scenario-based forecasting methods that model uncertainty to optimize microgrid operational decisions across various scenarios (Zhang et al., 2018; Xu et al., 2019).

Finally, QP formulations have been developed for fault-resiliency management within the microgrid's operational scope (Hosseini et al., 2023). For example, (Dong et al., 2024) suggest a QP-based fault detection power loss minimization, which aims to stabilize the network through proper reconfiguration. The optimal configuration of the microgrid is assessed against constraints on feasibility and restoration priorities in fault conditions. In a similar vein, (Hosseini et al., 2020) discuss robust optimal energy management of a residential microgrid with uncertainties of demand and renewable energy generation.

The potential for QP-based optimization in the microgrid domain provides a holistic approach relative to resource allocation, voltage stabilization/regulation, and control. Where many aspects of microgrid operation can be approached through practical consideration in comprehensive QP formulation, problem definition enables economically viable solutions to stabilize reliability efforts. Ultimately, the literature reinforces the notion of an optimized solution that would enhance microgrids reliant on renewable resources, storage facilities, and feedback response systems.

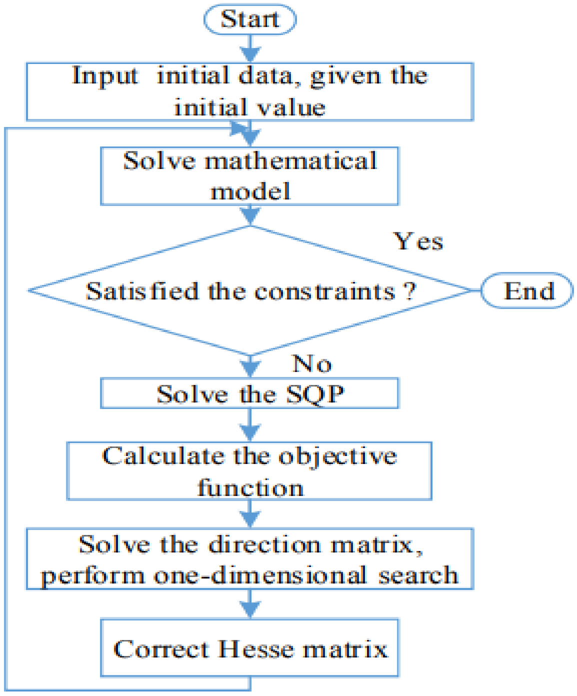

Figure 2. 6: Example of a Flowchart for Quadratic Programming Optimization Method
(Xu et al.,2019)

2.3.3 Convex Programming (CP)

Classical CP has also been used for the optimization of microgrid systems. CP for optimal power flow in microgrids was also explored. (Morstyn et al., 2016) (Wang et al., 2019) derived OPF using CP in microgrids based on cost/economic efficiency, power flow, and constraints, and balance (comparing the latter two) of a microgrid. CP dispatches the different power generation resources in the microgrid—renewables, batteries, and conventional generation—to best meet load demand while accounting for operational and system constraints (Giraldo et al., 2018; Elkazaz et al., 2020).
CP is also used for storage/energy-optimization microgrid solutions (Gil-González et al., 2023). (Liu et al., 2017) Use CP formulation for microgrids to implement energy storage for operational optimization, where load demands influence microgrid renewable generation vs. storage levels. CP problem formulation relies on time as a defined parameter to avoid system constraints, operational and energy storage efficiency and economic considerations (Silva et al 2022).
CP solutions for microgrid operations include battery energy storage systems, demand response, and load shaping for intermittency solutions (Nazaripouya et al 2017). Where Meliani et al. (2021) discuss how the often-recommended CP problem is a convex function in minimization, whereas it is treated as a concave function for maximization

in relation to demand response resources and time-of-use pricing in microgrids, in line with proposed flexible load scheduling.

Solutions are provided with a focus on resiliency and reliability. For example, (Liu et al., 2019) utilize a CP solution relative to reconfiguration and restoration based on microgrid/grid interconnected fault disturbance by taking into account prioritized loads. Thus, CP models generate recommendations for operational restoration in reconfiguration based on constraints, resources available for the restoration attempt, restoration timing, and critical loads (Nazaripouya et al., 2017).

According to Li et al. (2017), CP is also extended to a multi-objective optimization problem for the microgrid system to support systems with conflicting objectives, employing CP-based models in realistic microgrids. CP models are effective because they emphasize time, which helps determine scheduling for time-of-use pricing, demand response, and critical load priorities in microgrids by performing a Pareto-based analysis of those objectives over the life of the microgrid.

Thus, the application of CP classical optimization to microgrid problem solutions relates to efficiency improvements across resource management, load delivery, and operational determination based on cost/efficiency, resiliency, and reliability, creating a more effectively sustainable microgrid system from all angles, with interdisciplinary contributions to the study.

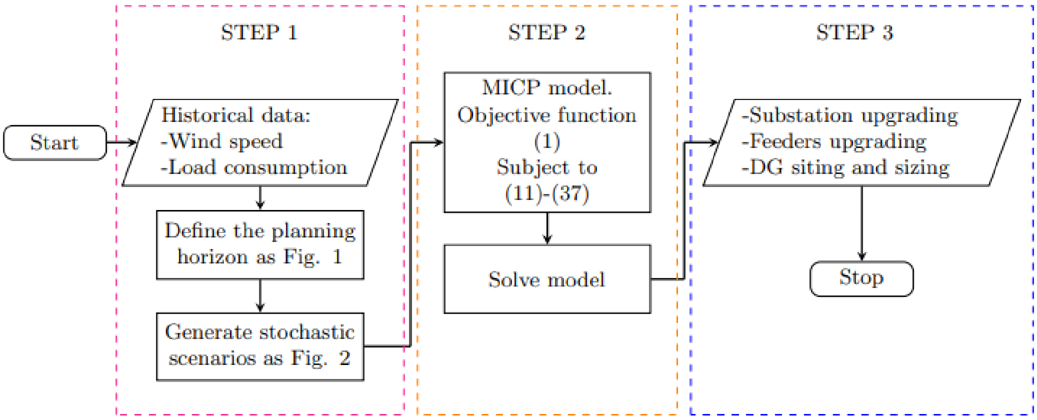

Figure 2. 7: Typical Flowchart of Convex Programming
(Home-Ortiz et al.,2019)

2.3.4 Linear Programming

Linear Programming (LP) is a deterministic resource, mathematically definitive and explores an optimal solution with pre-existing criteria that are linear in nature and have linear objective functions. LP is also appreciated for its rigor and for decision makers' ability to handle extensive amounts of information and quantitative variables. Linear programming has been studied in the context of microgrid energy management (Shufian & Mohammad, 2022). In addition, linear programming has been researched in regard to cost reduction through demand-response systems (Babu et al 2025). Linear programming has also been applied to assess the structural optimization of land use for low-carbon, sustainable regional development (Wu et al., 2022). The areas of cultivated and unused land are less than the base year of 2020 but greater than the planning year of 2020-2035, according to their study.

An LP model is constructed for system configuration optimization and to calculate optimal energy storage power (Li & Shen 2024). The microgrid scheduling problem was formulated and solved by mixed integer linear programming (MILP) by (Minh et al., 2024). Operational costs are minimized to ensure the reserve adequacy probability is appropriate. Then, a mixed-integer LP optimization approach for a hybrid microgrid consisting of PV and wind turbines, biogas generators, BESS, EVs, and load was created by (Lautert et al., 2024). The three primary objectives of the study are power balance, cost reduction, and limits and restrictions to guarantee safe operation of the system. Likewise, LP has been used to optimize the size design of a multi-energy microgrid with multiple energy storage systems (Yin et al., 2025). They emphasize minimizing non-linear, non-convex life cycle costs. Furthermore, the PV curtailment ratio was included. Their final finding demonstrates that a PV HES/BESS microgrid can significantly enhance overall system performance.

The study by (Liu, et al., 2023) involves mixed-integer LP to incentivize microgrids and DERs with a utility-facing interface and responsive load. Critical findings of the study include total operating costs of the systems, bus voltage deviations, feeder losses, and power factor improvement.

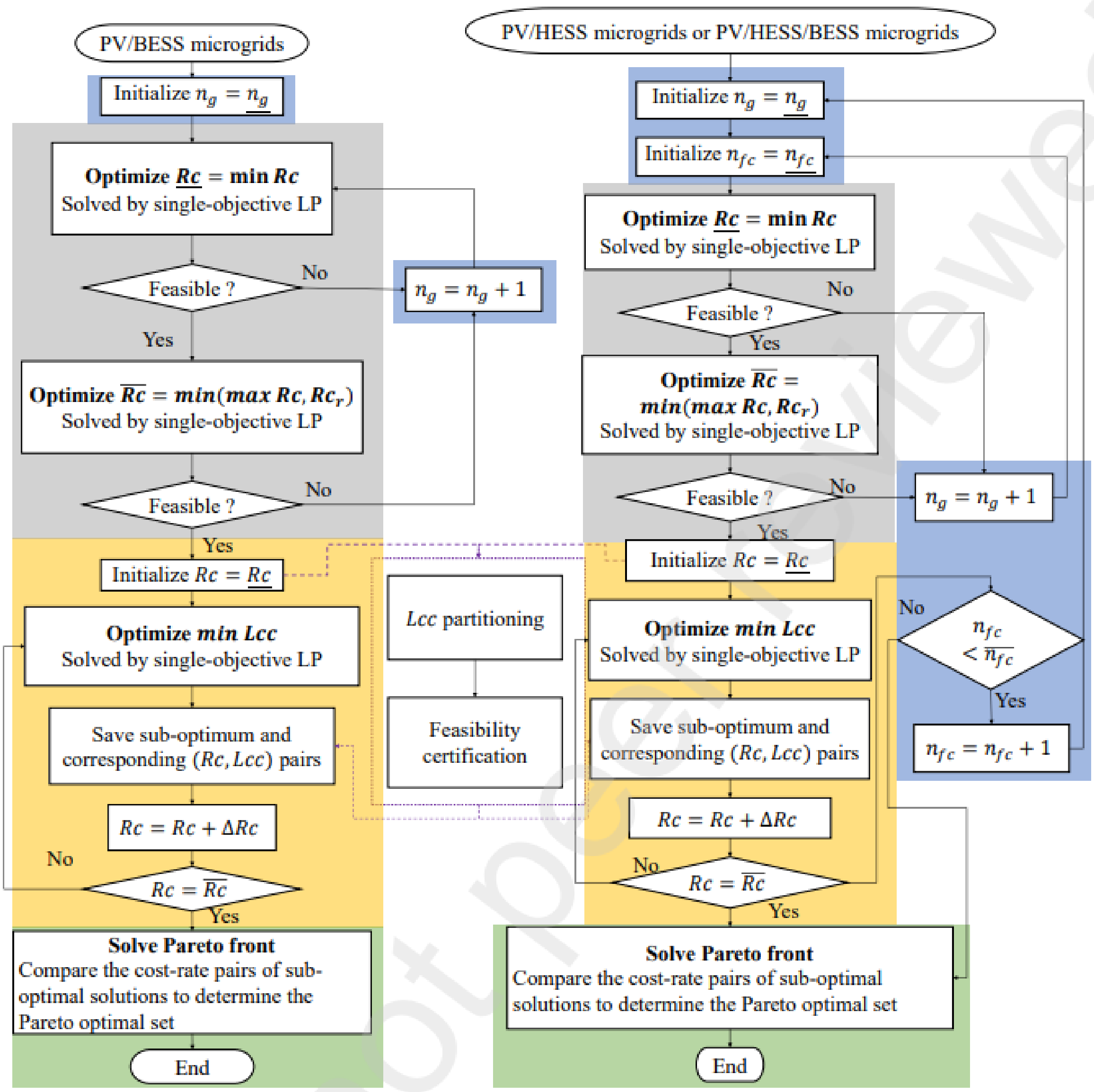

Figure 2. 8: Flow chart for Linear Programming method (LP)
(Yin et al.,2025)

2.3.5 Nonlinear Programming (NLP)

Nonlinear Programming (NLP) optimization has also been used for microgrid system applications. For example, NLP optimization has been used for renewable energy-based microgrids (Akulker and Aydin 2023), and the sizing and placement of renewable energy sources in hybrid microgrids have been assessed using NLP modeling (Liu et al., 2019). These assessments take into consideration renewable energy potential, load requirement and incorporate NLP constraints relative to hybrid microgrid systems (Liu et al., 2018). Thus, NLP optimization is based on renewable efficiency and operational considerations, storage, back-up generation, and operational microgrid needs (Alhumaid et al., 2021).

Similarly, NLP modeling has been undertaken for energy management and storage systems. For example, Anvari-Moghaddam et al. (2016) provide an NLP model for microgrid storage system operations based on load demand, renewable generation, and storage capacity with optimal scheduling of energy storage operations under real constraints (Calderaro et al., 2012; Wu et al., 2018; Zia, 2020). These operations are efficient and cost-effective, based on system constraints and compared with other means to highlight their advantages (Zia, 2020).

In addition to such conventional operations, NLP has been used to address uncertainty in microgrid operations. For example, Jamii et al. (2022) examine microgrid energy management under uncertain forecasts for load and renewable generation using NLP models that assess uncertainty through probabilistic forecasting and scenario-based approaches that account for uncertainty across all scenarios (Huang et al., 2019).

NLP models have also been used for demand response in microgrid systems (Abdul Muqeet et al., 2021). For example, user-preferred, price-based demand response potential has been modeled via NLP optimization (Hu, & Xiao, 2018) where demand response findings are flexible in implementation and control based on dynamic pricing across varying load profiles and system constraints (Hu, Xiao, and Wang, 2021; Fazlalipour, et al., 2019).

Finally, grid integration has been facilitated with market participation modeling based upon NLP. For example, Esmaeili et al. (2018) propose an NLP model for microgrid market participation that includes a bidding strategy for balancing costs and system constraints. Optimal dispatch of microgrid resources can be incorporated through a real-world approach to resource trading that accounts for constraints applicable to regulated systems (Liu et al., 2020).

Thus, in general, classical NLP optimization provides a more realistic approach to constrained nonlinear systems, yielding more feasible solutions. Such findings from NLP applications optimize renewable integration, energy management, and market participation, enabling microgrid systems to operate as economically feasible, reliable, and sustainable systems.

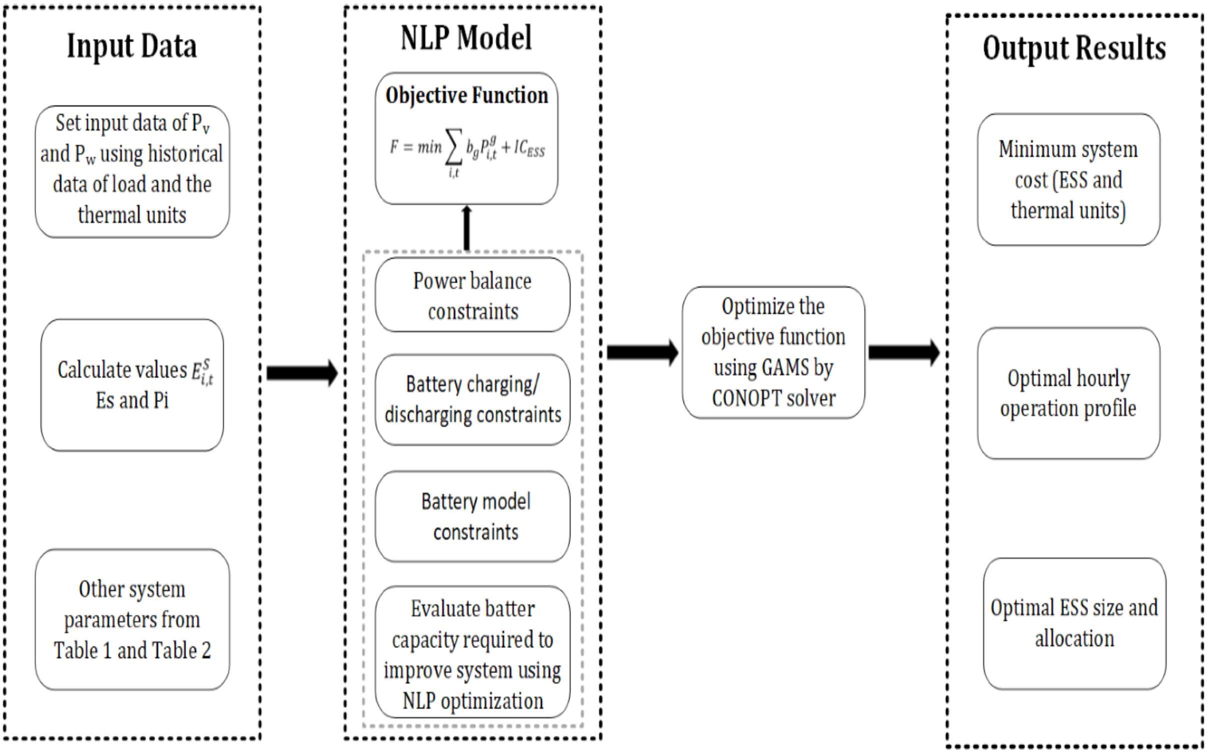

Figure 2. 9: Typical flowchart for Non-linear Programming
(Alhumaid et al.,2021)

2.3.6 Dynamic Programming (DP)

Dynamic programming (DP), as a classical approach to optimization, has been applied to various operational problems for microgrid systems. DP was advanced for energy management optimization and dispatch in microgrid systems (Shuai et al., 2018). For example, a DP approach was developed for optimal energy management of microgrids comprising renewable generation, storage, and load demand (Savatti et al., 2020). DP functions by modeling the scheduling and control of energy resources over a discrete time horizon, factoring in system constraints and optimization goals such as cost minimization or emissions reduction (Heymann et al., 2018). Moreover, optimal control for energy storage systems in microgrids has been accomplished via DP approaches (Wei et al., 2017). A DP energy storage control system is modeled based on load demand, renewable generation, and storage capacity (Wei et al., 2017). The DP function provides optimal charging/discharging profiles based on system constraints, operational efficiency, and economic imperatives (Wu & Wang, 2018).

DP optimization was also employed for optimal grid-interactive microgrid operation and for revenue participation in energy markets (An and Tuan, 2015). For example, a DP-based approach for optimal microgrid trading with the grid found that market pricing, system constraints, and economic advantage all have to be considered to assess optimal market operation (Liu et al., 2022). Furthermore, DP was used to optimally manage ESS in the face of haphazardness (Rigaut, 2019). The DP output operation ultimately provides the optimal buy/sell decision to either sell to the grid or purchase from the grid to meet demand based on pricing mechanisms and operational imperatives of the system (Wenzhi et al., 2022). Furthermore, DP has been applied to improve microgrid reliability and resilience through fault detection and restoration solutions for the system (Li & Rochel 2021; Wang et al., 2022). Research assessed how DP considers fault detection, reconfiguration, and load prioritization to restore microgrid resilience. Modeling with DP will provide optimal decision-making for microgrid restoration post-grid disturbances, accounting for all other system constraints, priority loads, environmental concerns, and the availability of energy production resources. (Sun et al., 2019).

Finally, DP optimization was used for dynamic demand response in microgrids and the optimal management problem for price-making for community energy storage (Li et al.2024). Research proposed a DP-based dynamic demand response approach that considers load flexibility and price-based demand response within system constraints (Schledorn et al., 2022). Kanchev et al. (2014) applied the DP-based Energy Management System to operate these systems in microgrid systems.

Ultimately, applying a classical approach with DP to microgrid systems provides the optimal resource allocation, control strategies, and decision-making over time. Building dynamic programming models and implementing the DP algorithm have successfully solved many operational issues in microgrids, accounting for economic, environmental, and reliability factors. In summary, these studies contribute to the performance enhancement of microgrid systems that optimally operate renewable, storage, and demand response resources.

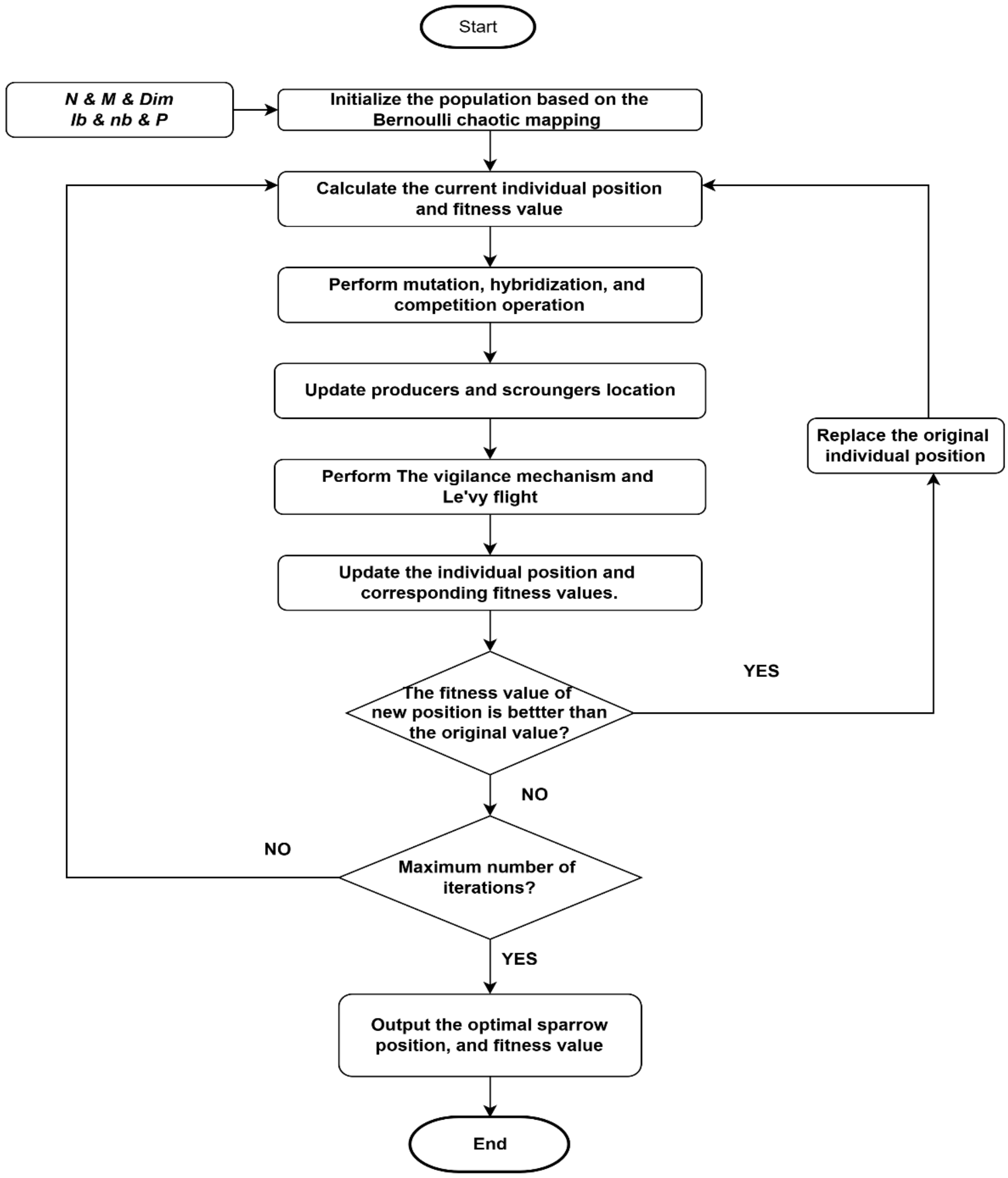

Figure 2. 10: Flow chart for Dynamic Programming Optimization
(Wenzhi et al 2022).

2.3.7 Integer Programming (IP)

Integer Programming (IP) is a classical optimization technique used in the field of microgrid studies. In addition, IP-related optimization models are used for microgrid layout and topology (Paul et al., 2018; Igder et al., 2022). Furthermore, (Reich and Oriti 2021) offers an integer programming model for optimal sizing and selection of microgrid components based on load demand, renewable generation and system constraints. For example, IP models determine the most suitable arrangement of microgrid components—generators, storage, control systems—for minimal costs, reliable operation and ecological benefits (Liu et al., 2016).

IP optimization has been applied to microgrids for optimal resource allocation and dispatch (Guo et al., 2013). In addition, Sigalo et al. (2020) demonstrate an integer programming model of optimal resource allocation and dispatch based on load demand, renewable generation potential, storage capacity, and system constraints. Thus, IP models determine the most effective distribution of available resources—energy resources, generators, storage systems, and flexible loads—and dispatch timing based on various factors, including savings potential, emission reductions, and reliability improvements (Moretti et al., 2019).

Furthermore, IP conceptualization has been successfully applied relative to the optimization of grid interconnection and participation in energy markets (Gomes et al., 2021). For example, (Liu, et al., 2015) developed an integer programming model for optimal grid interconnection and trading strategies based on market costs, system constraints and economic advantage (Rezaei, Pezhmaxi and Khazali, 2022). In this case, IP models determine the most advantageous decision-making situations for grid interconnection, energy trading, or pricing decisions and bid evaluations based on costs versus system requirements.

Thus far, IP has been conducted to determine increased microgrid reliability and resilience. For example, (Babaei et al., 2020) utilize an integer programming model for optimal microgrid restoration and reconfiguration based on reliability of a stand-alone energy system, load prioritization, and system constraints. Thus, integer programming models optimize decision-making for reconfiguring a microgrid post disturbance for re-energization of certain components and if needed, load shedding to minimize the length of time without power, especially if critical loads are simultaneously awaiting power restoration (Zare-Bahramabadi et al 2023).

Finally, IP optimization is applied to demand response/responsive management in a microgrid-coordinated manner (Nguyen-Duc et al., 2022). For example, Raji et al. (2022) formulate an integer programming model for a coordinated demand response approach based on load flexibility, system constraints, and user preferences. Therefore, IP models optimize the scheduling/control of flexible loads across user systems based on dynamic pricing across different system components in addition to load profiles and limitations.

Overall, IP-based classical optimization in the microgrid realm supports the idealized configuration of interconnected systems for optimal control. By creating integer programming models from real-life challenges in cost recovery in the field, researchers can apply IP algorithms to identify solutions that balance economic advantages with ecological factors and reliability. Thus, these studies support a more resilient and integrated approach to microgrid systems that facilitate the integration of renewable energy assets from multiple sources.

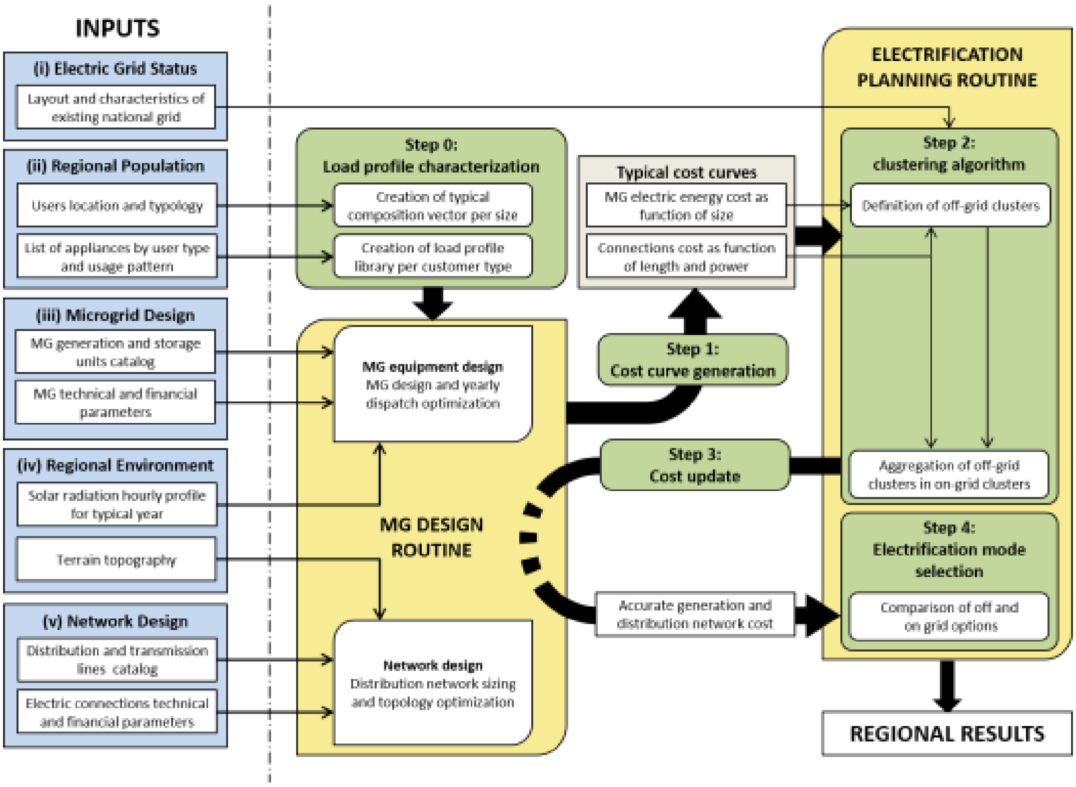

Figure 2. 11: Typical Flow chart for Integer Linear Programming
(Moretti, et al., 2019)

Table 2. 3: Summary of Optimization techniques utilized on microgrids (Rani and Kumar,2015)

Name of technology	Application and findings
Genetic Algorithm	Successfully applied in unit commitment problems,
Linear Programming	Used in mathematical programming and linear objective functions.
Particle Swarm Optimization	Modern Heuristic methods are used for problems whose solutions are points or areas in N-dimensional space.
Robust Optimization method	Used in problems in which a certain measure of robustness is required against uncertainty.
Mixed Integer Linear Programming	Differential equation and logical statement
Multi-Objective Genetic Algorithm	The Pareto frontier is the most heuristic search method.
Simulated Annealing	Locating a good approximation to the global optimization problem. It is used when the search space is discrete. More complex than exhaustive enumeration.
Bacterial Foraging Optimization	Applicable to the field of computational intelligence and metaheuristics. Utilized in a Hybrid algorithm with other computational intelligence algorithms and metaheuristics,
Chaotic Quantum Genetic Algorithm	Quantum computing concepts, such as the superposition state and the unique coding format.
Hyper geometric Optimization of Motif Enrichment (K-HOMER)	Most Discovery Sequential analysis.

2.3.8 Review discussion on Classical Optimization techniques reviewed on Microgrid Systems

This section reviews publications over 12 years, from 2013 to 2025. Figure 2.5 depicts a graphical comparison of the number of publications per year. For the bar chart in Figure 2.5, the publication number increased from 2013 to 2018, then dropped from 2019 to 2021. In the years 2013 and 2014, only one paper was reviewed. The number of published papers has fluctuated between 2018 and 2023. In 2018, it had the highest number of papers, then dropped to eleven in 2019 and ten in 2020. From 2021, it increased until 2022, when it decreased to 8 papers in 2023. Again in 2023, papers decreased, then increased again in 2025.

Many methods for classical optimization of microgrid systems are described in the literature. The year of publication, application on the microgrid system, and the algorithm used are presented in Table 2.4. The most commonly used methods include Nonlinear Programming, Quadratic Programming, and Convex Programming. These are reviewed in this chapter in order to compare and analyze their characteristics.

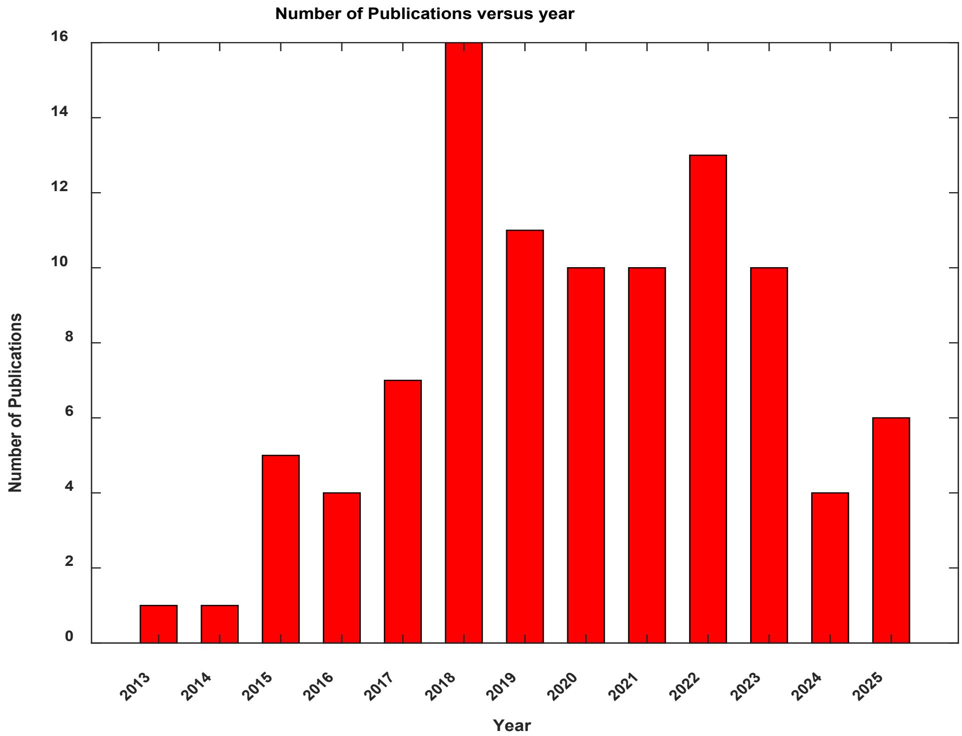

Figure 2. 12: Bar graph for publications for classical optimization methods for microgrid Applications

Table 2. 4: Summary of Classical Optimization techniques reviewed on microgrids

Year	Authors	Application on Microgrid System	Algorithm used
2013	Guo, L et al	Resource Allocation and Dispatch	Integer Programming
2014	Kanchev, H et al	Energy Management Systems	Dynamic Programming
2015	Liu, G., Xu.and Tomsovic	Grid Interconnection and Market Participation	Integer Programming
2015	Lu, Y et al	Grid Interconnection and Market Participation	Nonlinear Programming
2015	Heymann, B et al	Grid Integration and Market Participation	Dynamic Programming
2015	Luungoc & Tran	Grid Interaction and Market Participation	Dynamic Programming
2015	Deng, R et al	Resilience and Reliability	Dynamic Programming
2016	Morstyn Hredzak, & Agelidis	Optimal Power Flow	Convex Programming
2016	by Ahyari-Moghaddam et al	Energy Management and Storage	Nonlinear Programming
2016	Liu, G et al	Microgrid Design and Configuration	Integer Programming
2017	Calderaro, V et al	Energy Management and Storage	Nonlinear Programming
2017	Guo et al	Microgrid Resilience and Fault Management	Quadratic Programming
2017	Nazaripouya, H et al	Demand Response and Load Shaping	Convex Programming
2017	Liu, Y., Gooi, H.B.and Xin, H	Energy Management and Storage	Convex Programming
2017	Li, Y.Z et al	Multi-Objective Optimization	Convex Programming
2017	Nazaripouya, H et al	Microgrid Resilience and Reliability	Convex Programming
2017	Wei, Q et al	Storage Control and Optimization	Dynamic Programming
2018	Shuai, H et al	Grid Integration and Market Participation	Dynamic Programming
2018	Esmaeili, S et al	Grid Integration and Market Participation	Nonlinear Programming
2018	Wu, J et al	Energy Management and Storage	Nonlinear Programming
2018	Liu, C et al	Renewable Energy Integration	Nonlinear Programming
2018	Wu et al	Resource Allocation and Dispatch	Integer Programming
2018	Giraldo, J.S et al	Optimal Power Flow	Convex Programming
2018	Paul, S et al	Microgrid Design and Configuration	Integer Programming
2018	Zhang. Y, et al.	Economic Dispatch and Unit Commitment	Quadratic Programming
2018	Li et al	Optimal Dispatch with Uncertainty	Quadratic Programming
2018	Jin, M et al	Optimal Dispatch with Uncertainty	Quadratic Programming
2018	Bandyopadhyay et al	Coordinated Demand Response	Integer Programming
2018	Zhang, C et al	Optimal Dispatch with Uncertainty	Quadratic Programming
2018	Zhang, Y et al	Optimal Dispatch with Uncertainty	Quadratic Programming
2018	Hu & Xiao	Optimal Demand Response	Nonlinear Programming
2018	Wu, N & Wang, H	Storage Control and Optimization	Dynamic Programming
2019	Faly & Mathieu, D	Grid Interaction and Market Participation	Dynamic Programming
2019	Fazlalipour, Ehsan, & Mohammodi- Yatloo,	Optimal Demand Response	Nonlinear Programming
2019	Liu, Wang, and Yin	Renewable Energy Integration	Nonlinear Programming
2019	Wang, M et al	Optimal Power Flow	Convex Programming
2019	Liu et al	Microgrid Resilience and Reliability	Convex Programming
2019	Moretti, L et al	Resource Allocation and Dispatch	Integer Programming
2019	Xu, J et al	Optimal Dispatch with Uncertainty	Quadratic Programming

2019	Xu, et al	Energy Management and Storage	Convex Programming
2019	Huang, Y et al	Uncertainty and Stochastic Optimization	Nonlinear Programming
2019	Kumtepeli, V et al	Energy Storage Optimization	Quadratic Programming
2020	Sgalo, M.B	Resource Allocation and Dispatch	Integer Programming
2020	Savatti, G.A et al	Grid Integration and Market Participation	Dynamic Programming
2020	Liu, J et al	Grid Integration and Market Participation	Nonlinear Programming
2020	Babaei, M et al	Reliability and Resilience	Integer Programming
2020	Zhou, Q et al	Microgrid Resilience and Reliability	Convex Programming
2020	Zia, M.F et al	Optimal Demand Response	Nonlinear Programming
2020	Zia, M.F et al	Energy Management and Storage	Nonlinear Programming
2020	Liu, Z et al	Grid Integration and Market Participation	Nonlinear Programming
2020	Xie, et al	Optimal Control and Voltage Regulation	Quadratic Programming
2021	Reich, D and Oriti, G.	Microgrid Design and Configuration	Integer Programming
2021	Hu, Xiao & Wang	Optimal Demand Response	Nonlinear Programming
2021	Meliani, M et al	Demand Response and Load Shaping	Convex Programming
2021	Elkazaz, Sumner, & Thomas	Optimal Power Flow	Convex Programming
2021	Abdul Muqeet, H et al	Optimal Demand Response	Nonlinear Programming
2021	Jing. J et al	Economic Dispatch and Unit Commitment	Quadratic Programming
2021	Takano, H et al	Energy Storage Optimization	Quadratic Programming
2021	Zhang, X et al	Optimal Control and Voltage Regulation	Quadratic Programming
2021	Shi, D et al	Optimal Control and Voltage Regulation	Quadratic Programming
2021	Silva, J.A.A et al	Energy Management and Storage	Convex Programming
2021	Li et al	Resilience and Reliability	Dynamic Programming
2021	Gomes, Melicio, & Mendes	Grid Interaction and Market Participation	Integer Programming
2022	Liu, J et al	Grid Interaction and Market Participation	Dynamic Programming
2022	Scwedorn, A et al	Resilience and Reliability	Dynamic Programming
2022	Wang, Z et al	Resilience and Reliability	Dynamic Programming
2022	Zhu, J et al	Uncertainty and Stochastic Optimization	Nonlinear Programming
2022	Raji, Sarkar, & Goswami,	Coordinated Demand Response	Integer Programming
2022	Jamii, J et al	Uncertainty and Stochastic Optimization	Nonlinear Programming
2022	Wenzhi, S et al	Grid Interaction and Market Participation	Dynamic Programming
2022	Igder, Liang, and Mitolo, M	Microgrid Design and Configuration	Integer Programming
2022	Rezaei, Pezhmaxi, & Khazali,	Grid Interconnection and Market Participation	Integer Programming
2022	Shang et al	Optimal Control and Voltage Regulation	Quadratic Programming
2023	Akulker, H. and Aydin.E	Renewable Energy Integration	Nonlinear Programming
2023	Zhang. J, et al	Economic Dispatch and Unit Commitment	Quadratic Programming
2023	ZAre-Bahramabadi, Forzin, & Ehsan	Reliability and Resilience	Integer Programming
2023	Long, B et al	Optimal Control and Voltage Regulation	Quadratic Programming
2023	Nguyen-Duc, T et al	Coordinated Demand Response	Integer Programming
2023	Ahmad, S et al	Optimal Control and Voltage Regulation	Quadratic Programming
2023	Hosseini; Radriquez-Garcia & Parvania, M.	Microgrid Resilience and Fault Management	Quadratic Programming
2023	Gil-Gonzalez, W., Motay, O.D. and Hemandez, J.C	Energy Management and Storage	Convex Programming

2023	Guodong Liu, Maximiliano F. Ferrari, and Yang Chen	Network operational objectives and constraints	Mixed-Integer Linear Programming
2024	Kabe et al	Optimal planning and design of microgrids	Mixed-Integer Linear Programming
2024	Dessalegn Bitew Aeggegn, George Nyauma Nyakoe, and Cyrus Wekesa.	Renewable distributed energy resources	Grey Wolf Optimization
2024	Wang et al	Optimizing Economic Dispatch for Microgrid Clusters.	Grey Wolf Optimization
2024	Huynh et al	Optimal Configuration of a DC Microgrid	Grey Wolf Optimization
2025	Lobos-Cornejo et al	Smart Energy Strategy for AC Microgrids	Grey Wolf Optimization
2025	Dagal et al	Energy systems optimization	Grey Wolf Optimization
2025	Chen et al	Smart demand side management	Grey Wolf Optimization
2025	Alejandro Valencia-Díaz a, Eliana M. Toro, Ricardo A. Hincapié	Microgrids Sustainable Development	Mixed-Integer Linear Programming
2025	Melissa Eklund, Alexey Voinov, M.J. Hossain, and Kaveh Khalilpour	Integration of social dynamics into the Microgrid design	Mixed-Integer Linear Programming
2025	García et al	Cost-Effective Operation of Microgrids	Mixed-Integer Linear Programming

2.4 Review of Heuristic Optimization Methods for Microgrid Applications

Heuristic optimization methods use approximate, iterative techniques to explore the search space more efficiently than classical methods. Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, Simulated Annealing, Dynamic Arithmetic Optimization Algorithm, Grey Wolf Optimization, Artificial Bee Colony, and Differential Evolution are examples of heuristic optimization methods. These methods are handy when the problem is complex, and a classical optimization method may not be able to solve it efficiently or effectively.

2.4.1 Genetic Algorithm Heuristic Optimization in Microgrid Systems

This review presents a systematic literature review of the GA approach applied in microgrid systems. Microgrid systems are a growing area of energy research, where localized grids of energy distribution — emphasizing energy efficiency, reliability, and sustainability — have yet to receive a comprehensive review of how successful GA-based heuristic optimization has been across microgrid subcomponents that beckon further research.

Microgrid systems are the solutions to energy distribution problems that serve as localized grids that can operate independently or be connected to a larger power grid. According to Zheng et al. (2023), microgrid systems require operational optimization to facilitate appropriate resource distribution and enhance functionality. The GA represents an optimizing potential solution for complex problems with resolution processes constructed incrementally based on evolutionary factors (Kalajahi et al., 2021). Genetic Algorithms use principles of evolution to represent problem solutions across successive generations. Over generations, representative individuals defined by solution factors emerge, are selected, bred or crossed, and mutated to produce offspring that are more likely to represent ideal solutions (Daniel et al., 2023).

An array of fields incorporates GA-based heuristic optimization in the context of operational microgrid development. For instance, the scheduling of generation resources minimizes operational costs for the microgrid and addresses system limitations (Daniel et al., 2023; Nemati et al., 2018). GA can assess power loads/storing utilization as found by Torkan et al. (2022) for practical energy distribution that aligns with the microgrid's expected balance. In Nemati et al. (2018; Elsied et al., 2014; Askarzadeh, 2017), GA enhances energy consumption efficiency, relative to power generation costs, as the best practices for energy acquisition, accumulation, and planning can be determined. Other operational dimensions concern scheduling strategies that reduce operating costs and improve management effectiveness.

According to the analysis by Arif et al. (2014), GA can reduce costs by optimizing the performance of renewable energy sources, such as solar and wind. GA refers to performance metrics that work best for these resources, as determined by John et al. (2022). GA can also find optimal controls for energy use from prosumer devices/machines (Torkan et al., 2022). Demand response strategies can be optimized across flexible consumption loads and demand-side resources (Arif et al., 2014), while the optimal time to connect/disconnect from the main grid can be determined by economic and reliability considerations. Microgrids have operational limitations, energy demands, access, reserves, etc., that GA can successfully operate within through proper encoding and solutions that penalize ineffective attempts at potential solutions (Yeh et al., 2020). The versatility of GA lies in its ability to handle continuous, discrete, and combined variables in microgrids. Therefore, its stochastic nature compounds this, where potential solutions are determined, and the likelihood of localized ideal solutions is diminished. However, as with many metaheuristics, especially GA (Yu et al., 2015; De Santis et al., 2017), parameters must be properly assessed to achieve successful GA outcomes. Time considerations must be weighed when using population-based approaches to solutions. While it facilitates simultaneous processing to gain a potential time advantage, Wang et al. (2021) note operational issues associated with overly complex large systems. The good news is that GA can be integrated into real-time applications (Ahmadi Ahangar et al., 2019). Research has determined that tourism-related real-time integration needs microgrid adaptations that change on the fly, and GA must work to integrate optimal microgrid functionality under demand-relative adaptations. In real-time environments, complications are more frequently associated with microgrids because operational conditions change.

This furthermore applies to operational performance. Performance requires iterative functionality, which may present other methods in a better light due to realized performance in the field (Suresh & Janik, 2019). An acceptable time-intensive performance review may come at the expense of appropriate real-time potential.

Research suggests GA can be used in conjunction with additional optimization patterns or machine learning methods for ideal performance considerations supported by Zheng et al. 2018 and Semero et al., 2018. Studies have found hybrid solutions that combine the benefits and eliminate the detriments of two methods improve operational conservation in microgrid systems. Extendability is critical for multi-objective optimization (Chen et al., 2013; Zhou et al., 2013; Ghavifekr, 2021). Microgrid operations often require competing results—minimum cost, reduced environmental harm, maximum reliability—and while this is feasible through GA, established results empower experts with appropriate Pareto levels of effectiveness. To conclude, the benefits of GA-based heuristic optimization solution generation are an effective means for strategic operations to widely implement versatile subcomponent applicability. The various operations support all areas of the microgrid as applicable, and any adjustments needed to address challenges serve as a vindication of future research opportunities, with specific tactical adjustments made over generations.

Ultimately, the findings from this systematic literature review substantiate the need for GA-based heuristic optimization for all accountable efforts across microgrid systems, given the intricately complex optimization needs required by inexorably interconnected concerns across extensive grid patterns. The ability to generalize from theoretical and practical applications through literacy review with GA assessment proves GA to be the go-to solution for successful questions in equity-based systems that address value-driven operational risk-reward needs across energy satisfaction.

GA is preferable for complex, non-linear, and multi-objective concerns of arbitrary systems where ubiquitous conflicting optimization problems arise due to a versatile component focus, particularly in energy decentralization and equipment reliability. However, extreme parameters must be closely controlled in large systems, as it's easier said than done to achieve scalable solutions in the present literature for microgrid real-time needs.

Continued work is still needed to assess optimized hybridized approaches across intra- and inter-component continual developments across diversified fields, as the present literature suggests an increasingly diverse research base over time, since transparent options are extant beyond the present research in energy-related international value assessments.

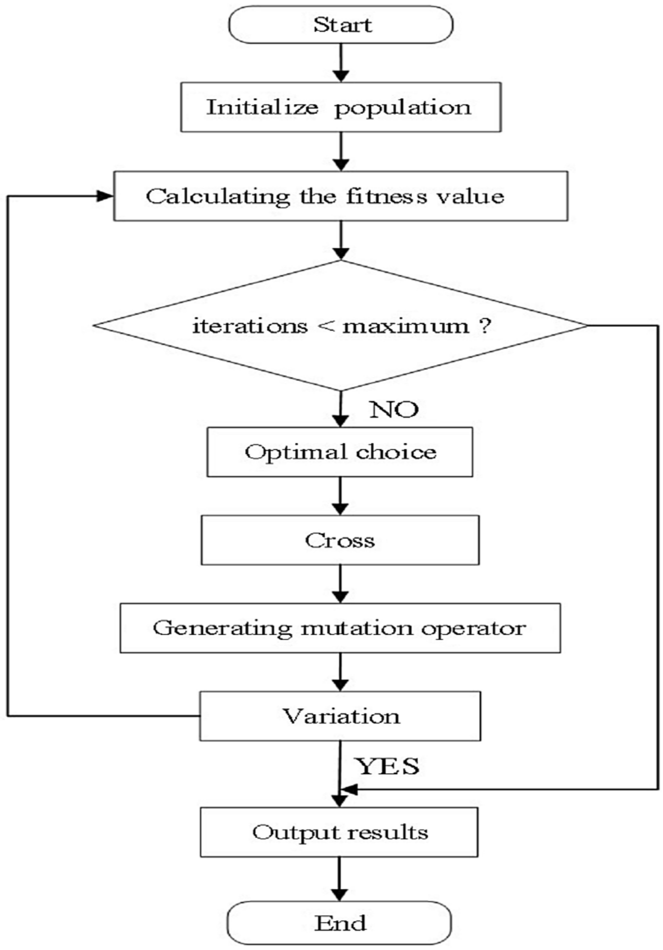

Figure 2. 13: Genetic Algorithm Flowchart
(Jiang et al.,2021)

2.4.2 Particle Swarm Optimization Heuristic Optimization in Microgrid Systems

Particle Swarm Optimization (PSO) is a heuristic optimization method inspired by social behavior in nature, such as birds flocking or fish schooling. Since 2006, Particle Swarm Optimization has emerged as a feasible option for microgrid solutions across many engineering and scientific fields. Microgrid Optimization. Microgrids are small energy systems that can operate independently or be connected to the primary grid. Therefore, decentralized energy solutions have emerged as a significant research focus for improving energy efficiency and advancing sustainable development. This literature review will explore Particle Swarm Optimization for microgrid solutions, advantages and disadvantages, and notes for future research endeavors.

Microgrid solutions are a growing alternative for localized energy, enabling energy consumers to be independent and resilient. Energy efficiency is the name of the game, where energy solutions can achieve optimized resource use, and project managers must optimize microgrid operations to enhance resource utilization and operational capabilities. Particle Swarm Optimization is a solution inspired by social behavior and collective intelligence. It is a swarm of solutions to a given problem, with the candidates for solutions referred to as particles that move through solution space to find solutions. The particles adjust position based upon their previously experienced solutions and what they've experienced based on a "best" solution for others. Thus, particles are socially inspired and called into action through inertia components and cognitive and social components that result from particle behavior within the swarm.

Particle Swarm Optimization has been used to help schedule energy sources for an entire microgrid in an optimal orientation that keeps operational costs at a minimum while staying in line with microgrid parameters (Karthikeyan et al, 2016; Zhang, Wang, et al 2022; Yeh et al., 2020). Particle Swarm Optimization will effectively help integrate renewable energy sources into a microgrid to maximize excess generation from solar panels, wind turbines, and other renewable energy sources (De and Mandal, 2022; Hossain et al., 2019; Aguila-Leon et al., 2022).

Theoretically, Particle Swarm Optimization facilitates demand response by best scheduling flexible loads and demand-side resources (Jordehi et al., 2020; Li et al., 2020). Furthermore, Particle Swarm Optimization will help determine optimal connection times/disconnection times from the main grid for reliable microgrid operations that help keep costs down while boosting responsiveness for sustainable systems (Radosavljevic et al, 2016; Shan et al 2021).

According to Phommixay et al. (2021), Particle Swarm Optimization is relatively simple to implement and inexpensive computationally, allowing real-time incremental deployment in microgrid systems and offering simpler parameter tuning than other solutions. Particle Swarm Optimization also facilitates the exploration of multiple solutions simultaneously, helping maintain global or near-optimal solutions rather than local ones that may be found by chance due to limited access.

Particle Swarm Optimization has been implemented, with artificial neural networks optimized to form a self-adaptive energy management system for microgrid operations (Aguila-Leon et al., 2022). Each artificial neural network is optimized using Particle Swarm Optimization, and the proposed model aims to predict and provide this information to the energy management system. However, Phommixay et al. (2021) find that Particle Swarm Optimization can be implemented for continuous or discrete variables, adjusting It to microgrid control/management needs.

Thus, Particle Swarm Optimization performs well on high-dimensional optimization problems common to complicated microgrid systems and successfully handles complex nonlinear objective functions typical of microgrid system selection efforts and most feasible operations/runs. (Yavuz et al 2023; Soares et al 2023) believe that Particle Swarm Optimization is computationally more efficient in small microgrids, but larger, more complex ones are better served by various alternatives or a Hybridization of efforts for better success. (Phommixay, et al 2021) acknowledge that Particle Swarm

Optimization limits ideal solutions to sub-optimal conditions through premature convergence, and if improperly implemented due to poor parameter settings, there may be problems. Therefore, it's been acknowledged in research that microgrid systems are subject to parameter sensitivity analyses (Ali et al 2021; Hou and Fujimura, 2023). Sensitivity analyses are needed to determine optimal settings, as the selection process requires substantiation of the optimal parameter values. Ideal selections call for suitable convergence values/optimal result values.

Microgrid systems operate in the presence of uncertainty (Hossain et al., 2019). Microgrid systems operate with uncertainty because of geographical considerations (Karthikeyan et al, 2016), environmental concerns, or chaos from natural disasters/turbulence (Radosovljevic, et al 2016). Particle Swarm Optimization can operate with greater robustness and stability when uncertainty arises, as when adjustments are made based on dynamic unknowns (Albogamy et al., 2022; Hossain et al., 2019). For example, Particle Swarm Optimization has been successfully applied in microgrid systems, especially for scheduling and dispatching renewable energy resources (solar and wind) with energy storage solutions (De and Mandalk, 2022). Maintaining population diversity can be difficult—and may yield suboptimal exploration. Therefore, investigating hybridized approaches to Particle Swarm Optimization with other optimization systems or machine learning processes/performance analyses will enhance performance. For example, (Xin-Gang et al., 2020; Ahmadipour et al. 2022; Yavuz et al. 2023) explore variables that prefer PSO solutions plus Genetic Algorithms (GA) or Differential Evolution (DE) as alternatives for microgrid operations better suited with more than one heuristic or problem-solving methodology.

Feasibility suggests that it's acceptable to extend Particle Swarm Optimization to accommodate multi-objective problems in microgrids, since many are simultaneously optimized for cost minimization, pollution minimization, and efficiency maximization (Zeng et al., 2022; Zhang et al., 2022). New solutions exist, such as Fuzzy Clustering, Multi-Objective Particle Swarm Optimization, as Hybrid solutions prove effective, especially since Yu et al. (2014 have shown that combining Particle Swarm with Fuzzy Clustering works well as a customized real-life situation dealing with adjustments/requirements.

Particle Swarm Optimization is a heuristic with great potential to facilitate optimal microgrid systems, as high-quality solutions emerge across microgrid sectors, suggesting adaptability and access. Pinpointing drawbacks—exclusionary tendencies are also crucial, while Hybridized opportunities are paramount.

The overall conclusion drawn from this literature review is that Particle Swarm Optimization is a reliable heuristic within microgrid systems for complex problems that require solutions across various findings related to microgrid systems, which would allow for successful endeavors had energy efficiencies or reliability/sustainability been found.

Overall, Particle Swarm Optimization is a reliable heuristic that can be used across many categories within the microgrid profession. As qualitative and successful solutions arise, new avenues of potential based on feasibility found will emerge, suggesting further developments, while consistency of findings with new conditions connected to current goals will need to be communicated, as Hybridization with consistent other optimization assessments will be necessary as since newer developmental advances are raised, time has presented benchmark collections since this point.

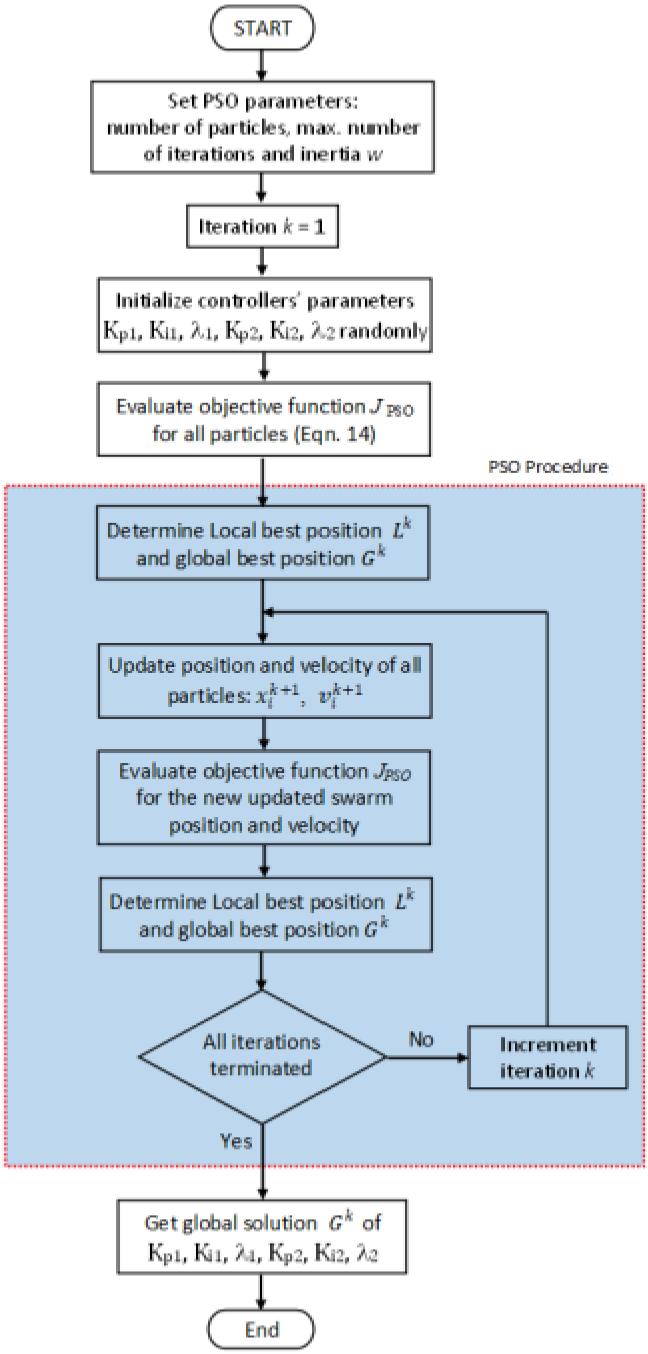

Figure 2. 14: Typical Flowchart for Particle Swarm Optimization
(Azab and Servano-Fontova, 2021)

2.4.3 Ant Colony Optimization Heuristic Optimization in Microgrid Systems

This review substantiates that Ant Colony Optimization (ACO), as a heuristic optimization solution, holds great value for microgrid systems. Microgrids are localized systems for energy production and distribution that hold great promise for energy efficiency. Therefore, the performance, advantages, and disadvantages of ACO for microgrid systems will be determined for potential future study and implementation. With the globalization efforts that require energy, microgrid systems have emerged in areas with energy distribution challenges, where localized solutions are more appropriate than large-scale endeavors. Thus, microgrid optimization is necessary for efficient communication and operation of microgrid resources. Ant Colony Optimization, according to Olivas et al. (2017), is an optimization solution for such needs. Ant Colony Optimization is a heuristic optimization method in which artificial ants move through solution spaces. The more pheromones they leave in one area over another, the more ants are attracted down that path. Ultimately, over time, predetermined successful paths pave the way with success through stronger pheromone trails. Ant Colony Optimization is an effective means of determining generation sources to operate cost-effectively while aligning with microgrid needs (Trivedi et al., 2015; Suresh et al., 2024). The optimal flow and energy storage options are enhanced through ACO for enhanced energy effectiveness and greater grid stability (Marzband et al, 2016; Fatima et al. 2017; Güven et al 2022).

In addition, ACO optimally considers renewable energy uses through solar and wind and other means of renewable optimization (Emerson & Srinivasan 2015; Kreishan and Zobaa, 2023; Priyadarshi et al, 2019; Lorenzini et al 2021). ACO solutions for demand side resources and flexible load scheduling aid in demand response (Marzband et al.2016; Albogamy et al., 2022; Movahedpour et al., 2022). According to the literature, ACO is optimal in deciding when a microgrid should be interconnected to the grid and when it should island itself based upon economic and reliability needs (Fatima et al.2017), (Sellamna et al.2018; Khaleel, 2023). ACO helps solve routing/scheduling problems (Marzband et al., 2016; Silva & Han, 2019). In a microgrid setting, for example, this could be used to optimally dispatch between sources and have a set schedule for energy storage units (Lorenzini et al 2021). ACO has a good balance between exploring potential solutions and exploiting plausible ones.

Kreishan and Zobaa (2023) use ACO as their solution to explore exploitation in relation to microgrid problem-solving. ACO optimization is most reliable for microgrid problem-solving, as it provides a solution-based approach that balances practicality without getting lost in the complexity of feasible solutions.

Research cites that ACO is decentralized. In the world of microgrids, decentralization is key, as microgrid operation is decentralized itself (Gao et al., 2023). ACO is decentralized by nature since it is an agent (ant) based approach (Xu, Yang, and Li, 2019). Many decisions in a microgrid setting are made at the local level rather than at a global level (Khelifa & Laouar, 2020), so ACO is naturally applicable.

ACO performance does not differ significantly from that of dimensional optimization problems, which is common in microgrid settings. Kreishan (2022) also notes that ACO can be parallelized, enabling systems to run more quickly under greater system or real-time analysis constraints (Khelifa & Laouar, 2020).

(Gao et al. 2021; Zhao, 2025) cite that ACO can converge slowly, which means that it takes longer than other methods to come to a conclusion than necessary (Deng et al 2019). Furthermore, Sellamna et al. (2018) note that performance can depend on specific settings, which means extensive parameter tuning is required for the most reliable outcome. Mohamed et al. 2023 used ACO for parameter tuning in their findings. This essentially means that although ACO has specific parameters that rely on efficient results, finding the right sweet spot can be difficult and problem-dependent; performance can depend on specifics, which can be challenging.

The review aspect of this function notes that findings demonstrate that relative results specify hybrid use where ACO can be combined with other optimization/machine learning based methods for enhanced performance relative to microgrid systems (Güven, et al 2022; Abo-Elyousr et al, 2021) (Kefayat et al 2015) or extended use as a method for more than one optimizing objective which often conflict, but researchers want validation in the system (Kreishan, and Zobaa, 2023). The use of ACO can be integrated relative to real-time assessments/optimizing efforts (Trivedi et al 2015; Priyadarshi et al, 2019; Skackauskas and Kalganova, 2023).

Ultimately, Ant Colony Optimization has great promise for microgrid systems, offering a valid, innovative heuristic-based solution for their problem-solving.

ACO applicability spans multiple microgrid components, suggesting effectiveness across the board in high-value contexts; furthermore, current value concerns about the speed of convergence or the lack of exploration of hybrids/further testing are addressed, with potential on both fronts for increased usefulness over time.

Ultimately, this review shows that Ant Colony Optimization as a heuristic provides substantial, plausible solutions for microgrid systems. The ability to solve complex problems across various components of the microgrid suggests that this is a truly valuable tool for improving efficiency, effectiveness, and reliability in these decentralized energy distribution systems.

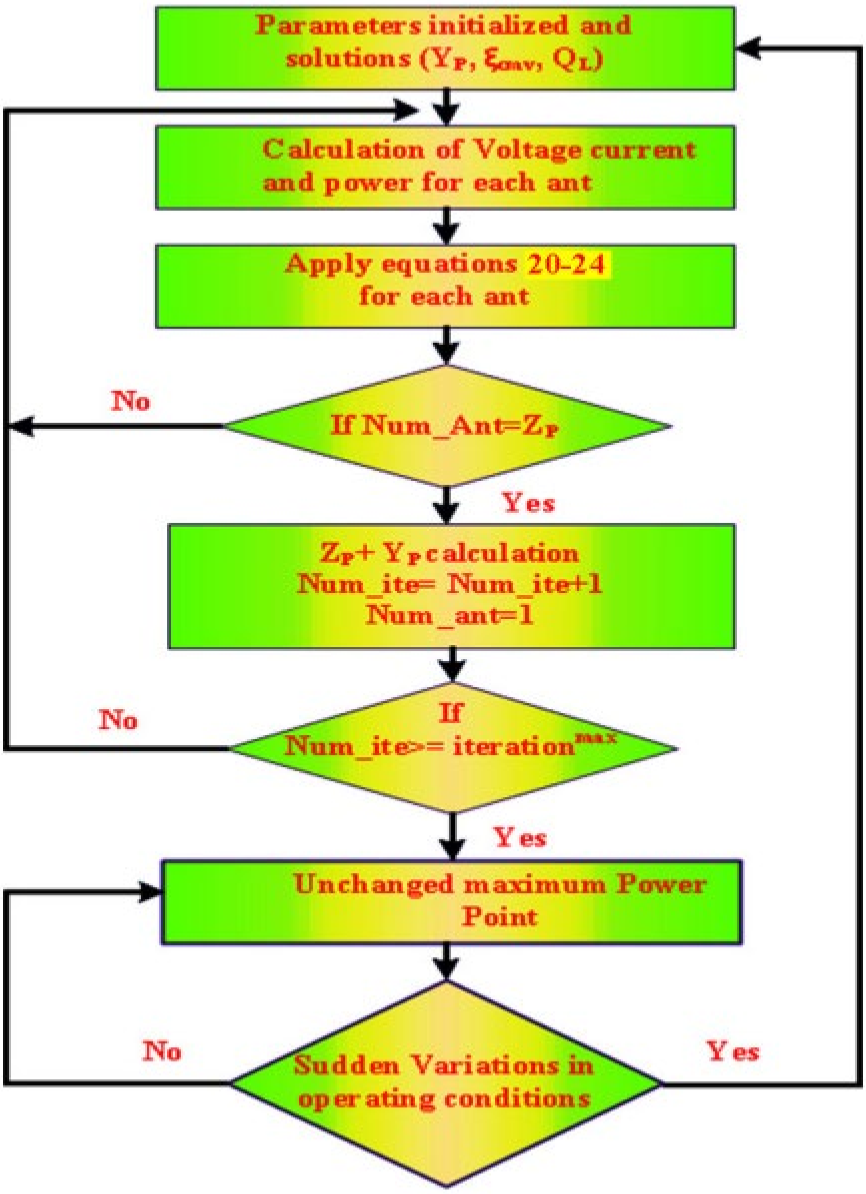

Figure 2. 15: Typical flow chart for Ant Colony Optimization (ACO)
(Priyadarshi et al.,2019)

2.4 .4 Simulated Annealing Heuristic Optimization in Microgrid Systems

This review is a systematic literature review of the Simulated Annealing heuristic optimization process and its findings in microgrid systems. Microgrids serve as decentralized energy distribution systems with the potential to improve energy efficiency and sustainability. This paper champions the relative success of Simulated Annealing as a microgrid optimization solution, whilst noting benefits and drawbacks and future research opportunities. With the global failure of energy distribution in recent years, more people have had to rely on localized solutions. Therefore, the success of microgrid systems as they become increasingly popular depends on optimal resource distribution and other strategies that support comprehensive microgrid success.

Simulated Annealing (SA) is a heuristic based on the annealing process in metallurgy that provides insights relative to optimization challenges (Arfeen et al., 2021). Simulated Annealing is a stochastic optimization process that starts at a higher solution and incrementally explores the solution space until, through decreasing temperatures, worst cases no longer have a chance of being retained, and localized or best feasible results emerge. Microgrid optimization is connected to SA as (Jun et al., 2020; Jiang et al., 2019) try to minimize operating expenses while satisfying microgrid requirements through power generation source distribution as (Velik and Nicolay, 2014; Angelim & Affonso, 2018) and (Hafez et al., 2021) clarify how SA better understands optimal flows and energy storage for more efficient energy management to ensure grid stability and overall efficiencies.

Renewable resources added to the microgrid (Aiswariya and Ahamed 2020; Zhang et al. 2018) stand to benefit from SA improved optimization processes for solar and wind and other renewables, (Qian et al., 2013; Aiswariya & Ahamed, 2020; Han et al., 2019) explain how SA is beneficial for the ultimate demand response decisions for flexible load scheduling and demand-side responsive resources while in addition, helps determine the best times for when the microgrid should connect/disconnect with the main grid based on economic factors and reliability.

SA exploits effective simulated results across various microgrid relative properties as a microgrid optimization challenge. For example, SA appropriately balances exploration and exploitation: at the beginning, the algorithm can explore the solution space, and as temperatures decrease, it can place greater emphasis on effective exploitation. Effective balance can find global or near-global optimal solutions where microgrid optimizations are complicated (Velik and Nicolay, 2014; Ignat-Balaci et al., 2022).

In addition, SA explores the notion that it's not uncommon to have multiple formulations of a problem across different systems relative to interconnections. Much microgrid optimization is a continuous problem of decision making, like resources compared to finite decisions like on-off equipment or other limitations. Findings by Aiswariya and Ahamed (2020) and Ignat-Balaci et al. (2022) note that SA is appropriate for continuous components but can also manage discrete aspects.

Furthermore, relative to other optimal processes, SA is conceptually simple and doesn't require extensive parameter tuning for appropriate implementation measures. Other heuristic concepts require performance-based improvements based on perfectly tuned standards set by various research projects (Bayoumi 2019). Parameter value findings boast impressive convergence rates, making objective realities easily approached (Bagheri al. 2016; Teekaraman, et al. 2019; Azab & Serrano-Fontova, 2021).

Research from (Islam et al, 2021) and (Gil-González et al 2023) recognizes how Simulated Annealing tolerates noise from objective functions relative to microgrid environmental uncertainty. This is beneficial for real-world application data (Zhang et al., 2018), which supports the idea that objective functions often exhibit nonlinear characteristics across multiple applications. Simulated Annealing is a computational approach for complex nonlinear realities where local optima are not possible (Arfeen et al., 2021).

There are drawbacks to the implementation process as well, which facilitate the potential for real-world application. Simulated Annealing, for example, can converge slowly into optimal situations that require too many iterations (Fares, et al 2022). While this flexibility is welcoming, (Huang & Hsieh, 2011) state that Simulated Annealing does not respond as well compared to other alternatives for real-time microgrid changes (Jaraiz-Simon, 2013). In addition, solutions rely highly on initial parameters, so poor starting points without quality options aren't good. High convergence can make performance seem suspect, depending on the initial components.

In addition, research from (Hafez et al., 2021; Peng et al., 2015), and (Zhang et al., 2021) shows how interrelated efforts with SA support hybridized methods for other research options or machine-learning solutions, which combine performance for better results. Research from Chen et al. 2022) and Vaish, Tiwani, and Siddiqui's (2025) performance evaluation for SA to other assessment metrics from the latest statistical analysis indicates similarly relevant microgrid performance assessments from Genetic Algorithms, Particle Swarm Optimization, and Differential Evolution as well.

Finally, where effective results prevail, multi-objective SA can extend beyond microgrid considerations, even with conflicting objectives, given SAI's potential for multi-solution development. Research by (Angelim and Afforso 2018) and Jiang, Ning, and Ge 2019) suggests that SA considers multi-objective projects; appropriately hybridized solutions can support Pareto optimal realities via compromise with an appropriately connected microgrid system.

In conclusion, applying the Simulated Annealing heuristic optimization process yields a uniquely arbitrary solution to problem-defining objectives complicated by competing interests defined across varying systems within the scope of microgrid projects. Ultimately, if researchers can capture Simulated Annealing's phenomenal possibilities through more well-defined challenges relevant to competing interests via solution-based definitions of project objectives, this paper champions the Simulated Annealing heuristic to provide microgrid systems with effective project challenges that complicate real-world operational potential, thereby fostering efficiency. Reliability in decentralized energy distribution systems develops excellent patterns across localized energy projects but better assessments beyond this scope offer sensationalizing benefits for all involved or impacted at any stage/successful implementation process.

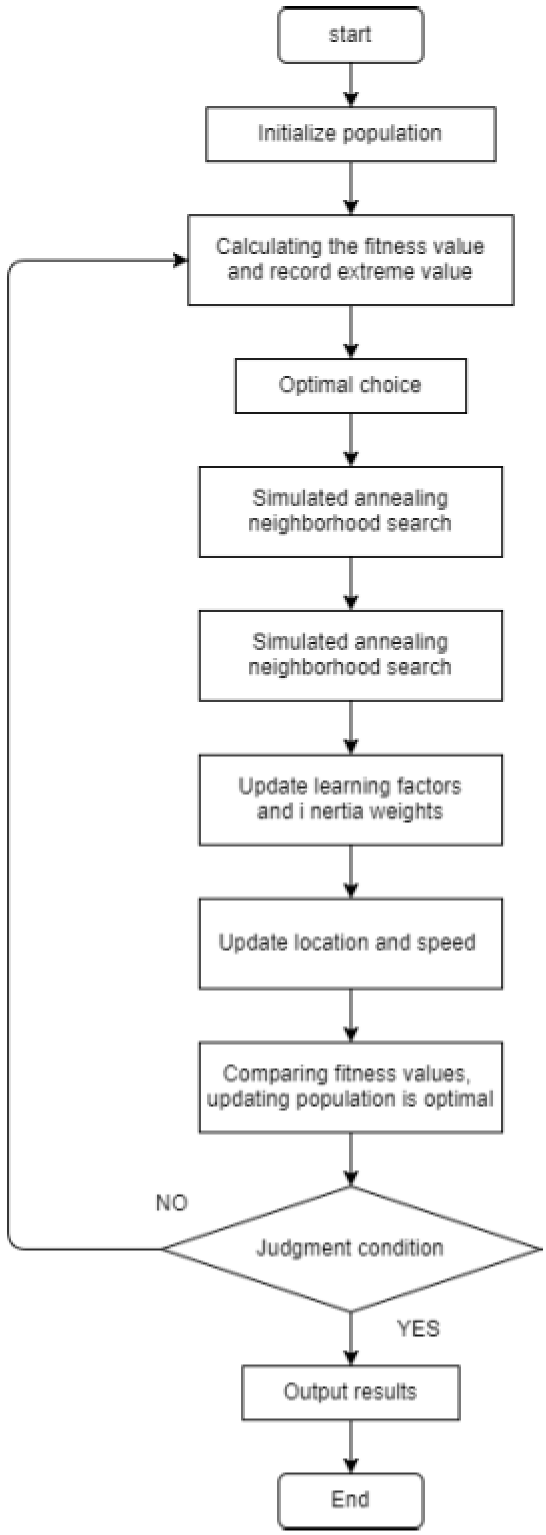

Figure 2. 16: Sample flowchart for the Simulated Annealing (SA) heuristic optimization
(Jiang et al.,2019)

2.4.5 Artificial Bee Colony Heuristic Optimization in Microgrid Systems

The Artificial Bee Colony (ABC) algorithm is based on the foraging pattern and behavior of honeybees. Three types of artificial bees (Ullah et al., 2022) are: employed bees, onlooker bees, and scout bees. The employed bee explores the search space around its food source. In contrast, the onlooker bee selects a food source in the hive based on its quality, while the scout bee explores an unknown area. The solutions generated by the algorithm are validated iteratively, and the positions of the bees (the food sources) can move within the predefined boundaries of the search space (Bagheri et al., 2021).

This literature review qualitatively assesses the applicability of the Artificial Bee Colony heuristic optimization algorithm to microgrid systems. A microgrid is a localized energy distribution system that enhances energy efficiency and resiliency. The effectiveness of the AIC algorithm is evaluated by examining its application in microgrid operations, with advantages and disadvantages assessed, as well as gaps in the current literature that require further study. A microgrid has become a practical solution for localized energy distribution. Microgrid systems must be optimized to enhance efficiency and performance. ABC is an algorithm that recognizes developments in optimized power generation/distribution based on the foraging behavior of bee colonies (Gonzalez-Castana et al., 2021).

ABC optimizes power generation distribution between the microgrid itself and the central grid. For example, Marzband et al. (2015) implemented the ABC algorithm for economic dispatch optimization based on offered generation, storage, and responsive load offerings. Additionally, Ullah et al. (2022) focus on operational decisions to achieve optimal power transmission costs between microgrids.

At this point, ABC serves to optimize power flow through and power supply to each grid, as well as identify the best options for energy storage, thereby fostering enhanced efficiency and resiliency for interconnected and central grid systems. For example, Paliwal, Singh, and Singh 2016 demonstrate the best energy management process for a microgrid as reliable and cost-effective for end users. Moghaddam et al. (2017) and Kamarposhti et al. (2021) utilized ABC optimization for optimal energy management in microgrids. Habib et al. (2020) implement ABC optimization for electric vehicle (EV) penetration and hybrid renewable sources, factoring economic dispatch optimization and contamination reduction from such initiatives.

ABC then optimizes sources of renewable energy to maximize solar, wind and other resources.

ABC determines demand response actions based on flexible load scheduling and demand-side resources. Moghaddam et al. (2017) and Dashtdar et al. 2022 implemented the ABC algorithm for demand response microgrid systems. Kuo (2021) analyzed how a microgrid's master-slave control can identify different operational states following a fault through self-healing; thus, an optimal ABC time for interconnection/disconnection from the large grid is determined through reliability-based economic forecasting.

ABC finds solutions in a limited solution space through employed and onlooker bees, each of whom traverses a designated perimeter; otherwise, they would avoid local optima if they continuously returned to source areas in search of more immediate solutions based on real-time feedback from foraging assessments. (Cayanini et al 2016; Ullah et al. 2022; Bharatbhai and Gupta 2022) Confirm that ABC operates with a population of solutions (bees) that makes it possible to find solutions within multiple sectors of the solution space at the same time. This is especially useful for microgrid solutions that may span multiple dimensions, with solutions that cross various areas.

Research articles from (Paliwal et al, 2020) indicate that microgrid optimization solutions come with nonlinear objective functions and constraints due to the variety of energy resources, loads and storage. ABC can support non-linearity; however, it has phases that operate at local and global levels, which constitute both search attributes for effectively developing solutions that are responsive to non-linearity in optimization. Microgrid systems must consider optimal operational constraints related to demand, renewable availability, and storage options. ABC can promote feasible solutions through local searches and/or application adjustments to constraints that make solutions more tenable (Marzband et al., 2015; Saeed et al., 2021).

As a population-based algorithm like the rest, (Hu et al 2020) and (Gao et al 2018) found that ABC can be parallelized; this facilitates efficiency of computational application, especially for microgrid systems with extensive reach or instances where real-time optimization is needed (Peng et al., 2022). Thus, ABC is simple to use, as it requires fewer parameter adjustments than other algorithms.

As with any other algorithm, however, there are concerns about parameterization; (Bai, et al 2017) found a proper parameter tuning approach that achieves convergence most frequently for quality improvement solutions sought in microgrids—parameter values do affect performance, and microgrid systems must adjust them for efficacy.

(Zhang et al 2020), However, found that ABC by itself converges slowly over iterations; while it finds optimal solutions, they're not always done in a timely fashion. As with many others, it needs extended iterations for complex objective functions pertinent to microgrid systems. Thus, a balance between exploration and justification needs to be found; findings from literature support (Bai, et al 2017; Ullah et al. 2023) that ABC balances exploration versus exploitation like honeybees that exploit what they know while searching out new resources. This is beneficial in microgrid optimization as well as it homes in on nearly optimal solutions without getting stuck in local optima.

Other algorithms used historically with ABC include (Singh et al., 2021), who confirmed that hybridizing with PSO maximized sizing elements for hybridized systems, thereby improving techno-economic goals. (Habib et al. 2020) used PSO for economic dispatch optimality from hybridization. Other studies include (Jouda & Kahraman, 2022) who used PSO and ABC for optimal stability via voltage/frequency integrity; again, microgrid operation via demand side management was achieved through Genetic Algorithm Artificial Colony Bee hybridization per (Dashtdar et al., 2022).

Multi-objective optimization problems are often part of microgrid discourse, since requirements may conflict; some studies assess such an approach with many studies (Paliwal et al, 2020) applied multi-objective conflict problems that microgrid objectives must consider—(Habib, et al. 2020; Peng et al, 2022; Zaid et al 2023) extended ABC to effectively solve multi-objective problems through proper evaluation techniques that account for trade-off diversifications among objectives.

The simultaneous approach was used by Habib et al. (2020), who tested three objectives of operation cost/contamination cost/carbon emissions through V2G technology. Ye et al. (2022) studied the group operation of a microgrid cluster, determining the economic/environmental benefits of well-regulated group operation processes, which are hypothetically applicable to V2G technology endeavors. The practical issue will only be realized if parameters allow, however, because real-time circumstances fluctuate, what research showed to be feasible variations were deemed realistic change agents.

Overall, the ABC heuristic represents promising optimizations among systems within a microgrid integrated solution, thus far against other solved optimization dilemmas to date, with various components showcasing integrated applicability of what works best for specific system needs/complementation against objective functions at complicated intersections—solving some intersections of whys/wheres/hows and pursuing effective hybrids will present the next problems.

Ultimately, this study sets an important precedent relative to Heuristic ABC optimization in systems that find microgrid systems most applicable relative to the resource essential optimization problems microgrid systems face as decentralized energy solutions seeking energy efficiency/resiliency and sustainability as compared to cumulative learnings across results found within other topics studied thus far outside of microgrids as cumulative comprehensive successful achievements.

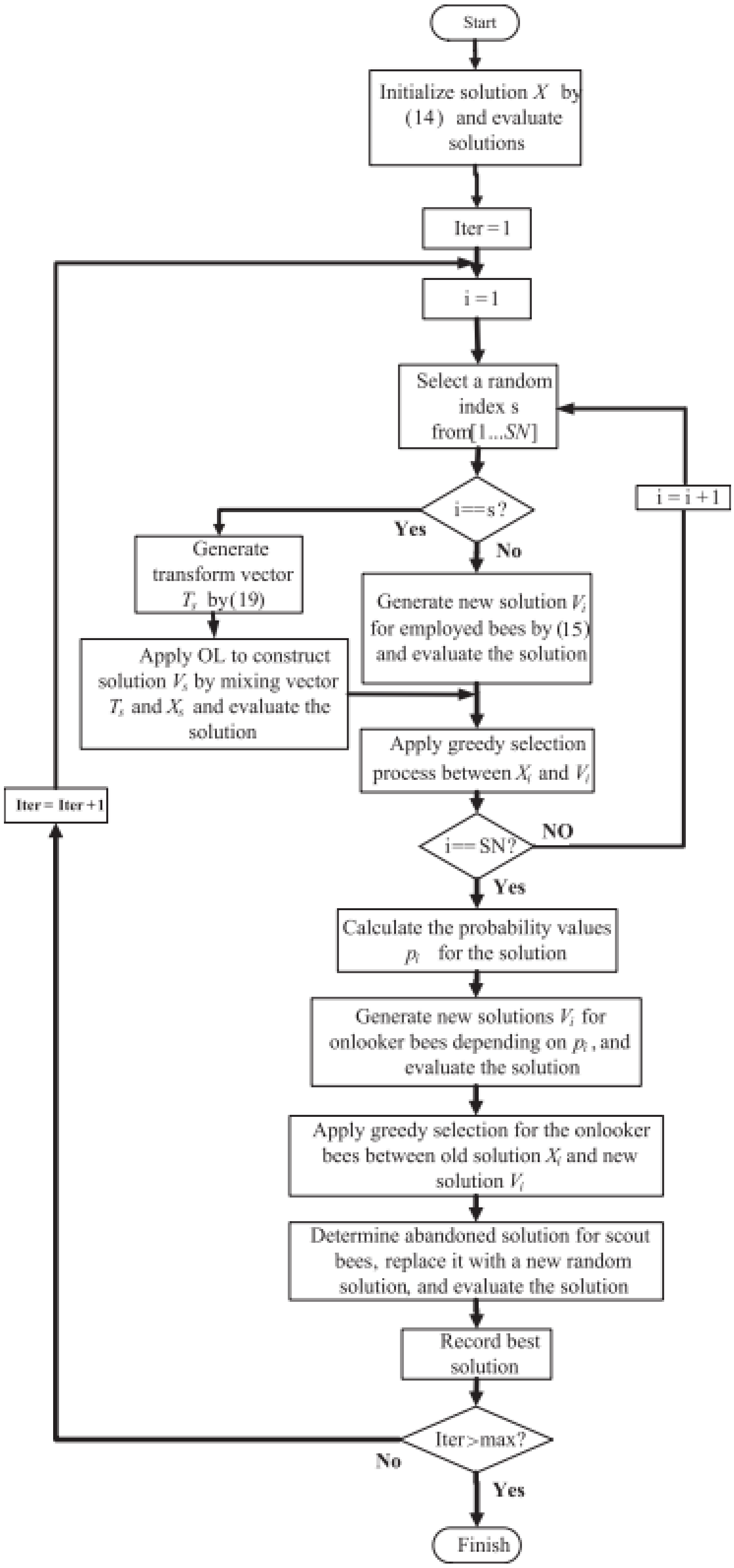

Figure 2. 17: Typical flow chart for the Artificial Bee Colony (ABC) algorithm
(Bai et al., 2017)

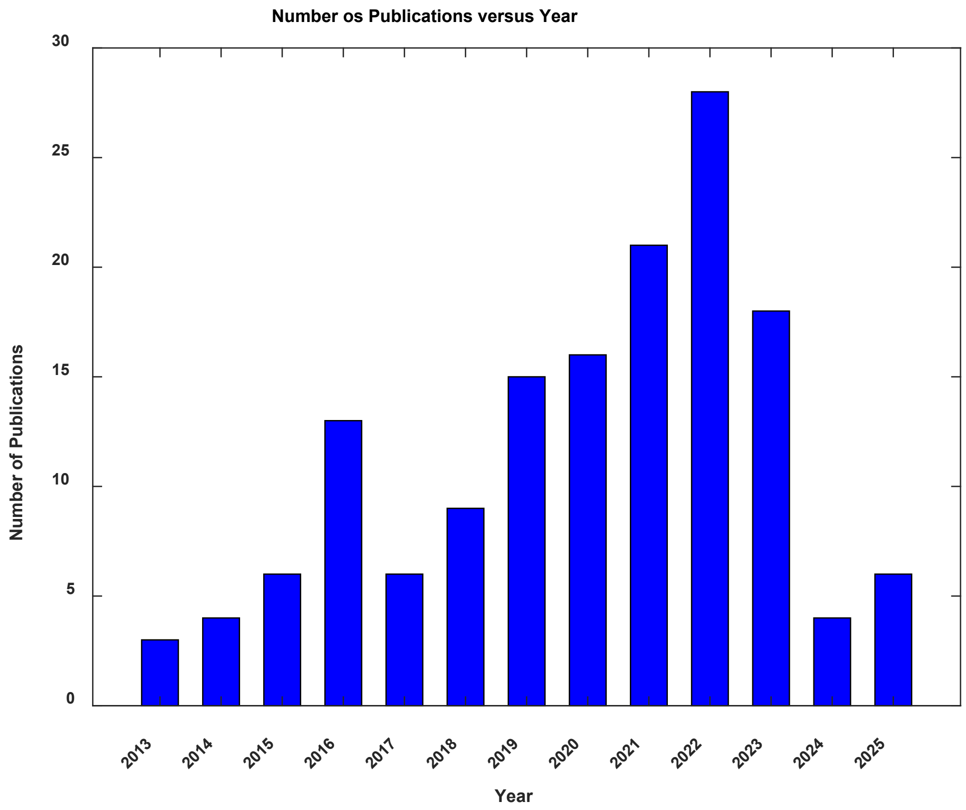

Figure 2. 18: Bar graph for publication for heuristic optimization methods for microgrid applications

Table 2. 5:Comparison of heuristic optimization methods for Microgrid Systems

Paper	Algorithm used	Application on Microgrid System	Advantages	Limitations and challenges	Future Directions
[Zheng, Z et al. (2023); (Daniel, L., Chaturvedi, & Kolhe, (2023); Nemati, Braun, &Tenbohlen, (2018); Torkan, Ilinca, & Ghorbanzadeh, (2022); Elsied, M.,et al (2014); ;Askarzadeh, A., (2017); Arif, Javed, and Arshad, (2014); John, Jadoun, & Kudva, (2022); Yeh, W.C et al. (2020); Yu,K et al (2015) ; Desantis, Rizzi, & Sadeghian, (2017); Wang, Rousis, & Strbae, (2021); Ahmadi Ahangar, R et al. (2019); Shariazadeth, F et al. (2014); Elsied, M et al. (2016); Suresh, & Janik, (2019); Zheng, D et al.(2018); Semero, Y. K. (2018); Chen, J et al. (2013); Zhou, X. Y et al. (2013); Ghavifekr. A.A. (2021)]	Genetic Algorithm	-Economic Dispatch -Energy management. -Renewable Integration -Demand Response -Grid Connectivity	-Versatility -Global Search and Parameter Tuning -Parallelism and Scalability -Real-Time Implementation	-Convergence Speed -Parameter Tuning	- Hybrid Approaches -Multi-Objective Optimization
[Phroximmity, Doumbia,& Lupien St. Pierre, (2020); Karthikeyan, Manikandan, & Somasundaram, (2016); Zhang, Wang, & Lu, (2022) ; Yeh, W.C.et al.(2020); De, & Mandal, (2022); Hossain, M.A.,et al.(2019); Aguila-Leon, J.,et al (2022); Jordehi, Javadi, & Catalão, (2020); Li, C.,et al.(2020); , Radosavljević, Jevtić, & Klimenta, D., (2016); Shan, Hu, & Liu, (2021); Phommixay, S., et al. (2020); Ali, L et al. (2021); Yavuz,A et al.(2023); Soares, J et al. (2023); Liang, & Zou, (2022); Hou, & Flyimura, (2023); Proximmity, Doumbia, & Cui, (2021); Hossan, M.A et al. (2019); (Radosovljevic, Jevtic, &Kilmenta, (2016); Albogamy, F.R et al. (2022); (Radosovljevic, Jevtic, and Kilmenta, 2016); (Albogamy, F.R et al. (2022); De, & Mandalk, (2022); Xin-Gang, Z et al. (2020); Zhao et al 2022 Ahmadipour, M et al. (2022); Yavuz, A et al. (2023); Zeng, Y et al. (2022); Zhang, Wang, and Lu, (2022); Yu, L., et al. (2014)]	Particle Swarm Optimization	- Economic Dispatch - Renewable Integration - Demand Response - Grid Connectivity	-Ease of Implementation -Population-Based Algorithm -Energy Management System -Scalability	-Premature Convergence. -Parameter Sensitivity. -Uncertainty and Dynamic Condition. -Integration of Renewable Energy. -Diversity Preservation.	-Hybrid Approaches. -Multi-Objective Optimization. -Dynamic Environments.
[Trivedi, I.N.,et al. (2015); Suresh, V.et al. (2023); Marzband, M., et al. (2016); Fatima, I., et al.(2017); Güven, A.F., Yörükeren, N. and Samy, M.M., (2022); Emerson, N. and Srinivasan, S., (2015); Kreishan, & Zobaa, (2021); Priyadarshi, N., et al (2019); Lorenzini Kamarposhti & Solyman, (2021); Marzband, M., et al.(2016); Albogamy, F.R., et al.(2022) ; Movahedpour, M., et al. (2022); Fatima, I., et al.(2018), (Sellamna et al 2018;Khaleel, M., (2023); Gao, Wu, &Wang, (2023) ; Kreishn et al 2023 Marzband, M et al. (2016); Silva, & Han, (2019); Lorenzini, Kamarposhti, & Solyman, (2021);	Ant Colony Optimization	-Economic Dispatch -Energy Management Systems -Renewable Integration -Demand Response	-Distributed Nature. - Scalability	-Convergence Speed -Parameter Tuning -Sensitivity to Problem Formulation	-Hybrid Approaches -Multi-Objective Optimization -Dynamic Environments

Kreishan, & Zobaa, (2023) (Olivsa.F. et al. (2017); Kreishan, and Zobaa, (2023); Xu, Yang, and Li, (2019); Khelifa, & Laouar, (2020); Kreishan, (2022); khelifa, and Laouar, (2020); Gao et al 2021; Zhao, (2025); (Deng, Xu, & Zhao, (2019); Sellamna, H., et al. (2019) Mohamed, A.H., et al. (2023); Güven, Yörükeren, & Samy, (2022); Abo-Elyousr, Guerrero, & Ramadan, (2021); Kefayat, Ara, & Niaki, (2015); Kreishan, & Zobaa, 2023); Trivedi, I.N., et al.201); Priyadarshi, N., et al. (2019); Skackauskas, & Kalganova, (2023);		-Grid Connectivity -Routing and Scheduling.			
[Arfeen, A.A et al. (2021); Jiang, Ning, and Ge, (2019); Jun, Jinhui, and Zhe, (2021); Velik, and Nicolay (2014); Angelim, & Affonso, (2018); Hafez, A.A., et al. (2021); Aiswariya, and Ahamed, (2020); Zhang, W., et el. (2018); Abdel-Mawgoud, H., et al. (2021); Qian, L.P., et al. (2013); Aiswariya, & Ahamed, (2020); Han, N., et al. (2019); Velik, & Nicolay, (2014); Ignant-Balaci, Petreus, and Ferencz, (2022); Aiswariya, and Ahamed, (2020); Ignat-Balaci, Petreus, and Ferencz, (2022); (Bayoumi, E.H., (2019); (Bagheri.Tolabi,H., Hossani, &Shakarami, (2016); Teekaraman, Kuppusamg, & Nikolovsci, (2019), and Azab, & Serrano Fontova, (2021); Islam, M et al. (2021); Gli-Gonzalez, Montaya, & Hernandez, (2023); (Zhang, Wu et al. (2018); Arfeen, Z.A.,et al (2021); (Fares, Fathi, & Mekhilef, S., (2022); Huang, and Hsieh, (2011); and Vega-Rodriguez, (2007); Jaraiz-Simon, (2013); Hafez, A.A., et al. (2021); Peng, D., (2015); and Zhang, J., et al. (2021); Chen, K., et al. (2022); Vaish,Tiwani, and Siddiqui, (2023); Angelim, J.H.and Afforso, C.M. (2018); Jing, Ning, and Ge, (2019); Zhang, G et al. (2018); Peng et al 2015; Vaish et al 2025	Simulated Annealing	- Economic Dispatch -Energy Management -Renewable Integration -Demand Response	-Global Exploration -Flexibility Simplicity -Robustness to Noise and Uncertainty -Handling non-linearity	-Convergence Speed -Sensitivity to Initial Solution	- Hybrid Approaches and Comparative Performance -Multi-Objective Optimization

[Ullan, K et al. (2022); Bagheri, Jabbari, & Mobayen, (2021); Gonzalez-Castana, C et al. (2021); . (Marzband, M., et al (2015); Ullah, K., et al. (2022); Paliwal, Singh, and Singh, (2020); Moghaddam, M.M., Marzband, and Azarinejadian, (2017); Kamarposhti, Colak, and Eguchi, (2021); Habib, H.U.R., et al. (2020); (Anbarasu, Subramanian, & Karthikeyan, (2021); Moghaddam, Marzband, and Azarinejadian, (2017); Dashtdar, M., et al. (2022); Kuo, M.T., (2021); Cayanini, L et al. (2016); Bharatbhai, and Gupta, (2022); Paliwal, Singh, and Singh, (2020); Rabiee, A et al. (2020); Marzband, M et al (2015); Saeed, M.H et al. (2021); Hu, H et al (2020); Gao,R. et al (2018); Peng, H. et al (2022); Bai, Eke, and Lee, (2017); Zhang, H., (2020); Zamee, Han, & Won, (2023); Bai, Eke, and Lee. (2017); Ullah, K. et al. (2020); Peng, H et al. (2022). Singh, S et al. (2021); H.U.R., et al. (2020); Jouda, and Kahraman, (2022); Dashtdar, M., et al. (2022); Paliwal, Singh, & Singh, (2016); H.U.R et al. (2020); Peng, H et al. (2022); Zaid, S.A et al. (2023); Habib, H.U.R., et al (2020); Ye, R., et al (2022)]	Artificial Bee Colony	-Economic Dispatch -Energy Management -Renewable Integration -Demand Response -Grid Connectivity	-Diversity: -Handling non-linearity: -Adaptability to Constraints. -Parallelism. -Ease of Implementation	-Convergence Speed -Exploration Exploitation Balance	-Hybrid Approaches -Multi-Objective Optimization -Dynamic Adaptation
Duy.C et al 2024; Lobos-Cornejo.et al 2025; Chen. et al 2025;Jouma, et al.,(2024); Vasu. Kumar &Jasmi (2025); Song. et al.,(2025);(Tukkee et al., 2024); (Singh et al., 2022); (Aljribi & Yusupov, 2024);Jasim et al., 2022); (Mirjalili et al., 2014; Jain et al., 2023;Pradhan et al., 2016);(Pandit et al., 2022)(Dubey et al., 2020);(Jiang et al., 2024)(Chen.B et al.,2025); (Chen.B et al.,2025); Song.D et al., (2025).	Grey Wolf Optimization (GWO				

2.4.6 Grey Wolf Optimization Method

The GWO method is derived from the leadership hierarchy of wild grey wolves and their hunting strategies. Therefore, these authors derive their GWO algorithm from the social structure and hunting of grey wolves. The Grey Wolf Optimization is a population metaheuristic with a social hierarchy and hunting strategies that mimic those of the grey wolf (Huynh et al., 2024). The method is also adaptive, meaning it can provide solutions in linear and multimodal situations without creating complications typical of other methods. In the microgrid research arena, GWO was used for optimal economic load dispatch with battery/storage with reduced operational cost (Aljribi and Yusupov, 2023) and optimal sizing of hybrid microgrids with low TNPC (Tukkee et al., 2024; Jasim et al., 2022).

The GWO's effectiveness is supported by the literature, which shows that it has been used for nonlinear, multi-objective optimization problems in particular. For example, Aljribi and Yusupov (2023) performed optimal energy dispatch for battery-storage microgrids, demonstrating reduced operational costs and improved dispatch efficiency. Tukkee et al. (2024) performed optimal sizing of standalone hybrid microgrid systems that achieved lower TNPC, reduced energy losses, and lower emissions than the base case.

Furthermore, Jasim et al. (2022) proposed GWCSO (GWO–Cuckoo Search Optimization) for Grid-Connected Microgrid Sizing, which showed lower annual costs than Cuckoo Search and GWO alone, with better NPC and levelized cost of energy (LCOE), suggesting that GWCSO is more robust than independent GWOs.

The process of applying GWO in a hybrid microgrid consists of five steps (Mirjalili et al., 2014; Jain et al., 2023;Pradhan et al., 2016):

- Position vector of a wolf.
- Encircling the prey.
- Updating position using **α**, **β,** and **δ**
- Decreasing parameters
- Termination

The GWO algorithm has garnered significant attention for its simplicity, few control parameters, and effective balance between exploration and exploitation. This makes it competitive with other metaheuristic methods, such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) (Pandit et al., 2022; Dubey et al., 2022). However, like many metaheuristic approaches, its performance can decline in high-dimensional spaces or when the initial population's diversity is limited. To mitigate these issues, recent research has introduced hybrid or enhanced versions, such as Elite Inheritance and Balance Search strategies, that improve convergence speed and accuracy (Jiang et al., 2024).

(Huynh et al.,2024) proposed GWO to apply and obtain an optimal configuration. The sources of energy involved are PV, a diesel generator, a BESS, and a supercapacitor energy storage system. A hybrid method combining GWO and Robotic Process Automation was used to achieve a balance between supply and demand. The outcomes of their research include real-time load scheduling, demand response optimization, and the integration of controllable and non-controllable loads. It also enhances flexibility and efficiency (Chen et al.,2025). Additionally, studies conducted by Jouma et al. (2024) employed GWO to minimize daily operational cost, including the cost of procuring energy from the primary grid, emission cost, and revenue from selling energy to the primary grid. Subsequently, Vasu et al. (2025) used GWO for demand-side management. Thus, optimizes load scheduling and cost reduction for power consumed. GWO enhances energy efficiency in the multi-energy microgrid research conducted by (Ji et al. 2025).

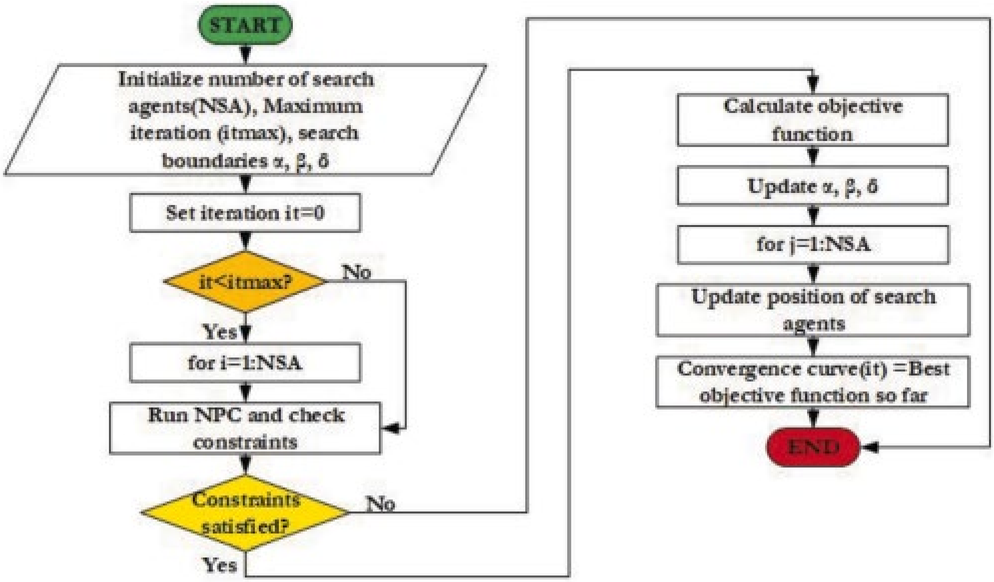

Figure 2. 19: **Typical Flowchart for GWO**
(Aeggegn et al.,2024)

2.4.7 Dynamic Arithmetic Optimization Algorithm

The Dynamic Arithmetic Optimization Algorithm (DAOA) is a family of arithmetic-optimization variants that introduce dynamic control mechanisms, such as time-varying parameters, random/binary operators, Levy steps, and opposition learning, to improve the exploration-exploitation balance of the original Arithmetic Optimization Algorithm (AOA). The literature indicates that the DAOA idea became interesting around 2022; recent work by the researchers has applied DAOA variants to several power-system problems. The problems include renewable distributed generation placement and control for power-quality improvement, hybrid microgrid energy management under uncertainty, and EV charging station (EVCS) siting on the distribution network. The most prominent, peer-reviewed power application is (Eid & Alsafrani, 2024).

Upsizing the integration of renewable energy sources at the distribution level of the power system increases system power losses and reduces stability. There is a lack of explicit guidance on the use of optimization methods for distribution networks (Eid & Alsafrani, 2025). In this study, arithmetic optimization was considered one of the prominent techniques suitable for microgrid optimization. (Dey and Kumar Roy, 2025) used DAOA to design a PV-Wind-BESS hybrid system in a radial distribution network (RDN). The results indicated that DAOA produced superior performance in terms of power loss and voltage deviation, as well as benefits in active power loss cost.
Again, the emphasis was on the algorithm's fast response and high solution quality for the PV-Wind-BESS hybrid system. Furthermore, (Fotis, 2025) applied an advanced DAOA method to determine an optimum placement and size of EV charging stations, while (Barua et al.,2024) utilized Arithmetic Optimization Algorithm (AOA) combined with the Levy random step, the Levy arithmetic algorithm (LAA) for the enhancement of getting the optimal solution for energy management system for a PV-Wind-Diesel microgrid system. (Qiu et al.,2023) developed an optimal scheduling of a solar-surface water source heat-up system using AOA. The application of DAOA was delved into to enhance power quality in unbalanced distribution systems by controlling distributed generators for demand balancing. Phase’s best location, size, and power factor were determined through the application of DAOA (Eid and Alsafrani, 2024). Their study improved the voltage profile and reduced the voltage variance across all three phases of the system.

(Abualigah et al.,2024) Conducted a comprehensive review on AOA where different fields of study, including microgrid, were mentioned as assistance for researchers in the future (Qu et al.,2024). DAOA was used by Ibrahim et al. (2025) to improve and enhance power system management for a grid-integrated PV-EV battery system. Their study provided a techno-economic analysis and a comprehensive solution to the evolving landscape of EV integration with the grid. (Dhal et al.,2024) captured data analysis for the different publishers used from 140 papers reviewed and presented that, 28%of Springer, 18%of IEEE, 13% of Elsevier, 11% of MDPI search engines for the application of AOA-based algorithms. Subsequently, (Mohamed et al.,2023) presented a study on a maximum power tracing grid-connected PV system. The microgrid system with 100kW PV capacity used MATLAB software environments, and the comparison was conducted with GWO, GA, and PSO for verification.

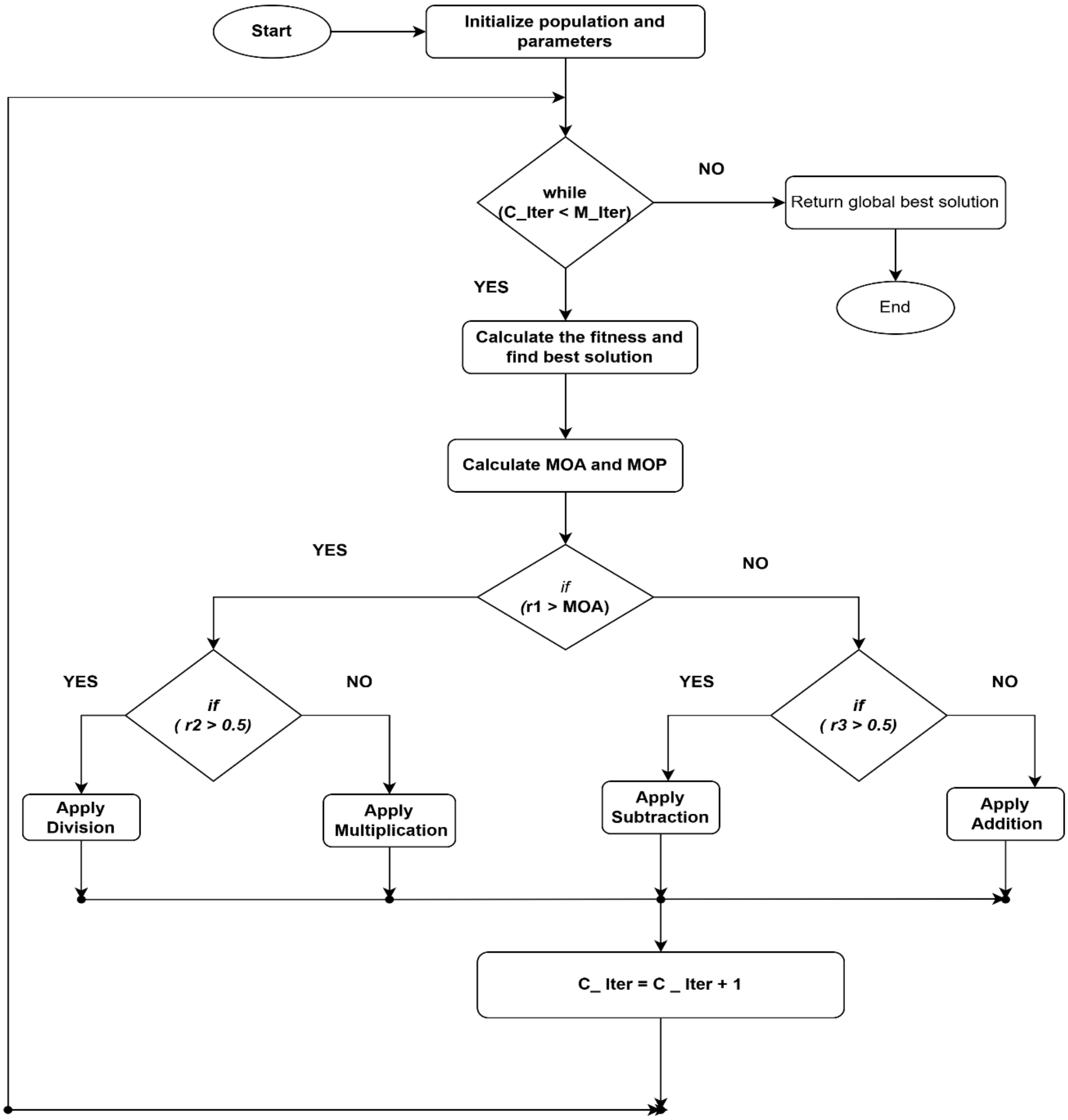

Figure 2. 20: Typical flow chart for Dynamic Arithmetic Optimization Algorithm (DAOA)
(Dhal, et al.,2024)

2.4.8 Discussion on Heuristic Optimization Methods

The literature from 2013 to 2025 showed a peak in publications in 2023. The use of heuristic optimization increased gradually from 2013 to 2015. Nevertheless, publications increased again in the year 2016. In 2017 and 2018, it decreased again, while the increment emerged again from 2019 to 2025. Consequently, only 17 publications were reviewed in 2023. From 2024 to 2025, only Table 2.5 compares heuristic optimization methods for microgrid systems, highlighting their applications, advantages, limitations, and challenges, as well as future directions.
Moreover, ACO (41) has the most papers, followed by ABC (39), SA (38), PSO (32), Genetic Algorithm (21), DAOA (10), and then GWO (20).

2.4.9 Discussion of the Optimization Problem Solution Methods

Summary of the applications of optimization algorithms: Genetic Algorithm, PSO, and some other evolutionary and nature-inspired algorithms used for the optimization, control, and power generation schemes. Moreover, a report on the analysis of methods and potential applications of advanced algorithms for optimization, control, and power system management of hybrid renewable energy sources is also presented.

The review of cost optimization of microgrids via PSO (Phommixay et al, 2020) emphasized that economic analysis is an essential tool in assessing the performance of microgrid operations and sizing. Most of the optimization techniques used in microgrids are classical and artificial intelligence-based. Therefore, according to their research, PSO was the most commonly used technique due to its superior performance and flexibility (Tazi et al., 2019; Phammixay et al., 2020). Classical and Artificial intelligence techniques are tabulated in their work. Artificial intelligence methods are considered a suitable technique for cost optimization because they can be combined with other methods, whereas classical optimization methods cannot provide optimal solutions.

According to Oymak and Tur (2022), it is more accurate to use systems based on mathematical algorithms for the distributed generation of renewable energy. Their work review outcomes indicated that PSO is a better method because no algebraic operations are required to evaluate the change in the target function. (Meilinger, 2022) Research work is a review of new developments in optimization techniques. Additionally, Eluri and Naik (2021) also presented a review of optimization techniques of microgrids.

In a nutshell, this review highlights the latest scenarios, solar potential, wind energy, and control strategies and optimization methods for microgrids, which are elaborated in detail. Moreover, their work also includes basic concepts of microgrid problems encountered in grid integration, as well as distributed energy resources (Eluri & Naik, 2021).

In this lexicon, Tazi et al. (2019) conducted a well-described review of the optimization techniques applied to microgrids from 1990 to 2018. Their work outlines optimization methods such as Reinforcement learning, data-driven modelling, mathematical programming models, heuristic and metaheuristic optimization, non-linear control, and other algorithms, such as auctions and programming platforms. It discusses and compares them based on convergence time, application areas, and main features. Most of the algorithms in their research are well-studied and widely used to address several issues in microgrid systems. Particle Swarm Optimization (PSO) is a well-known and widely used algorithm in microgrids due to its efficient memory usage and rapid convergence.

Moreover, their work shows that most algorithms perform well, but their computational resources, memory requirements, and learning time are expected to be very high (Tazi et al., 2019). An overview of their study indicates that many researchers used microgrids as time constants and intended them to be PnP. Finally, it is important to research the impact of the proposed optimization frameworks and algorithms under time-variant topologies and to finalize guidelines for adopting the existing algorithm (Tazi et al., 2019).

(Mekontso et al, 2019) presented another review study on recent optimization techniques for sizing renewable energy systems. Their work also described various methodologies, standards, and the recent trend toward optimization in hybrid RES. Accordingly, bio-inspired methods of sizing microgrids have been reviewed. Artificial intelligence methods have great potential; therefore, appropriate application is highly recommended due to their impact on global prosperity.

(Salehi et al., 2022) provided a comprehensive review of several optimizations for microgrids, addressing practical and technical constraints, information and communication delays, and computational burden. Furthermore, single- and multi-objective solutions, categorised by optimization methods, are well described in their research work. In this regard, performance can be improved by minimizing computational burden and obtaining correct optimal solutions (Salehi et al., 2022). They also mentioned that microgrids deploy effective energy harvesting from distributed energy resources.

Accordingly, optimization problems extracted from the literature; therefore, Figure 2.8 depicts the classification of optimization problems.

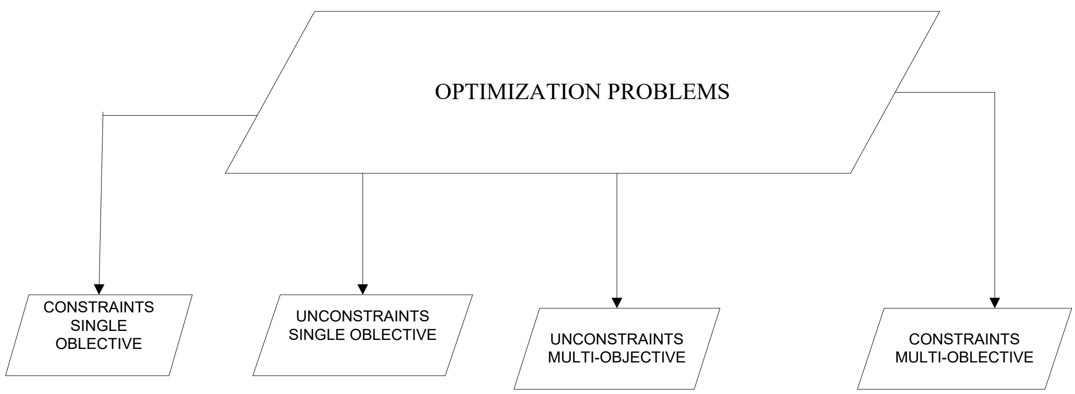

Figure 2. 21: Classification of optimization problems
(Salehi et al 2022)

Most review publications in the literature share the same objective functions: minimizing cost, reducing greenhouse gas emissions, and curtailing load. The research conducted covers recent optimization methods currently available. Table 2.6 summarizes their survey of microgrid techniques. The research outcomes indicate that microgrids are of great importance in power systems for achieving environmental benefits, improving voltage profiles, reducing distribution losses, and enhancing system stability. Nonetheless, it was also stated that as generation integration increases, the power grid might face serious challenges with voltage and frequency. Thus, there is a need for the prevention of degradation on the existing grid, and this requires proper planning as well as planning of renewable energy-based microgrids (Suchetha, and Ramprabhakar, 2018).

In this lexicon, their results indicate that most of their objectives were successful, and the most commonly used algorithms are the Genetic Algorithm, PSO, and Fuzzy logic. Advanced optimization techniques achieve even better results due to their superior performance; therefore, they can be used to solve optimization problems such as optimal power flow, optimal load dispatch, reliability enhancement, and supply chain management (Jyot Saharia et al., 2018). A Flower Pollination Algorithm and PSO were utilized to optimize the microgrid system. Results indicated that combining the two methods produces better results (Ali, 2022).

Various optimization techniques and criteria for microgrid optimization are summarized. Thus, justifying the investment cost and ensuring the economic and reliability of the microgrid. The resulting work indicated that computational alternatives, such as evolutionary, heuristic, and non-classical algorithms, yield better results than conventional methods. Furthermore, superior performance was achieved by combining intelligent optimization and adaptive techniques for multi-objective optimization problems (Suchetha & Rampabhakar, 2018).

Again, Doumbia and St. Pierre conducted a review of optimization techniques, especially PSO, showing PSO's high performance and flexibility compared with other techniques. Their work is based on the cost minimization of the microgrid's operation as well as sizing (Phommixay et al., 2020). Table 2.6 shows the types of optimization methods used on microgrid systems.

Table 2. 6: Types of optimization methods (Doumbia and David, 2020)

Artificial intelligence method	Classical method
Artificial Neural Network	Linear Programming
Fuzzy Logic	Nonlinear Programming
Genetic Algorithm	Quadratic Programming
Ant Colony Optimization	Evolutionary Programming
Particle Swarm Optimization	Dynamic Programming
Simulated Annealing	Interior Point

(Mohamad and Subiyanto, 2022) conducted robust optimization and sustainable research to develop a feasible microgrid design at low cost. Both Genetic Algorithm and Particle Swarm Optimization are combined to achieve the objectives of their research, producing better solutions with faster convergence and lower cost than conventional methods. The percentage decrease in costs is 11.99%. Moreover, a combined algorithm has developed a self-sustained RES at minimum cost (Mohamad & Subiyanto, 2022).

Table 2. 7: Summary of the review publications on optimization techniques used on microgrid

References	Year	Number of citations	Comments (Research gaps found)
K. Tazi et al	2019	165	▪ Power utilization and delivery need more research. ▪ A Multi-Agent System is the best control strategy to handle all optimization problems in power grids
G.S. Thirunavukkarasu et al.	2022	182	▪ EMS is an essential component of the MG configuration. ▪ An optimal EMS technique is proven essential. ▪ Meta-heuristics algorithms and multi-agent-based algorithms are computationally less expensive to address the complex EMS problem and result in better efficiency. ▪ The need for futuristic EMS to focus more on the collaborative community MG set up and develop more accurate forecasting and scheduling algorithms to increase the economic and computational benefits.
S. Ishaq, I. Khan, S. Rahman et al.	2022	214	▪ Optimization techniques are categorized based on the main objective according to requirements or as per the method used for achieving optimality. ▪ Optimization techniques may also be used in the choice of sizing as well as siting of RES in the MG. ▪ Optimization techniques are also applied for the control as well as operational management of MGs.
Gao, K. et al	2021	114	▪ Energy generation system, an energy distribution system, an energy storage system, and energy end users are included in their review. ▪ GAs and SA algorithms are the most commonly used optimization algorithms. ▪ Literature bibliometric analysis was provided. ▪ Some models and methods are theoretical formulations without a real application focus. ▪ The optimization of microgrid operation will be much more difficult in the future.
Sengthavy Phommixay, Mamadou Lamine Doumbia1 and David Lupien St-Pierre2	2020	134	▪ An economic tool for MG operations and sizing can be helpful for research on MGs and other power systems. ▪ Provides a deeper understanding of cost analysis in MG optimization. ▪ Features of sizing and operations for cost minimization are analysed.

			▪ Analysis of planning and scheduling problems,to minimize the cost is presented.
A.Oymak and M. R. Tur	2022	61	▪ It was concluded that it would be more accurate to use systems based on mathematical algorithms in distributed generation optimizations. ▪ Studies can be carried out on energy storage systems to increase the efficiency of renewable energy resources.
Vincent Meilinger	2022	10	▪ Al of the discussed papers provide relevant additions to the unit commitment problem. ▪ Proposed multiple improvements to (micro) grid operation, which will be increasingly important for the rising share of renewable energy. ▪ The distributionally robust optimization approach is especially worth further research in, since it improves the already familiar robust optimization through the use of ambiguity sets.
Himabindu Eluri and M. Gopichand Naik	2021	55	▪ Management energy is discussed as an inevitable challenge to manage distributed renewable sources connected to the grid. ▪ Renewable energy sources create new challenges in devising enterprises of the electric power grid. ▪ To overcome the arguments of voltage, rise, voltage swell, and protection issues in utility of AC grids, solutions have been proposed by "Microgrid (MG)" and "Smart grids (SGs)" for future electrical power systems. AC Microgrids, DC Microgrids, and Hybrid Microgrids have been discussed. ▪ Grid codes, which are used to evaluate the stability of microgrids, are also discussed.
N. Karthik, A. K. Parvathy, and R. Arul	2020	68	▪ The superior performance of optimal generation scheduling approaches in microgrids has drawn attention from researchers and power system companies all over the world. ▪ Most of the reported approaches have considered the microgrid in a grid-connected mode. ▪ All optimization techniques have considered the power generation limits in the set of constraints. ▪ Most of the approaches have considered the microgrids as unbalanced distribution systems. ▪ New appropriate and comprehensive analysis software to solve the optimal generation scheduling problem.
C. Mekontso, A. Abdulkarim, I. S. Madugu, O. Ibrahim and Y. A. Adediran	2019	83	▪ Several optimization methods and optimization design criteria are explained with their strength. ▪ Reliable transformation of the energy sources into electrical energy, at a minimum cost, remains a challenge in designing RES. ▪ Artificial intelligence application in RES will impact the performance of RES for the ▪ world prosperity.

N. Salehi et al.	2022	181	▪ The performance of the optimization algorithms can be enhanced by incorporating deep learning approaches. ▪ planning and scheduling programs for MGs are investigated to determine the practical and technical specifications of the operating system. ▪ An energy management system is essentially required not only to guarantee the optimal operation and economic feasibility. ▪ A more appropriately utilized optimizer results in a more reliable MG operation.
Marina Petrelli1 and, Paco Vasco Aldo Melià	2019	22	▪ A complete evaluation is essential in order to give higher chances of success to rural electrification projects. ▪ There is a great need for further research on the integration of optimization.
Twaisan, K.; Barı¸sçı, N.	2022	119	▪ Future energy networks will encounter a variety of issues as the percentage of sustainable energy resources increases. ▪ In comparison to grid-connected mode, the microgrid's total operation cost is significantly higher in isolated mode. ▪ The proposed paradigm for co-optimizing the construction and planning of microgrids may be used in larger-scale community initiatives.
Seyfettin Vadi, Sanjeevikumar Padmanaban, Ramazan Bayindir , Frede Blaabjerg and Lucian Mihet-Popa	2019	106	• Optimization and control methods are used to maintain energy continuity.
Gao, K.; Wang, T.; Han, C.; Xie, J.; Ma, Y.; Peng, R.	2021	114	▪ From 2014 to 2016, operation management, inverter, smart grid, unit commitment, stability, and distributed generation were hot keywords. ▪ Although the pace of development of operation optimization of microgrids has been rapid in recent years, there is still a long way to go. ▪
B Goutham, H An Anoop	2020	35	▪ Nearly 95% of the MGs are fitted with renewable energy sources.
Amit Patidar, and Dr. Arvind Kumar Sharma.	2022	13	▪ Reduction of both installation and maintenance cost obtained through the use of optimization techniques. ▪ The system is able to produce maximum power. ▪ Analysis was deployed by considering Gaussian distributed hourly load demand. ▪ Generation of a plot of the probability of failure against unmet load.
Islam et al	2021	127	▪ The summary of recent studies indicates that, compared with dealing with the energy optimisation problem, minimal quality research has been conducted on power flow control in Networked Microgrids. ▪ The effect of microgrids' cooperative operation on distribution network stability and quality should be addressed in the future. ▪ Effects of communication networks and protection issues on Networked Microgrids performance should be the focus in future research.

			▪ Suitable power electronic devices and energy trading guidelines should be developed to control power flow through power networks amongst microgrids.
Danish Mahmood, Nadeem Javaid, Ghufran Ahmed, Suleman Khan and, Valdemar Monteiro	2021	141	▪ Without dealing with RE power generation uncertainties, it is impossible to operate a networked grid within its full capacity. ▪ Management of uncertainty at the upper or community level resulted in increased computation overhead and time complexity with the increase of microgrids in the network due to centralized control. ▪ Mitigating uncertainties in a distributed environment increases time and complexity constraints.
Mohamad Almas Prakasa and Subiyanto Subiyanto	2022	49	▪ The energy-management system manages the energy generation, and allocation based on the system behaviour in grid-connected and stand-alone modes. ▪ The MGAPSO optimization can save up to 2–11% of cost as compared to conventional optimization methods. ▪ MGAPSO method has designed a self-sustained RES in the campus area at minimum cost by enhancing renewable-energy utilization.
Guodong Liu, Maximiliano F. Ferrari & Yang Chen	2023	55	▪ Future works include validating the proposed MILP-based distributed method on bigger test cases with hundreds of buses and tens of microgrids. ▪ Also, how to handle inherent inter-mittency and uncertainty of loads and renewable sources under the proposed distributed framework will be investigated.
Joseph Aristotle DE Leon, Raymond Tan, and Robert Kerwin Billones	2024	45	▪ Future development on the MOLP model may consider including the developer and the electric cooperative/company in the objectives.
Dessalegn Bitew Aeggegn, George Nyauma Nyakoe &, Cyrus Wekesa	2024	51	▪ The work is supposed to be extended to see how each MG can be traded along with the main grid and compare the proposed GWO with other optimization methods like grasshopper optimization algorithm (GOA), harmony search optimization (HSO), TeachingLearning-Based Optimization (TLBO), and genetic algorithm (GA).
Sebastian García, Stefano Bracco, Antonio Parejo , Matteo Fresia b, Juan Ignacio Guerrero &, Carlos Leon	2025	45	▪ Future research will address the impact of the forecast accuracy due to the inherent stochasticity of RESs. ▪ Future research will also address the inclusion of secondary and primary control (p-f and v-q control) to support the operation of the CATEPS MG in islanded mode as well as the integration of the proposed EMS into the SCADA system.
Bin Chen, Zeke Li, Bijing Liu, Haiwei Fan & Qiutian Zhong	2025	38	▪ Future research will focus on enhancing the proposed RPA-GWO framework in several key areas to improve its applicability and robustness in real-world scenarios.
Sebastian Lobos-Cornejo, Luis Fernando Grisales-Noreña, Fabio Andrade,	2025	36	▪ *Adaptive penalty strategy:* Include a penalty factor based on adaptive values for improving the exploration and reducing the processing times to improve

Oscar Danilo Montoya & Daniel Sanin-Villa			the quality of the results obtained for the optimization methodologies. ▪ *Multi-objective optimization:* Future extensions could incorporate environmental objectives (like emission reduction) alongside economic performance to address broader sustainability goals. ▪ *Real-time control strategies:* Implementing the method in real-time environments using rolling horizon or model predictive control could address short-term generation and demand fluctuations
Idriss Dagal, AL-Wesabi Ibrahim, Ambe Harrison, Wulfran Fendzi Mbasso, Ahmad. Hourani & Ievgen Zaitsev,	2025	129	▪ **Deep Learning Integration:** Exploring hybrid approaches by integrating HMS-GWO with deep learning techniques to solve complex optimization problems in domains such as image processing, natural language processing, and reinforcement learning. ▪ **Real-time Applications:** Investigating real-time applications of HMS-GWO for dynamic optimization problems in energy systems, such as demand response and grid frequency control. ▪ **Multi-Objective Optimization:** Extending HMS-GWO to handle multi-objective optimization problems, such as minimizing cost while maximizing renewable energy penetration.

Various optimization techniques and criteria for microgrid optimization are summarized. Thus, justifying the investment cost and ensuring the economic and reliability of the microgrid. The resulting work indicated that computational alternatives, such as evolutionary, heuristic, and non-classical algorithms, yield better results than conventional methods. Furthermore, superior performance was achieved by combining intelligent optimization and adaptive techniques for multi-objective optimization problems (Suchetha & Rampabhakar, 2018).

Again, Phommixay et al. (2020) review optimization techniques, especially PSO, and show PSO's high performance and flexibility compared with other techniques. Their work is based on the cost minimization of the microgrid's operation as well as sizing (Phommixay et al., 2020). Table 2.8 shows the types of optimization methods used on microgrid systems.

Table 2. 8: Types of optimization methods (Doumbia and 2020)

Artificial intelligence method	Classical method
Artificial Neural Network	Linear Programming
Fuzzy Logic	Nonlinear Programming
Genetic Algorithm	Quadratic Programming
Ant Colony Optimization	Evolutionary Programming

Particle Swarm Optimization	Dynamic Programming
Simulated Annealing	Interior Point
Grey Wolf Optimization	Mixed Integer Programming

(Mohamad and Subiyanto, 2022) extracted a robust optimization and sustainable research to develop a feasible design of a microgrid at a low cost. Both Genetic Algorithm and Particle Swarm Optimization are combined to fulfil the objectives of their research, thereby producing better solutions with faster convergence and lower cost than conventional methods. The percentage decrease in cost is 11.99%. Moreover, a combined algorithm has developed a self-sustained RES at minimum cost (Mohamad & Subiyanto, 2022).

2.4.10 Summary and Discussion

In this lexicon, the researchers have done much good work, as shown in Table 2.7. The focus is on the years 2019 to 2025, with a review of papers on optimization techniques for microgrids. Thus, it reflects a good sign that the research gap will soon be filled as the researchers are very active in the study. The reference by Ishaq et al. (2022) has the highest number of citations. Moreover, this symbolized a comprehensive review conducted. More interest is in the year 2022. Consequently, more papers are obtained.

2.4.11 Research Findings

Microgrids represent an increasingly optimal solution for sustainability, efficiency and resiliency of electrical power grids. Microgrids are defined as localized, smaller energy grids capable of functioning autonomously or in reliance on the larger grid. Despite the many benefits of microgrids, significant research gaps remain in microgrid systems to bridge the gap between implementation and optimal performance.

As for microgrid-based rural electrification, a considerable body of research has emerged over the years, but many gaps remain in the field. For example, Luo et al. (2018) identified research gaps in EAMC applications, and Pecenak et al. (2020) identified gaps in LCA. Many research opportunities include:

Techno-economic analysis: Microgrid-based rural electrification requires more comprehensive techno-economic analysis and feasibility assessments than other rural electrification approaches, given the higher cost and reliability requirements (Luo et al., 2018; Barbalho et al., 2019; Shariatkhah et al., 2016). Economic feasibility is a major concern for microgrid-based systems. Research should support costs versus benefits for implementation versus any alternative rural electrification systems, especially regarding initial and ongoing maintenance costs, and viability for profit.

*Infrastructure integration: * Microgrid-based rural electrification needs more research to determine how such systems will integrate with other rural infrastructure like road systems, water supply systems, communication, etc. (Luo et al., 2018; Barbalho et al., 2019; Kundu & Banerjee, 2022). Infrastructure integration is necessary to sustain microgrid-based benefits without disruption; a research gap exists regarding a grid-tied system that employs bidirectional power-flow control and supply management during grid-connected/island transitions.

Microgrid optimization: Research should focus on energy delivery cost-related factors affecting system sustainability, stability, etc. Resource optimization is a gap because sources such as solar panels, turbines, and energy storage require proper distributed energy resource management. Optimizing resource management is critical because some microgrids rely on solar power, which can be inconsistent, creating supply-and-demand issues.

Socio-economic impacts: Microgrid-based rural electrification requires studies to determine local impacts on socio-economic factors such as poverty, health, education, and gender equity (Heeter et al., 2021; Dogan, 2021; Radley and Lehman-Grube, 2022; Raghav et al., 2021; and Trivedi et al., 2022). Community participation is crucial for planning and operations management, yet there are limited avenues for citizen/resident/business/governmental actor feedback and participation.

Environmental impacts: Microgrid-based rural electrification requires assessments of potential impacts from GHGs, land use, and biodiversity (Heeter et al., 2021; Alam et al., 2019; Pecenak et al., 2020). Relative deployment/implementation impact must be known, as well as potential impacts of renewable sources should they be utilized.

Regulatory/policy issues: Microgrid-based rural electrification requires investigations into legal/policy issues, ownership and management laws for operations, and governmental/political actor or private industry actor preferences moving forward. Regulatory issues include grid interconnections, tariff structures and existing energy policy. Research gaps exist in frameworks/policies that could connect findings from implemented systems with microgrid potential to avoid silos.

Community engagement: Microgrid-based rural electrification requires research into best engagement practices during pre-planning, pre-implementation, implementation, and post-implementation for continued successful operations.

Until these research opportunities are answered, the potential for microgrids as a "greener" alternative will not be realized until cumulative implementation can be substantiated without gaps in necessary research. Ideally, researchers could work with those who've successfully implemented systems through smaller scale microgrid activities and demonstrated benefits, to avoid staggered implementation over time.

2.4.12 Conclusion

The review found classical, heuristics, and hybrid optimization approaches for microgrid systems. Review papers from 2019 to 2025 show that the most feasible and flexible form of optimization remains PSO, with acceptable convergence time and performance. Furthermore, it can be integrated with other intelligent approaches. In addition, the reviews show that the mixed-integer programming formulation has been widely used. Therefore, this study's findings show that microgrids can significantly enhance energy control and management efficiency with advanced, optimized approaches. The previously established Linear Programming (LP), GWO (Grey Wolf Optimizer), and the more contemporary DAO (Dynamic Arithmetic Optimization Algorithm), detailed in this dissertation, are strong candidates for minimizing operational costs and maximizing renewable energy utility effectiveness, as well as supply reliability, for rural electrification projects.

The optimization model of this chapter's Data Arithmetic Optimization Algorithm aims to minimize total energy costs while maintaining sustained system reliability and minimizing environmental costs. The model considers the DAOA algorithm a variable approach based on renewable energy production options, variable energy loads and EV charging trends.

CHAPTER 3

DEVELOPMENT OF A DYNAMIC ARITHMETIC OPTIMIZATION METHOD FOR RENEWABLE ENERGY-BASED MICROGRID SYSTEM

3.1 Introduction

Microgrids are still characterized by a large share of energy from PVs and wind energy systems. Therefore, demand for intelligent, adaptable optimization solutions is growing. LP and novel metaheuristics like GWO seem to suffice for optimal scheduling of microgrids, but they fail when faced with highly uncertain renewable profiles, nonlinear battery behavior, and multidimensional costs (Ibrahim et al., 2025). Therefore, this book chapter addresses the optimization of a PV-Wind-Battery-Grid-connected microgrid system over the 24-hour period using the Dynamic Arithmetic Optimization Algorithm (DAOA).

DAOA is a new and improved version of the AOA approach. It explores/exploits better and converges faster over time. Therefore, it's suggested that this would fare well for scheduling purposes, since uncertain, intermittent resources inherently possess operationally imposed limits that do not consistently function within the means of interactions that would otherwise be transparent (Abualigah et al., 2024).

DAOA is therefore applied in this chapter to reduce the overall operational costs of the microgrid system through optimal dispatch of renewable power generation, battery charging/discharging, and grid interaction. This novel adaptive approach implements dynamic arithmetic operators that are more effectively applicable to constantly fluctuating resources than AOA and other metaheuristics, which are more rigid. In addition, this will compare the performance of DAOA with LP and GWO in terms of dispatch efficiency, cost reduction, cost effectiveness, and the best fit for microgrids with renewable-energy-based sources. Moreover, DAOA will be compared with LP and GWO relative to system cost, appropriate constraints, and similar configurations across every comparative strategic approach within the same theoretical microgrid template.

Chapter 3.2 presents the theoretical hybrid background of DAOA, and Chapter 3.3 discusses the theoretical microgrid system in more detail. Chapter 3.4 outlines the index, decision variables, and parameters needed for DAOA to operate before the mathematical formulation of the approach is made in Chapter 3.5. Chapter 3.6 outlines the major assumptions made in order to streamline and simplify the modelling. Chapter 7.3 presents the DAOA with a step-by-step hybrid approach for better assessment and analysis testing. Therefore, Chapter 3.7 presents the reader with case studies and simulations that are tested for results. This is followed by Chapter 3.9, which provides an extensive discussion of the results for each of the three dispatch scenarios generated by such an implementation with DAOA. Finally, Chapter 3.10 concludes with an overview of the conclusions and notes based on findings that DAOA is a suitable approach for improved microgrid operations.

3.2 Hybrid theoretical background of the Dynamic Arithmetic Optimization Algorithm (DAOA)

The dynamic Arithmetic Optimization Algorithm (DAOA) is a dynamic and more effective version of the Arithmetic Optimization Algorithm (AOA). The Arithmetic Optimization Algorithm (AOA) was primarily derived from the actions of arithmetic operators used in mathematics. AOA was the first to consider basic operators (addition, subtraction, multiplication, and division) as revolutionary operators that mimic the exploration and exploitation techniques of optimization (Abualigah et al., 2024). The dynamic Arithmetic Optimization Algorithm takes it to the next level by employing an adaptive control parameter that allows the search steps to adapt during iterations, facilitating a deeper equilibrium between global exploration and local exploitation (Eid, A., and Alsafrani, A., 2024).

In the realm of AOA, multiplication and division serve as exploratory operators that generate a large number of solutions spanning a wide range of the solution space. However, addition and subtraction serve as exploitation solutions, generating operations that closely approximate the promising solutions. DAOA transforms the dynamic search equilibrium of gradually evolving control parameters from exploration in the early iterations to more exploitation in the later iterations. Such a dynamic control benefit increases convergence speed while decreasing the likelihood of early stagnation that traditional metaheuristics are prone to (Ibrahim et al., 2025).

In addition, DAOA supports adaptive boundary management and improved initialization with dynamic scale factors, making it less sensitive to excessive dimensionality and nonlinearities. Factors of DAOA apply nearly directly to microgrid operations, where SOC boundaries, ramp-up/ramp-down rates, and uncertainties in renewable and import/export must be adhered to simultaneously. The ability to dynamically adjust the search depth and step size means DAOA can hold a variable at controlled extremes, ranging from extensively searching for a global solution to intensively searching around significant operating solutions (Qu et al., 2024).

Theoretical advantages involve successfully sustaining an energy landscape with multiple local minima from intermittency in renewable supply and responsive load changes. The mathematical operators that control the dynamically controlled variables assist each other to safeguard solution variety. Therefore, enhanced convergence and dependability characteristics make DAOA a promising solution for microgrid scheduling in renewable-energy-based microgrids (Qu et al., 2024).

3.3 Hybrid microgrid system

This study presents a hybrid microgrid system as an effective means to increase reliability, sustainability, and efficiency of energy by integrating various renewable energy sources and energy storage systems. This study definitively presents a hybrid microgrid system of grid power, photovoltaic (PV) solar panels, and battery technology. In such an efficient hybrid system, wind generation and PV panels provide excessive operational demand while battery storage bolsters the grid and selectively diverts energy. In addition, this microgrid system operates in both grid-connected and islanded configurations, underscoring its extraordinary resiliency and innovative approach to clean energy generation. In addition, as the industry and technology grow, global energy demand becomes clear, and it becomes evident that nations are connected to one another as countries rely on each other for energy resources worldwide.
By optimizing these parameters, overall operating costs are reduced while microgrid power generation is maximized and emissions are minimized (Meteab et al., 2023). Typically, the objective function is stated as a weighted sum of multiple criteria.

3.4 Indexes, decision variables, and parameters of the DAOA algorithm

This section extrapolates indexes, decision variables, and parameters as used in microgrid systems.

3.4.1 DAOA Indices

$$t \in \{1, ..., T\}, \quad whereindex(T = 24) \tag{3.1}$$

The decision (design) variables (these are the DAOA search vector)

- W is wind capacity (kW)
- P is PV capacity (kW)
- B is the battery capacity/ peak power (kW)
- G is the grid capacity/ allowed grid power (kW)

3.4.2 DAOA Operational variables.

- $g_{w(t)}$ is the wind generation at hour t (kW)
- $g_{pv}(t)$ is the PV generation at hour t (kW)
- $g_{bat}(t)$ is the battery power contribution at hour t (kW)

- $g_{grid}(t)$ is the net grid power at hour t (kW) (Positive=import, negative = export)

3.4.3 DAOA Given input time series/ parameters

To address parameter sensitivity, a systematic sensitivity analysis was conducted, demonstrating solution stability within practical parameter ranges. Regarding computational cost, the algorithm is implemented at the tertiary control level (energy management layer), where scheduling intervals allow sufficient computational time for population-based optimization. Furthermore, the framework supports rolling-horizon re-optimization, enabling responsiveness under dynamic operating conditions.

- $L(t)$ is the load profile (kW)
- $I_{pv}(t)$ is the solar irradiance
- $\upsilon_w(t)$ is the wind speed.
- c_{gi} is the grid import price ($/kW)
- c_{ge} is the grid export price ($/kW)
- c_b is the battery degradation cost($kW)
- c_{pv} is the PV, O&M cost ($/kW)
- c_w is the wind O&M cost ($/kW)

Other code constraints used for the battery $P_{bat}^{\min}$, $P_{bat}^{\max}$

and a battery mode schedule $m(t) \in \{-1, 0, 1\}$.

design variable bounds: $0 \le W \le 5000,\ 0 \le P \le 1000,\ 50 \le B \le 500,\ 400 \le G \le 4000.$

3.4.4 Generation Models

The model uses a simple normalized function. Although large-scale real-world deployment of DAOA remains limited, extensive benchmarking against established optimization methods and simulation using realistic load and renewable generation data provide strong validation of its effectiveness. Therefore, this study contributes to both methodological advancement and practical assessment of DAOA for real-time microgrid energy management.

Wind generation (hour t)

$$g_w(t) = \min\left(W \cdot \frac{\upsilon_w(t)}{\max_t \upsilon_w(t) + \varepsilon'} W \right) \quad (3.2)$$

Where, ε is the tiny number to avoid being divided by zero.

PV generation (hour t) with a day mask $M_{pv}(t) \in \{0,1\}$ 9 active hours 8-17):

$$g_{pv}(t) = \min\left(P \cdot \frac{I_{pv}(t)}{\max_t I_{pv}(t) + \varepsilon} \cdot M_{pv}(t), P \right) \quad (3.3)$$

Battery power (code's simplistic mapping using battery-mode $m(t)$)

$$g_{pv}(t) = P_{bat}^{\min} + \left(P_{bat}^{\max} - P_{bat}^{\min} \right) \cdot m(t), \qquad m(t) \in \{-1,0,1\} \cdot \quad (3.4)$$

Net grid power (power balance

$$p_{grid}(t) = L(t) - \left(g_w(t) + g_{pv}(t) + p_{bat}(t) \right) \cdot \quad (3.5)$$

By the code's sign convention: $p_{grid}(t) > 0$ means import from the grid; $p_{grid}(t) < 0$ means export to the grid.

Separate import/export energy (per-hour, as vectors):

$$p_{grid}^{+}(t) = \max\left\{ p_{grid}(t), 0 \right\}, \qquad p_{grid}^{-}(t) = \min\left\{ p_{grid}(t), 0 \right\} \cdot \quad (3.5)$$

Energy sums used in costs formulas:

$$E_{pv} = \sum_{t=1}^{T} g_{pv}(t), \quad E_w = \sum_{t=1}^{T} g_w(t), \quad E_{grid}^{imp} \sum_{t=1}^{T} p_{grid}^{+}(t), \quad E_{grid}^{\exp} \sum_{t=1}^{T} p_{grid}^{-}(t) \cdot \quad (3.6)$$

Battery degradation cost in code: (elementwise sum of $p_{bat}(t)$ times cost)

$$Cost_{bat} = c_b \sum_{t=1}^{T} p_{bat}(t) \quad (3.7)$$

3.4.5 Objective function to minimize the daily operating cost.

$$\min_{W,P,B,G} \quad Operating\_Cost = Cost_{pv} + Cost_w + Cost_{grid}^{imp} + Cost_{grid}^{\exp} + Cost_{bat}$$

$$\begin{aligned} where \quad & Cost_{pv} = c_{pv} E_{pv}, \quad Cost_w = c_w E_w \\ & Cost_{grid}^{imp} = c_{gi} E_{grid}^{imp}, \quad Cost_{grid}^{\exp} = -c_{ge} E_{gri}^{\exp} \\ & Cost_{bat} = c_b \sum_{t=1}^{T} p_{bat}(t) \end{aligned} \quad (3.8)$$

3.4.6 Constraints

DAOA constraints are as follows:

1. Power balance for every hour t

$$L(t) = g_w(t) + g_{pv}(t) + p_{bat}(t) + p_{grid}(t) \qquad \forall t \cdot \tag{3.9}$$

2. Generation limits.

$$0 \le g_w(t) \le W, \quad 0 \le g_{pv}(t) \ge P \qquad \forall t \cdot \tag{3.10}$$

3. Grid Capability

$$\left| p_{grid}(t) \right| \le G \qquad \forall t. \tag{3.11}$$

4. Design variable bounds

$$lb \le \left[W, P, B, G \right] \le ub. \tag{3.12}$$

5. Battery implemented simplified mode

$$p_{bat}(t) = P_{bat}^{\min} + (P_{ba}^{\max} - P_{bat}^{\min}) \cdot m(t), \qquad m(t) \in \{-1, 0, 1\} \cdot \tag{3.13}$$

In the code, the battery schedule $m(t)$ is fixed rather than optimized (It is an input profile).

3.5 Dynamic Arithmetic Optimization Algorithm (DAOA) formulation

Mathematical and algorithm formulation of the Dynamic Arithmetic Optimization Algorithm (DAOA).

This section provides a DAOA formulation that includes position-update operators (exploration and exploitation), dynamic control rules (MOA and MOP), and pseudocode for handling constraints.

3.5.1 Problem definition

Given minimization problem:

$$\min_{x=\chi} f(x) \tag{3.14}$$

where $x \in \square^d$ is the design vector and $\chi = \{ | \le x \le u \}$ are bound constraints (componentwise) in MATLAB.

- $d = 4(\, wind\ W,\ pvP,\ battery\ \ B, grid\ \ G)$
- $f(x)$ is the daily operating cost computed by the costHybrid routine.

3.5.2 Population and initialization

- Population size: ***N*** agents (wolves).
- Each agent i has position

$$X_i^{(0)} = \ell + r \odot (u - \ell), \qquad r \sim u([0,1]^d) \cdot \tag{3.15}$$

- Evaluate fitness:

$$F_i^{(0)} = f\left(X_i^{(0)}\right) \cdot \tag{3.16}$$

- Track global best:

$$X^* = \arg\min_i F_i F^* = \min_i F_i . \tag{3.17}$$

3.5.3 Dynamic Control Parameters

Two dynamic scalars control exploration vs exploitation:

1. Math Optimizer Accelerator (MOA), increasing with iteration:

$$MOA(k) = MOA_{\min} + \left(MOA_{\max} - MOA_{\min}\right)\left(\frac{k}{K}\right)^{\alpha} \tag{3.18}$$

with k iteration index, K max iterations. In code $\alpha = 1.5,\ MOA_{\min} = 0.2,\ MOA_{\max} = 1.0$

Math Optimizer Probability (MOP), decaying that favours exploration early:

$$MOP(k) = MOP_0\left(1 - \frac{k}{K}\right), \tag{3.19}$$

With $MOP_0 = 0.5$ in the code.

3.5.4 Per-dimension stochastic update operators

For agent i, dimension d, at iteration k let current value be $x = X_i^{(k)}(d)$ and best be $x^* = X^*(d)$. Three independent random scalars $r_1, r_2\ r_3 \sim u(0,1)$ are used.

DAOA chooses between two modes with probability MOP: exploration (math-based global search) vs exploration (move toward best).

A. Exploration (with probability MOP)

- Subtraction-driven exploration (probability 0.5):

$$\tilde{x} = x - MOA \cdot (r_1(u_d - \ell_d)) \tag{3.20}$$

- Addition-driven exploration (probability 0.5):

$$\tilde{x} = x + MOA \cdot (r_2(u_d - \ell_d)) \tag{3.21}$$

Intuition: add/subtract a random portion of the design range to escape local regions.

B. Exploitation (with probability 1-MOP)

- Multiply move (compress toward best) (probability 0.5):

$$\tilde{x} = x^* - MOA \cdot r_3 \cdot \frac{x^*}{x+\varepsilon} \tag{3.22}$$

- Division-like adjustment (expand/shrink toward best) (probability 0.5):

$$\tilde{x} = x^* + MOA \cdot r_3 \cdot \frac{(x^* - x)}{(x + |r_2|)} \tag{3.23}$$

Induction: nonlinear moves that scale with the ratio/difference to the current best.

C. Stochastic attractor (fine-tuning)

After the chosen operator, add a small random attractor toward the best:

$$x_{new} = \tilde{x} + \delta(u) \cdot (x^* - x) \tag{3.24}$$

D. Bounds Projection

After update:

$$X_i^{(k+1)}(d) = \min\{u_d, \max\{\ell_d, x_{new}\}\}. \tag{3.25}$$

3.5.5 Elitism

Keep the best agent unchanged (or reinsert the best into the population):

$$X_{i^*}^{(k+1)} \leftarrow X^* \tag{3.26}$$

Where i^* is the index of the best agent before the update.

3.5.6 Fitness evaluation and selection

At each iteration k after the position update, evaluate $F_i^{(k+1)} = f(X_i^{(k+1)})$. update global best:

$$if\ F_i^{(k+1)} < F^* then\ (X^*, F^*) \leftarrow (X_i^{(k+1)}, F_i^{(k+1)}) \tag{3.27}$$

3.5.7 Termination

Stop when $k = K$ (maximum iterations) or optional convergence tolerance (e.g., no improvement after M iteration.

3.6 Assumptions of DAOA

- **Deterministic forecasting:** All load, PV generation, wind generation, Battery, and Grid parameters are assumed to be known in advance for the scheduled period, consistent with standard deterministic microgrid optimization (Ibrahim et al.,2025).

- **Fixed system constraints:** Microgrid constraints such as battery SOC limits, charge/discharge limits, PV Capacity, and grid import/export limits must remain constant during optimization (Guo et al.,2071).
- **Smooth and continuous search space:** DAOA assumes the optimization problem can be represented as a continuous or piecewise-continuous search space suitable for arithmetic operators (Abualigah et al.,2021)
- **Population-based initialization:** Initial candidate solutions are generated randomly within feasible operating boundaries as done in metaheuristic AOA/ DAOA applications (Abualigah et al.,2021).
- **No communication or actuation delays:** It is assumed that the microgrid can implement control decisions in real time without communication latency (Qu et al.,2024).
- **Stable dynamic parameters:** DAOA's adaptive exploration and exploitation parameters are assumed to remain valid and stable throughout iterations (Abualigah et al.,2025).
- **Well-behaved objective function:** The cost function is assumed to be smooth and suitable for iterative heuristic improvement, even though no derivatives are required (Ibrahim et al.,2025).
- **Reliable constraint handling:** Boundary checks and feasibility restoration methods can always keep solutions within allowable limits (Ibrahim et al.,2025)
- **Deterministic operating environment:** Uncertainties such as weather visibility, forecast errors, or component degradation are not explicitly modelled, as is typical in deterministic DAOA applications.

3.7 Steps of DAOA

DAOA extends the original Arithmetic Optimization Algorithm (AOA) by embedding dynamic control parameters and adaptive transitions between exploration and exploitation to improve solution stability and convergence (Abualigah et al., 2021; Ibrahim et al., 2025).

3.7.1 Step One: Initialize the population

DAOA begins by generating a set of candidate solutions (search agents) randomly within predefined variable bounds. This ensures broad initial exploration of the microgrid search space (Abualigah et al., 2021)

3.7.2 Step Two: Evaluate the fitness of each solution

Each individual is evaluated using the microgrid cost or objective function, such as minimum operating cost, minimum power imbalance, or reduced grid import (Ibrahim et al., 2025)

3.7.3 Step Three: Compute Dynamic Control Parameters

DAOA introduces time-varying parameters such as the Dynamic Search Pressure (DSP) and Adaptive Coefficient (ACA). Enabling smoother transitions from exploration to exploitation (Chen et al., 2024; Qu et al., 2024).

- The current iteration number,
- Population diversity
- Performance of the best solution.

3.7.4 Step Four: Update the position of search agents (exploration phase)

When DSP is high, the algorithm prioritizes exploration.

Agents update their positions using arithmetic operators (multiplication/division) and randomization to expand the search globally (Abualigah et al., 2021).

3.7.5 Step Five: Update the position of search agents (exploitation phase)

When DSP decreases, DAO shifts to exploitation. Agents update their posting using arithmetic subtraction/addition operators around the best solution to refine convergence (Abualigah et al., 2021).

This stage improves fine-tuning of dispatch schedules in microgrid optimization (Ibrahim et al., 2025).

3.7.6 Apply dynamic adaptation rules

DAOA periodically applies:

- Dynamic parameter scaling,
- Local search intensification, and
- Self-adjusting learning rates.

3.7.7 Recalculate fitness values

The newly generated positions are evaluated again using the microgrid cost function to assess improvement (Ibrahim et al., 2025).

3.7.8 Update the global best solution

DAOA stores the best-performing solution to guide the search process (Abualigah et al., 2021).

3.7.9 Check termination criteria

The algorithm stops when:

- Maximum iteration is reached, or
- Solution improvements fall below a threshold (Qu et al., 2024).

3.7.10 Output the optimal microgrid dispatch

The final DAO solution provides an optimized multi-source microgrid schedule that includes PV, wind, battery, and grid decisions (Ibrahim et al., 2025).

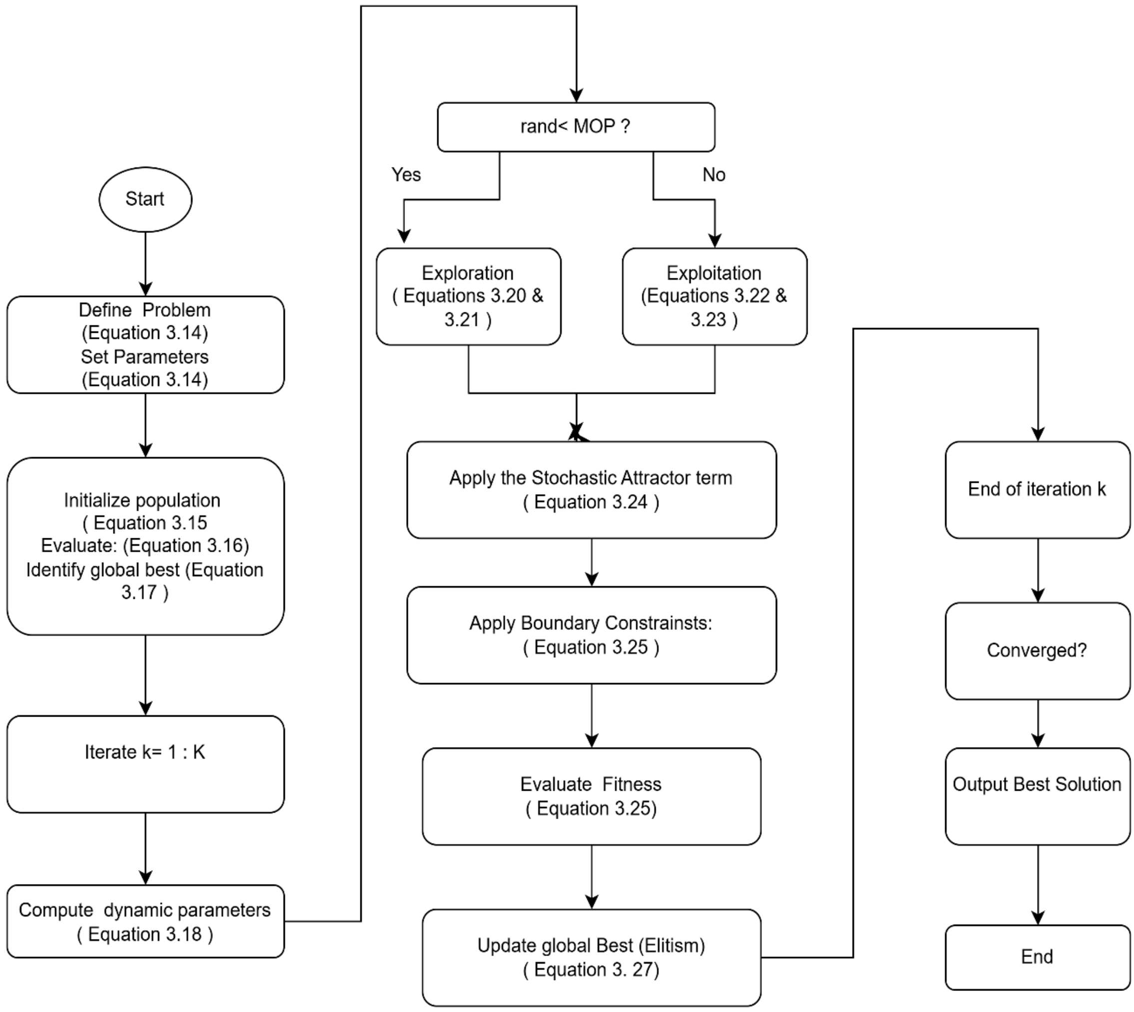

Figure 3. 1: Flowchart for Dynamic Arithmetic Optimization Algorithm (DAOA)

The flowchart in Figure 3.1 shows a step-by-step description of how the Dynamic Arithmetic Algorithm (DAOA) operates on an optimization problem such as renewable energy microgrid dispatch. The algorithm operates on a population of candidate microgrid dispatches. In other words, each candidate can represent a different configuration of renewable resources and storage to determine which is best. The more candidates propose microgrid configurations that are incorrect/inaccurate, the better they are for the goal of optimality. As DA reassesses its control parameters of candidates in the process, a need for dynamic change arises. In addition, DAO must determine whether to stop the process, meaning the maximum number of iterations has been reached, or the resulting dispatch is ideal. Otherwise, DAO will continue through the iterations with small candidate changes and minimal dynamic arithmetic-like adjustments to positioning, assessing the arithmetic calculation, and determining new candidates until the reassessment can once again say that stopping the iterations is possible. Finally, when the stop assessment indicates that it can, the output is the best solution.

3.8 Case Studies and Simulation Results.

This section will align an international comparative assessment of the microgrid's operational performance across the three selected case studies, designed to indicate how differing renewable resources impact energy dispatch and system costs. For example, Case Study 1 is a complete microgrid with wind, PV, Battery storage, and Grid. This is how the microgrid will operate holistically as different resources interact, creating a microgrid with reduced dependency on the Grid and lower operating costs. Thus, Case Study 2 is Wind and Grid. This is because it allows for an assessment of Wind's variable nature (overproduction and underproduction) and what that means for Grid imports, as well as the system's resiliency. Thus, Case Study 3 is a PV and Battery storage microgrid, including Battery storage and Grid. This is because it looks at solar generation (only during daytime) and how Battery charging during peak production hours means Battery discharging during off hours, either for use or for imports during peak load hour, which means strong dependence on the Grid as well for any nighttime use with no ability to generate renewable resources; thus, the discharging nature combined with the dependence on the Grid for nighttime use means these three cases present a comparison to performance of the system based upon resource specific circumstances that make sense to assess and support the overall assessment and comparison of the DAOA for reasoned support.

3.8.1 Case Study 1: Grid-connected Microgrid dispatch with Wind, PV, and Battery using DAOA

As established above, Case Study 1 relates to the information compiled in Table 3.1, resulting from the application of the DAOA algorithm. The DAOA algorithm is coded and executed in MATLAB. Load fluctuation occurs between 2200kW and 5400kW. Wind generation seems to be the largest contributor, with an hourly max of 10 and fluctuations between 1313.75kW and 5000kW. PV generation is detected from hour 7, peaks at hours 12 and 14, and then becomes non-existent again from hour 16. Thus, the battery system seems to be an essential component of load shifting as it gives power when renewable generation doesn't meet the load (hours 7 and 20) and absorbs power when there is an excess of generation; this is only from hours 1-2, 7 and 11-20 that power is given from the grid as renewable generation does not meet the load needs. Interestingly, hour 10 shows a negative power reading on the grid; this implies that the generation for the 10th hour exceeded the load demand for the entire microgrid, suggesting a potential supply to the grid. This also correlates to operational costs, which fluctuate based on the generation source requirements versus grid support. For example, when the microgrid depends most on grid supply (hours 10, 18, and 19), operational costs are higher because the cost of grid-supplied electricity is higher than any minigeneration option at those times. Thus, operational costs vary throughout the day depending on grid supply versus renewable support.

Table 3. 1: Microgrid Power Dispatch with Wind, PV, and Battery using ADAO algorithm

Hour	Load Power in kW	Wind Power in kW	PV Power in kW	Battery Power in kW	Grid Power in kW	Total Operating cost in $
1	2200	1424.70	0.00	100.00	675.30	140.80
2	2400	1401.69	0.00	100.00	898.31	180.71
3	2800	1313.75	0.00	100.00	1386.25	267.66
4	3200	1528.51	0.00	500.00	1171.49	251.15
5	3400	1778.69	0.00	500.00	1121.31	244.62
6	3800	1936.16	0.00	500.00	1363.84	289.85
7	4000	1842.72	0.00	-300.00	2457.28	445.74
8	4200	2315.93	239.69	-300.00	1944.39	359.35
9	4600	4196.89	326.84	-300.00	376.27	96.33
10	5000	5000.00	348.63	500.00	-848.63	110.69
11	5200	3435.61	418.36	500.00	846.03	213.73
12	5400	1880.51	435.79	500.00	2583.70	511.05
13	5300	1635.74	427.08	500.00	2737.18	536.19
14	5200	2821.90	435.79	500.00	1442.30	315.01
15	5000	3556.73	348.63	100.00	994.63	221.34
16	4600	3848.08	305.05	100.00	346.87	107.44
17	4000	4271.10	130.74	100.00	-501.83	68.44
18	3700	2892.48	0.00	-300.00	1107.52	213.28
19	3400	1831.03	0.00	-300.00	1868.97	339.72
20	3200	3227.72	0.00	-300.00	272.28	66.29
21	3000	3921.91	0.00	-300.00	-621.91	49.10
22	2800	4349.46	0.00	500.00	-2049.46	150.47
23	2600	3586.75	0.00	500.00	-1486.75	120.34
24	2400	1474.98	0.00	100.00	825.02	168.25

Table 3.2 presents a detailed breakdown of the operating and maintenance costs for a microgrid system integrating wind, PV, and battery storage.

PV power costs are mostly low, ranging from \$0.00 to \$2.18, indicating that solar energy is economical during the evaluated hours.

While wind power costs fluctuate throughout the day, with notable peaks. For instance, at hour 6, the wind power cost rises to \$19.36. Then, at hour 12, it is significantly reduced to \$18.81.

Table 3. 2: Microgrid Operating and Maintenance Cost with Wind, PV, and Battery using DAOA algorithm

Hour	PV Power cost in \$	Wind Power cost in \$	Grid Power Import cost in \$	Grid Power Export cost in \$	Battery Power degradation cost in \$	Total Operating cost in \$
1	0.00	14.25	121.55	0.00	5.00	140.80
2	0.00	14.02	161.70	0.00	5.00	180.71
3	0.00	13.14	249.53	0.00	5.00	267.66
4	0.00	15.29	210.87	0.00	25.00	251.15
5	0.00	17.79	201.84	0.00	25.00	244.62
6	0.00	19.36	245.49	0.00	25.00	289.85
7	0.00	18.43	442.31	0.00	-15.00	445.74
8	1.20	23.16	349.99	0.00	-15.00	359.35
9	1.63	41.97	67.73	0.00	-15.00	96.33
10	1.74	50.00	0.00	33.95	25.00	110.69
11	2.09	34.36	152.28	0.00	25.00	213.73
12	2.18	18.81	465.07	0.00	25.00	511.05
13	2.14	16.36	492.69	0.00	25.00	536.19
14	2.18	28.22	259.61	0.00	25.00	315.01
15	1.74	35.57	179.03	0.00	5.00	221.34
16	1.53	38.48	62.44	0.00	5.00	107.44
17	0.65	42.71	0.00	20.07	5.00	68.44
18	0.00	28.92	199.35	0.00	-15.00	213.28
19	0.00	18.31	336.41	0.00	-15.00	339.72
20	0.00	32.28	49.01	0.00	-15.00	66.29
21	0.00	39.22	0.00	24.88	-15.00	49.10
22	0.00	43.49	0.00	81.98	25.00	150.47
23	0.00	35.87	0.00	59.47	25.00	120.34
24	0.00	14.75	148.50	0.00	5.00	168.25

Grid power import costs aren't cheap either, with a high of \$492.69 at hour 13. It seems that grid power is imported at high levels during both peak hours and average-use hours. There are very few grid power export costs as well, indicating that excess energy has been programmed to return to the grid. Finally, battery degradation power costs are relatively consistent at \$25.00 or \$5.00 per hour. They are not assessed for some hours, and go negative in hours 7, 8, 9, and 18, 19, 20, 21, which further suggests that either the battery is not actually being used for profit purposes or that exporting the battery to the grid during those hours renders it financially disadvantageous. For total operating cost, the high hour of the day is 536.19, and the low is 68.44 during hour 17, meaning that there is a large variability over the course of time for operating cost. This implies that there is no correlation between incremental efficiency or savings and operating better at one time than another; rather, it suggests that the use of renewable energy is better investigated over the course of the day for power generated, grid import/export, and battery use.

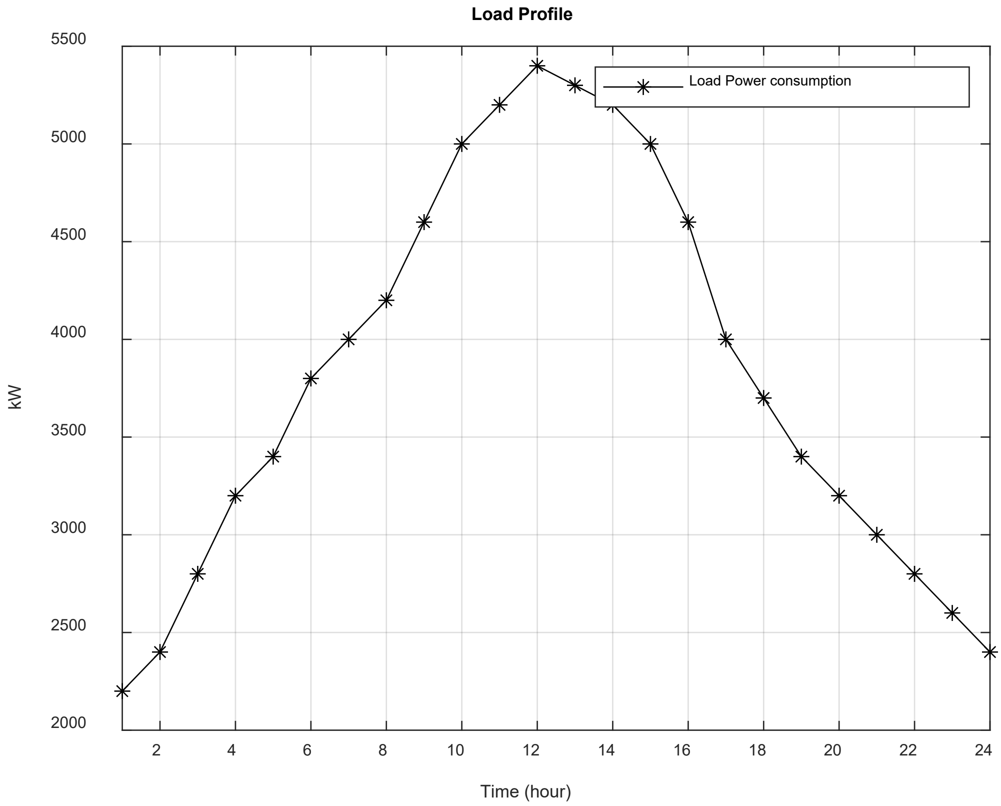

Figure 3. 2: **Load profile results using DAOA**

The load profile in Figure 3.2 corresponds to the expected demand over the course of a day in an energy and renewables microgrid, with lower loads during the overnight hours (approximately 2200kW-3200kW) due to limited community and industrial engagement. As the daytime hours progress, this rises to almost 4600kW by hour 10 as anticipated, with a projected peak expected of approximately 5400kW by hour 12 since it is believed that midday will have the most household, commercial, and productive engagement. Thereafter, the load is expected to decrease gradually from this midday peak. By hour 16, it is 4500kW, but 20 decreases further, as nighttime energy demand is lower than daytime energy demand. Thus, by hour 24, the load reaches anticipated values seen in hours 1-2 (approximately 2400kW), and the cyclical load ends the day. This load profile indicates patterns for dispatch planning as it indicates which hours are more likely to require more renewal generation, battery support or grid import to ensure stable systems.

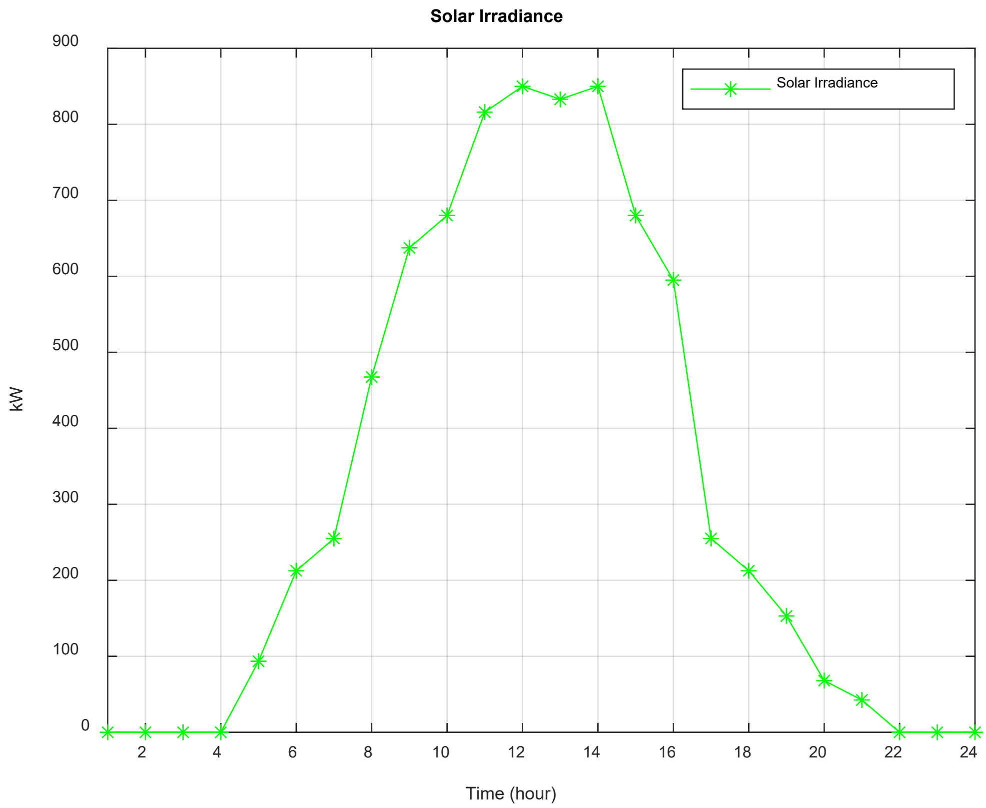

Figure 3. 3: **Solar Irradiance results using DAOA**

The solar irradiance profile depicted in Figure 3.3 shows a clear, realistic daytime pattern that reflects typical solar behaviour in a renewable-energy-based microgrid. As expected, irradiance remains at zero during the night hours before gradually rising with the sunrise. The first noticeable increase appears around 6, reaching roughly 90kW/ m^2 and then rising sharply as the morning progresses. By hour 9, irradiation reaches about 640kW/. m^2. The curve peaks between hours 12 and 14, where irradiation reaches its maximum, approximately 850kW/ m^2, indicating the period of highest PV potential and the best opportunity for battery charging or reducing grid imports.
After this midday peak, irradiation begins a smooth decline as the sun lowers in the sky, dropping to around 600kW/ m^2 by hour 16. And falling again after hour 17. By hour 20, solar input becomes minimal and eventually returns to zero by hour 22.

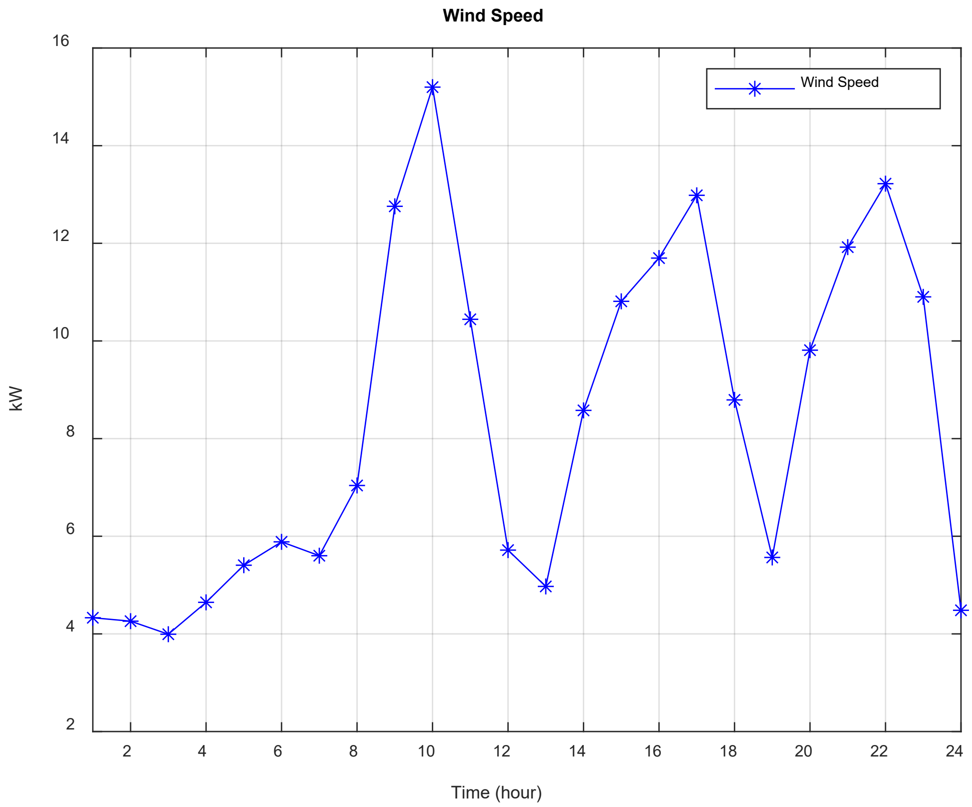

Figure 3. 4: **Wind speed results using DAOA**

The wind speed profile shown in Figure 3.4 reflects the natural intermittency of wind resources in a typical microgrid environment. The early morning hours start with relatively low, stable wind speeds of 4-5 m/s, providing minimal contribution to power generation. There seems to be quite a gust of wind around hour 11 before lunch, when it's highly suspected this is a high-wind provision and perhaps max turbines. However, after this, the wind dies down right around lunch as anticipated. However, this raises concerns about wind energy reliability. In the afternoon and evenings, winds pick back up to accommodate a few spikes at 12 and 22, but by and large, more moderate to high (8-13m/s). Such fluctuations are exactly why microgrid energy efficiency relies on supplementary energy sources and proper optimization efforts to maintain a consistently reliable source. Figure 3.5 shows battery storage charging and discharging, as referenced throughout the study. The microgrid's charging and discharging capabilities run in more of a relative effect throughout the day due to the overlapping load demand and renewable availability. For much of the earlier timeframe (hours 1-14), the battery was discharged at nearly 100kW. As this volume actively supports discharge when no renewables are provided, it shows that the battery served as a consistently reliable intermediary.

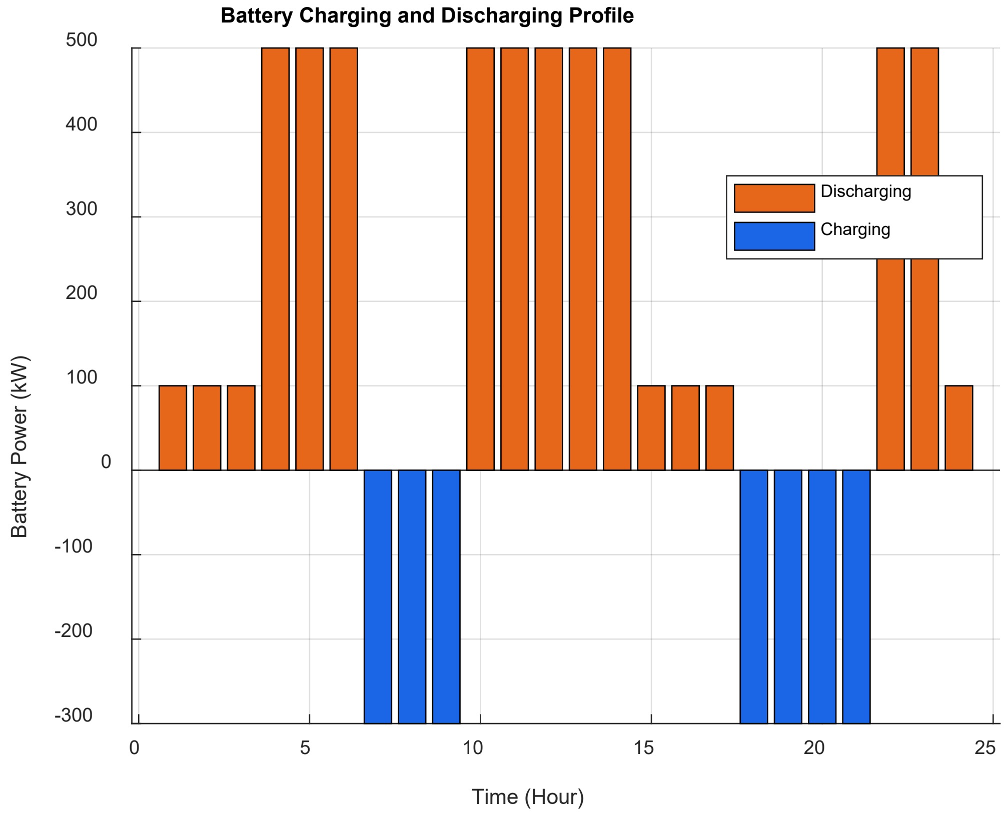

Figure 3. 5: Case study 1 Battery charging and discharging results using DAOA

The battery charges (negative power) between hours 8, 9, and 10, suggesting that excess power is indeed coming from PV and is stored rather than wasted, which is a clear good thing. The fact that charging occurs at the lows of high-demand periods and discharging occurs at the highs of highly demanded periods maintains stability and reduces operational costs, especially since the need for grid imports occurs during more costly hours. This general trend suggests an effective energy cycle: the battery is not always a primary resource but more of a flexible one that fills gaps between varying renewable generation and microgrid demand profiles, ultimately enhancing efficiency and supporting a more sustainable operation.

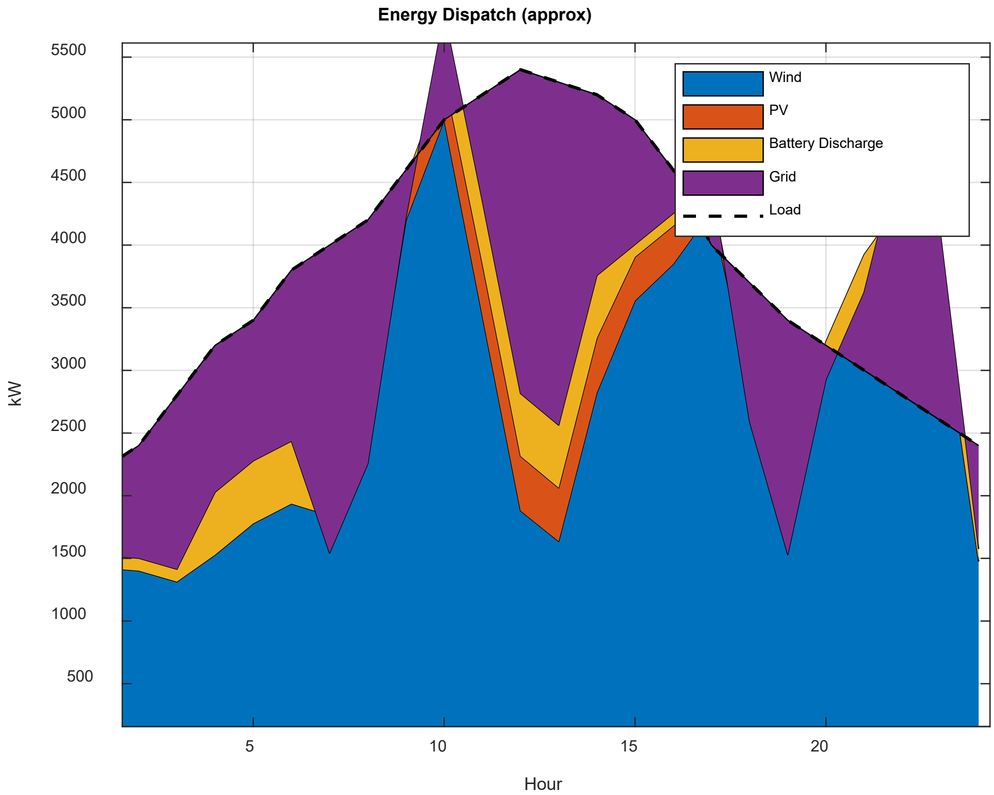

Figure 3. 6: Case study 1 Energy Dispatch results using DAOA

In relation to Figures 3.6 and 3.7, match the operating data for the hybrid microgrid at different hours of the day, based on wind, grid, battery, and PV generation. At certain hours, grid or wind is given priority, offering more generation/more efficient capabilities than the other. At certain hours, however, the opposite is true; the intention is not to render one solution ineffective, but to operate with a fluidity that fosters collaborative energy solutions across diverse means. Moreover, Figure 3.8 supports this data from a day-and-night operating and maintenance cost perspective, showing that the by far highest operating cost comes from grid import. Therefore, with limited load resources, any additional grid power in the form of electrical assistance becomes an operational expense to avoid. In addition, costs associated with DAOA, grid export, and battery degradation versus wind versus solar and PV show that while wind is an expensive operation, it at least runs on the cheaper side. In addition, solar supported as an effective collaborative energy solution for the microgrid as this is the lowest cost of operating and maintaining microgrid over a day period.

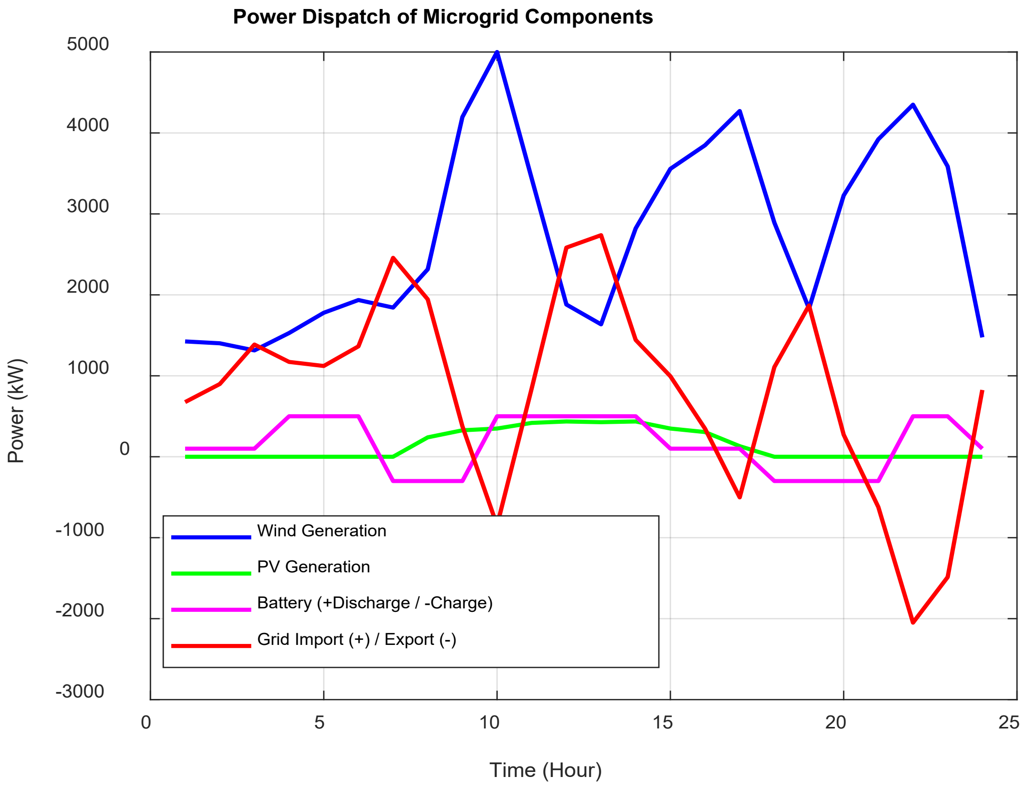

Figure 3. 7: Case study 1 Graphical Energy Dispatch results using DAOA

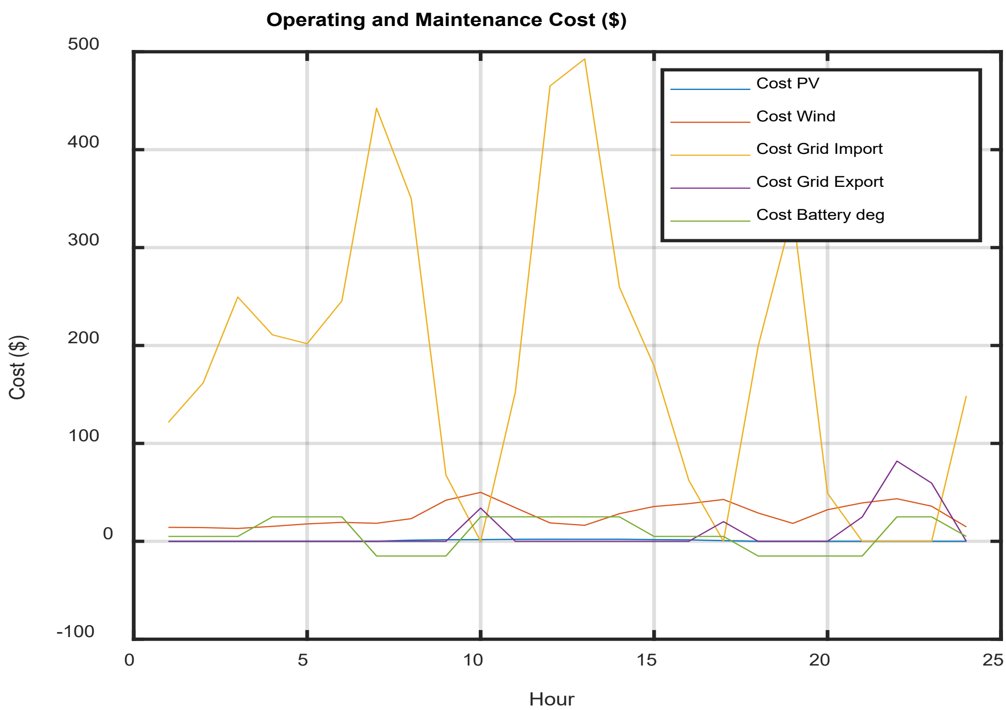

Figure 3. 8: Case study 1 Operating and Maintenance results using DAOA

3.8.2 Case Study 2: Grid-connected Microgrid dispatch with Wind renewable energy resources using DAOA method

In this case study, the objective is to dispatch a grid-connected microgrid with renewable energy resources. The DAOA algorithm is applied to solve the wind-grid energy-based supply problem, and the results are reported in Table 3.3. The obtained results are reported in Table 3.3. The load demand is still the same as in Case Study 1. Also, the total operating costs are listed inclusively in Table 3.4, while PV power and battery storage are excluded in this case study.

Table 3. 3: Wind energy-based Microgrid Power Dispatch using DAOA algorithm

Hour	Load Power in kW	Wind Power in kW	Grid Power in kW	Total Operating cost in $
1	2200	1424.70	775.30	153.80
2	2400	1401.69	998.31	193.71
3	2800	1313.75	1486.25	280.66
4	3200	1528.51	1671.49	316.15
5	3400	1778.69	1621.31	309.62
6	3800	1936.16	1863.84	354.85
7	4000	1842.72	2157.28	406.74
8	4200	2315.93	1884.07	362.29
9	4600	4196.89	403.11	114.53
10	5000	5000.00	0.00	50.00
11	5200	3435.61	1764.39	351.95
12	5400	1880.51	3519.49	652.31
13	5300	1635.74	3664.26	675.92
14	5200	2821.90	2378.10	456.28
15	5000	3556.73	1443.27	295.36
16	4600	3848.08	751.92	173.83
17	4000	4271.10	-271.10	53.55
18	3700	2892.48	807.52	174.28
19	3400	1831.03	1568.97	300.72
20	3200	3227.72	-27.72	33.39
21	3000	3921.91	-921.91	76.10
22	2800	4349.46	-1549.46	105.47
23	2600	3586.75	-986.75	75.34
24	2400	1474.98	925.02	181.25

The load demand is between 2200kW and 5400kW, the wind production is between 1313.75kW and 5000kW, and all the overproduced power is exported to the grid. During hour 22, the highest export is facilitated throughout this entire optimization. Excess exports will always go to the grid. In addition, power is also imported from the grid. Grid cost is grid import + grid export - operating cost due to wind operation on the wind farm. Table 4.4 provides more details.

Grid export occurs during hours 17, 20, 22, and 23. For the rest of the hours, however, power is being imported from the grid.

Table 3. 4: Wind Energy-based Microgrid Operating and Maintenance Cost using DAOA Method

Hour	Wind Power cost in $	Grid Power Import cost in $	Grid Power Export cost in $	Total Operating Cost
1	14.25	139.55	0.00	153.80
2	14.02	179.70	0.00	193.71
3	13.14	267.53	0.00	280.66
4	15.29	300.87	0.00	316.15
5	17.79	291.84	0.00	309.62
6	19.36	335.49	0.00	354.85
7	18.43	388.31	0.00	406.74
8	23.16	339.13	0.00	362.29
9	41.97	72.56	0.00	114.53
10	50.00	0.00	0.00	50.00
11	34.36	317.59	0.00	351.95
12	18.81	633.51	0.00	652.31
13	16.36	659.57	0.00	675.92
14	28.22	428.06	0.00	456.28
15	35.57	259.79	0.00	295.36
16	38.48	135.35	0.00	173.83
17	42.71	0.00	10.84	53.55
18	28.92	145.35	0.00	174.28
19	18.31	282.41	0.00	300.72
20	32.28	0.00	1.11	33.39
21	39.22	0.00	36.88	76.10
22	43.49	0.00	61.98	105.47
23	35.87	0.00	39.47	75.34
24	14.75	166.50	0.00	181.25

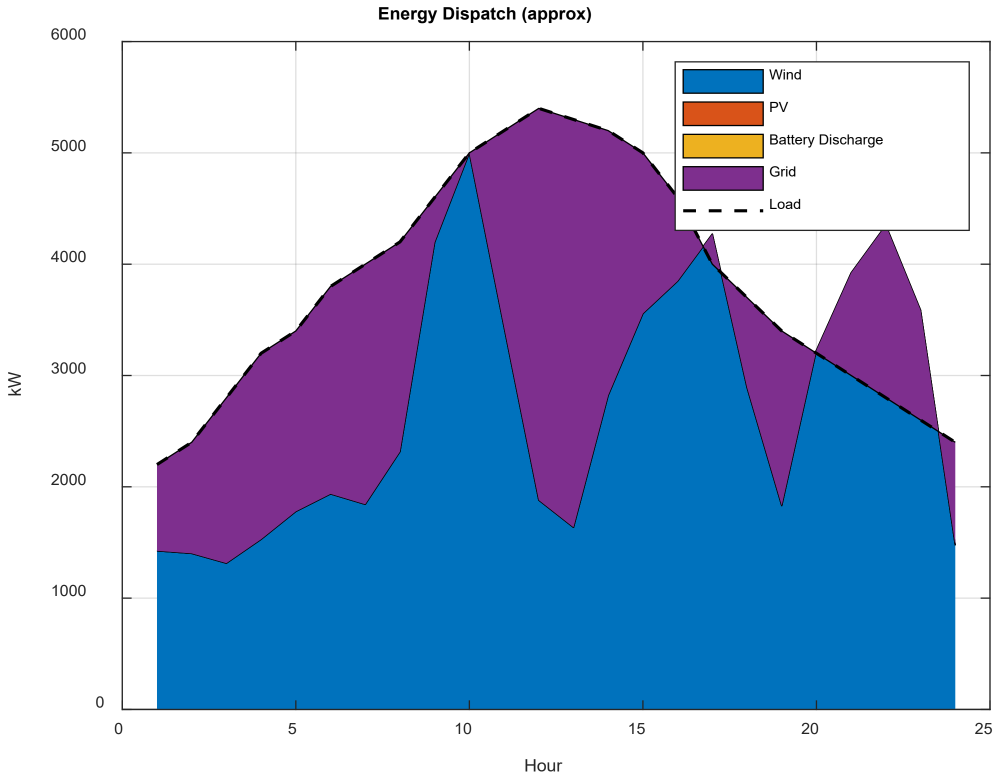

Figure 3. 9: Case study 2 Energy Dispatch results using DAOA

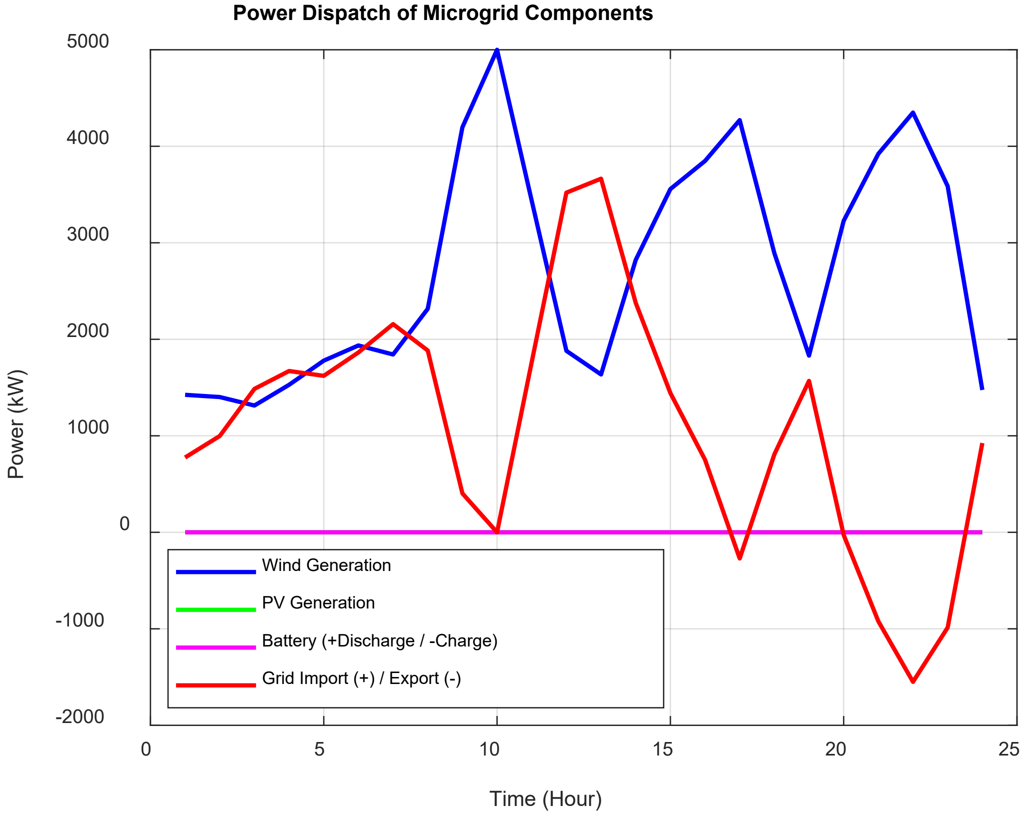

Figure 3. 10: Case study 2 Graphical Energy Dispatch results using DAOA

In this case study, the load is supplied by only two sources, namely wind generation and grid power. The cost of wind power fluctuates throughout the day, with relatively low costs during the night (hours 1-5) and early morning. Then increasing significantly during peak hours, particularly between hours 9 and 12. The highest wind energy cost papers at hour 10, where it reaches $50.00.

The grid power import costs vary widely throughout the day. Notably, the highest cost occurs during hours 12 ($633.51) and 13 ($659.57), suggesting that external grid support may be most expensive during these periods. In contrast, hour 10 shows no import cost, indicating a potential surplus from the wind energy.

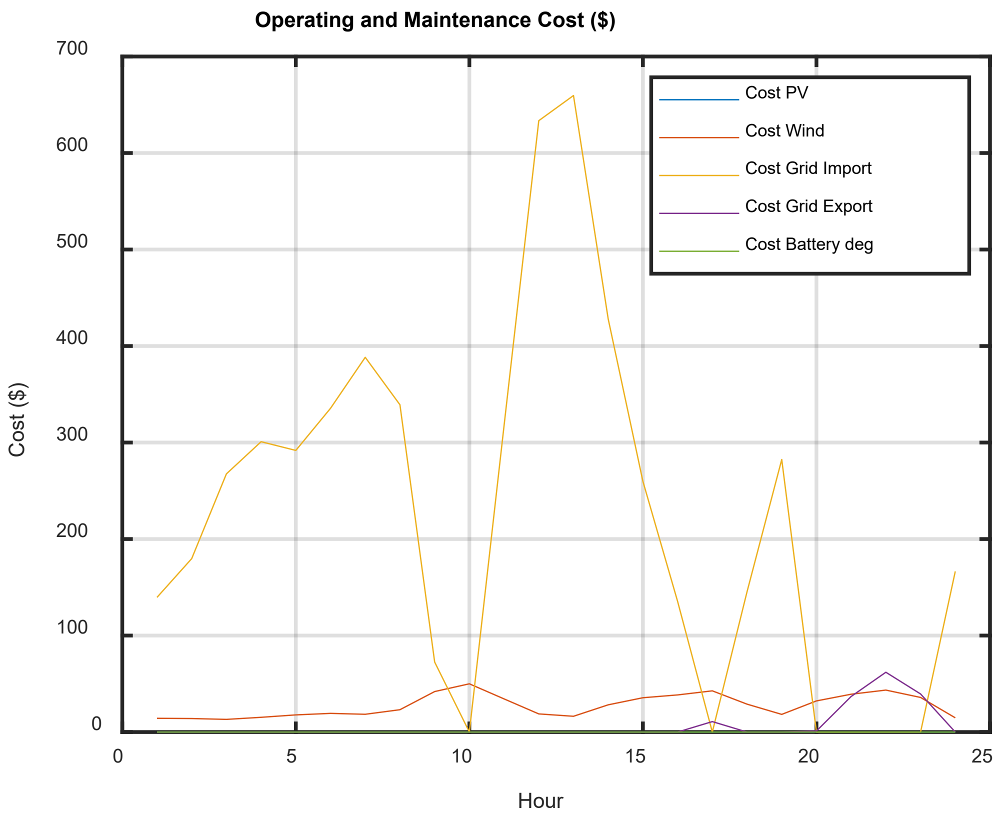

Figure 3. 11: Case study 2 Operating and Maintenance results using DAOA

Most of the time, the table's grid power export cost remains at $0.00, except for the hours (21-23). This indicates that the microgrid does not send much excess power back to the grid at any hour, which may reflect limitations in storage or in the grid's capacity to accept excess power.

3.8.3 Case Study 3: Grid-connected Microgrid dispatch with PV and Battery using DAOA Method

In this case, the energy dispatch of the grid-PV-Battery Storage hybrid is the objective function, and DAOA is used for optimization. The obtained results for grid power dispatch with PV and battery storage using DAOA are shown in Table 3.5 and are depicted in. Grid power dispatch with PV, as well as Battery storage using DAOA, is depicted in Table 3.5. The load demand is always the same as in other cases across all case studies and ranges from 2200 kW to 5400 kW. Table 3.6 presents the corresponding operating and maintenance cost results, listing the costs of the grid, PV, battery, grid import, and grid export.

Table 3. 5: Grid-connected Microgrid dispatch with PV and Battery using DAOA Method

Hour	Load Power in kW	PV Power in kW	Battery Power in kW	Grid Power in kW	Total Operating Cost in $
1	2200	0.00	100.00	2100.00	383.00
2	2400	0.00	100.00	2300.00	419.00
3	2800	0.00	100.00	2700.00	491.00
4	3200	0.00	500.00	2700.00	511.00
5	3400	0.00	500.00	2900.00	547.00
6	3800	0.00	500.00	3300.00	619.00
7	4000	0.00	-300.00	4300.00	759.00
8	4200	229.54	-300.00	4270.46	754.83
9	4600	313.01	-300.00	4586.99	812.22
10	5000	333.88	500.00	4166.12	776.57
11	5200	400.65	500.00	4299.35	800.89
12	5400	417.34	500.00	4482.66	833.96
13	5300	409.00	500.00	4391.00	817.43
14	5200	417.34	500.00	4282.66	797.96
15	5000	333.88	100.00	4566.12	828.57
16	4600	292.14	100.00	4207.86	763.88
17	4000	125.20	100.00	3774.80	685.09
18	3700	0.00	-300.00	4000.00	705.00
19	3400	0.00	-300.00	3700.00	651.00
20	3200	0.00	-300.00	3500.00	615.00
21	3000	0.00	-300.00	3300.00	579.00
22	2800	0.00	500.00	2300.00	439.00
23	2600	0.00	500.00	2100.00	403.00
24	2400	0.00	100.00	2300.00	419.00

PV power output starts from zero (hours1-7) and gradually increases as the day progresses, peaking toward midday (11-14). During periods of high load and insufficient PV generation, the battery provides up to 500kW of support, while the grid compensates for the shortfall, particularly during high-load periods when PV contributions are limited. The grid power required varies significantly, sometimes 4000kW when a battery support is utilized.

Table 3. 6: Microgrid Operating and Maintenance cost with PV and Battery using DAOA Method

Hour	PV Power cost in $	Grid Power Import cost in $	Grid Power Export cost in $	Battery Power degradation cost in $	Total Operating Cost
1	0.00	378.00	0.00	5.00	383.00
2	0.00	414.00	0.00	5.00	419.00
3	0.00	486.00	0.00	5.00	491.00
4	0.00	486.00	0.00	25.00	511.00
5	0.00	522.00	0.00	25.00	547.00
6	0.00	594.00	0.00	25.00	619.00
7	0.00	774.00	0.00	-15.00	759.00
8	1.15	768.68	0.00	-15.00	754.83
9	1.57	825.66	0.00	-15.00	812.22
10	1.67	749.90	0.00	25.00	776.57
11	2.00	773.88	0.00	25.00	800.89
12	2.09	806.88	0.00	25.00	833.96
13	2.04	790.38	0.00	25.00	817.43
14	2.09	770.88	0.00	25.00	797.96
15	1.67	821.90	0.00	5.00	828.57
16	1.46	757.41	0.00	5.00	763.88
17	0.63	679.46	0.00	5.00	685.09
18	0.00	720.00	0.00	-15.00	705.00
19	0.00	666.00	0.00	-15.00	651.00
20	0.00	630.00	0.00	-15.00	615.00
21	0.00	594.00	0.00	-15.00	579.00
22	0.00	414.00	0.00	25.00	439.00
23	0.00	378.00	0.00	25.00	403.00
24	0.00	414.00	0.00	5.00	419.00

Table 3.6 provides a detailed overview of the operating and maintenance costs associated with a microgrid system that uses PV and battery storage. The analysis is done using the DAOA algorithm. The PV cost is very low, which indicates a lower cost for generating PV power, and essentially reflects the utilization of renewable energy. There are no costs associated with exporting power to the grid, as indicated by the $0.00 across all hours. This could suggest that all generated power is either consumed or stored rather than sold back to the grid.

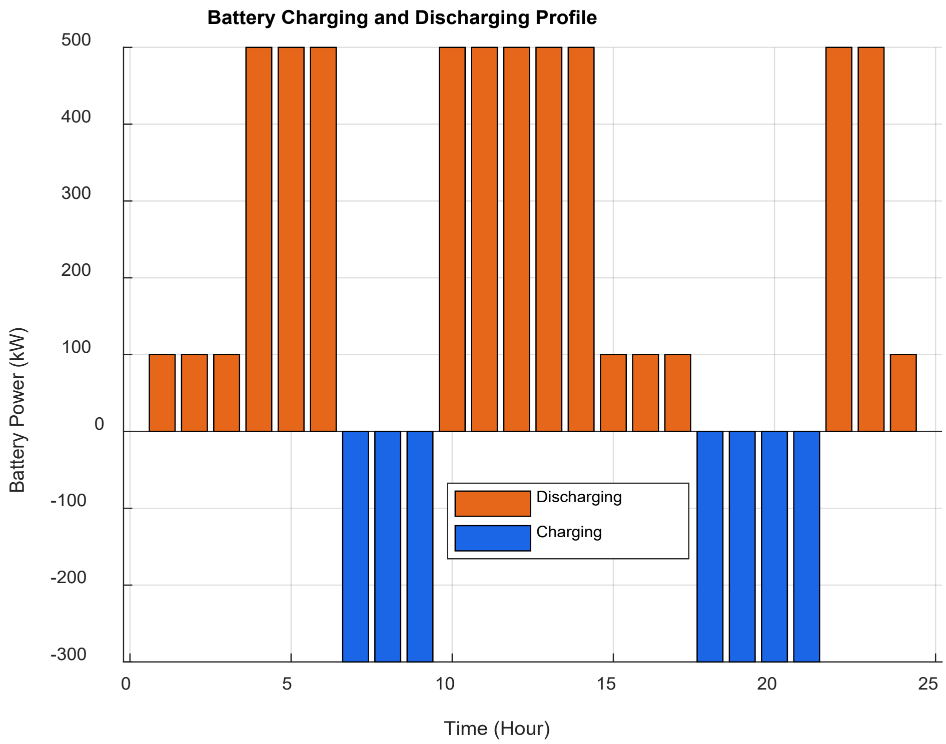

Figure 3. 12: Case study 3 Battery charging and discharging results using DAOA

The results of the battery charging and discharging in Figure 3.12 are similar to those of case study 1. Figures 3.13 and 3.14 display energy dispatch for the grid, PV, and battery scenario. The system mostly relies on grid import, as indicated by the purple area in Figure 3.13 and the red graph in Figure 3.14. PV generation is available between the hours 7 and 17, and it's not enough to meet the load, hence why grid import supports the system.

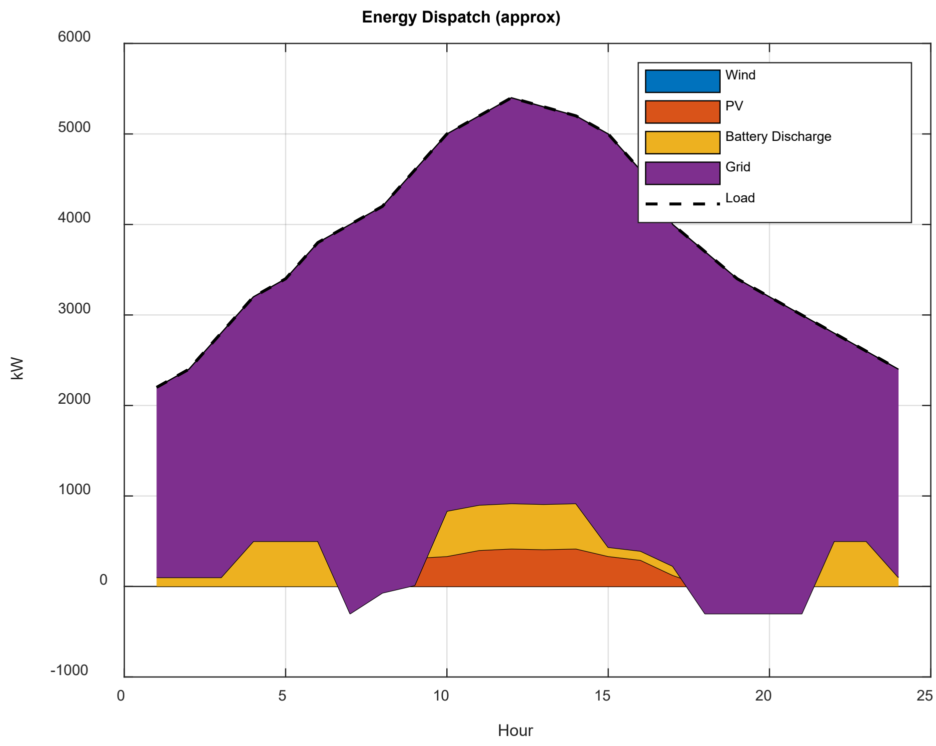

Figure 3.13: Case study 3 Energy Dispatch results using DAOA

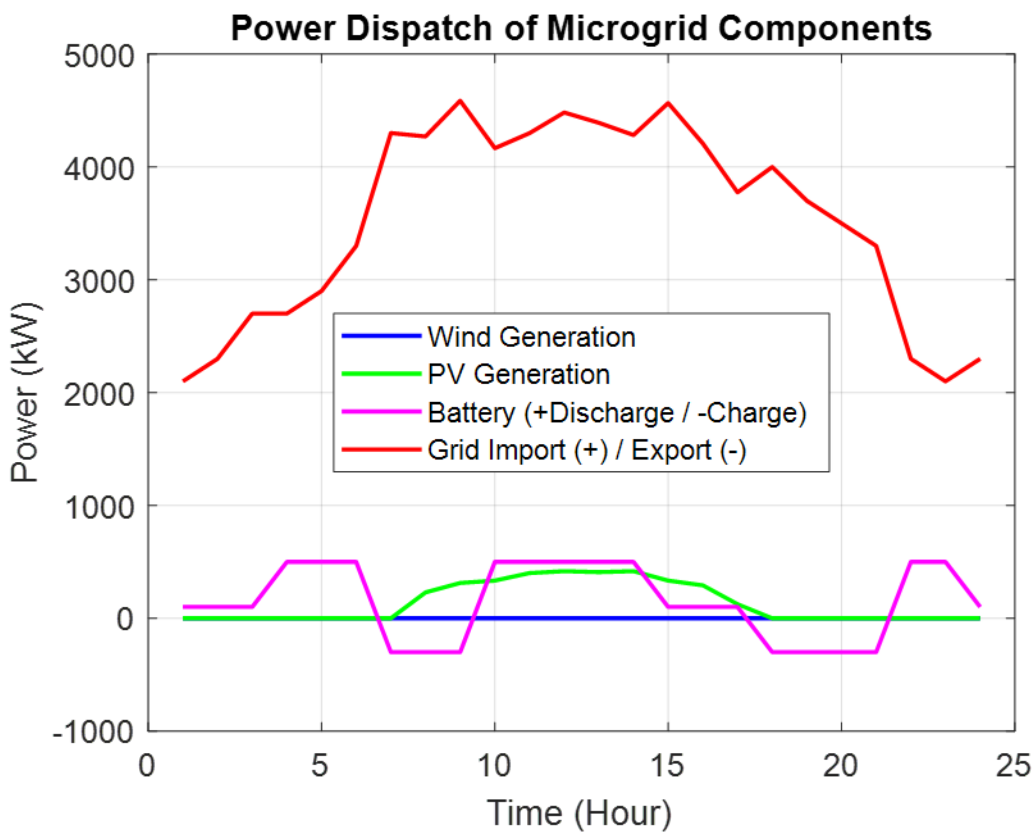

Figure 3. 14: Case study 3 Power Dispatch results using DAOA

Regarding the operational and maintenance costs for this case study, Figure 3.16 shows the grid import graph, which is higher than all the other costs due to the system's reliance on the grid. Then the battery cost exceeds the PV cost. The variation in battery cost depends on charging/discharging patterns, as shown in Figure 3.13, and ranges from \$5 to \$25.

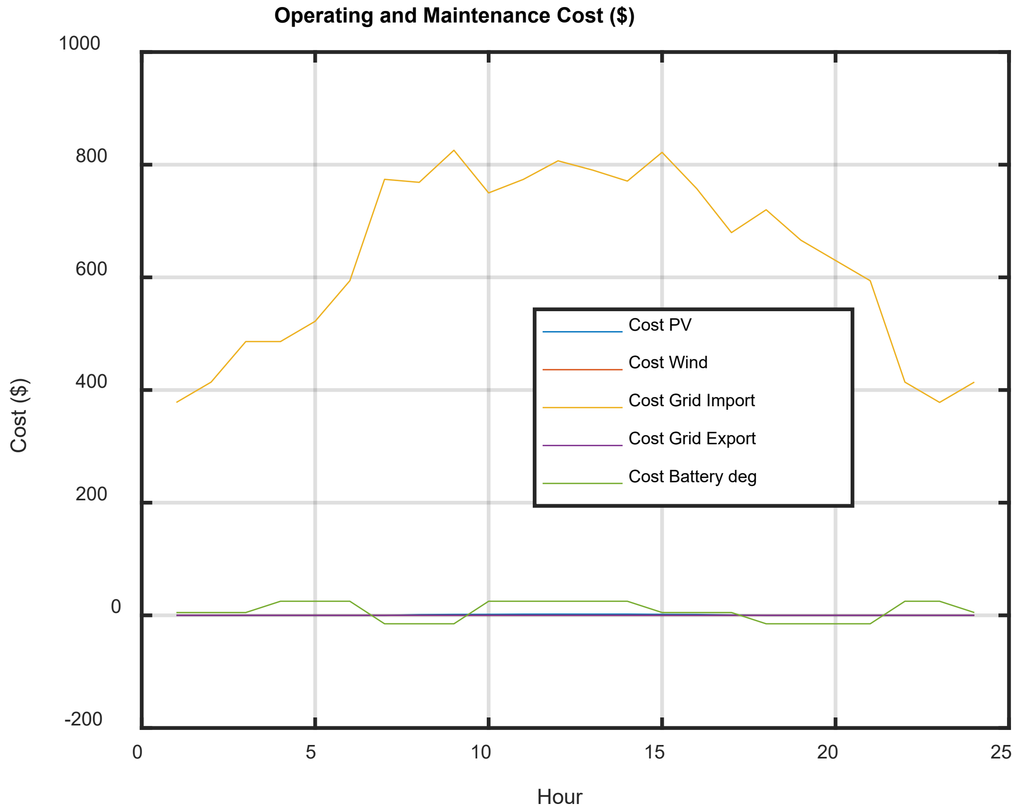

Figure 3. 15: Case study 3 Operating and Maintenance results using DAOA

The battery power degradation cost reflects the wear and tear on the battery system that occurs as it cycles between charging and discharging. The charges vary, with several hours showing negative costs, indicating potential battery optimization or incentives. While other reveals the cost of \$25.00 during the hour of heavy battery use from hour 10 to hour 14.

The total operational costs are lower during the daylight hours, as shown in Figure 3.15, when PV is abundant (hour 1 at \$383.00), but increase again later in the day as reliance on the grid power becomes more pronounced, reaching \$833.96 by hour 12. Therefore, the cost results show that the microgrid operates most efficiently during daylight hours when solar is utilized, minimizing grid imports and thereby lowering the total operating costs.

3.9 Discussion of the results for microgrid dispatch for the three scenarios using the DAOA Method

The comparative analysis of the three scenarios presented in this chapter is shown in Table 3.7. As the main objective is to minimize the operational and maintenance costs, the total costs for the three different scenarios are compared in Figure 3.16. The scenarios include a cost breakdown for combinations of wind, solar PV, battery, and the grid.

Table 3. 7: Microgrid Operating and Maintenance cost for three scenarios using the DAOA Method

Hour	Microgrid Dispatch Cost in $ (Wind, PV, Battery, and Grid)	Microgrid Dispatch Cost in $ (Wind and Grid)	Microgrid Dispatch Cost in $ (PV, Battery, and Grid)
1	140.80	153.80	383.00
2	180.71	193.71	419.00
3	267.66	280.66	491.00
4	251.15	316.15	511.00
5	244.62	309.62	547.00
6	289.85	354.85	619.00
7	445.74	406.74	759.00
8	359.35	362.29	754.83
9	96.33	114.53	812.22
10	110.69	50.00	776.57
11	213.73	351.95	800.89
12	511.05	652.31	833.96
13	536.19	675.92	817.43
14	315.01	456.28	797.96
15	221.34	295.36	828.57
16	107.44	173.83	763.88
17	68.44	53.55	685.09
18	213.28	174.28	705.00
19	339.72	300.72	651.00
20	66.29	33.39	615.00
21	49.10	76.10	579.00
22	150.47	105.47	439.00
23	120.34	75.34	403.00
24	168.25	181.25	419.00
Total Operating cost comparison for three scenarios using DAOA	**5467.56**	**6148.10**	**15411.4042**

The costs fluctuate significantly throughout the day in all three scenarios: case study 1, with a total operating cost of $5467.56; case study 2, with $6148.10; and case study 3, with **$15411.40.** The scenario in case study 1 generally shows lower costs than the case study 2 scenario, which uses only wind and the grid, particularly during peak hours, as depicted in Figure 3.16. The scenario that relies solely on PV, battery, and grid incurs the highest costs across most hours ($833.96 in hour 12), indicating a greater reliance on less efficient resources at certain times.

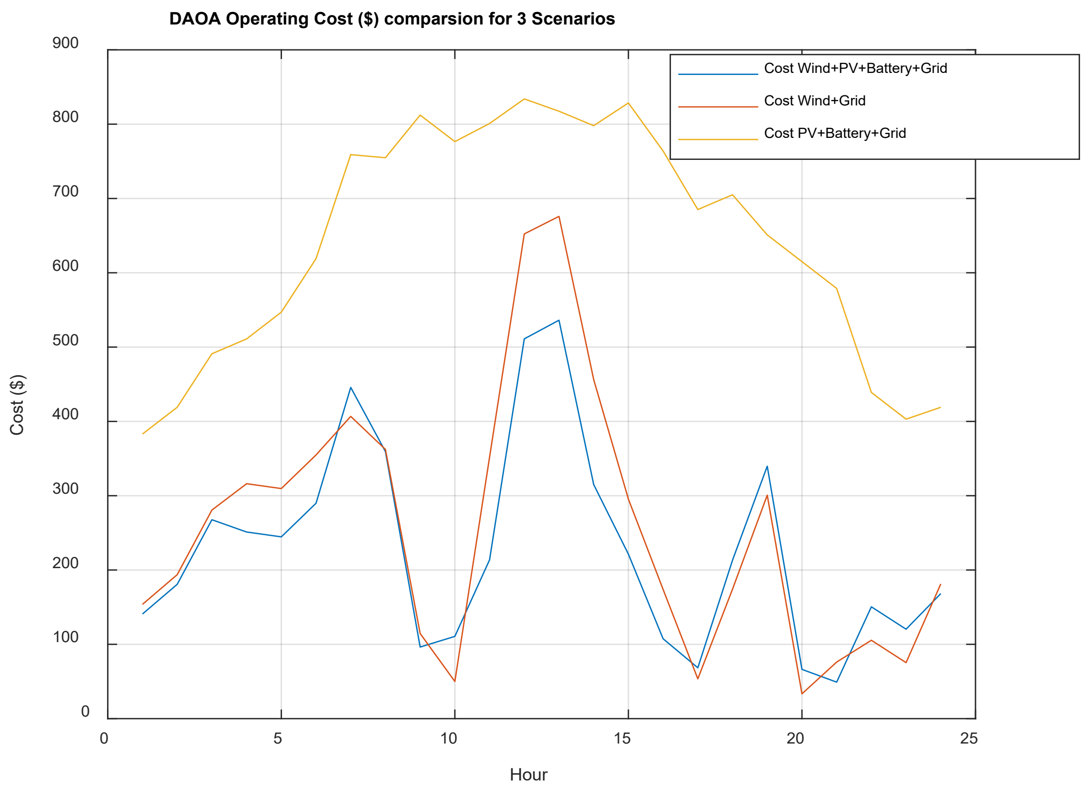

Figure 3. 16: Case study 3 Operating and Maintenance results using DAOA

In addition, it seems that the highest costs occur during peak potential demand, meaning that the financially most expensive hours also coincide with the highest energy demand (hours 12 and 13). Thus, the greater the demand for energy, the more it will cost. This is critical for the PV, Battery, and Grid case since it suggests that these hours are more focused on how best to provide power to meet demand.

However, it seems that lower running costs occur in the early morning and late at night (hours 1 through 4 and 20 through 23), probably because demand isn't as high and dispatch costs are more affordable.

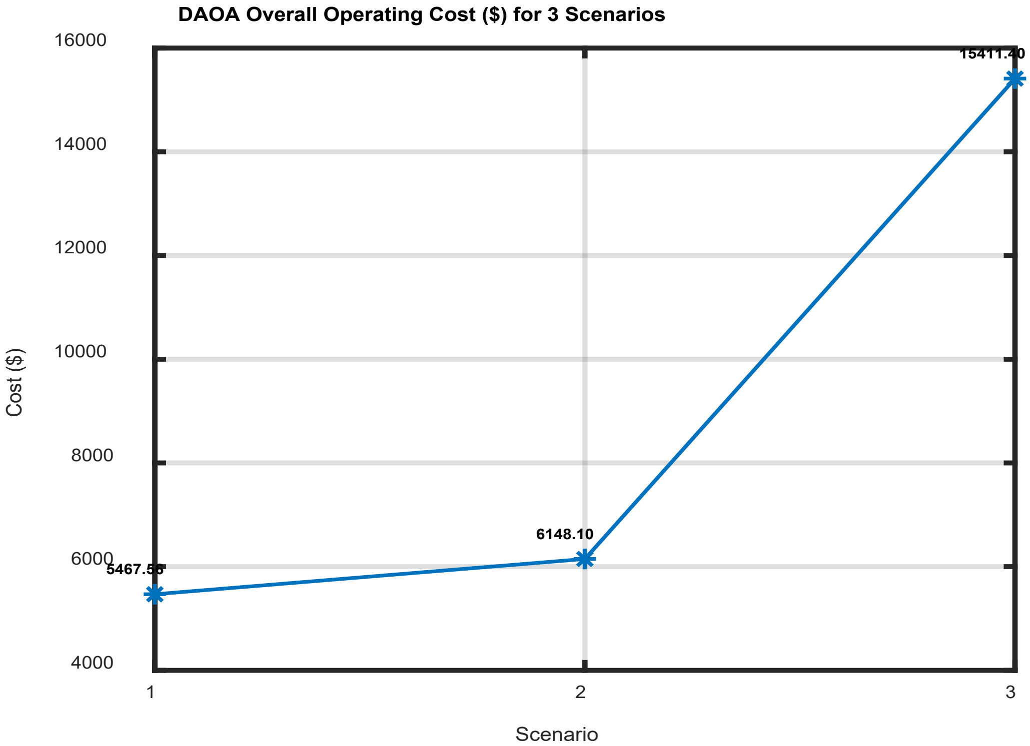

Figure 3. 17: Case study 3 Operating and Maintenance results using DAOA

The findings from Figure 3.17 indicate that the economic dispatch of the microgrid would be best served by a wind, solar, battery, and grid-input solution. This is because demand will vary throughout the day, and multiple resources in play, especially storage, will reduce costs and enhance resiliency. Thus, it implies that although wind and solar alone can be quite beneficial, with drastic cost reductions, they may not be enough during critical demand periods, and a combination may be better suited for an economically feasible approach. Therefore, it would be interesting to note whether certain configurations yield better cost reductions under different demand stresses.

3.10 Comparative analysis of operating costs for Linear Programming (LP), Grey Wolf Optimization (GWO), and DAOA techniques

Table 8 presents a comparative analysis of three optimization techniques for minimizing operational costs. DAOA results are optimal across all three scenarios.

Table 3. 8: Comparative analysis of operating costs for Linear Programming (LP), Grey Wolf Optimization (GWO), and DAOA techniques.

Case Study	LP Cost in ($)	GWO Cost in ($)	DAOA Cost in ($)
Grid-Connected Microgrid with Wind, PV, and Battery	14090.91	5802.44	**5467.56**
Grid-connected microgrid with wind	9761.02	6605.37	**6148.10**
Grid–PV–Battery Microgrid	16070.56	15668.82	**15411.4042**

3.11 Conclusion

Whereas the previous chapter was validated, this chapter uses DAOA as a successful controller because the weighted operating cost of the grid-connected PV-Wind-Battery microgrid is driven mostly by grid imports, as the weighted operational cost was expressed. Thus, for these optimal schedules, it's clear that, despite the operation of renewable resources, a full grid connection is worth it, as excess demand during generation-deficient times is considered the most valuable and thus most grid-import is connected. The operation of the battery, however, is the second most valuable operating cost, as a constant charge and discharge is needed to eliminate the surges associated with different resources. For PV, this is the lowest operating cost because it is a low-value operation; however, not operating PV at all, or to a lesser degree, shows the impact of its effective but low-cost operation compared to large contributions. At the same time, it shows that PV is beneficial for load sharing from renewable resources rather than from the grid, even though it operates infrequently due to its transient nature. The fact that grid export occurred at no time during the microgrid evaluation suggests that renewable generation equalled load demand and excess demand but never exceeded demand for anything else. Therefore, this problem assessed a dispatch operations evaluation that can provide optimal means for realistic development, envisioning maximum renewable contributions, minimal battery excess, and tactical grid use when necessary. Therefore, DAOA provides cost-effective operation through balanced components, improving economic feasibility in practice for hybrid renewable microgrids. Chapter 4 will revisit this microgrid for DAOA validation, as a Linear Programming method will be applied and the results compared with those in this chapter and Chapter 3.

CHAPTER 4

LINEAR PROGRAMMING OPTIMIZATION METHOD FOR RENEWABLE ENERGY-BASED MICROGRID SYSTEM

4.1 Introduction

This chapter implements LP optimization for a hybrid wind, photovoltaic (PV), Battery Storage System (BSS), and grid energy system, with the objective of minimizing total daily energy costs ($) subject to the required system constraints. Therefore, a mathematical formulation is established, and optimization is performed in MATLAB. The study formulates cost models for wind, PV, and battery systems, including daily cost and cost per energy delivered. Each cost formulation is run through using MATLAB simulations. Thus, this study serves as an applied investigation into the economic viability and operational efficiency of renewable systems. The hybrid system addresses the intermittency of solar PV and wind generation and load demand through the appropriate optimization of the BSS within the designed hybrid system.

One of the main cost-related objectives in energy systems (and especially hybrid renewable systems) planning and operation is that of minimization. Furthermore, it is often involved in complex decision-making processes, for which Linear Programming (LP) and Grey Wolf Optimization have proven effective, and where advanced system performance relies on such applications. The LP method observed in this study narrows the focus using a deterministic, mathematically rigorous algorithm that provides clear optimal solutions while properly satisfying the constraints and objective functions defined in advance.

The structure, parameters, and ease of use of the LP algorithm provide decision-makers with an accessible option for parsing large amounts of data and identifying variables available for action. For example, LP has been used in microgrid energy management (Shufian & Mohammad, 2022), where electricity savings up to 19% were achieved, while mixed-integer LP-based demand response solutions saved up to 38% (Babu et al., 2025).

Ultimately, implementing such a solution supports increased performance reliability across the entire system. An optimization where the objective is cost minimization while maximizing total power output in the microgrid, and where the general objective function is a weighted formulation where maximizing total power output from each specific resource is combined with the minimization of energy generation costs from wind, PV, and battery storage. Thus, it also minimizes total carbon emissions from energy generation. Therefore, a weighted solution seeks to maximize available energy while minimizing emissions.

Linear programming (LP) is an effective approach for optimizing economic dispatch in hybrid microgrids due to its computational efficiency. As long as the dispatch issue can be framed in a linear objective function where costs associated with fuel provision, operation, maintenance or overall system demand tend to be minimized, LP successfully positions itself among system constraints like power balance, generator/storage capacity constraints, and renewable resource constraints that effectively provide optimal generation schedules for all resources involved. In this situation, PV and wind generation outputs will be analyzed as forecasted resources expected to be provided, while simultaneously optimizing BESS charging and discharging when load demand exceeds capabilities, either from renewable resources or from other costly/high-emission generation resources. Thus, the LP model guarantees an adequate supply to meet demand at every timestep while maximizing system efficiency.

The theoretical background of this study is presented in Section 4.2, while Section 4.3 presents a hybrid microgrid system model from the mathematical formulation of the standardized linear programming optimization for the general case. Furthermore, all power sources involved in the mathematical formulation for cost analysis are presented in 4.3. The general mathematical formulation begins with a comprehensive analysis of all components of the system, systematically summarized. Then specific cost formulations are derived for wind (4.3.2), photovoltaic (4.3.3), and battery storage (4.3.4) to accurately represent the economic contributions of each technology. The Linear Programming algorithm is presented in Section 4.4, beginning with general assumptions (4.4.1) that remain consistent with real-world feasibility and a justified objective function (4.4.2). The LP application to the dispatch problem occurs in Section 4.5.

Section 4.6.0 presents the case studies and simulation results that demonstrate the performance of the LP optimization method in hybrid renewable energy scenarios (4.6.1). Case study 1: grid-connected Microgrid Dispatch for PV-Wind-Battery-Grid system (4.6.2), Case study 2: grid-connected Microgrid with Wind (4.6.3), and Case study 3: grid-connected Microgrid Dispatch for PV-Battery-Grid system (4.7), which highlight the effectiveness of LP in optimizing microgrid dispatch. Lastly, Section 4.8 synthesizes the findings and provides conclusions that bridge the theoretical formulations with practical implications for the operation of renewable-based microgrids.

4.2 Theoretical background of the Optimization for Renewable Energy-Based Microgrid System

At present, Renewable Energy generation technologies play a very pivotal part in the power system. Microgrid solutions recover the mismatch between generation and load demand. Thus, gained traction due to their ease of operation and ability to operate remotely, using both renewable and fossil fuel-based power sources. Moreover, Renewable Energy solution technologies can establish comparatively large and stable power source capabilities even in remote villages situated in dense forests or mountainous regions (Bhanja et al., 2020; Salkuti, 2019). Greenhouse gas emissions, network overloading, and bloated energy consumption costs are the major problems faced by both developing and developed countries (Abdel-Mawgoud et al., 2021). A microgrid is a localized electricity distribution system that integrates multiple distributed generation units to supply nearby loads. It can operate independently from the central grid, enhancing resilience and energy autonomy. However, integrating inverter-based distributed generators into microgrids poses challenges that must be addressed in planning and operation (Zaben et al., 2024).

(Bhanja et al., 2020) Stated that India has achieved 100% village electrification, but many rural areas still face reliability and quality-of-supply issues. With a 42% supply adjustment to rural demand needs, a clear message emerges: the necessity of Renewable Energy-based microgrids for improved generation across the rural landscape. The energy management systems for commercial units involve reducing energy consumption through electrical means without jeopardizing work quality, for energy and cost effectiveness.

We coexist in an environment of rising energy demand. According to data, global energy consumption is expected to increase by 48% before 2040. Energy Information Administration (EIA) Report by the United States. A microgrid is a system that includes distributed micro-generation resources such as solar, wind, fuel cells, and storage devices, which connect to the main grid and interface intermittently for stand-alone purposes. Systems are enhanced through a process called distributed generation. A three-phase, long-term, medium-term, and short-term approach exists for power system control.

Generators must be planned under long-term prediction about loads; load growth needs to be anticipated, maintenance needs to be assessed over medium-term planning based on fuel costs, and short-term planning requires output power from the determined intervals (Dashtdar et al., 2022). The reporting planning intervals, which help assess results, are 1 week, 1 day, and 1 hour.

Reported by (Vaish et al., 2025)Formulations of economic scheduling and cost minimization for microgrid networks focus on the crucial element in every microgrid system for sustainable operations.

Recent advancements in technology have boosted today's performance of photovoltaic (PV) systems; thus, shorter Energy Payback Time (EPBT) results in fewer carbon footprints. However, in an attempt to highlight the many attractive benefits of renewable energy technology, it has become a crucial resource for countless researchers. Hybrid systems (like PV and ESSs) and recycling systems don't count as much. Many studies have been conducted on the sizing, configuration, and control of hybrids while accounting for implementation considerations. Reference (Abebe et al., 2019) provided a genuine aspect of sizing standalone hybrid photovoltaic-wind systems.

Microgrid optimization is pertinent to rural India because it's not realistic for all regions to have access to pre-existing infrastructure without national grid connection costs so high that no one could ever afford them. Therefore, decentralized renewable energy systems enable localized electrification efforts. Where communities can operate independent systems managed through distributed generation (Bhanja et al., 2020).

A study by (Gil-González et al., 2023) proved that both DC renewables and Battery Storage Systems are optimally managed. A successful decentralized microgrid developed effective control strategies for demand and solar and wind resource uncertainties. Therefore, these major issues help minimize total energy costs. In addition, a microgrid distribution system is studied, with distribution limits associated with voltage constraints and constrained operations. The study showed how distributed generators and hybrid energy control technologies were assessed to better leverage. Finally, a study about mechanical energy by AI methodologies showed how a microgrid can benefit from a multitude of renewable resources combined for sustainability and quality of supply (Khaleel et al., 2023).

4.3 Modeling Hybrid Microgrid Systems

This research explored the potential of a hybrid microgrid system combined with BSS, focusing on enhancing performance and optimization. The effort involved comprehensive modeling of photovoltaic (PV) systems, wind energy generators, and load demands, with methodologies drawn from established references. (Fayek and Abdalla, 2022) and(Salkuti, 2019).

4.3.1 Linear Programming Optimization Mathematical formulation

The focus of this research is the potential exploration of a hybrid microgrid system combined with BSS to enhance performance and optimize operation using the Linear Programming method. Comprehensive modeling of photovoltaic PV systems, wind generators, and load demand involved methodologies drawn from established references. (Fayek & Abdalla, 2022) and(Salkuti, 2019).MATLAB simulations for the basic LP and GWO algorithm models to minimize the cost of supplying the load utilizing wind power, PV solar, grid import, and load demand are considered.

Equations (4.1) and (4.2) state the study's primary objective: to minimize the total energy cost.

$$P_{load(t)} = \left(P_{wind(t)} + P_{pv(t)} + P_{grid(t)}\right) \quad (4.1)$$

$$Minimize: \sum_t \left(C_{grid} . P_{grid(t)}\right) \quad (4.2)$$

Where, $P_{load(t)}$ is the load demand power.

$P_{wind(t)}$ is the power produced by a wind turbine.

$P_{pv(t)}$ is the power produced by a solar PV system.

$P_{grid(t)}$ is the power supplied by the grid.

Power limits for wind are indicated by Equation (4.3), while power limits for PV are indicated by Equation (4.4). As for the grid limits, Equation (4.5) is applied.

$$0 \le P_{wind(t)} \le P_{wind(t)}^{\max} \quad (4.3)$$

$$0 \le P_{pv(t)} \le P_{pv(t)}^{\max} \quad (4.4)$$

$$0 \le P_{grid(t)} \le P_{grid}^{\max} \quad (4.5)$$

$$E_{pv(t)} + E_{wind(t)} + E_{Battery-out(t)} + E_{grid(t)} \ge E_{load(t)} \quad (4.6)$$

Equation (4.7) denotes SOC limits for the battery SOC constraints, while charge/discharge power is expressed in Equation (4.8), but excluding simultaneous charge/discharge.

$$SOC_{\min} \le SOC_{(t)} \le SOC_{\max} \quad (4.7)$$

$$0 \le P_{charge}, P_{discharge} \le P_{bat,\max} \quad (4.8)$$

Grid energy limits are also considered, as expressed in Equation (9)

.

$$0 \le E_{grid(t)} \le E_{grid}^{\max} \quad (4.9)$$

4.3.2 Wind Power cost Mathematical formulation

Several key factors must be considered to effectively compute the daily cost of wind power in dollars. The overall total cost incurred each day, ongoing operation and maintenance costs, and capital costs are the key factors. There are categories in microgrid planning and dispatch models for the costs associated with wind and PV systems: (a) annualized capital (investment) costs, (b) fixed operation and maintenance (O&M) costs, and (c) variable O&M costs, in conjunction with occasional replacement or degradation expenses.

Annualized cost terms are comprised of components directly incorporated into a planning objective. The hourly objective includes variable O&M costs as well as curtailment and incentive terms for operational models.

In both academic and technical practice, the LP algorithm is considered standard. (And & Gorini, 2021).

$$Y_{Y_{(O\&M)}} = \frac{\left(C_{Y_{(O\&M)}}\right)}{(365)} \times P_{RE(rated)} \tag{4.10}$$

$Y_{Y_{(O\&M)}}$ is the annual operation and maintenance cost.

$C_{Y_{(O\&M)}}$ is the operation and maintenance cost per kW per year.

$P_{RE(rated)}$ is the rated wind power.

$$\lambda_{Daily(O\&M)} = \frac{\left(Y_{Y_{(O\&M)}}\right)}{(360)} \tag{4.11}$$

Annual operation and maintenance costs are calculated using Equation (4.10), which accounts for several factors that influence expenses.

Furthermore, Equation (4.11) provides a structured method for assessing the financial impacts of the system's routine maintenance and operational efficiency.

An accurate assessment of daily costs is achieved by considering all relevant factors, including the computation. Additionally, the total cost of capital, as well as operational and maintenance costs, is encapsulated by Equation (4.12).

$$\delta = 24 \times P_{wind} \times \partial \tag{4.12}$$

δ is the daily energy output (kWh)

P_{wind} is the rated wind power.

∂ is the capacity factor.

$$C_{(per\_kWh)} = \frac{\beta}{\delta} \tag{4.13}$$

Consequently, the daily energy output and the cost per kWh can be calculated using Equations (4.12) and (4.13, respectively.

4.3.3 PV Power Cost Mathematical formulation

Photovoltaic PV annual operation and maintenance cost associated with irradiation time series data are calculated based on the capacity of the plant, utilizing Equation

(4.10). Usually, LP models transform irradiance data into a time series that reflects available PV power. In this juncture, transformation enables a more accurate representation of the PV energy development over time, comprising variations in sunlight exposure (Jordan and Kurtz, 2017; Jordan and Kurtz, 2012)

$$C_{Y_{(O\&M)}} = C_{(O\&M)_{per-kW-year}} \times PV_{cap} \tag{4.14}$$

$C_{Y_{(O\&M)}}$ is the annual operation and maintenance cost for the PV power.

$C_{(O\&M)_{per-kW-year}}$ is the operation and maintenance cost per kW per year.

PV_{cap} is the PV power capacity.

While Equations 4.11 and 4.12 are utilized to compute the daily operation and maintenance cost and the total daily cost of the PV power generation.

$$C_{D_{E_{(out)}}} = P_{pv_{(cap)}} \times h_{(peak-sun)} \tag{4.15}$$

$P_{pv_{(cap)}}$ is the rated capacity of PV in kW

$h_{(peak-sun)}$ is the peak sun hours per day

$C_{D_{(tot)}}$ is the daily energy output cost in kWh

4.3.4 Cost calculations for BESS

The daily operation & maintenance cost for PV generation is calculated using Equation (4.11), yielding Equation (4.12). Equation (4.12) computes the total daily cost, and Equation (4.15) calculates the daily energy output cost of the PV system. One of the crucial roles in holding and allocating energy is battery storage, which stores energy instead of producing it directly (Luo et al., 2015). Components of the battery are as follows:

a) **Operation & Maintenance (O&M)**
   - Often small or included in CAPEX
   - Can be added as $/kWh-year or $/kWh throughput

b) **Cycle Life**
   - Number of full charge-discharge cycles before replacement

c) **Optional: Cost per kWh Delivered**
   - Based on daily throughput (how much energy is cycled daily

The significant roles of BSS in ensuring stable renewable intermittency, supply-demand balance, and providing ancillary services in microgrids.

$$C_{D_{(O\&M)}} = \frac{\left(C_{Y_{(O\&M)}} \times BSS_{cap}\right)}{(365)} \tag{4.16}$$

$C_{D_{(O\&M)}}$ is the daily operational and maintenance cost

$C_{Y_{(O\&M)}}$ is the operational and maintenance cost per kWh per year.

BSS_{cap} is the BSS capacity.

Equation (4.16) calculates daily operational and maintenance costs.

Wind and PV generation exhibit low costs once installed in a comparative perspective. PV offers predictable yields, while wind costs are more dependent on on-site conditions. Recurring costs incurred by BSS due to limited lifespan and efficiency losses make it indispensable for enabling high renewable penetration in microgrids.
Integration into optimization models, such as LP, is feasible when all resource costs are expressed in $/kWh or $/day. A robust basis for selecting the optimal resource mix is provided by this unified cost modelling framework, which enables a balance between economic efficiency and system reliability (Bhandari et al., 2015; Luo et al., 2015).

4.4 Linear Programming Algorithm

Linear Programming (LP) is a form of optimization in which the objective function is linear and is maximized/minimized subject to linear equality/inequality constraints. The fact that LP can achieve global optimality relative to the linear bounds imposed upon it has made LP a viable means of energy management (EMS) for microgrids. For example, Tenfen and Finardi (2015 developed a MILP-based formulation of microgrid operation to include microturbines, fuel cells, battery banks, and PV and wind resources with grid entry and exit and real technical constraints such as ramping limits and minimum up/down times (Tenfen and Finardi, 2015). Therefore, a constrained LP-based EMS with the objective function of minimizing electricity consumption costs with a customer operating in an integrated microgrid was compared to a heuristic-based constrained LP EMS and found that LP as a means of energy management yielded much larger savings (Shufian and Mohammad, 2022). Furthermore, documented fuel savings and optimization within LP models have referenced case studies with a reduction of 13.5% of diesel generation through justified LP models while increasing the generation of solar resources (Dolara et al., 2017). Finally, current literature reviews suggest that LP and MILP are the most studied mathematical methods of microgrid operation as well, where global optimality is the greatest advantage over heuristic solutions that achieve local optimum (Kalajahi et al., 2021).

4.4.1 Assumptions of Linear Programming

1. Linearity: Objective and constraints are linear.

The model is linear, meaning that the objective function and constraints can all be expressed by linear equations, and that the model can properly exist without overstepping boundaries.

2. Continuity: Variables can take any absolute values (can be relaxed in MILP)

In this situation, variables can take any absolute values, so it's straightforward to assess what would be optimal. This is less complicated because, in MILP, constraints are sometimes relaxed, allowing better-optimized solutions.

3. Determinism: All coefficients are known and fixed

All coefficients are known and fixed in this case, meaning that it will not deviate or change by circumstance, as the case is predetermined.

4. Additivity: Contributions to the objective and constraints are additive

Contributions to the objective and constraints of a mathematical model are additive, meaning that contributions towards an overall additive result (sum) can be assumed as a sum for an additive result.

4.4.2 Single-objective function formulation

The standard representation of the LP problem is a unique objective function that minimizes operational costs, as expressed in (4.17). This applies to PV, wind, battery, load, and grid real power. The LP problem consists of a formulation of sets, indices, variables, and parameters where:

4.4.3 Indices

$$t \in \{1, ..., T\} \tag{4.17}$$

$$\min J = \sum_{t=1}^{T} \left(c_{grid,t}^{buy} P_{grid,t}^{+} \Delta t - c_{grid,t}^{sell} P_{grid,t}^{-} \Delta t + c_{batt} \left(P_{b,ch,t} + P_{b,dis,t} \right) + c_{curt} \left(P_{pv,curt,t} + P_{w,curt,t} \right) \Delta t \right) \tag{4.18}$$

Decision variables:

$P_{pv,t}$ is the real power used from PV (kW)

$P_{pv\_curl,t}$ denotes curtailed PV power (kW)

$P_{w,t}$ symbolises real power used from wind (kW)

$P_{w\_curt,t}$ is the curtailed wind power (kW)

$P_{b,ch,t}$ is the battery charging power (kWh)

$P_{b,dis,t}$ is the battery discharging power (kW)

$E_{b,t}$ is the battery state-of -charge (SoC) (kWh)

$P_{grid,t}^{+}$ is the grid import power (kW, ≥ 0)

$P_{grid,t}^{-}$ is the grid export power (kW, ≥ 0)

$\mu_{b,t} \in \{0,1\}$ denotes binary to prevent simultaneous charge/discharge.

Equation (4.1729) is the formulated LP for the microgrid dispatch problem. The demand is intended to be satisfied while adhering to the technical constraints, and the objective is to minimize the total operational costs, as indicated by Equation (4.18). Power dispatch quantities from various energy sources and storage devices are typically included in the context of microgrids as decision variables.

4.4.4 Available parameters;

Import power incurs a positive cost, while export power generates revenue, which is a negative cost. Nevertheless, battery cycling cost is approximately linearly as the cost per kWh charged/discharged, and the curtailment penalty is set to discourage renewable energy losses.

$P_{pv}^{\max}$ is the rated PV capacity (kW)

$P_{w}^{\max}$ is the rated wind capacity (kW)

$a_{pv,t} \in [0,1]$ is the PV availability factor (clear-sky fraction)

$a_{w,t} \in [0,1]$ is the wind availability factor

$P_{load,t}$ is the demand/load (kW)

Δt is the time step length (h)

$E_b^{\min}, E_b^{\max}$ is the battery energy limit (kWh)

$P_b^{ch,\max}, P_b^{dis,\max}$ is the battery charge/discharge limits(kW)

η_{ch}, η_{dis} is the battery charge/discharge efficiencies (0< $\eta \leq 1$)

$c_{grid,t}^{buy}$ is the grid import energy price (currency/ kWh)

$c_{grid,t}^{sell}$ is the grid export energy price (currency/ kWh)

c_{batt} is the battery usage/degradation cost per kWh cycled

c_{curt} is the penalty cost for renewable curtailment

$E_{b,0}$ is the initial battery SoC (kWh)

4.4.5 Available generation

$$P_{pv.t}^{av} = P_{pv}^{\max} a_{pv,t} \tag{4.19}$$

$$P_{w.t}^{av} = P_{w}^{\max} a_{w,t} \tag{4.20}$$

4.4.6 Multi-Objective Function of Linear Programming

The main objectives are to minimize cost, emissions, and also to maximize the renewable fraction as presented by Equation (4.21)

$$\min\ J = \sum_{t=1}^{T} \omega_1 J_{\cos t} - \omega_2 \left(\vartheta\right) + \omega_3\, J_{emissions} \tag{4.21}$$

$$\vartheta = \frac{\left(\sum_t \left(P_{pv,t} + P_{w,t}\right)\Delta t\right)}{\left(\sum_t P_{load,t}\Delta t\right)} \tag{4.22}$$

4.4.7 Constraints

In practice, the constraints are set to require a minimum fraction to achieve minimization by negation.

4.4.7.1 Renewable availability and curtailment

The operational boundaries and inequality constraints for the microgrid components, as defined by Equation (4.23), represent an innovative approach to exploring new possibilities for improved system performance.

$$\begin{gathered} 0 \le P_{pv,t} \ \le P_{pv,t}^{av},\ 0 \le P_{pv\_curt,t} \le P_{pv,t}^{av} - P_{pv,t} \\ 0 \le P_{w,t} \ \le P_{w,t}^{av},\ 0 \le P_{w\_curt,t} \le P_{w,t}^{av} - P_{w,t} \end{gathered} \tag{4.23}$$

4.4.7.2 Battery Power Limits

In addition, the time efficiency of performance is also due to the variable battery state of charge (SoC), which governs Equations (4.24), (4.25), and (4.26) to facilitate practical storage system operation. Thus, a variable SoC is also important for improving performance and optimizing energy use in a battery. It reduces the time and energy of the performance.

$$\begin{gathered} 0 \le P_{b,ch,t} \le P_b^{ch,\max}, \qquad 0 \le P_{b,dis,t} \le P_b^{dis,\max} \\ P_{b,ch,t} P_b^{ch,\max_{\mu b,t,}} \qquad P_{b,dis,t} \le P_b^{dis,\max}\left(1 - \mu b, t\right) \end{gathered} \tag{4.24}$$

4.4.7.3 Battery Energy (SoC) dynamics

$$E_{b,t} = E_{b,t-1} + \left(\eta_{ch} P_{b,ch,t} - \frac{P_{b,dis,t}}{\eta_{dis}}\right)\Delta t, \qquad t = 1........T \tag{4.25}$$

$$\begin{gathered} E_b^{\min} \le E_{b,t} \le E_b^{\max}, \qquad E_{b,0} \quad given \\ E_{b,T} = E_{b,0} \end{gathered} \tag{4.26}$$

4.4.7.4 Grid Power non-negative separation

$$P_{grid,t}^{+} \ \ge 0, \quad P_{grid,t}^{-} \ge 0 \tag{4.27}$$

4.4.7.5 Power balance

The requirement that maintains the power balance at every individual time step is imposed by the equality constraints. The constraints specified by Equations (4.28) and (4.29) ensure that the total power generated matches the total power consumed, maintaining system stability and preventing operational imbalances.

$$P_{pv,t} + P_{w,t} + P_{b,dis,t} \; P_{grid,t} = P_{load,t} + P_{b,ch,t} + P^{-}_{grid,t} \tag{4.28}$$

$$P_{grid,t} = P^{+,\max}_{grid,t} - P^{-}_{grid,t} \tag{4.29}$$

4.4.7.6 Grid import/ export limits

$$0 \le P^{-,\max}_{grid}, \quad 0 \le P^{-}_{grid,t} \le P^{-\max}_{grid} \tag{4.30}$$

4.4.7.7 Compact LP form

Consequently, the objectives of this study for operating the microgrid at minimum cost, maintaining the supply-demand balance, and respecting the technical limitations are ensured by the LP optimization method. To achieve this goal, Equation (4.31) is being utilized.

$$J = \sum_{t=1}^{T} \left(c_{buy,t} P^{+}_{grid,t} \Delta t - c_{sell,t} P^{-}_{grid,t} \Delta t + c_{\;batt} \left(P_{b,ch,t} + P_{b,dis,t} \right) \Delta t + c_{curt,t} \left(P_{pv\_curt} + P_{pv\_curt,t} \right) \Delta t \right) \tag{4.31}$$

Subject to all t:

$$P_{pv,t} + P_{w,t} + P_{b,dis,t} + P^{+}_{grid,t} = P_{load,t} + P_{b,ch,t} + P^{-}_{grid,t} \tag{4.32}$$

$$0 \le P_{pv,t} \le P^{av}_{pv,t}, \qquad 0 \le P_{pv\_curt,t} \le P^{av}_{pv,t} - P_{pv,t} \tag{4.33}$$

$$0 \le P_{w,t} \le P^{av}_{w,t}, \qquad 0 \le P_{w\_curt,t} \le P^{av}_{w,t} - P_{w,t} \tag{4.34}$$

$$0 \le P_{b,ch,t} \le P^{ch,\max}_{b}, \qquad 0 \le P_{b,dis,t} \le P^{dis,\max}_{b} \tag{4.35}$$

$$E_{b,t} = E_{b,t-1} + \left(\eta_{ch} P_{b,ch,t} - \frac{P_{b,dis,t}}{\eta_{dis}} \right) \Delta t \tag{4.36}$$

$$E^{\min}_{b} \le E_{b,t} \le E^{\max}_{b} \tag{4.37}$$

$$P^{+}_{grid,t} \ge 0, \; P^{-}_{grid,t} \ge 0 \tag{4.38}$$

LP's computational efficiency and ability to handle large-scale optimization problems make it widely applied in microgrid scheduling and dispatch (Taha et al., 2022; Wu et al., 2021).

The parameters used in the LP optimization method are described in Table 4.1.

Table 4. 1: Description of parameters used in LP method of optimization

Symbol	Description
$x \in R^n$	Vector of decision variables
$c \in R^n$	Coefficient vector of the objective function
$A_{eq} \in R^{m \times n}$	Matrix of equality constraint coefficients
$b_{eq} \in R^m$	Right-hand side of equality constraints
A_{ineq}, b_{ineq}	Same as above, but for inequality constraints

4.5 Linear Programming algorithm for microgrid dispatch problem

Steps for the LP algorithm in the microgrid optimization problem are considered as:

4.5.1 Step 1: Start

The microgrid dispatch problem is widely regarded as a precursor to optimization. This includes an extended, specific definition of the purpose, limitations, and variables that will permit proper microgrid operation and control. For example, strictly from a dynamic perspective, one needs to take into account energy use forecasts and expected output from distributed energy resources, as well as operational limitations. Therefore, the only way to justify an effective basis for microgrid optimization of energy supply and use is to comprehensively examine these variables to ensure optimization makes sense.

4.5.2 Step 2: Input Data

Input to the optimization is generated from the following required data: load demand predictions, renewable generation predictions (PV and wind), grid electricity costs, and battery operational characteristics such as efficiency, capacity, and state-of-charge constraints (Wu et al., 2021).

4.5.3 Step 3: Define Decision Variables

Dispatched power from PV, wind, grid, as well as battery charging and discharging decisions over the scheduled horizon, are the specified control variables (Taha et al., 2022).

4.5.4 Step 4: Formulate Objective Function

The goal is to minimize the objective function representing the total microgrid operating cost. This typically means the grid's cost of electricity and battery cycling cost, renewable curtailment costs, and an unmet demand cost (Wu et al., 2021).

4.5.5 Step 5: Define Constraints

The LP constraints ensure the microgrid's feasible operation.

a) **Power balance:** total generation plus discharging equals load plus charging.
b) **Technical limits:** maximum and minimum bounds on PV, wind, and grid imports.
c) **Battery SOC dynamics:** the state-of-charge must remain within specified limits (Wu et al., 2021; Taha et al., 2022).

4.5.6 Step 6: Solve LP Optimization

The formulated LP model is solved using standard solvers such as MATLAB, which efficiently compute optimal solutions for linear problems.

4.5.7 Step 7: Obtain Optimal Dispatch

When to use PV and wind, how much to import from the grid, and when to charge or discharge the battery are outcomes of the optimization, which provides the optimal energy dispatch schedule (Wu et al., 2021).

4.5.8 Step 8: End

Consequently, the results provide an optimal plan for real-time microgrid operation and for microgrid planning and analysis, as shown in the LP algorithm flowchart depicted in Figure 4. 1.

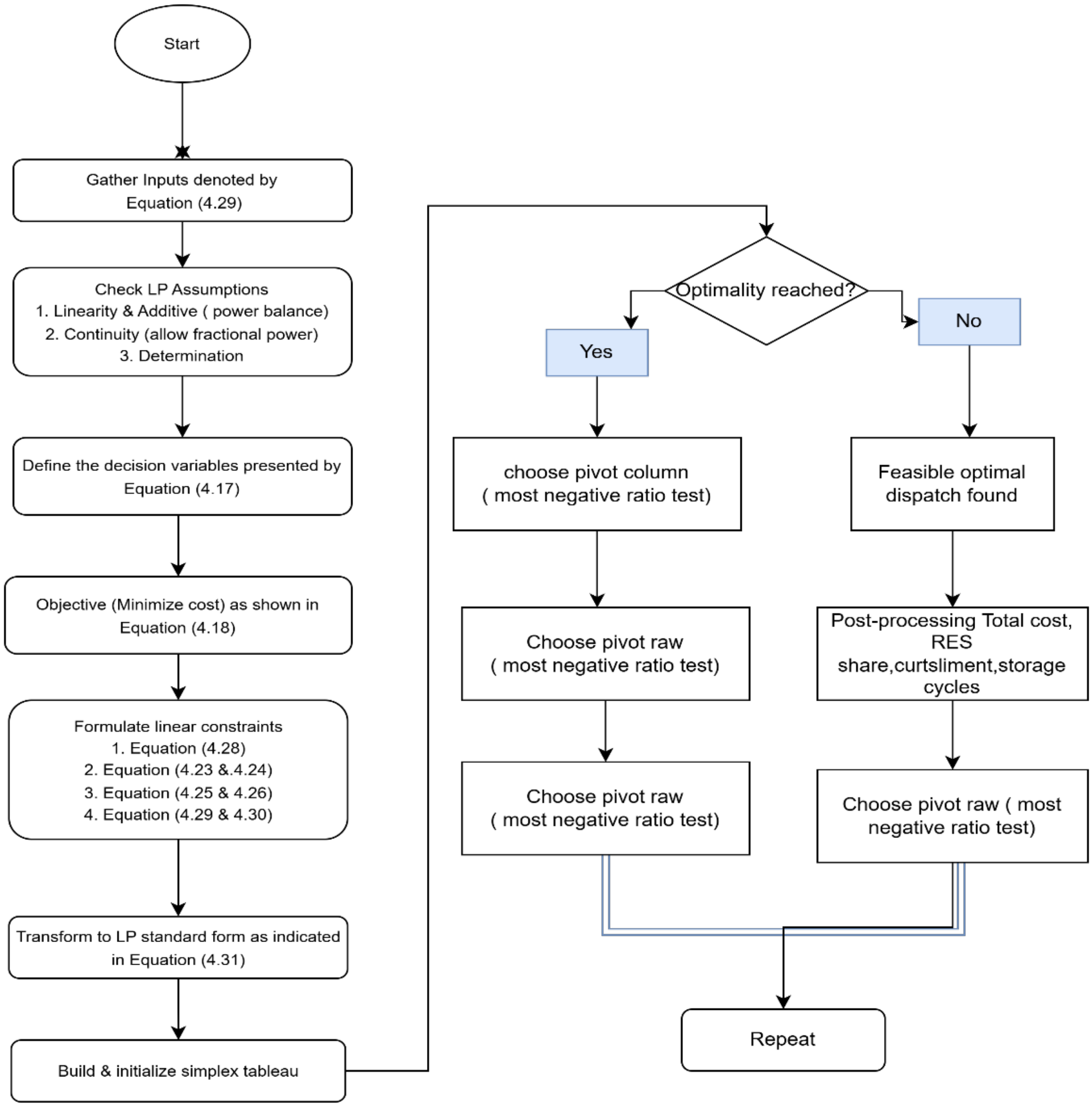

Figure 4. 1: Flow chart for Linear Programming Optimization

Figure 4.1 shows a typical LP optimization flowchart for microgrid applications. It begins with the input stage, where all necessary system data is gathered (load demand, renewable generation forecasts, grid buy tariff, etc.). Subsequently, the next step is to construct the objective function, which typically aims to minimize operating costs/maximize efficiency. After that, the constraint definitions follow, including power balance, minimum and maximum generation for each source, battery charging/discharging limitations, and the maximum power that can be bought from or sold to the grid. Thus, the problem is mathematically formulated and sent to an LP solver to determine how much power to allocate to each resource. Finally, a solution is provided for analysis and evaluation against operational requirements to achieve the best possible schedule and dispatch for the most cost-effective, efficient, and reliable microgrid.

The contribution of this manuscript is the minimization of the microgrid's operational and maintenance costs, while accounting for grid power interexchange, microgrid renewables, and battery energy storage. Thus, three different scenarios/case studies are analyzed, which are:

- **Case Study 1:** Performing simulations on the Grid-connected Microgrid dispatch with Wind, PV, and Battery
- **Case Study 2:** Considering Grid-connected Microgrid dispatch with Wind renewable energy resources
- **Case Study 3:** Conceptualize Grid-connected Microgrid dispatch with PV and Battery

4.6 Case Studies and Simulation Results

The network is shown in a single diagram, and an hourly table spanning 24 hours outlines the sequencing of costs for grid electricity and electricity from PV panels, wind, and battery storage. Figure 4.2 shows the single diagram of the constructed network.

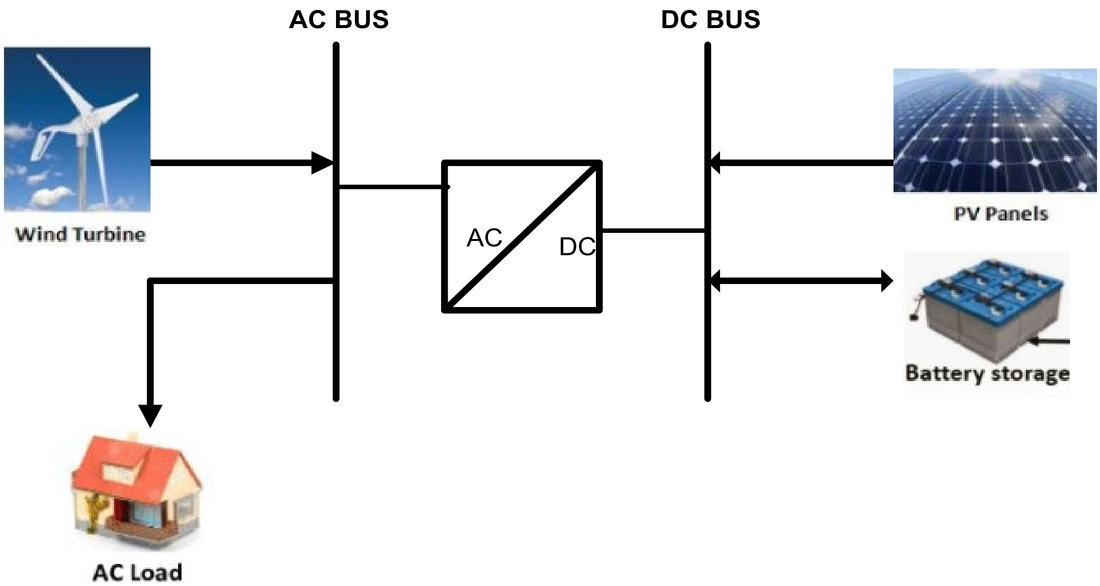

Figure 4. 2: **Single-line diagram of the proposed network**

Table 4.2 provides an exhaustive overview of hourly demand in conjunction with various environmental and energy parameters. Wind speed, wind energy generation, solar irradiation levels, and the accompanying photovoltaic (PV) power output are also included. This comprehensive representation allows for a deeper analysis of the relationship between energy demand and renewable energy sources throughout the day.

Table 4. 2: Power produced by PV, wind, and load demand for 24 hours

Hour	Power Demand in (kW)	Wind speed in (m/s)	Wind Power in (kW)	Solar irradiance in (W/m2)	PV Power in (kW)
1	2200	5.7	570	0	0
2	2400	6.5	846	0	0
3	2800	7.5	1299	0	0
4	3200	6.9	1011	0	0
5	3400	8.6	1958	93.5	108.722
6	3800	10.5	3564	212.5	247.095
7	4000	13.6	7744	255	296.514
8	4200	10.4	3463	467.5	543.609
9	4600	9.1	2320	637.5	741.285
10	5000	9.3	2476	680	790.704
11	5200	7.7	1406	816	948.845
12	5400	7	1056	850	988.38
13	5300	5.9	632	833	968.612
14	5200	4.9	362	850	988.38
15	5000	3.5	132	680	790.704
16	4600	3.4	121	595	691.866
17	4000	2.8	68	255	296.514
18	3700	3.1	92	212.5	247.095
19	3400	2.3	37	153	177.908
20	3200	2.9	75	68	79.07
21	3000	3.5	132	42.5	49.419
22	2800	3.8	169	0	0
23	2600	3.8	169	0	0
24	2400	4.8	340	0	0

Load demand ranges from 2200kW in the morning hours, and this gradually increases until 13:00 hours. Nevertheless, around 14:00 hours, it again starts to decrease until late afternoon, then into the night, reaching a value of 2400kW. Wind power shows an irregular pattern, with a peak at 07:00 of 7744kW. Thus, when the system exports power to the grid. As for the PV solar power, the output starts around 05:00 hours. It peaks at 12:00 noon and then decreases as solar irradiance declines, reaching 49.419kW at 21:00. From this hour, PV has no output until the morning when the sun rises.

4.6.1 Case study 1: Grid-connected Microgrid dispatch with Wind, PV, and Battery using LP algorithm

This case study delves into simulations and results analysis of the LP optimization method for the microgrid dispatch problem using hybrid renewable energy sources. Analysis of the results for the load demand from Table 4.2 and Table 4.3 shows that simulation with MATLAB results in less than (+/- 5%) Power Demand deviation from the Power produced by PV, Wind, and Load Demand, using the LP optimization Method. Therefore, the daily operating cost using the LP method for all PV generation, wind generation, and Battery discharge power was computed.

The daily PV Generation cost is computed using the LP method, and all costs are depicted in Table 4.3.

Table 4. 3: Grid-connected Microgrid dispatch with Wind, PV, and Battery using LP algorithm

Hour	Load Power in kW	Wind Power in kW	PV Power in kW	Battery Charging Power in kW (-ve)	Battery Discharging Power in kW (+Ve)	Battery SOC in kW	Power Import in kW	Power Export in kW	Total Operating cost in $
1	2200	16.17	0	0	0	500.00	2183.83	0.00	393.25
2	2400	13.75	0	0	0	500.00	2386.25	0.00	429.66
3	2800	6.73	0	0	0	500.00	2793.27	0.00	502.86
4	3200	30.61	0	108.89	0	603.45	3278.28	0.00	699.29
5	3400	95.63	0	0	0	603.45	3304.37	0.00	595.74
6	3800	164.79	0	364.79	0	950.00	4000.00	0.00	1086.44
7	4000	120.76	0	0	500	394.44	3379.24	0.00	1109.47
8	4200	452.25	550	0	175	200.00	3022.75	0.00	726.37
9	4600	5000	750	289.47	0	475.00	0.00	860.53	377.64
10	5000	5000	800	500	0	950.00	0.00	300.00	566.00
11	5200	2828.7	960	0	145.1	788.78	1266.16	0.00	406.10
12	5400	137.5	1000	0	262.53	497.08	4000.00	0.00	988.90
13	5300	52.63	980	0	267.37	200.00	4000.00	0.00	992.80
14	5200	1190.4	1000	0	0	200.00	3009.61	0.00	558.63
15	5000	3269.6	800	0	0	200.00	930.40	0.00	204.17
16	4600	4512.5	700	289.47	0	475.00	0.00	323.00	351.02
17	4000	5000	300	500	0	950.00	0.00	800.00	583.50
18	3700	1333.1	0	0	500	394.44	1866.90	0.00	849.37
19	3400	115.88	0	0	0	394.44	3284.12	0.00	592.30
20	3200	2167.7	0	0	175	200.00	857.30	0.00	350.99
21	3000	4871	0	0	0	200.00	0.00	1870.89	123.54
22	2800	5000	0	84.8	0	280.56	2183.83	2115.20	219.40
23	2600	3385.5	0	500	0	755.56	2386.25	285.52	545.28
24	2400	22.4	0	0	500	200.00	2793.27	0.00	838.19

Wind power generation is fluctuating, reaching peak at the hours (9,10,17, and 222), PV power is not available during morning periods (from 1 to 7 hours) and night periods (18 -24). Battery charging occurs when excess power is available, during the hours (4, 6, 9, 10, 16, 17, 22, 23), while battery discharge occurs during the hours (7, 8, 11, 12, 13, 18, 20, and 24). Battery SOC power is always active but varies between 200kW and 950kW, and grid power is either exported or imported, depending on the system's power exchange, as shown in Table 4.3. The high operating cost occurs during the maximum import power from the grid and when the battery's SOC is high.

Microgrid operating and maintenance cost using LP algorithm simulation results depicted in Table 4.4 present the cost of PV power, Wind power, grid power import and export, as well as the battery power cost, all in $. Total operating cost is the sum of all the costs incurred at a particular hour. The highest cost occurs at hour 7, when the system relies on battery power and imports power from the grid. Figure 4: The highest cost occurs at hour 7, when the system relies on battery power and imports power from the grid. Figure 4 illustrates the power dispatch characteristics over a 24-hour period. In this regard, wind power supports imported grid power while the PV and battery systems are only active at certain hours.

Table 4. 4: Microgrid Operating and Maintenance cost using LP algorithm

Hour	PV Power cost in ($)	Wind Power Cost in ($)	Grid Import Power in ($)	Grid Export Power in ($)	Battery Power in ($)	Total Operating Cost in ($)
1	0.00	0.16	393.09	0.00	0.00	393.25
2	0.00	0.14	429.53	0.00	0.00	429.66
3	0.00	0.07	502.79	0.00	0.00	502.86
4	0.00	0.31	590.09	0.00	108.89	699.29
5	0.00	0.96	594.79	0.00	0.00	595.74
6	0.00	1.65	720.00	0.00	364.79	1086.44
7	0.00	1.21	608.26	0.00	500.00	1109.47
8	2.75	4.52	544.09	0.00	175.00	726.37
9	3.75	50.00	0.00	34.42	289.47	377.64
10	4.00	50.00	0.00	12.00	500.00	566.00
11	4.80	28.29	227.91	0.00	145.10	406.10
12	5.00	1.37	720.00	0.00	262.53	988.90
13	4.90	0.53	720.00	0.00	267.37	992.80
14	5.00	11.90	541.73	0.00	0.00	558.63
15	4.00	32.70	167.47	0.00	0.00	204.17
16	3.50	45.12	0.00	12.92	289.47	351.02
17	1.50	50.00	0.00	32.00	500.00	583.50
18	0.00	13.33	336.04	0.00	500.00	849.37
19	0.00	1.16	591.14	0.00	0.00	592.30
20	0.00	21.68	154.31	0.00	175.00	350.99
21	0.00	48.71	0.00	74.84	0.00	123.54
22	0.00	50.00	0.00	84.61	84.80	219.40
23	0.00	33.86	0.00	11.42	500.00	545.28
24	0.00	0.22	337.97	0.00	500.00	838.19

Figure 4.3 presents the simulation results for load power consumption over 24 hours. In the early morning hours, the load consumption begins to rise steadily, starting from 2,200 kW and reaching a peak of 5,400 kW at midday. Following this peak, the consumption gradually declines, tapering off to approximately 2,400 kW by midnight.

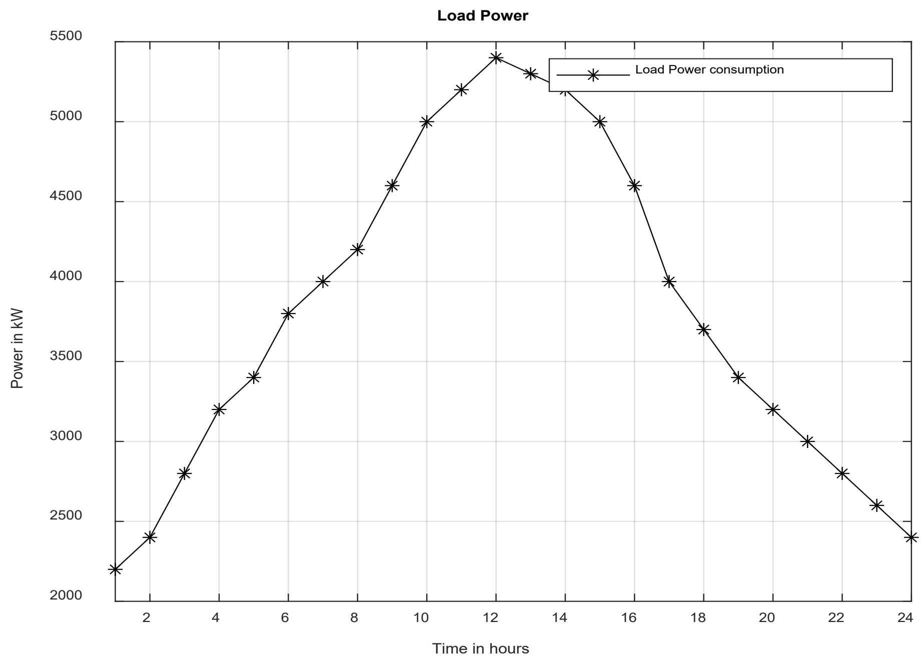

Figure 4. 3: Load Power Consumption simulation results for 24 hours

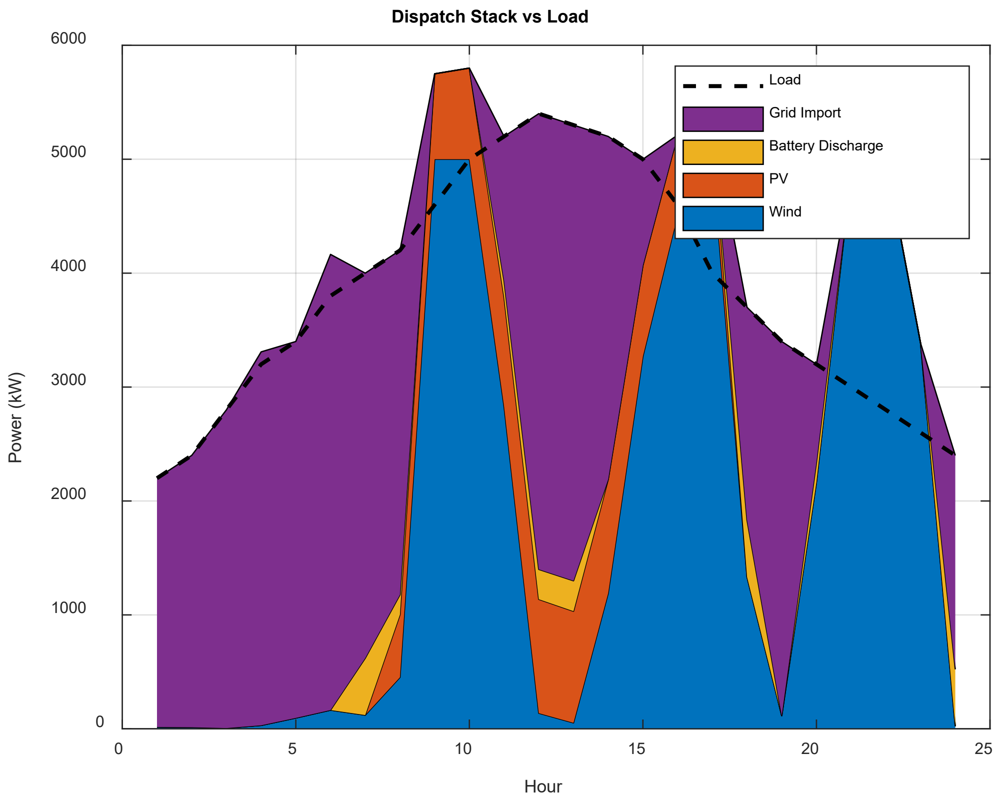

Figure 4. 4: Grid-connected Microgrid dispatch with Wind, PV, and Battery using LP algorithm for 24 hours using LP

Figure 4.4 illustrates how different energy sources (Wind-PV-Battery discharge and grid imports) work together to meet the hourly load demand over 24 hours. The dashed line represents the load profile, showing the demand gradually increasing from the early morning hours and peaking between 10 and 15. Eventually, the load demand starts to decline in the evening. Wind power (blue area) accounts for the largest share of the energy composition and effectively provides the greatest load satisfaction around hours 9 – 10 and again around hours 17 - 18, and even helps alleviate grid imports. Likewise, PV generation (orange) is only present during daytime hours, most notably at hours 7 and 16, and helps reduce grid reliance during peak hours it would otherwise need. In addition, battery discharge (yellow) is most prevalent during these key times when demand exceeds renewable generation. In fact, the battery aids load leveling during periods of renewable generation when demand cannot be met, and it discharges when necessary.

Grid imports (purple) add to any additional demand needed that cannot be met by renewables + battery discharge and occurs predominantly in early morning and nighttime hours when solar/wind generation is at its lowest. The majority of grid input observed during hours 6-8 and 12-14 illustrates those hours which are primarily consuming the most energy but have little to no output from renewables.

However, little reliance on the grid when wind runs (or PVs) indicates that renewables are effectively doing what they need to do to output so that reliance on exogenous measures isn't needed that often.

Overall, this case study provides an effective dispatch integration where renewables are first part of the process, battery assistance is accounted for at peak times, and the grid is the backup needed to satisfy energy performance requirements. Therefore, this is a strong indication that hybrid microgrid integration for load levelling is a good option since resources can help fulfil a diverse load pattern as the day plays out. For the convex linear formulation, Linear Programming was selected because it guarantees global optimality with minimal computational cost. Using more sophisticated methods would have added complexity without improving solution quality.

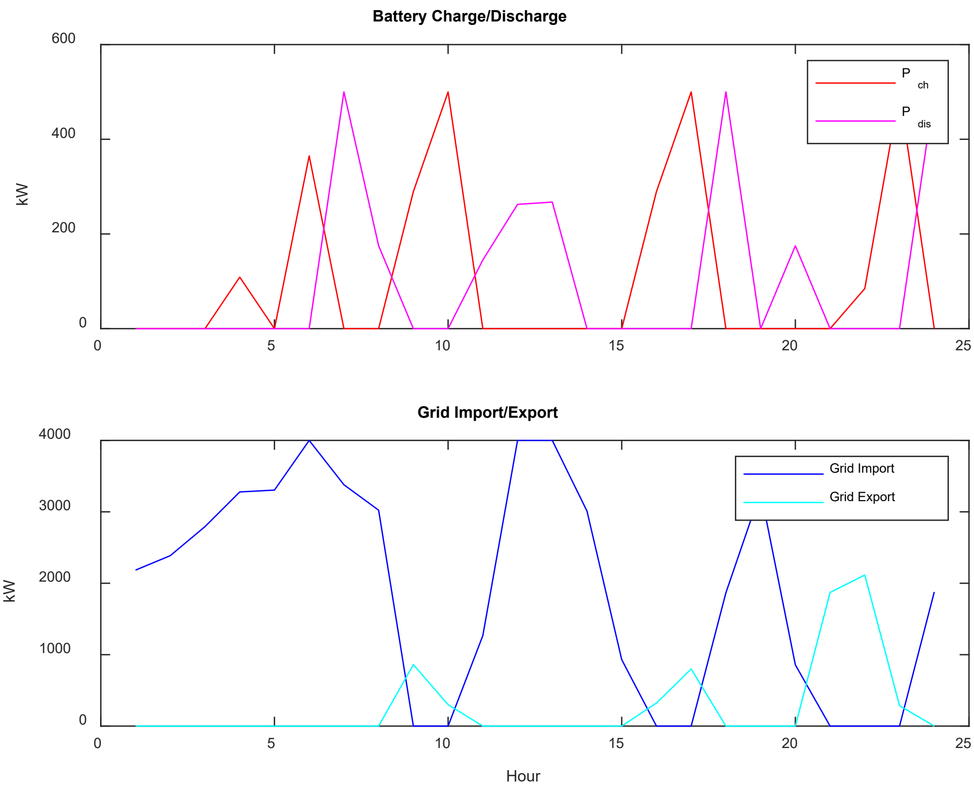

Figure 4. 5: Battery charge/Discharge and Grid Import/Export using LP algorithm

The battery charge/discharge schedule shown in Figure 4.5 corresponds to the microgrid demand for each day through certain hours. For instance, the battery charges during hours when excess generation from renewables occurs, mostly midday until late afternoon, as the peak charging hours show (at those hours) either wind or solar excess. The battery, however, predominantly discharges during high demand hours or lower generation hours somewhere between hours 8-12 and 18-22, as the peak discharges show at (that hour) that the battery is in play (at that hour) and supplying what is needed from previously stored energy. This indicates its contribution toward energy generation as if this charge is needed to minimize any type of dependence on the grid, it must be critical in supplying enough generation to meet demand.

Therefore, without the battery, this microgrid would be dependent on the grid to meet its entire demand, especially during these hours. Therefore, the battery operates mostly at 0% charge/discharge between peaks, showing its maximum capacity for utilization. For example, in the grid imports and exports chart, imports are generally high during the morning and evening hours when renewable generation cannot meet all demand or, as previously noted, generation is at its lowest. For example, grid imports occur between hours 4-7 in the morning and between hours 12-14 in the midday. The grid exports occur for less time between hours 10-20, which shows excess generation than anticipated for those hours. It seems unnecessary to export and generate from the battery at those hours and rely on the grid. The only option that works together are the battery generation and grid exports as renewable fluctuation assists in mitigating the necessity to pull on battery supply for hours on end as the grid, ultimately, can assist if needed, although for shorter time periods.

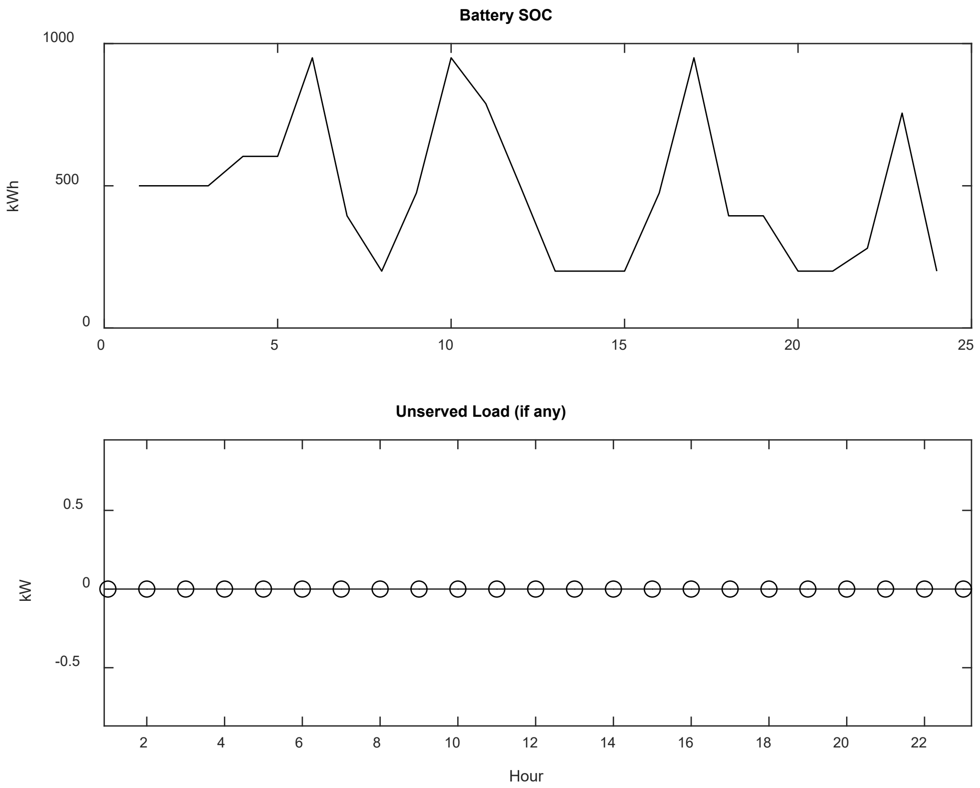

Figure 4. 6: Battery SOC and Unserved Load characteristics

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Figure 4.6 presents the results of case study 1 regarding battery state of charge and unserved Load over 24 24 hours, which best emphasizes how the battery is cycled based on what the microgrid has to offer and what it needs. As SOC increases, the transition from use to charge predominantly occurs around hours 5, 10, and 17, when the battery can actively charge itself, presumably because it has the excess energy it needs. Where SOC decreases, it represents discharge and occurs most prominently during morning load peaks or periods of reduced renewable generation, around hours 7-8, 13-14, and 20-21. Thus, the battery operates primarily during the daytime, with charging occurring when it has what it needs to discharge during specified peaks and recharge when applicable.

The unserved load characteristics reveal that the unserved load is zero, meaning that, for every hour, the system satisfied load demand without a shortage of available power supply. Essentially, there is sufficient supply, with the hybrid system and grid support, to meet all demand, meaning all criteria for reliable microgrid operation were met and no excursions in unserved load occurred. Therefore, consistently cycling the battery was effectively employed as this system provides 100% reliable supply over a 24-hour period.

4.6.2 Case Study 2: Grid-connected Microgrid dispatch with Wind Energy

In this case study, the objective is to optimize wind-grid hybrid power to minimize operating cost while meeting load demand.

Table 4. 5: Wind energy-based Microgrid Power Dispatch using LP algorithm

Hour	Load Power in (kW)	Wind Power in (kW)	Power Import in (kW)	Power Export in (kW)	Power unserved In (kW)	Total Operating cost in $
1	2200	16.17	2183.83	0.00	0.00	393.25
2	2400	13.75	2386.25	0.00	0.00	429.66
3	2800	6.73	2793.27	0.00	0.00	502.86
4	3200	30.61	3169.39	0.00	0.00	570.80
5	3400	95.63	3304.37	0.00	0.00	595.74
6	3800	164.79	3635.21	0.00	0.00	655.99
7	4000	120.76	3879.24	0.00	0.00	699.47
8	4200	452.25	3747.75	0.00	0.00	679.12
9	4600	5000	0.00	400.00	0.00	66.00
10	5000	5000	0.00	0.00	0.00	50.00
11	5200	2828.7	2371.26	0.00	0.00	455.11
12	5400	137.47	4000.00	0.00	1262.53	721.37
13	5300	52.63	4000.00	0.00	1247.37	720.53
14	5200	1190.4	4000.00	0.00	9.61	731.90
15	5000	3269.6	1730.40	0.00	0.00	344.17
16	4600	4512.5	87.53	0.00	0.00	60.88
17	4000	5000.0	0.00	1000.00	0.00	90.00
18	3700	1333.1	2366.90	0.00	0.00	439.37
19	3400	115.88	3284.12	0.00	0.00	592.30
20	3200	2167.7	1032.30	0.00	0.00	207.49
21	3000	4870.9	0.00	1870.89	0.00	123.54
22	2800	5000	0.00	2200.00	0.00	138.00
23	2600	3385.5	0.00	785.52	0.00	65.28
24	2400	22.40	2377.60	0.00	0.00	428.19

Demand ranged from approximately 2200kW to a peak of 5400kW, with grid strains essentially in the last peak hours of the assessment (Table 4.5). Wind generation starts small and ramps up to about 5000kW (hours 9 and 10), demonstrating hours when the regional grid can rely on wind to supplement daily operations. Grid imports occur only during the hours of greatest need (12-14). No grid imports are required in hours 9 and 10 because there is more than enough surplus produced from wind generation. Additionally, grid export occurs at hour 17 (a small amount of 1000kW). This means that the community in question has access to grid energy when surplus production occurs, though this happens infrequently (only at hour 17). Lastly, deficiencies are problematic. 1262.53kW at hour 12 is an enormous deficiency relative to peak production efforts, suggesting that even with strong wind generation, it is still not enough to overcome at certain peak times. Peaks are exacerbated by costs exceeding $700. Thus, surplus hourly distributions peak where adjustments can be made for efficiency and financial savings.

Table 4. 6:Wind energy-based Microgrid Power Dispatch using LP algorithm

Hour	Wind Power in ($)	Grid Power Import cost in $	Grid Power Export cost in $	Total Operating cost in $)
1	0.16	393.09	0.00	393.25
2	0.14	429.53	0.00	429.66
3	0.07	502.79	0.00	502.86
4	0.31	570.49	0.00	570.80
5	0.96	594.79	0.00	595.74
6	1.65	654.34	0.00	655.99
7	1.21	698.26	0.00	699.47
8	4.52	674.59	0.00	679.12
9	50.00	0.00	16.00	66.00
10	50.00	0.00	0.00	50.00
11	28.29	426.83	0.00	455.11
12	1.37	720.00	0.00	721.37
13	0.53	720.00	0.00	720.53
14	11.90	720.00	0.00	731.90
15	32.70	311.47	0.00	344.17
16	45.12	15.75	0.00	60.88
17	50.00	0.00	40.00	90.00
18	13.33	426.04	0.00	439.37
19	1.16	591.14	0.00	592.30
20	21.68	185.81	0.00	207.49
21	48.71	0.00	74.84	123.54
22	50.00	0.00	88.00	138.00
23	33.86	0.00	31.42	65.28
24	0.22	427.97	0.00	428.19

The cost per hour from the wind microgrid reveals how much system costs are influenced by wind generation (or lack thereof) and, thus, how much the microgrid depends on grid imports. Wind generation is consistently low cost, ranging from a couple of cents to a noticeable $50.00 in hours 9 and 10, the latter of which is the more typical cost expected from a wind microgrid (at least on a day when wind generation is consistent). This is due to time-based variables that shift based on wind output. Grid imports, however, range far more exorbitantly, $720.00 in hours 12 and 13, where generation could not accommodate spinning reserve. This increases the total cost per hour to $731.90 in hour 14, when high demand meets low renewable generation. The lowest operating cost of $50.00 occurs at hour 10, where effective wind generation reduced the imports required for spinning reserve and operating demand.

Ultimately, these trends reveal how much time and reliability impact costs in the system. These costs align with general demand patterns across the day, which means that the midday and evening hour strain of the microgrid, based on how much it is needed, increases cost because of how dependent it is upon imports; while wind generation offers a significant economic advantage, the dependency upon imports during low wind generations reduces the feasibility of these systems. If there were instead greater battery storage integration, or more effective microgrid-grid interaction, or more effective use of wind during high generation, the costs would be reduced.

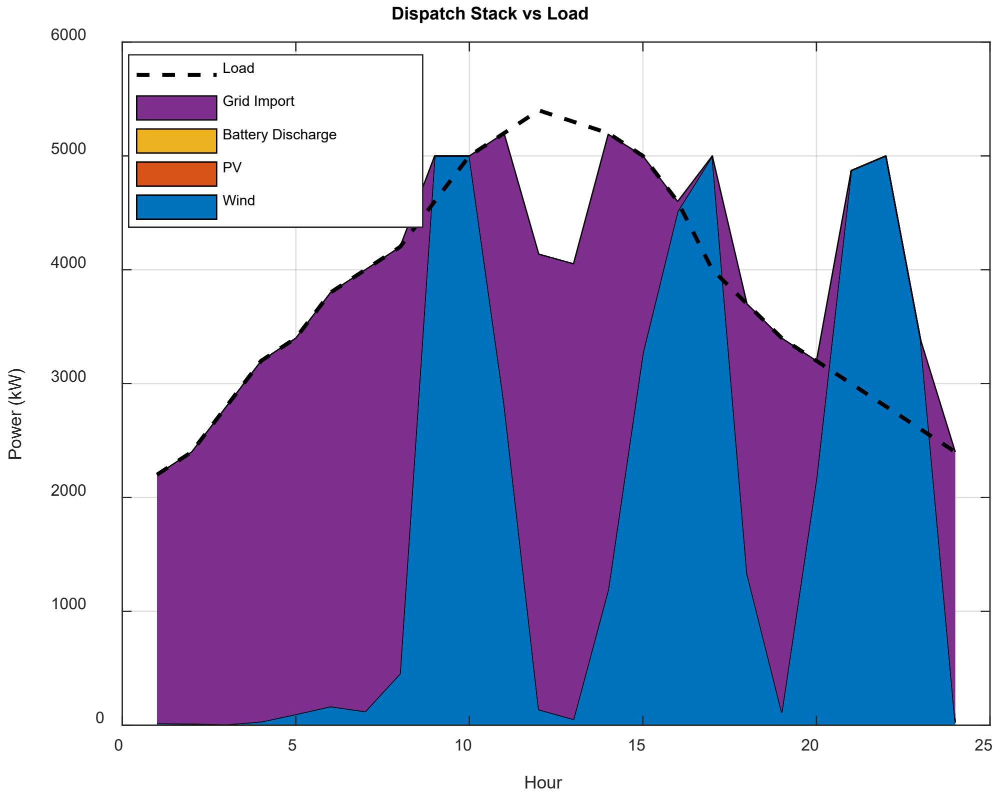

Figure 4. 7: Energy Dispatch using the LP method for the 24 hours

For the second test, as shown in Figure 4.7, there is no PV or battery; the load comes solely from wind generation, with help from grid import. Furthermore, this system operates under the unmet Load condition. Moreover, results show power unserved, which substantiates the unmet Load condition, particularly during peak load hours. Power unserved means that additional capacity or storage is needed to balance the influx. The power unserved occurs in hours 12 and 13, with power values of 1262.53kW and 1247.37kW.

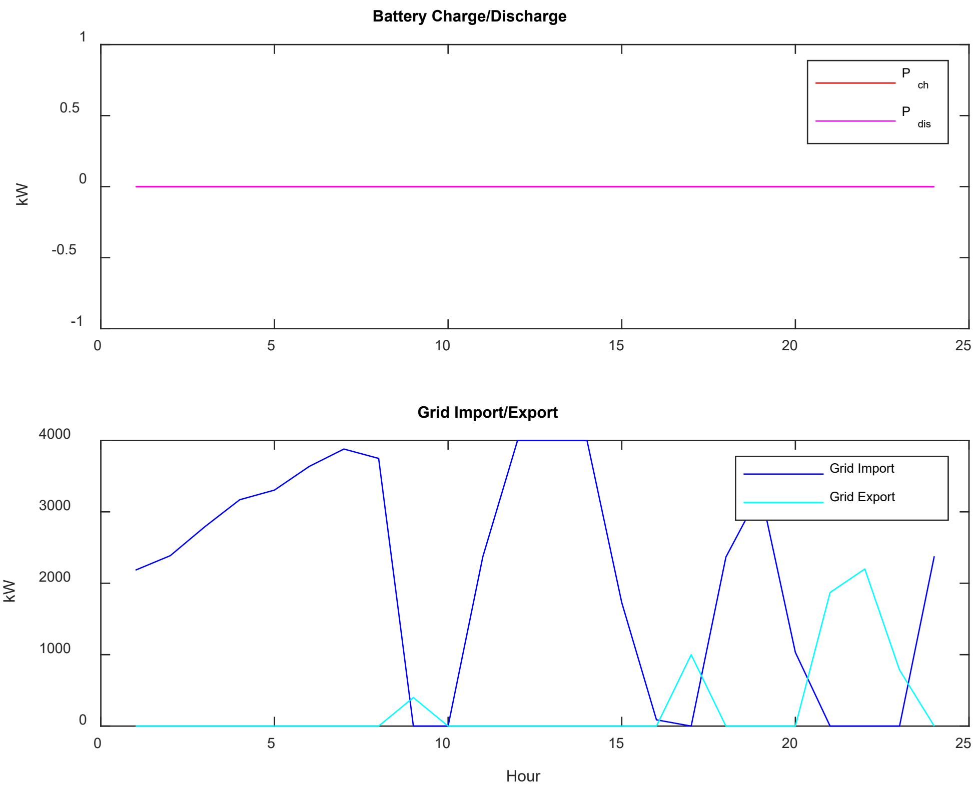

Figure 4. 8: Battery Charge/Discharge and Grid Import/Export using the LP method for the 24 hours

Since this system does not involve the battery storage system, the value of battery charge or discharge is null. Therefore, the system can only rely on imports up to 4000kW and a bit of export power up to 1000kW from the grid, as depicted in Figure 4.8.

4.6.3 Case Study 3: Grid-connected Microgrid dispatch with PV and Battery

This case study deals with Grid-PV-BSS dispatch. As mentioned earlier, the developed LP algorithm is utilized for the simulations under the MATLAB software environment. During the morning hours, the system relies on battery storage and grid import since the PV is active between 8 and 17. There is regular import power of 4000kW for several hours in this case study, thereby increasing operating and maintenance costs.

The results are tabulated in Table 4.7. The results obtained for operating and maintenance costs with PV and Battery using the LP algorithm are illustrated in Table 4.8.

Table 8 provides a clear view of how operating and maintenance costs shift throughout the day as the microgrid draws power from PV, the grid, and the battery. During the night, when solar energy is unavailable, the system relies almost entirely on grid imports. This becomes the main driver of operating costs. When daylight arrives, PV generation begins to offset demand, especially from hours 8 to 10. Therefore, it's an amazing mitigator of accumulated costs.

However, from hour 11 onward, the system runs almost entirely on batteries, thereby increasing total operating costs and associated battery discharge fees. In addition, the research results show that during the overnight-to-morning hours, all operating costs are due to grid imports. This is representative of a power system without PV support and shows how having renewable energy resources in the mix, versus not having them, makes a huge difference in microgrid costs.

Table 4. 7: Microgrid Power Dispatch with PV and Battery using LP algorithm

Hour	Load Power in kW	PV Power in kW	Battery Charging Power in kW (-ve)	Battery Discharging Power in kW (+Ve)	Battery SOC in kW	Power Import in kW	Power Export in kW	Power Unserved in kW	Total Operating cost in $
1	2200	0.00	0.00	0.00	250.00	2200.00	0.00	0.00	396.00
2	2400	0.00	0.00	0.00	250.00	2400.00	0.00	0.00	432.00
3	2800	0.00	0.00	0.00	250.00	2800.00	0.00	0.00	504.00
4	3200	0.00	0.00	0.00	250.00	3200.00	0.00	0.00	576.00
5	3400	0.00	36.84	0.00	285.00	3436.84	0.00	0.00	655.47
6	3800	0.00	200.00	0.00	475.00	4000.00	0.00	0.00	920.00
7	4000	0.00	0.00	0.00	475.00	4000.00	0.00	0.00	720.00
8	4200	550.00	0.00	0.00	475.00	3650.00	0.00	0.00	659.75
9	4600	750.00	0.00	0.00	475.00	3850.00	0.00	0.00	696.75
10	5000	800.00	0.00	0.00	475.00	4000.00	0.00	200.00	724.00
11	5200	960.00	0.00	240.00	208.33	4000.00	0.00	0.00	964.80
12	5400	1000.00	0.00	0.00	208.33	4000.00	0.00	400.00	725.00
13	5300	980.00	0.00	0.00	208.33	4000.00	0.00	320.00	724.90
14	5200	1000.00	0.00	97.50	100.00	4000.00	0.00	102.50	822.50
15	5000	800.00	0.00	0.00	100.00	4000.00	0.00	200.00	724.00
16	4600	700.00	100.00	0.00	195.00	4000.00	0.00	0.00	823.50
17	4000	300.00	250.00	0.00	432.50	3950.00	0.00	0.00	962.50
18	3700	0.00	0.00	250.00	154.72	3450.00	0.00	0.00	871.00
19	3400	0.00	0.00	49.25	100.00	3350.75	0.00	0.00	652.39
20	3200	0.00	0.00	0.00	100.00	3200.00	0.00	0.00	576.00
21	3000	0.00	0.00	0.00	100.00	3000.00	0.00	0.00	540.00
22	2800	0.00	0.00	0.00	100.00	2800.00	0.00	0.00	504.00
23	2600	0.00	0.00	0.00	100.00	2600.00	0.00	0.00	468.00
24	2400	0.00	0.00	0.00	100.00	2400.00	0.00	0.00	432.00

Table 4. 8: Microgrid Operating and Maintenance Cost with PV and Battery using LP algorithm

Hour	PV Power cost in ($)	Grid Power Import cost in ($)	Grid Power Export cost in ($)	Battery Power cost in ($)	Total Operating cost in ($)
1	0.00	396.00	0.00	0.00	396.00
2	0.00	432.00	0.00	0.00	432.00
3	0.00	504.00	0.00	0.00	504.00
4	0.00	576.00	0.00	0.00	576.00
5	0.00	618.63	0.00	36.84	655.47
6	0.00	720.00	0.00	200.00	920.00
7	0.00	720.00	0.00	0.00	720.00
8	2.75	657.00	0.00	0.00	659.75
9	3.75	693.00	0.00	0.00	696.75
10	4.00	720.00	0.00	0.00	724.00
11	4.80	720.00	0.00	240.00	964.80
12	5.00	720.00	0.00	0.00	725.00
13	4.90	720.00	0.00	0.00	724.90
14	5.00	720.00	0.00	97.50	822.50
15	4.00	720.00	0.00	0.00	724.00
16	3.50	720.00	0.00	100.00	823.50
17	1.50	711.00	0.00	250.00	962.50
18	0.00	621.00	0.00	250.00	871.00
19	0.00	603.14	0.00	49.25	652.39
20	0.00	576.00	0.00	0.00	576.00
21	0.00	540.00	0.00	0.00	540.00
22	0.00	504.00	0.00	0.00	504.00
23	0.00	468.00	0.00	0.00	468.00
24	0.00	432.00	0.00	0.00	432.00

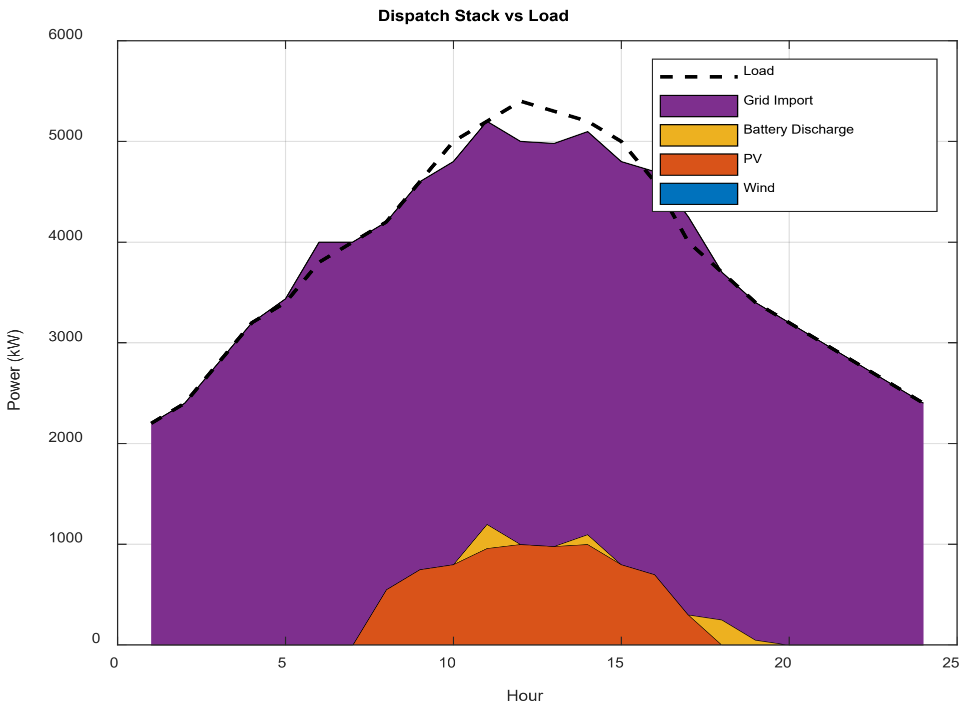

Figure 4. 9: Dispatch Stack vs Load for Grid-connected Microgrid with PV-Battery System costs using LP

Figure 4.9 presents the behavior of the dispatch power against the load demand. The system consists of PV generation, battery power, as well as the import power from the grid. The contribution of renewable energy is very low as indicated by the area in orange color for PV generation, while the yellow color symbolizes the battery power. Then the area in purple color indicates import power from the grid with up to the value of 4000kW as depicted in Figure 4.10, and lastly the dotted line represents the load demand. Again, there is an unserved load portion in the hours 10,12,13,14, and 15. The export power is not possible in this system.

In comparison of the optimal cost obtained in three case studies, case study 1 total operating cost is $9250.82, case study 2 with $9761.03, and case study 3 is $14912.15. Therefore, the best solution is case stduty1.

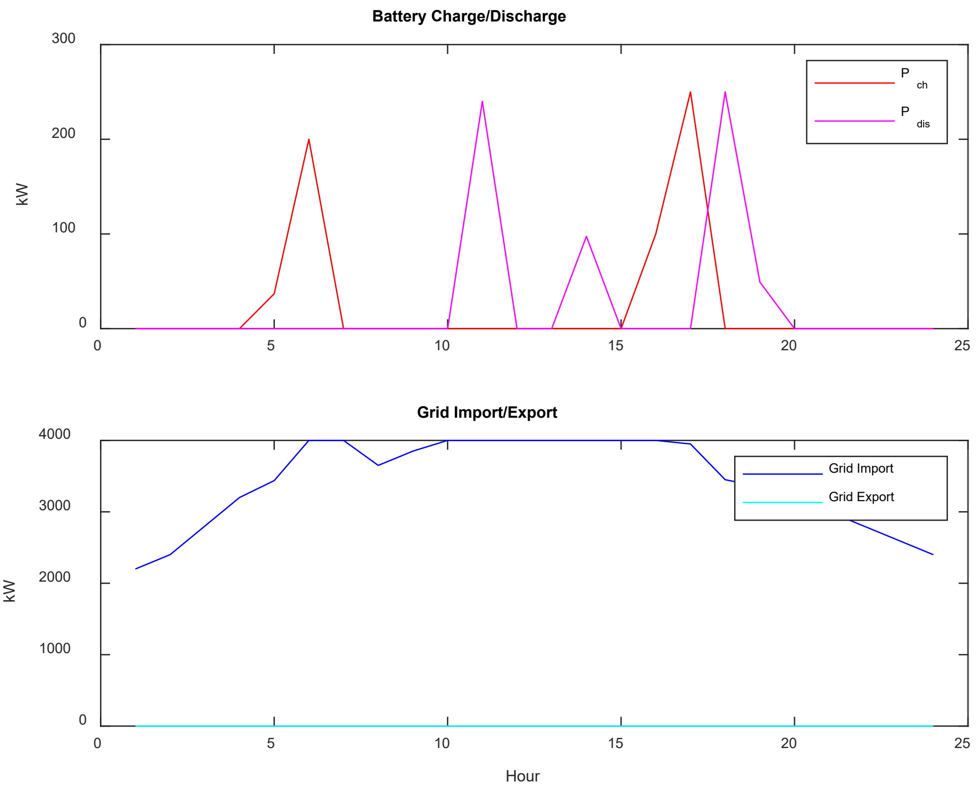

Figure 4. 10: Battery Charge/Discharge and Grid Import/Export results for 24 hours.

For the whole period of 24 hours, the battery SOC has fluctuated at different times as extrapolated in Figure 11. As for the unserved power, it occurs during hours 10, 12, 13, 14, and 15.

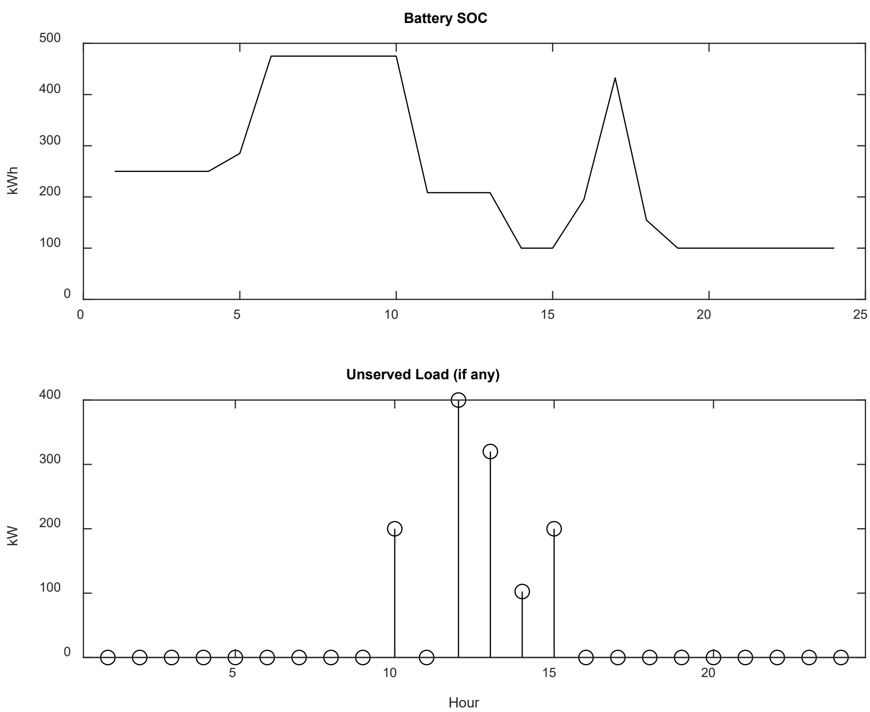

Figure 4. 11: Battery SOC and Unserved Load results for 24 hours.

4.7 Discussion of the Simulation Results

This dispatch profile indicates that the grid is essential to the supply mix, meaning there will be a significant reliance on the grid for additional power even with renewables, battery storage, and all. Optimal use of this hybrid microgrid means less reliance on a single system and more efficient operation, promoting resiliency and a better-performing, sustainable system in the future.

One way to promote integrated renewable generation and consumption is to improve the accessibility of both. For example, wind generation is high in the early morning hours and gradually decreases throughout the day, with a drastic cut-off in the evening. Therefore, increased battery storage can sustain early-morning wind generation until noon to meet peak consumption needs for the rest of the afternoon and early evening. Wind generation merely needs batteries on the tail end of its gradual consumption for the day. Similarly, solar PV peaks at noon, with increased consumption demand; noon is one of the main hours of the day for peak demand. Therefore, optimizing solar PV with new battery options or demand-side management will cut grid power needs in the afternoon.

Another beneficial possibility is shifting non-essential loads to times of high renewable generation. For example, excess loads that are not currently needed can be shifted to noon, when solar generation is powering demand, so that excess solar either benefits or reduces grid imports. Thus, grid imports are beneficial during this time but unnecessary throughout the rest of the day, as excess generated resources can now be absorbed more effectively when more renewable resources are available. Therefore, advanced Energy Management approaches, such as Linear Programming and Grey Wolf Optimization, for optimal scheduling of grid imports, battery use, and renewable dispatch will help reduce costs while increasing the system's performance reliability.

Incorporating storage with optimized dispatching techniques will reduce grid reliance and accommodate greater penetration of renewables with heightened operational resiliency.

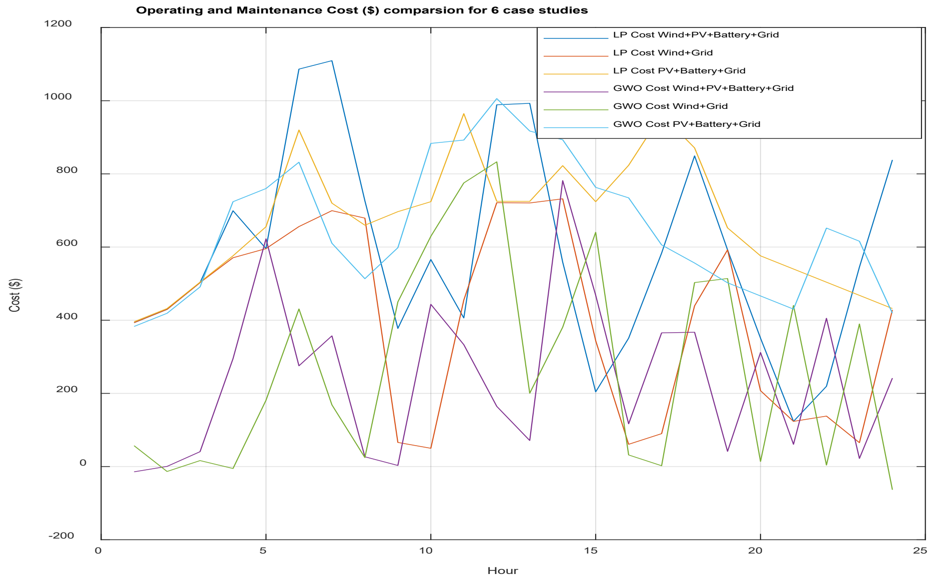

Figure 4. 12: LP and GWO Operating Cost for 6 case studies

Figures 4.12 and 4.13 provide the simulation results of the hourly operating cost and overall operating cost, respectively, for the six case studies using LP and GWO techniques. A comparative analysis of the results demonstrates that the GWO technique consistently achieves lower operating costs than the LP approach, particularly for the Wind–PV–Battery–Grid configuration, where the minimum cost of $5,802.44 is achieved in case study 4, as shown in Figure 4.13. These findings highlight the superior capability of metaheuristic optimization in handling the nonlinear and complex nature of hybrid microgrid energy management problems.

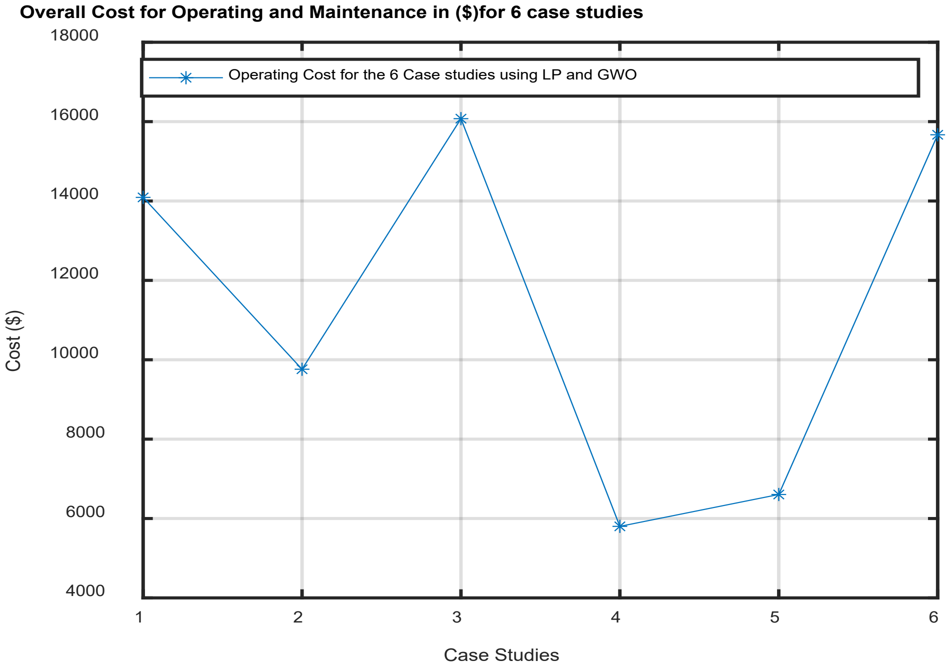

Figure 4. 13: LP and GWO Overall Operating Cost for 6 case studies

The computational efficiency of the optimization techniques was evaluated based on their elapsed execution time. The Linear Programming (LP) algorithm required 4.252047 seconds to converge to an optimal solution, whereas the Grey Wolf Optimization (GWO) technique converged in 2.062354 seconds. This reduction in computational time demonstrates the superior efficiency of the GWO approach for the considered microgrid optimization problem.

The longer execution time of the LP method can be attributed to its dependence on deterministic solvers and constraint-handling mechanisms, which become increasingly complex with the inclusion of multiple distributed energy resources, battery operational constraints, and grid interaction limits. In contrast, GWO employs a population-based metaheuristic that effectively explores the solution space and rapidly converges to near-optimal solutions with reduced computational overhead. The observed computational advantage of GWO is particularly beneficial for real-time or large-scale microgrid energy management applications, where fast decision-making is essential. These results indicate that, in addition to achieving lower operating costs, the GWO technique offers improved computational performance compared to LP, making it a more suitable candidate for practical and scalable hybrid microgrid optimization.

4.8 Conclusions

This chapter finishes by providing optimality for the hybrid system in BSS, PV, and wind as LP optimization was successfully achieved to minimize daily maintenance (O&M) costs, unlike the PV system, where demand was not fully met as it was supplemented by LP optimization regarding capacity and costs in order to not overgenerate but instead create more production through higher demand sunlit hours.

Such a low cost indicates that there's room to grow with resources and low-cost utilities in microgrid systems, which implies that, within today's energy systems — especially hybrid ones that lend themselves well to combining resources for one optimal output — reducing costs is an operational and planning framework that runs across the board.

The linear programming application to achieve economic dispatch for a microgrid of PV, wind, and BESS is an effective and efficient approach for optimization as it applies a cost minimization function that effectively renders energy demand satisfaction with the lowest costs possible while acknowledging available resources and limitations based upon the fluctuations of storage and renewable generation.

Generating data from predicted renewable energy resources and optimizing with BESS means greater LP potential to reduce conventional generation dependence and decrease O&M costs across the board. Therefore, the conclusions state that LP provides optimal dispatch plans that require minimal linear programming calculations, supporting the practical application of real-time advancements and the potential of day-ahead planning for these systems.

A linear programming approach to economic dispatch for renewables is a positive step toward hybrid systems achieving a sustainable, cost-efficient quality system. These systems are a positive output for today's energy management. In Chapter 5, can confirm the best costs that occur from the LP findings here as per the conclusions obtained from the Grey Wolf Optimization results from Chapter 4.

CHAPTER 5

GREY WOLF OPTIMIZATION FOR RENEWABLE-ENERGY-BASED MICROGRID SYSTEM

5.1 Introduction

This chapter focuses on the use of Grey Wolf Optimization (GWO) for renewable energy-based microgrid systems. GWO is a more recent population-based metaheuristic algorithm that mimics the social hierarchy and hunting patterns of grey wolves. GWO also differs from the LP algorithm, as it is a more recent adaptive algorithm that can solve nonlinear and multimodal problems that other methods often fail to solve.

For example, GWO is used in economic load dispatch with battery storage, where operational costs (operational cost) are significantly reduced (Aljribi and Yusupov, 2024). In a microgrid setting, optimal sizing of hybrid microgrids reduced the total net present cost value (the complete derived cost) by 1.06% while also reducing losses and emissions (Tukkee et al 2024). Furthermore, GWO is cost-effective and reliable in sizing components when a hybrid option exists, such as in GWO-Cuckoo search (Jasim et al 2022).

This research analyzes the optimization strategies LP and GWO and compares the performance benefits of the selected strategies relative to one another. In many cases, the performance benefit of the selected refers to cost-minimizing capabilities, computational efficiency, and reliable solutions for data with low standard deviations. Therefore, not only do the results yield pros and cons for each algorithm based on the findings of this study, but they also assist practitioners in determining which works best for the respective energies in question, thereby increasing efficiency and reducing costs.

Thus, this chapter is organized as follows. An introduction to GWO for hybrid renewable energy-based microgrid optimization is conducted first. Section 5.2 presents the theoretical background of GWO, generally (5.2.1) and relative to hybrid renewable energy-based microgrids (5.2.1), and its pros and cons (5.2.2). Subsequently, research gaps are presented in section 5.3 along with a conceptual framework of LP vs GWO (5.3.1), which flows into (5.4) where assumptions of Grey Wolf Optimization are included, then a mathematical formulation of an objective function and step-by-step calculations derived from the position vector of a wolf (5.5). Section 5.6 presents cost mathematical formulations for PV, wind, and BSS, while 5.6.1 presents the GWO flowchart. Finally, section 5.7 presents case studies and simulation findings, divided into case study 1 GWO (5.7.1), case study 2 (5.7.2), and case study 3 using GWO (5.7.3). The simulations' findings are discussed in Section 5.8, and Section 5.9 concludes the chapter.

5.2 Theoretical background of GWO

The literature notes that GWO has been highly successful in solving nonlinear, multi-objective optimization problems. (Aljribi & Yusupov, 2024) Utilized Applied GWO for economic load dispatching of battery storage microgrid systems, where highly reduced operating costs were noted through more dispatch-efficient systems. (Tukkee et al., 2024a) Applied GWO for stand-alone hybrid microgrid system sizing with 1.06% TNPC (total net present cost) reduction, 8.69% reduction in energy losses and 17.19% emission reductions when compared to conventional setups.

Furthermore, (Jasim et al., 2022) Applied GWO to GWO-Cuckoo Search Optimization (GWCSO) to size grid connected microgrids and found that GWCSO provided lower annual costs, net present cost (NPC) and levelized cost of energy (LCOE) with greater robustness than sizing through standalone GWO.

There are five steps that encompass how GWO is implemented in a hybrid microgrid:

- Encircling the prey.
- Updating position using α, β, and δ
- Decreasing parameters
- Termination

The GWO is unique due to wolves' social organization and hunting patterns. The wolves of the pack have the following hierarchy:

- Alpha (α): The alpha wolf is the strongest wolf of the pack. This is the best solution found within the optimization method. The alpha wolf travels to other territories to find the most valuable solutions, just as territories' new solutions seek the best one.
- Beta (β): The beta wolf is second in command as the second-best solution. Thus, the beta wolf helps the best in the pack find new territories and seeks better solutions.
- Delta (δ): The delta wolves are the third-best solutions. They support the alpha and beta wolves in seeking new territories, meaning they help them find better solutions when exploring the search space for new potential.
- Omega (ω): Omega wolves are the rest of the population; they are followers without strong power to do anything. They provide an opportunity to explore new territories and ensure that the social structure remains hierarchical.

The basic mechanism of GWO is that the search agents are always moving relatively to the position of the alpha, beta, and delta wolves (as shown in Table 5.1). Such a systematic means of an update will drive the search to the regions of interest and likelihood of solutions.

Table 5. 1: GWO search agents

Component	Description
$\vec{X}\alpha$	Position of the best (α) wolf
$\vec{X}\beta$	Position of the second-best (β) wolf
$\vec{X}\delta$	Position of the third-best (δ) wolf
$\vec{A}$	Influence factor (exploration/exploitation)
$\vec{C}$	Weighting factor for attraction
a	Linearly decreases from 2 to 0

5.2.1 Application of GWO in Hybrid Renewable Energy-Based Microgrids

Grey Wolf Optimization (GWO) is a recently developed population-based metaheuristic algorithm (Mirjalili et al., 2014). It originates in the social hierarchy of grey wolves in the wild, where the animals' hunting collaboration is significant. Thus, the algorithm mimics the leadership dynamic within the pack and posits four types of wolves in the search space of candidate solutions.

The greater the efficiency of the algorithm for optimization problems is the alpha **(α),** beta **(β)**, delta **(δ),** and omega **(ω).** The first three types are the best solutions up to that point; omega is the rest of the population. The omega then adjusts its location in the space relatively to the leaders (the alpha, beta, and delta wolves) (Mirjalili et al., 2014); (Wang & Shi, 2022).

Mathematically, three stages exist in the hunting behavior of grey wolves: prey encircling, seeking prey, and attacking prey/seeking prey. In the first stage, wolves assess how far they are from prey and subsequently move; they also move based on AA and CC (adaptive coefficient vectors). These values are assessed relative to a linearly decreasing control parameter. In the second stage, the positions of the alpha, beta, and delta wolves serve as attractors, and the omega adjusts its position based on the average influence of the three leading wolves. Ultimately, exploration (global search) and exploitation (local search) occur at once under the influence of the AA value: $|A| > 1$ confirms exploration; $|A| < 1$ increases exploitation as wolves move closer to an effective solution (Mirjalili et al., 2014); Jiang et al., 2024).

GWO has been widely used to solve various problems because it is simple and has the fewest control parameters among metaheuristics. Thus, it is a highly competitive alternative to Particle Swarm Optimization (PSO), Genetic Algorithms (GA), etc., However, like many metaheuristics, GWO performs poorly in high-dimensional spaces or when the initial population is low in diversity. Thus, hybrid or enhanced versions emerge in the literature to boost convergence speed and accuracy. The Elite

Inheritance + Balance Search version has greater convergence speed and accuracy (Jiang et al., 2024).

In the ever-changing dynamics of hybrid renewable energy-based microgrids, sizing, scheduling, and energy management are critical to success; thus, implementation/management applications generated by GWO produce desirable results in operation. GWO can successfully structure nonlinear and multi-objective optimization to address these needs. For example, (Pandit et al., 2022) determined how GWO operates for dynamic scheduling for microgrids containing thermal and photovoltaic energies, as compared to Artificial Bee Colony (ABC) and Differential Evolution (DE). GWO came out on top relative to these two.

Furthermore, Dubey et al. 2020 related a study of microgrids which integrate photovoltaic (PV), wind, diesel and batteries where relative to HOMER Pro-another commercial software still used in the industry today GWO had lower operational energy costs (COE) than HOMER Pro across most configurations; GWO also increased reliability at the same time findings contrary to others relative to such configurations before such configurations came to be. Thus, the configurations with PV, wind, and batteries prove successful for GWO.

Moreover, since multiple objectives exist for this information relative to these factors, it's crucial to integrate multi-objective variants of the GWO (MOGWO), which worked to minimize system costs and emissions while simultaneously maximizing operational reliability. This is important relative to modern transitions, as the findings proposed from (Kumar Behura et al., 2021) Suggest the feasibility of transitioning to such complex methods for sustainability assessments.

Finally, other studies assessed mixed techniques of established GWO and Cuckoo Search. For example, (Jasim et al., 2022) suggests that improvements occur regardless of the statistical technique used after implementing Mixed GWO over GWO alone. (Chen et al. 2022) Suggest NPC and LCOE are decreased relative to grid-connected microgrids due to a mixed combination with Cuckoo search. Compared with other established methods, professionals struggled to gain confidence in mixed techniques without excessive technical training.

The latest developments with Grey Wolf Optimizer and its diverse applications achieve superior results in solving composite problems.

5.2.2 Advantages and Limitations of the GWO Method

Grey Wolf Optimization (GWO) offers several advantages for microgrid planning and implementation. GWO possesses few parameters, is user-friendly, and explores/exploits solutions effectively, which render it advantageous for highly nonlinear, multi-modal, and constrained optimization problems posed by renewable-based microgrids (Mirjalili et al., 2014; Al-Wajih et al., 2021). Relative to other common solutions (Genetic Algorithms (GA), Particle Swarm Optimization(PSO)), it holds a faster convergence and superior solution quality for optimal dispatch, unit commitment and sizing of distributed energy resources. (Pandit et al., 2022) Dubey et al., 2020; Al-Wajih et al., 2021. It also supports multi-objective formulation when solving for costs/emissions under reliable assumptions, enhancing GWO's flexibility for hybrid renewable microgrids. (Kumar Behura et al., 2021).

However, GWO has disadvantages. One of the major disadvantages is a dependence on population diversity within the variable search space, which can lead to premature convergence and local minima solutions that are effective in smaller dimensional spaces but not in larger ones (Wang & Shi, 2022).

Furthermore, GWO's effectiveness in exploration and exploitation is reduced in large-scale, complex microgrid systems, as better results are achieved through hybridization to increase robustness or by making adjustments to GWO's initial algorithm (Chen et al., 2022). To mitigate the challenges, improved variations such as Multi-objective GWO (MOGWO) and hybrid algorithms that combine GWO with other optimization methods, such as Cuckoo Search, Differential Evolution, have been proposed, demonstrating superior global convergence and reliability in optimizing renewable microgrids (Jiang et al., 2024). Notably, Table 5.2 summarizes the advantages and limitations of GWO.

Table 5. 2: Advantages and Limitations of the GWO Method

Algorithmic Advantages	Known Limitations
Simplicity: Boasts fewer control parameters compared to many metaheuristics (e.g., Genetic Algorithms, Particle Swarm Optimization).	Dependence on Initial Population: Performance depends on the choice of initialization.
Balance: Adaptive management of exploration and exploitation enhances both convergence and diversity.	Slow Convergence in High Dimensions: May struggle to navigate large, intricate search spaces.
Computational Efficiency: Well-suited for complex optimization tasks with relatively minimal tuning requirements.	Solution: Utilizing hybrid or enhanced variants (e.g., incorporating fuzzy logic or Differential Evolution) can mitigate these challenges.

5.2.3 Comparison of LP and GWO Applications for Microgrid Cost Minimization

Research output from 2022 to 2025 is used to comparatively analyse the differences between the two algorithms, namely Linear Programming (LP) and Grey Wolf

Optimization (GWO). This is tabulated in terms of applications, objective functions, key findings, as well as the references of the conducted studies selected. Table 5.7 extrapolates the review table to the recent literature on the applications of LP and GWO optimization methods in microgrids.

Table 5. 3: Comparison of LP and GWO Applications for Microgrid cost Minimization

Method	Application Context	Objective	Key Findings	Reference
Linear Programming (LP)	Integrated microgrid energy management	Minimize operational electricity cost	Achieved ~19% cost reduction compared to heuristic methods	(Shufian & Mohammad, 2022)
Mixed-Integer Linear Programming (MILP)	Demand response scheduling in microgrids with DERs	Reduce energy cost through optimal scheduling of loads and DERs	Achieved 13–38% cost savings depending on solar generation level	(Babu et al., 2025)
Grey Wolf Optimization (GWO)	Economic load dispatch with battery storage in microgrids	Minimize generation cost and optimize power sharing	Reduced operational costs; improved dispatch efficiency	(Aljribi & Yusupov, 2024)
GWO	Stand-alone hybrid microgrid sizing (solar, wind, battery)	Minimize total net present cost (TNPC), energy loss, and emissions	Reduced TNPC by 1.06%, energy loss by 8.69%, and emissions by 17.19%	(Tukkee et al., 2024a)
Hybrid GWO–Cuckoo Search (GWCSO)	Grid-connected microgrid optimal sizing (solar, wind, biomass, storage)	Minimize annual cost, NPC, and LCOE	Achieved lower costs and improved robustness vs. standalone GWO	(Jasim et al., 2022)
Improved Grey Wolf Optimization (IGWO)	Smart City Environment, load-balanced clustering	Load balancing and minimizing	An increase in lifetime and a reduction in energy consumption improve operational reliability.	(Singh et al., 2022)

		energy consumption.		
GWO	Scheduling of multi-fuel energy resources in a microgrid	Solve a multi-objective problem in a dynamic environment in microgrids	The GWO algorithm converged efficiently to solve the environmental/economic dispatch problem without violating any constraints. DERs have a lower cost of operation and lower fuel costs by 15 % cost as well as lesser emissions up to 25%	(Pandit et al., 2022)

5.3 Research Gaps

While both LP and GWO have been individually applied to microgrid cost minimization with notable success, direct comparative studies between the two approaches under identical operational conditions remain limited. Existing LP-focused works broadly address linear or mixed-integer linear formulations. (Shufian & Mohammad, 2022;Babu et al., 2025), whereas GWO-based studies predominantly target non-linear, multi-modal optimization problems (Aljribi & Yusupov, 2024; Tukkee et al., 2024), and (Jasim et al., 2022).

However, microgrid operation often involves a mix of linear and non-linear characteristics such as storage dynamics, renewable intermittency, and variable demand, which may affect the suitability and performance of each method.

Furthermore, published results on cost reduction, computational time, stability, and robustness are not only consistent with each other but also inconsistent to a degree that, without such a controlled, comparative assessment, it's not feasible for any practitioner to determine the best method. Therefore, in addition to a thorough, side-by-side comparative assessment of LP and GWO microgrid cost reduction, there's an advantage for the scholarly community and system operators, who can subsequently implement more sustainable and cost-effective energy systems.

5.3.1 Conceptual Framework of LP vs GWO for Microgrid cost Minimization

Proposing the Conceptual Framework for the study. The cost minimization performance of the LP and GWO methods as a comparative analysis for microgrids. Figure 5.1 Schematic of the application of both methods for cost reduction.

Additionally, the performance advantages of each approach have been considered.

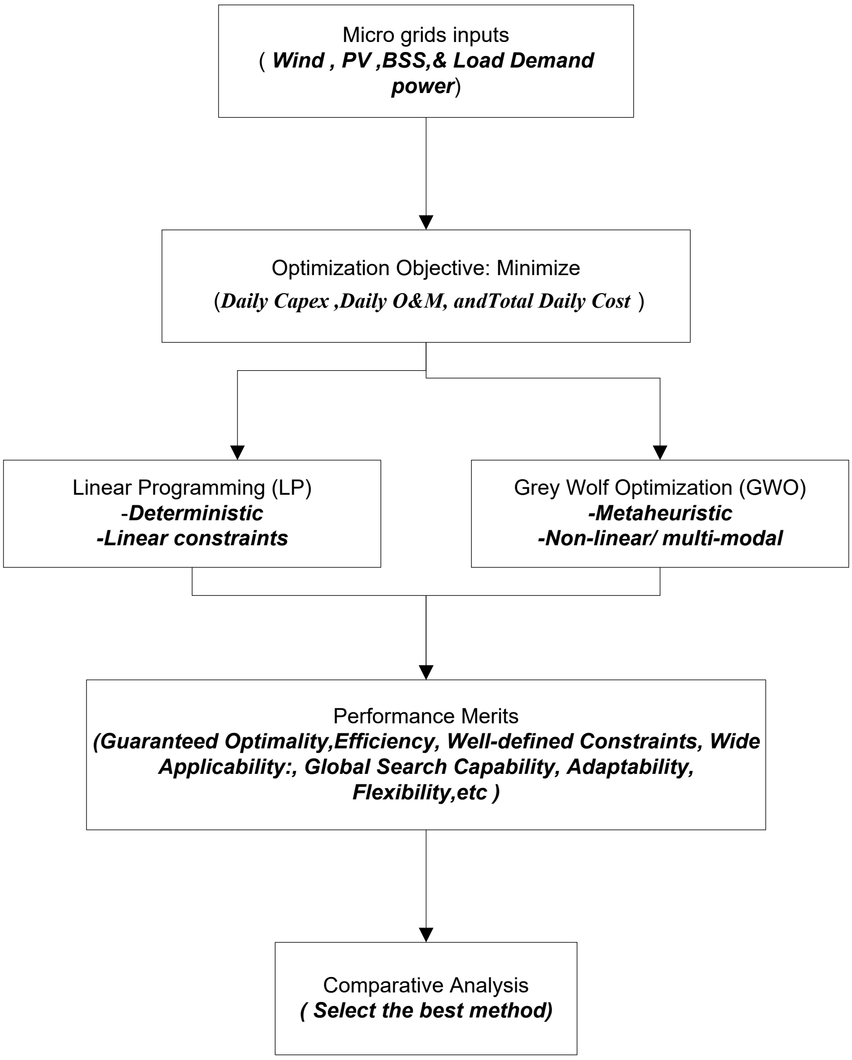

Figure 5. 1: Conceptual Framework of LP vs GWO for Microgrid Minimization

5.4 Assumptions of Grey Wolf Optimization

The GWO algorithm is based on several assumptions inspired by the natural hunting and leadership hierarchy of grey wolves:

a) **Social Hierarchy**

The wolf pack is divided into four levels: alpha **(α),** beta **(β)**, delta **(δ)**, and omega **(ω)**, where **α, β**, **δ**, and **ω** represent the best three candidates' solutions, which guide the rest of the population **ω** in the optimization **(**Mirjalili et al., 2014)**.**

b) **Hunting Strategy**

Wolves are assumed to hunt cooperatively by encircling the prey (the optimal solution), utilizing mathematical operators that simulate the movement in search space (Mirjalili et al., 2014); (Jain et al., 2023).

c) **Prey position Unknown**

Since the prey's exact position (global optimum) is unknown, GWO assumes that the best approximation can be obtained from the positions of the α, β, and δ wolves, which collectively guide the search. (Jain et al., 2023);(Pradhan et al., 2016).

d) Leadership Influence

It is assumed that the leading wolves have better knowledge about the prey's position, and therefore, the rest of the pack updates their positions relative to the leaders, balancing exploitation and exploitation (Mirjalili et al., 2014).

e) Mathematics Encircling

The encircling prey behavior of wolves is simulated using adaptive coefficient vectors (A and C), which adjust the step size and heading towards the prey, making the algorithm adaptive between global exploration and local exploitation. (Jain et al., 2023).

f) Randomness

The hunting process is mimicked by stochastic parameters that randomize the movement of the wolves to create different search locations to avoid falling into local optima (Jain et al., 2023).

Cooperative Behaviour

Finally, GWO assumes that wolves operate cooperatively rather than individually, leveraging collective intelligence to increase the likelihood of finding the global optimum (Mirjalili et al., 2014).

5.5 Grey Wolf Optimization Objective Function Formulation

The objective function guiding the search is to minimize the total cost of the microgrid, expressed as (:

$$Minimize\ C_{total} = C_{pv} + C_{wind} + C_{BSS} + C_{grid} + C_{O\&M} \tag{5.1}$$

Where, C_{pv} is the cost for PV generation.

C_{wind} is the cost for wind generation.

C_{BSS} is the battery charging/discharging cost.

C_{grid} is the cost of buying or selling energy to the utility grid.

$C_{O\&M}$ is the renewable operation and maintenance costs.

The dispatch solutions are evaluated under the following constraints (Tukkee et al., 2024) :

a) Power balance:

$$P_{pv(t)} + P_{wind(t)} + P_{BSS(t)} + P_{grid(t)} = P_{load(t)} \tag{5.2}$$

Where, $P_{pv(t)}$ is the power produced by the PV system.

$P_{wind(t)}$ denotes the power generated by wind energy.

$P_{BSS(t)}$ is the power stored in the BSS.

$P_{grid(t)}$ is the power from the utility grid.

$P_{load(t)}$ is the load demand capacity

b) Battery SoC limits:

$$SoC_{\min} \leq SoC_{(t)} \leq SoC_{\max}$$

$$SoC_{(t=1)} = SoC_{(t)} + \eta_c P_{ch(t)} \Delta t - \frac{P_{dis(t)} \Delta t}{\eta_d} \tag{5.3}$$

Where, $SoC_{\min}$

$SoC_{(t)}$ is the battery state of charge

$SoC_{\max}$ is the maximum battery state of charge, expressed as a percentage.

η_c is the efficiency of the battery charging.

$P_{ch(t)} \Delta t$ is the rate of change of the battery charging power

$P_{dis(t)} \Delta t$ is the rate of change of the battery's discharging power

η_d is the efficiency of the battery discharging

c) Renewable availability:

$$0 \leq P_{pv(t)} \leq P_{pv,\max(t)}, \qquad 0 \leq P_{wind(t)} \leq P_{wind,\max(t)} \tag{5.4}$$

Where, $P_{pv,\max(t)}$

$P_{wind,\max(t)}$

As stated in section 5.2, five steps are performed in the GWO application process; therefore, a population of grey wolves is randomly initialized within the given bounds of PV, wind, battery, and grid.

All the GWO cost computation Equations are inherited from the LP optimization algorithm in Chapter 4. The Equations presented in the Chapter are thoughtfully applied to analyse the current financial implications. The methodology is therefore transparent and consistent throughout so that costs are adequately assessed.

Equation (5.1) is the objective function used to assess and minimize the total microgrid cost. The dispatch solution is validated against power balancing constraints in equation (5.2) and battery SOC constraints in equation (5.3). Equation (5.4) represents renewable availability

While the LP optimization approach is simpler, with 5 steps, GWO has a slightly more involved implementation process of 5 steps. A grey wolf population is randomly created within the established limits of the PV/Wind, BATTERY, and GRID limits (Tukkee et al., 2024).

5.5.1 Step 1: Position vector of a Wolf

Within the solution space, a solution candidate is a grey wolf, and each grey wolf has specific attributes. The model's social hierarchy and collaborative hunting efforts are derived from the physical features of grey wolves in their natural habitats. Similarly, each candidate solution (wolf) must work with and against others to survive and optimally adapt to the problem. The exploratory and exploitative modes are based on wolves' efforts in the wilderness, making this algorithm highly effective and capable of delivering good results in complex solution spaces. Figure 5.5 is a solution candidate vector within the solution space for each grey wolf (Tukkee et al., 2024b):

$$Wolf = \left[PV_{size}, Wind_{size}, Battery_{capacity}, Grid_{usage} \right] \tag{5.5}$$

With the assumption that;

$\vec{X}_{(t)}$ is the position vector of the wolf at iteration t

$\vec{X}_{\alpha(t)}, \vec{X}_{\beta(t)}, \vec{X}_{\delta(t)}$ are the three wolves' positions are considered the best solution. $\vec{X}_{\omega(t)}$ is the followers, which are usually omitted.

5.5.2 Step 2: Encircling the Prey

A series of movements in GWO models that mimic wolves' hunting patterns encapsulate encircling behaviour. Dynamic adjustments in position and distance are required to create a framework in which wolves maintain proximity to prey during optimization. Efficient exploration and exploitation of the search space are possible due to the simulation of the natural behaviour of the complex models, leveraging algorithms (Mirjalili et al., 2014); (Al-Wajih et al., 2021); (Ahmadi et al., 2022). Both Equations (5.6) and (5.7) are applied in step 2.

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_{leader(t)} - \vec{X}_{(t)} \right| \tag{5.6}$$

$$\vec{X}_{(t+)} = \vec{X}_{leader(t)} - \vec{A} \cdot \vec{D} \tag{5.7}$$

Where: $\vec{A} = 2a \cdot \vec{r}_1 - a$

$\vec{C} = 2 \cdot \vec{r}_2$

a is linearly reducing from 2 to 0 over iterations.

$\vec{r}_1, \vec{r}2$ are the haphazard vectors 10 [0,1].

5.5.3 Step 3: Updating Position Using $\alpha, \beta, and\ \delta$

Utilization of the GWO (Gray Wolf Optimization) Equations to effectively update the positions of the search agents, referred to as wolves. Alpha wolf represents the best solution found; the Beta wolf, embodying the second-best solution; and the Delta wolf, representing the third-best based on the movement of wolves within the hierarchy towards the top three leaders. To optimize the search for the best solution in the solution space as depicted by Equation (5.8), each search agent will adjust the position strategically, taking into account the positions and influences of the three superior wolves α, β, and δ **(**Jiang et al., 2024);**((**Singh et al., 2022); (Al-Wajih et al., 2021).

$$
\begin{aligned}
\vec{D}_\alpha &= \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| \quad \Rightarrow \quad \vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\
\vec{D}_\beta &= \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right| \quad \Rightarrow \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\
\vec{D}_\delta &= \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \quad \Rightarrow \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta
\end{aligned}
\tag{5.8}
$$

In this context, the updated position of the wolf is determined by averaging the three key factors α, β, and δ. Equation (5.9) illustrates how the different variables come together to influence the wolf's new location. This relationship adds depth to understanding what drives the movement (Jiang et al., 2024)**;** (Al-Wajih et al., 2021); (Ahmadi et al., 2022).

$$
\vec{X}_{(t+1)} = \frac{1}{3}\left(\vec{X}_1 + \vec{X}_2 + \vec{X}_3\right) \tag{5.9}
$$

5.5.4 Step 4: Decreasing Parameter a

Striking a balance between exploration and exploitation is the focus in this step to decrease the parameter a .

Also, utilizing and optimizing existing resources and knowledge, while embracing the pursuit of new ideas and opportunities, is considered. To maximize the best solution (Ahmadi et al., 2022The dual approach ensures not only the discovery of innovative solutions but also the effective utilization of what already exists.

$$
a = 2 - \frac{(2 \cdot t)}{(\max\_iterations)} \tag{5.10}
$$

a reduces from 2 to 0, shifting from exploration to exploitation as iterations progress, and this is possible through the application of Equation (5.10).

5.5.5 Step 5: Termination

The procedure ends either when the predetermined maximum number of iterations is reached, or after step 3 and step 4 are repeatedly performed and results successfully converge, or the procedure repeatedly engages in constant repetition. Also, note the results every round to see if they become stable and whether stabilization is needed to proceed (Jirdehi and Ahmadi, 2022)(Ahmadi et al., 2022).

5.6 cost Mathematical Formulation for PV, Wind Power, and BESS

All cost estimators in this chapter are the result of legitimate calculations from the Equations cited in Chapter four. Therefore, the Equations from Chapter Four are properly cited, and their relative application to the results found in the present provides a legitimate basis for a transparent understanding of costs.

5.6.1 GWO flow chart

Initially, the wolf population is created, with one wolf per candidate dispatch for the renewable sources (PV and Wind) and BSS units. Then the fitness function is evaluated based on the total operating cost. Therefore, to assess feasibility, all technical constraints need to be taken into account, including maximum renewable generation, minimum and maximum SoC, and power balance.

Then, three solutions are identified to guide the other wolves in the searching process: α (alpha), β (beta), and δ (delta).

In every iteration, the parameter a is updated to explore and exploit the newly found dispatches per wolf. Relative to α, β, and δ is the new dispatch position. Also, to maintain the feasibility of the position, power balance, and SoC constraints are checked. The same occurs in subsequent iterations for all wolves until the stopping criteria are met. Thus, the optimal dispatch solution will be a feasible solution that minimizes operational costs within the microgrid. Thus, α is selected as the optimal dispatch solution.

Figure 5.2 shows the GWO flowchart for dispatching solutions in the microgrid.

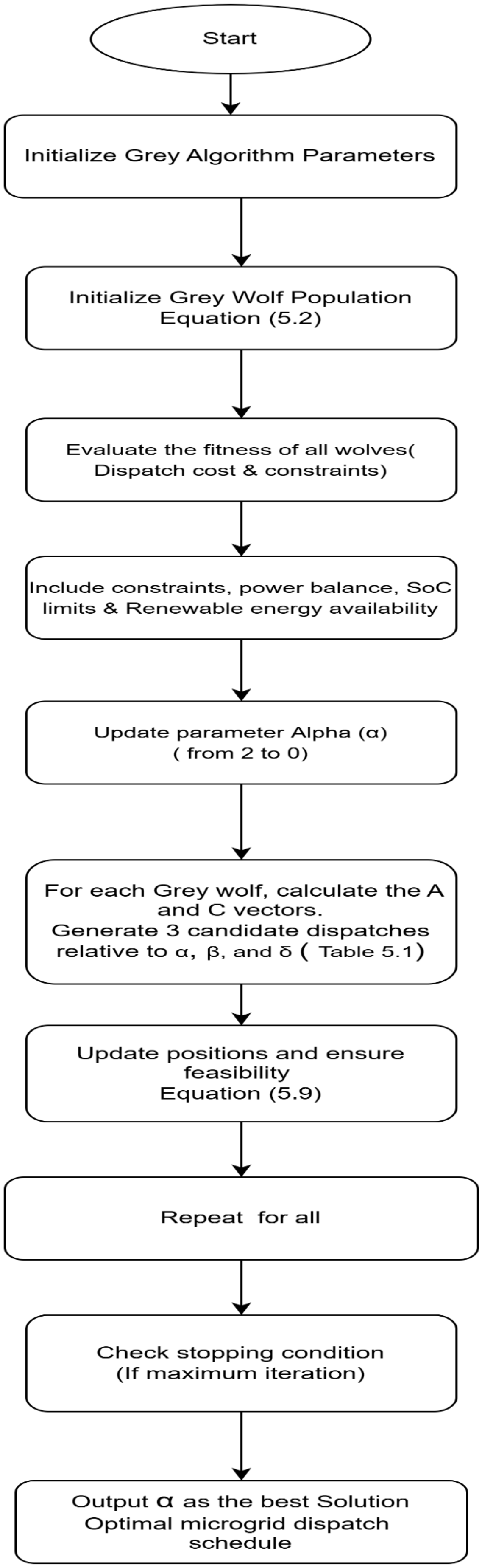

Figure 5. 2: **Flow chart of GWO**

5.7 Case Studies and GWO Simulation Results

This chapter presents extensive simulation results that substantiate the GWO algorithm's practicality for optimal dispatch. The scenarios are based on an optimal dispatch of a system-wide renewable energy operation for solar PV, wind generation, and battery storage systems (BSS). Each scenario demonstrates the issues and benefits of technology interconnectivity in an optimal dispatch setting. Therefore, substantiating the GWO algorithm's practicality for resource dispatching and improvement of operational requirements.

The primary novelty of this research is to improve operating and maintenance costs for the microgrid from a trading standpoint, impacting grid power or microgrid hybrid renewable generation sources, including battery storage systems. Therefore, three scenarios will be undertaken, and they are:

- **Case Study 1:** Performing simulations on the Grid-connected Microgrid dispatch with Wind, PV, and Battery
- **Case Study 2:** Considering Grid-connected Microgrid dispatch with Wind renewable energy resources
- **Case Study 3:** Conceptualize Grid-connected Microgrid dispatch with PV and Battery

5.7.1 Case study 1: Grid-connected Microgrid dispatch with Wind, PV, and Battery using GWO

Table 5.4 provides power generation, use, and supply over a 24-hour period, along with the cost implications of how such an operation operates. The total load demand starts at 2200 kW, increases progressively, and ultimately peaks at 5400 kW as power generation efforts decline. Wind generation occurs for a substantial number of hours in this time frame, except for hour 9, where the number is 5132.67 and is low in other hours, while other hours show no wind generation. Then solar PV is non-existent for hours 1-3 but becomes active in generation from hour 4, peaking at 1263.72 in hour 12. Negative values occur when the battery is discharging, supplying enough to meet demand, and the battery is also an inconstant element, with generation efforts at 100kw at times but at other times generating less than zero, which decreases those efforts. So it needs to charge and discharge to balance power and maintain consistent effort across charging and discharging. Sometimes discharging works better than charging when it's in the negative. The grid is the failsafe, meaning where all else does not suffice to meet demand energy needs, the grid will even discharge what is has to offer should it come to it. So it's an effort to turn negative efforts into positive ones. As this power generation effort is a purchase of power essentially, and when the time to sell excess generated power back to the grid occurs the operational expenditures reflects this purchase/sale dynamic, it would make sense that where efforts/sold excess are higher than other surplus at some times, values become income relevant in hours 1,2,4,5 and 9 as they are higher than values with excess. At the same time, however, it should be noted that the highest cost related to the purchase of grid power occurs in hour 5, where efforts to purchase grid power amount to 622.52 kW in expenditures.

Ultimately, this means that the operation is relatively flexible and can engage renewable efforts to the maximum and rely upon storage and grid efforts when power need is at its most critical. This can indicate when it's most feasible to put effort in or generate effort based on excess generated effort/sold needs.

Table 5. 4: Microgrid Power Dispatch using GWO algorithm

Hour	Load Power in kW	Wind Power in kW	PV Power in kW	Battery Power in kW	Grid Power in kW	Total Operating cost in $
1	2200	3444.74	0.00	100.00	-1344.74	-14.34
2	2400	3216.03	0.00	100.00	-916.03	0.52
3	2800	2648.94	0.00	100.00	51.06	40.68
4	3200	2559.36	0.00	-669.22	1309.86	294.83
5	3400	843.55	0.00	-669.22	3225.67	622.52
6	3800	3308.77	0.00	-669.22	1160.45	275.43
7	4000	1468.85	0.00	869.22	1661.93	357.30
8	4200	4213.15	550.00	869.22	-1555.37	26.74
9	4600	5132.67	750.00	869.22	-2420.96	3.04
10	5000	2869.78	800.00	-669.22	2099.26	443.53
11	5200	3962.56	960.00	-669.22	1432.20	333.26
12	5400	4354.19	1000.00	-669.22	451.30	164.56
13	5300	5399.63	980.00	-669.22	-545.23	71.22
14	5200	960.86	1000.00	-669.22	4080.16	781.64
15	5000	1604.19	800.00	100.00	2461.87	468.35
16	4600	3422.45	700.00	100.00	412.93	116.87
17	4000	1489.19	300.00	100.00	1905.83	365.47
18	3700	1092.97	0.00	869.22	1737.81	367.20
19	3400	3437.84	0.00	869.22	-907.07	41.56
20	3200	889.54	0.00	869.22	1441.24	311.78
21	3000	2260.01	0.00	869.22	-129.23	60.89
22	2800	1485.54	0	-669.22	1983.68	405.38
23	2600	4733.99	0	-669.22	-1464.77	22.21
24	2400	1042.36	0	100.00	1257.64	241.80

Table 5.5 for the 24-hour period shows how much total operating costs are for the energy sources used to supply demand PV, wind, battery, and grid. First, there is a significant relationship with solar PV power because it is consistently one of the cheaper alternatives, meaning an inexpensive capex or no solar power is used. Then, there are many more fluctuations with wind power. The greater the wind, the lower the costs, and the lesser the wind, the higher the costs. Wind costs of $8.44 and $54.00 are extremes. In addition, grid import contributes significantly to total operating costs,

as it costs a lot when the grid is at its highest from hours 4 through 14, with hour 14 costing $734.43, indicating that a lot of access is used from the grid. In contrast, grid export provides credits for certain hours, the highest being -$62.21 (hour 8), suggesting excess power was sent back to the grid at that time. Battery use shows a consistent degradation charge of $5.00 for most hours; however, at one point (43.46), it becomes an additional cost to total operating expenses, which should not be the case. Therefore, total operating costs run from a low of 40.52 (hour 2) to a high of 781.64 (hour 14). In addition, operating costs equal the same value as the maximum incremental period due to grid import (earlier in the day, there are lower costs as more renewables contribute, and by later in the day, more access to grid power is needed, making it more expensive). There is a balance between renewable generation, battery needs, and grid reliance, suggesting significant room for improvement, especially during the most expensive time.

Table 5. 5: Microgrid Operating and Maintenance cost using the GWO algorithm

Hour	PV Power cost in $	Wind Power cost in $	Grid Power Import cost in $	Grid Power Export cost in $	Battery Power degradation cost in $	Total Operating Cost in $
1	0.00	34.45	0.00	-53.79	5.00	-14.34
2	0.00	32.16	0.00	-36.64	5.00	0.52
3	0.00	26.49	9.19	0.00	5.00	40.68
4	0.00	25.59	235.77	0.00	33.46	294.83
5	0.00	8.44	580.62	0.00	33.46	622.52
6	0.00	33.09	208.88	0.00	33.46	275.43
7	0.00	14.69	299.15	0.00	43.46	357.30
8	3.37	42.13	0.00	-62.21	43.46	26.74
9	5.10	51.33	0.00	-96.84	43.46	3.04
10	3.50	28.70	377.87	0.00	33.46	443.53
11	2.37	39.63	257.80	0.00	33.46	333.26
12	6.32	43.54	81.23	0.00	33.46	164.56
13	5.57	54.00	0.00	-21.81	33.46	71.22
14	4.14	9.61	734.43	0.00	33.46	781.64
15	4.17	16.04	443.14	0.00	5.00	468.35
16	3.32	34.22	74.33	0.00	5.00	116.87
17	2.52	14.89	343.05	0.00	5.00	365.47
18	0.00	10.93	312.81	0.00	43.46	367.20
19	0.00	34.38	0.00	-36.28	43.46	41.56
20	0.00	8.90	259.42	0.00	43.46	311.78
21	0.00	22.60	0.00	-5.17	43.46	60.89
22	0.00	14.86	357.06	0.00	33.46	405.38
23	0.00	47.34	0.00	-58.59	33.46	22.21
24	0.00	10.42	226.38	0.00	5.00	241.80

Figure 5.3 represents the load curve over a 24-hour period and illustrates demand during a single day. It's important to note that from 00:00–06:00, demand is

approximately 2200 kW, as this is when most people are at least still, and from 20:00–24:00, demand is 2300 kW, as this is when most people are at least still once again. However, in between (06:00–20:00), with all persons awake and going about their daily lives for work, industry, domestic requirements, in conjunction with commercial needs, a peak of demand is called for. As the day progresses and those commercial needs dissipate, demand for power declines after working hours. Therefore, the minimum demand occurs during the nighttime hours (00:00–06:00), when few people need power, and it is not in high demand. Demand then increases from 06:00 until it peaks at approximately 5400 kW at 12:00 noon. Thereafter, it gradually decreases to approximately 4600 kW at 16:00, then continues to decrease until approximately 20:00, where it remains at about 3400 kW until 12:00 the next day. Such a load curve would assist in power system design, generation scheduling, and demand-side forecasting, as it is a typical one that peaks at noon, etc.

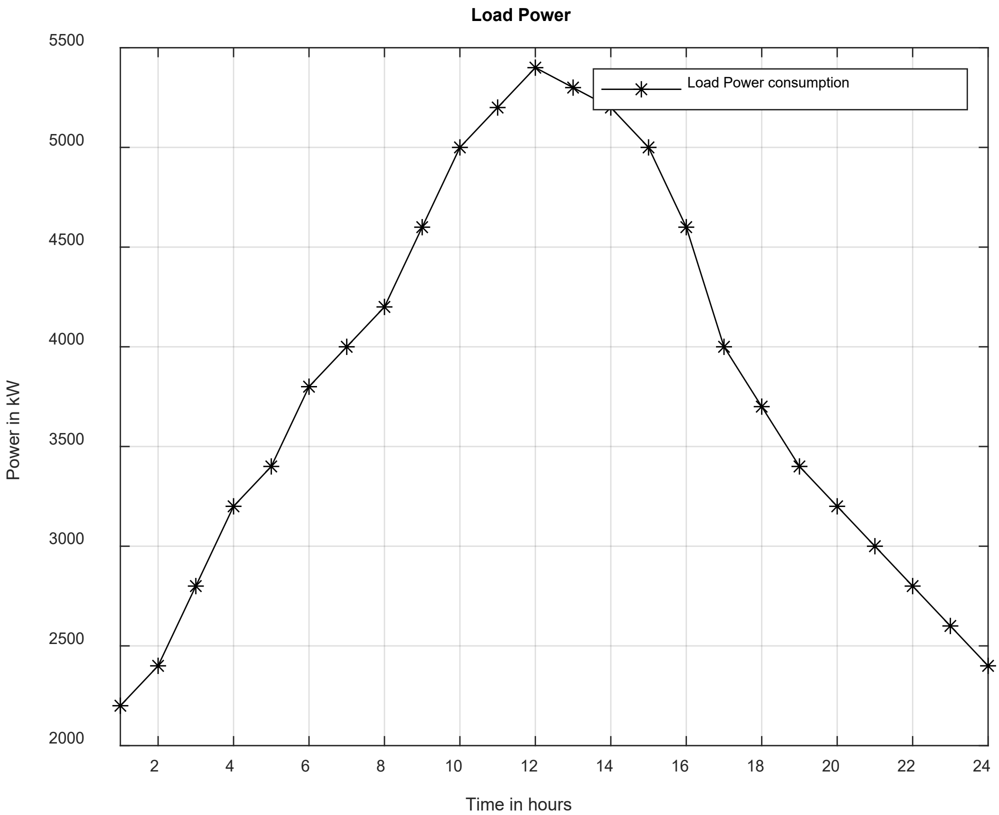

Figure 5. 3: Load Power Consumption simulation results for 24 hours

The expected solar power generation over a 24-hour period represents expected photovoltaic values. The expected values reflect zero generation within the expected hours of generation, as there is no sunlight available (00:00–08:00). Yet, from 08:00 onwards, expected values increase sharply, with expected levels of generation at about 800 kW, consistently moving upward over the morning hours. Between (09:00- 14:00), expected solar generation levels are met, with generation over 1200 kW, as solar irradiance is expected to be high then. Thereafter, the expected generations decrease steadily, reaching about 800 kW at 17:00 and falling to almost zero at night (18:00–23:00) when the sun sets. Therefore, this expected daily cycle shows a dependence on existence and a regular pattern of expected solar-generated production based upon proximity to sunlight. Thus, the middle of the day sees high generation, and there is none during the hours of no sunlight. Therefore, solar energy is not a firm resource, as it is not inherently sustainable without other generation sources or storage to maintain a consistent energy flow.

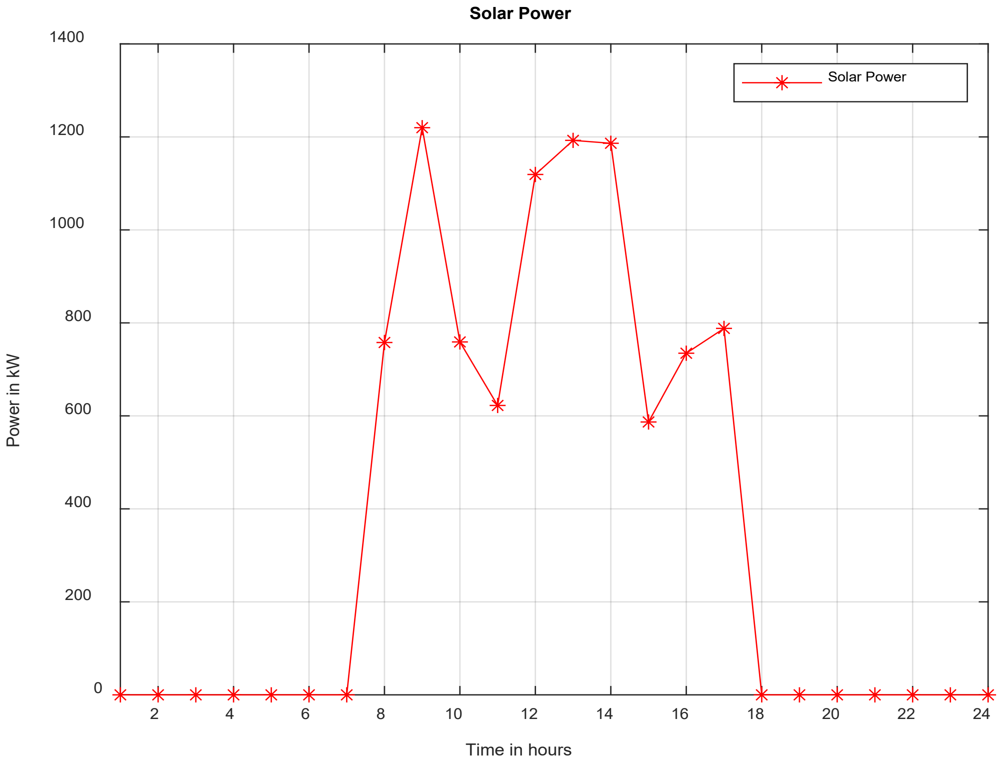

Figure 5. 4: Solar Power Consumption simulation results for 24-hour period.

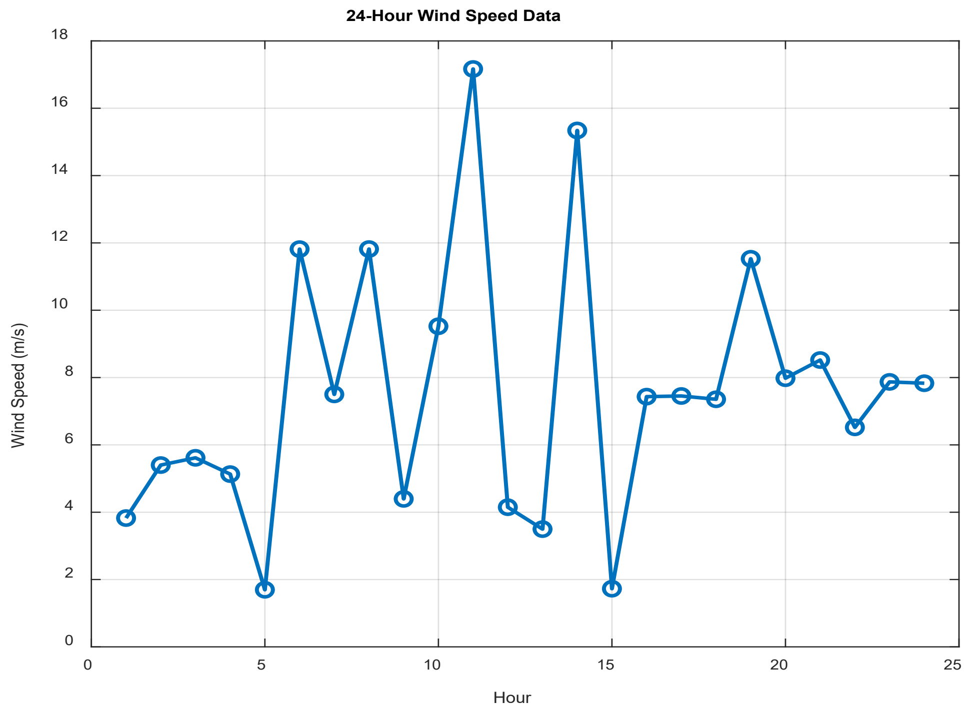

Figure 5. 5: **Wind speed data for 24 hours.**

The wind speed implied by Figure 5.5 feels like 24-hour wind speeds that increase and decrease in a very irregular fashion. For instance, at the top of the day, wind speed increases sharply from about 4 to 5 m/s, then decreases, and then increases exponentially to the point where the anticipated peak windspeed in hour 11 hits about 17 m/s. This also correlates with the predicted peak wind speed in hour 11. However, after this increase, values plummet down into hour 1 (almost 2m/s) as we transition towards early afternoon and gradually stabilize around 7 to 9m/s for the rest of the day and into the night. This implies that daytime heating really affects wind speed, stirring things up and increasing it, while cooler temperatures during the following evenings calm things down, returning everything to a steady state. Therefore, it feels like gusty and sporadic winds, which are stronger, crazier, in the middle of the day, and calmer, and part of a pattern, the rest of the time.

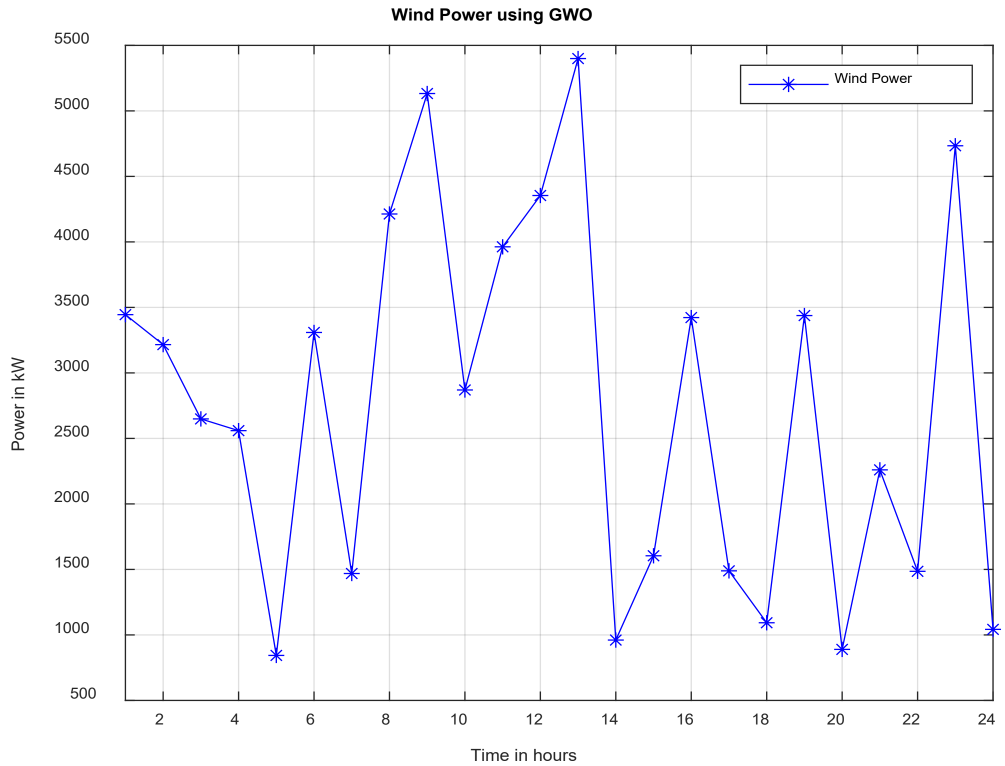

Figure 5. 6: Wind Power Consumption simulation results for a 24-hour period using GWO.

Regarding wind, the reality of intermittency underscores the importance of optimization, especially GWO, for microgrid operation (Figure 5.6). For instance, during the peaks and valleys when wind drops (hours 5, 14, and 20), the microgrid is aided by the GWO model to meet demand with other available resources (PV, battery discharge); even the extent of grid imports can be determined at the lowest operational cost. However, the opposite is true for wind out spikes in hours 9, 13, and 23: the optimization of the GWO algorithm through increased use across different dispatchers means an increased reliance on this free renewable resource, reduced operational costs, and reduced grid reliance. The system in place responds optimally to fluctuations. Thus, GWO essentially rounds up the extra flexibility at arbitrary times, leading to high fluctuations and intermittency that otherwise reduce supply reliability and increase operational costs.

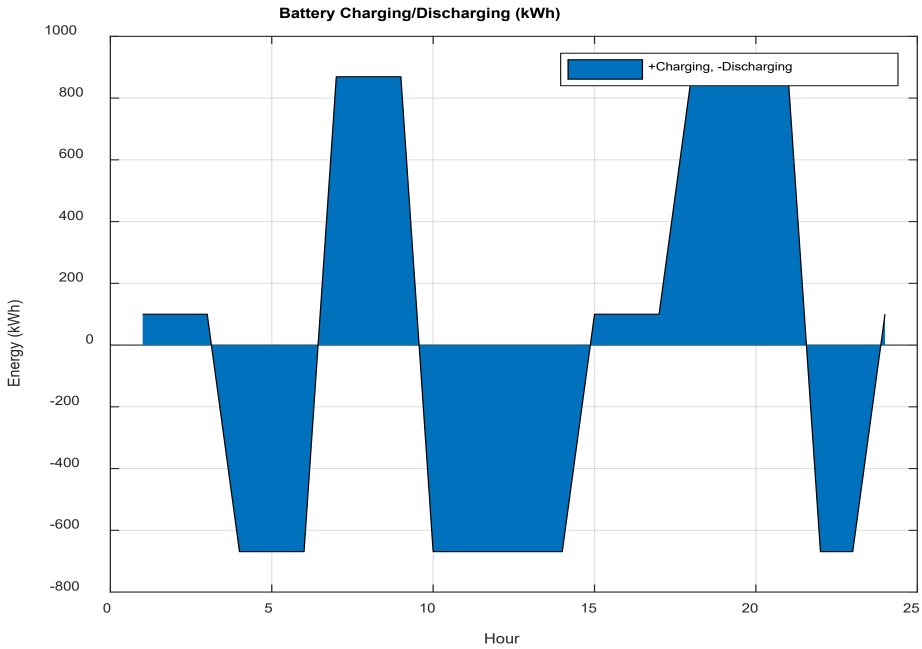

Figure 5. 7: Battery Charging/discharging (kWh) simulation results for 24 hours using GWO.

Figure 5.7 shows the results of battery charging and discharging using the GWO algorithm. The (+) sign indicates charging the battery, while the (-) sign indicates discharging the battery. From the analysis of the results, the battery can charge from as little as 100kW in the morning hours, then followed by discharging of -669.22 kW, which happens during the hours (4,5 and 6), (10-15). During this period, Table 5.5 shows the battery degradation cost of $33.46.

As the charging pertains, the degradation cost are $5.00 for 100kW and $43.46 for 869.22kW, and the charging hours are (1, 2, and 3), (7, 8, and 9), (15, 16, and 17), and (18, 19, 20, and 21). By considering these analyses of discharging and charging portions of the battery storage, one can attain a comprehensive understanding of the operational characteristics and optimization potential of the energy storage system, as shown in Figures 5.7 and Table 5.5.

In relation to Figures 5.8 and 5.9, the analysis of energy dispatch for the hybrid renewable energy system indicates that the system relies on wind, grid, battery, and PV, with the majority of supply from each source. Moreover, Figure 5.10 conceptualizes the operating and maintenance cost results for 24 hours using GWO. Grid import has the highest cost, followed by grid export, battery degradation cost, wind cost, and PV cost with the least cost.

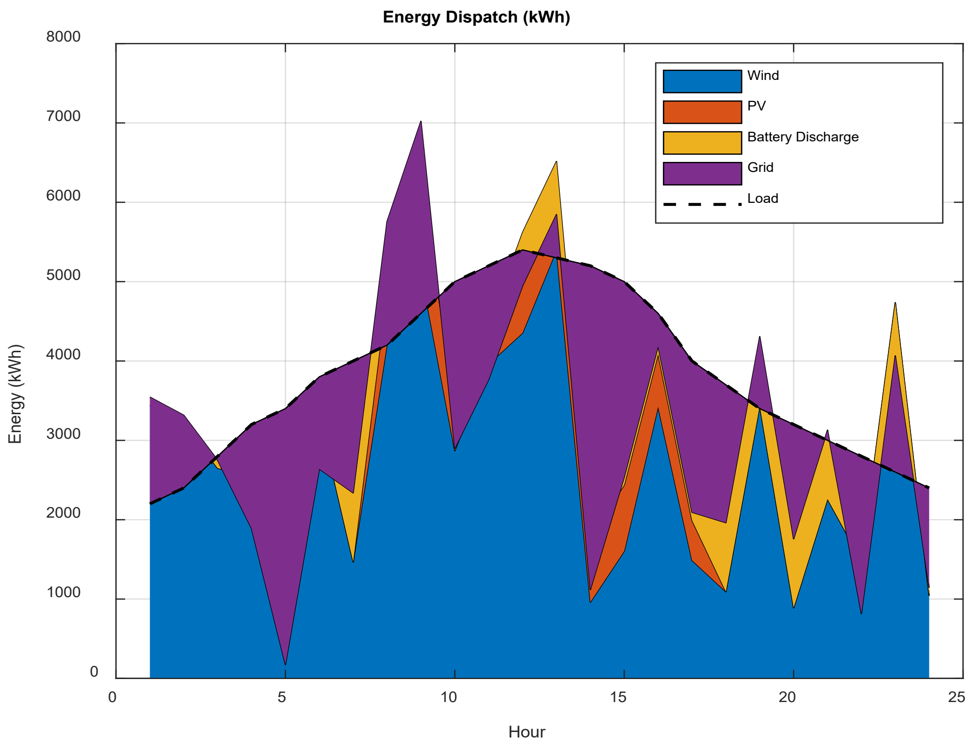

Figure 5. 8: Energy Dispatch simulation results for 24 hours using GWO

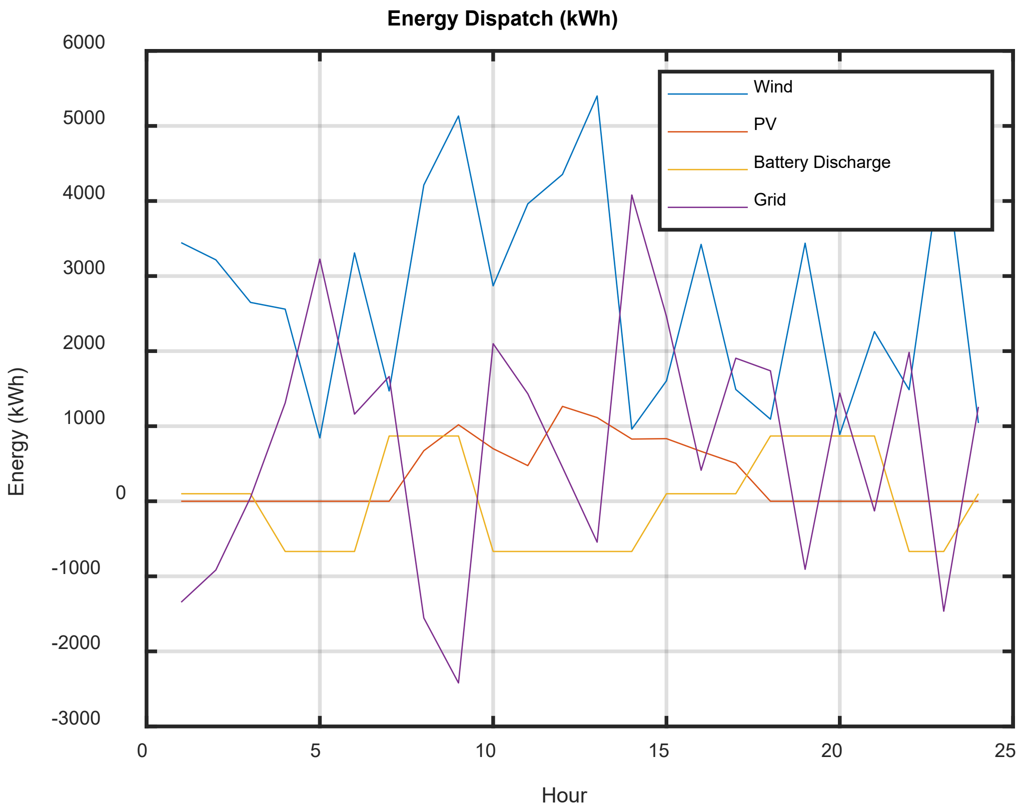

Figure 5. 9: Graphical Energy Dispatch simulation results for 24 hours using GWO

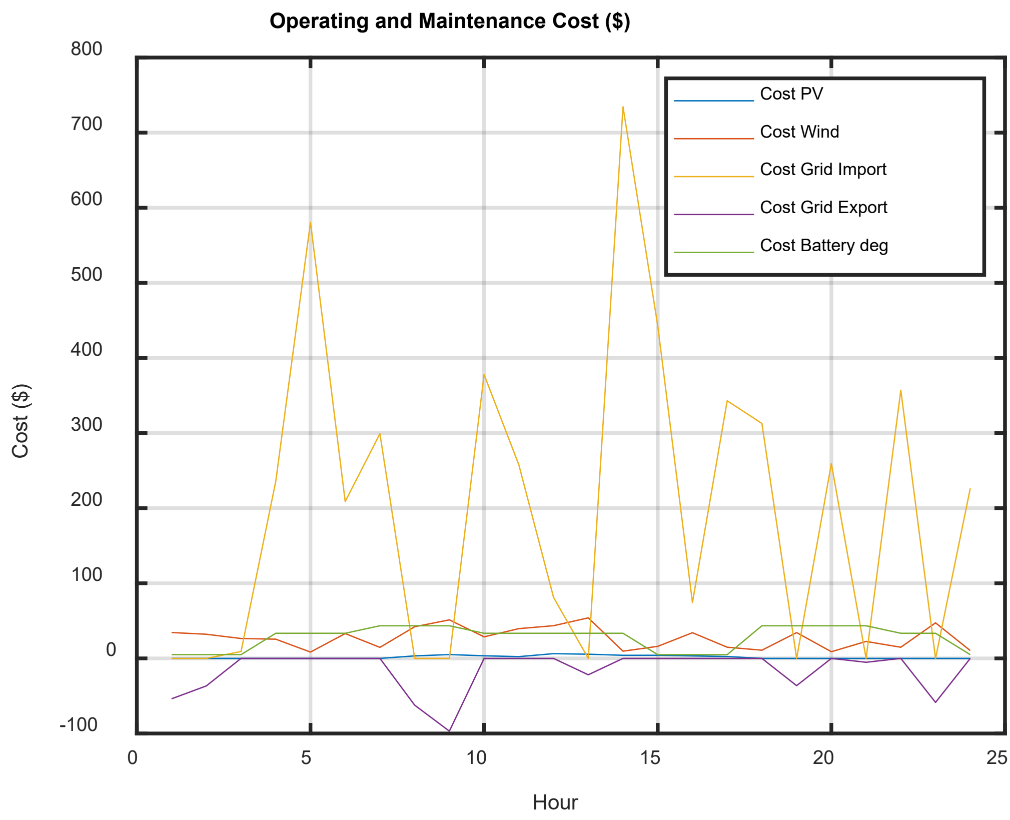

Figure 5. 10: Operating and Maintenance cost results for 24 hours using GWO

5.7.2 Case study 2: Grid-connected Microgrid dispatch with Wind using GWO

In this case study, the objective function is the dispatch of a grid-connected microgrid with renewable energy resources. The GWO algorithm is applied to solve wind-grid energy-based supply. The results obtained are reported in Table 5.6. Load demand is still the same as in case study 1. Also, the total operating costs are included in Table 5.6, whereas PV power and battery storage are excluded in this case study. Load demand varies between the values of 2200kW and 5400kW, while the wind output varies from 459.97kW to 5312.05kW as presented in Table 5.6. Surpluses are always exported to the grid. Moreover, the total operating cost is the sum of grid and operating costs, as depicted in Table 5.7. Grid exporting happens in the hours 2, 3, 4, 8, 16, 20, 22, and 24; the rest of the time. The power is being imported from the grid.

Table 5. 6: Wind-energy-based Microgrid Power Dispatch using GWO algorithm

Hour	Load Power in (kW)	Wind Power in (kW)	Grid Power in (kW)	Total Operating Cost in ($)
1	2200	1993.81	206.19	57.05
2	2400	3646.83	-1246.83	-13.41
3	2800	3188.38	-388.38	16.35
4	3200	4442.35	-1242.35	-5.27
5	3400	2534.41	865.59	181.15
6	3800	1489.10	2310.90	430.85
7	4000	3242.72	757.28	168.74
8	4200	4779.35	-579.35	24.62
9	4600	2223.54	2376.46	450.00
10	5000	1592.26	3407.74	629.32
11	5200	945.54	4254.46	775.26
12	5400	817.60	4582.40	833.01
13	5300	4432.56	867.44	200.47
14	5200	3264.86	1935.14	380.97
15	5000	1527.01	3472.99	640.41
16	4600	5074.74	-474.74	31.76
17	4000	5257.64	-1257.64	2.27
18	3700	958.92	2741.08	502.98
19	3400	576.33	2823.67	514.02
20	3200	3801.08	-601.08	13.97
21	3000	586.23	2413.77	440.34
22	2800	3597.72	-797.72	4.07
23	2600	459.97	2140.03	389.80
24	2400	5312.05	-2912.05	-63.36

The optimal cost incurred over 24-hour periods is presented as the total operating cost, which is the power exchange cost between wind power generation and the grid. The highest cost occurred at hour 12, when demand is at its peak, while wind generation is very low; therefore, the total operating power cost is also at its maximum.

The 24-hour wind speed data is illustrated in Figure 5.11. This is considered the objective function in this case study. GWO is used to optimize wind power generation, and the results are shown in Figure 5.12. The optimal wind speed is captured approximately 18 hours into the time series, while the minimum occurs in the late hours, such as 23 hours. Thus, indicating the key role in enhancing energy dispatch strategies. The variation in wind speed highlights the importance of optimizing energy dispatch and grid interaction. During high-wind hours, as stated earlier, excess power is exported to the grid. When the time of lulls in wind hours, the grid becomes essential. At this juncture, lower speeds during high demand elevate operating costs ($833.01). thus emphasizes the need for cost-effective battery storage or hybrid systems to secure reliability and economic efficiency.

Table 5. 7: Wind Energy-based Microgrid Operating and Maintenance Cost using GWO Algorithm

Hour	Wind Power cost in $	Grid Power Import cost in $	Grid Power Export cost in $	Total Operating cost in ($)
1	19.94	37.11	0.00	57.05
2	36.47	0.00	-49.87	-13.41
3	31.88	0.00	-15.54	16.35
4	44.42	0.00	-49.69	-5.27
5	25.34	155.81	0.00	181.15
6	14.89	415.96	0.00	430.85
7	32.43	136.31	0.00	168.74
8	47.79	0.00	-23.17	24.62
9	22.24	427.76	0.00	450.00
10	15.92	613.39	0.00	629.32
11	9.46	765.80	0.00	775.26
12	8.18	824.83	0.00	833.01
13	44.33	156.14	0.00	200.47
14	32.65	348.32	0.00	380.97
15	15.27	625.14	0.00	640.41
16	50.75	0.00	-18.99	31.76
17	52.58	0.00	-50.31	2.27
18	9.59	493.39	0.00	502.98
19	5.76	508.26	0.00	514.02
20	38.01	0.00	-24.04	13.97
21	5.86	434.48	0.00	440.34
22	35.98	0.00	-31.91	4.07
23	4.60	385.21	0.00	389.80
24	53.12	0.00	-116.48	-63.36

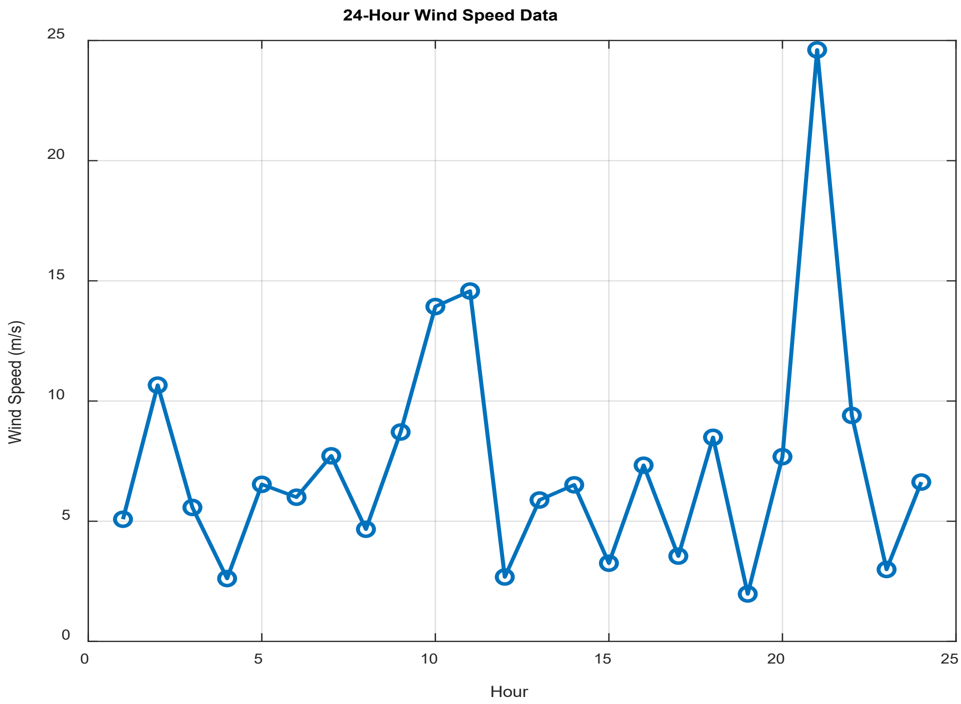

Figure 5. 11: Wind Speed Data results for 24 hours

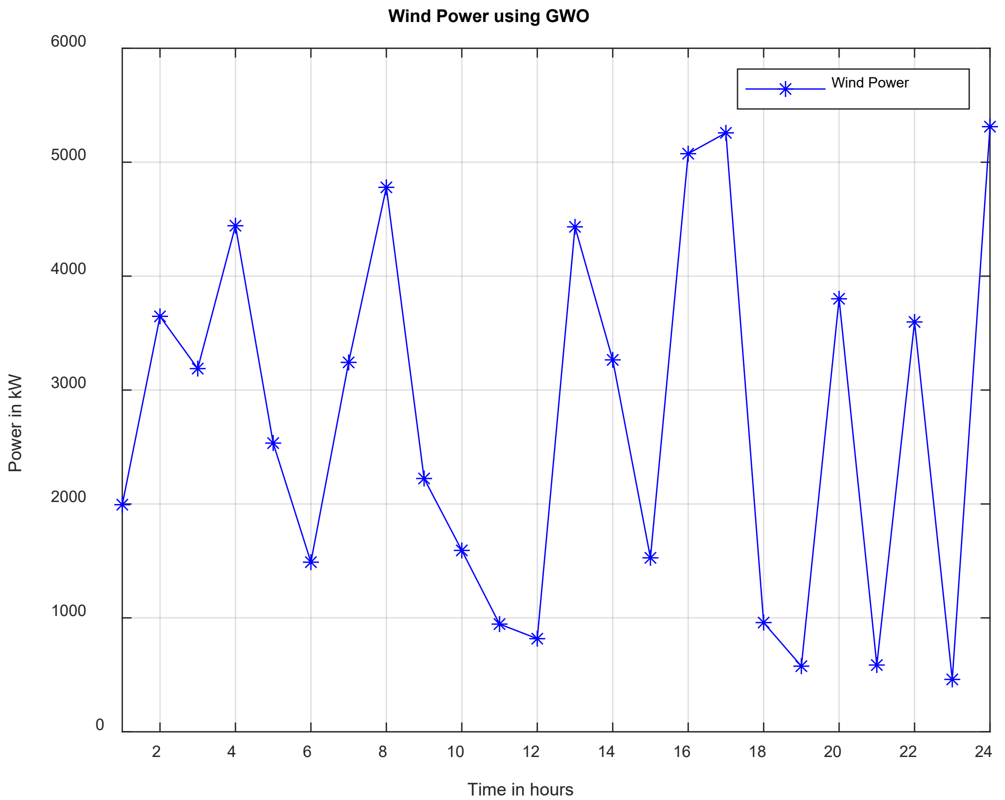

Figure 5. 12: Wind power results for 24 hours using GWO

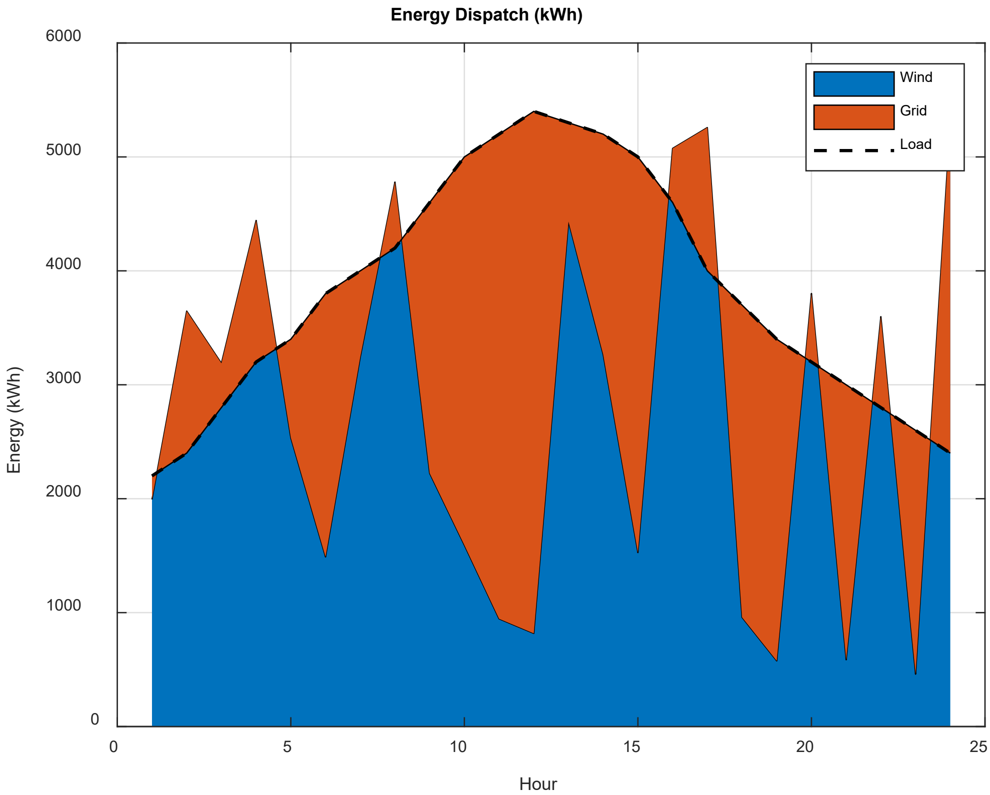

Figure 5. 13: Energy Dispatch results for 24 hours using GWO

The analysis of energy dispatch for the wind-grid hybrid system requires a better understanding of how to effectively manage and utilize the generated wind energy from both the wind energy system and the conventional grid. Figure 5.13 shows the wind contribution in a wind-grid hybrid system. Wind output is variable and dependent on wind speed; therefore, grid integration provides a stable supply of electricity that can be dispatched as needed. Grid supports wind energy when output is very low and draws excess power from wind when generation is high, as depicted in Figure 5.14.

As for the operating and maintenance cost of the wing-grid system analysis, the cost for the grid import is very high. Compared with the grid export, the low cost of grid export is captured, due to the characteristics illustrated in both Figure 5.13 and Figure 5.15. This conceptualization of the operating and maintenance costs provides valuable insight into economic viability. The efficiency of utilizing both wind energy and traditional power must be considered.

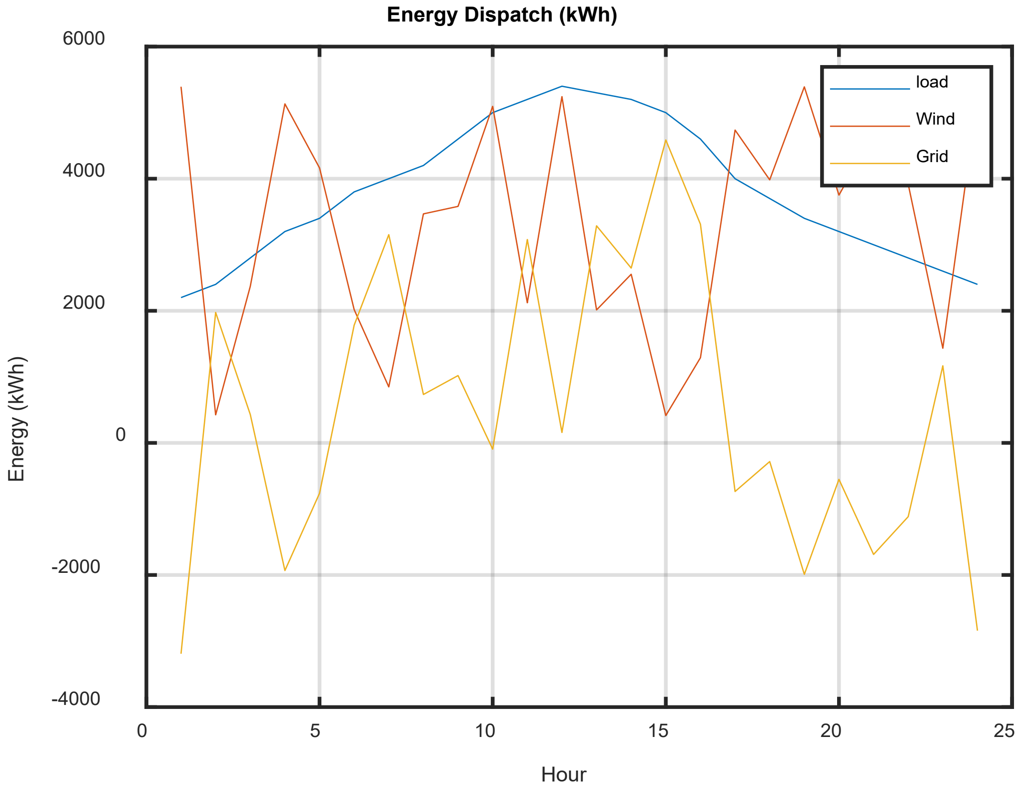

Figure 5. 14: Graphical representation of Energy Dispatch results for 24 hours using GWO

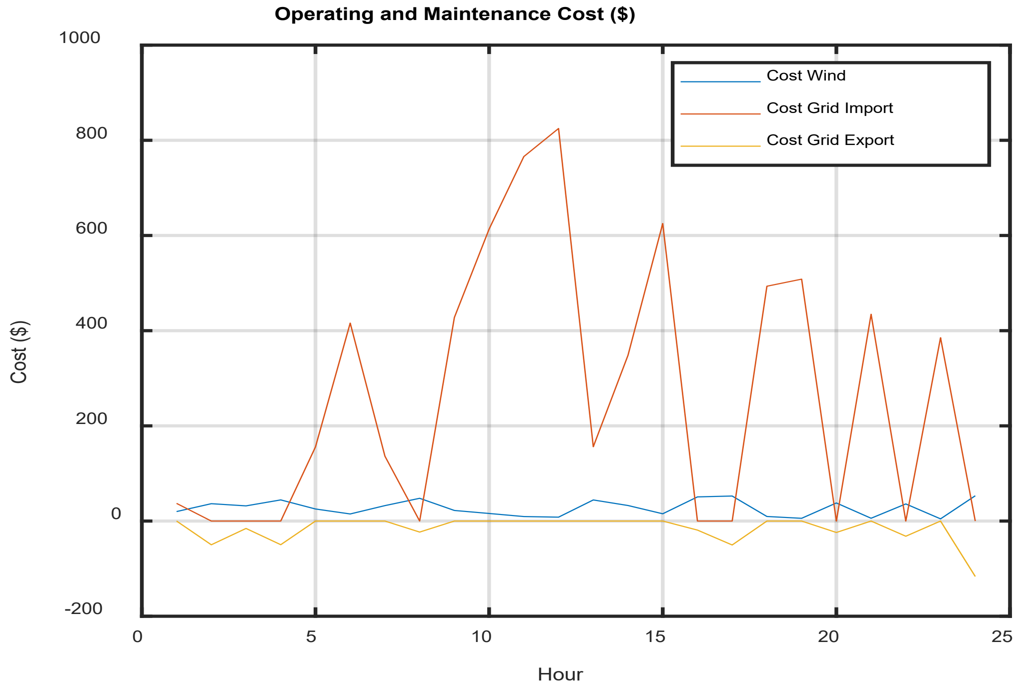

Figure 5. 15: Operating and maintenance cost for 24 hours using GWO

5.7.3 Case study 3: Grid-connected Microgrid dispatch with PV and Battery using GWO

In this case, the energy dispatch of the grid-PV-Battery Storage hybrid is the objective function, and GWO is used for optimization. The results obtained for Grid power dispatch with PV and Battery storage using GWO are presented in Table 5.8. The load demand is the same across all case studies and ranges from 2200kW to 5400kW. Table 5.9 presents the operating and maintenance cost results obtained. This is where the grid, PV, Battery, grid import, and grid export costs are captured and tabulated in Table 5.9.

Table 5. 8: Microgrid Power Dispatch with PV and Battery using GWO algorithm

Hour	Load Power in kW	PV Power in kW	Battery Power in kW	Grid Power in kW	Total Operating Cost in ($)
1	2200	0.00	100.00	2100.00	383.00
2	2400	0.00	100.00	2300.00	419.00
3	2800	0.00	100.00	2700.00	491.00
4	3200	0.00	-643.22	3843.22	723.94
5	3400	0.00	-643.22	4043.22	759.94
6	3800	0.00	-643.22	4443.22	831.94
7	4000	0.00	843.22	3156.78	610.38
8	4200	759.41	843.22	2597.37	513.49
9	4600	686.74	843.22	3070.04	598.20
10	5000	940.47	-643.22	4702.74	883.36
11	5200	1094.10	-643.22	4749.11	892.47
12	5400	651.96	-643.22	5391.26	1005.85
13	5300	1055.98	-643.22	4887.24	917.14
14	5200	1089.73	-643.22	4753.49	893.24
15	5000	707.68	100.00	4192.32	763.16
16	4600	460.09	100.00	4039.91	734.48
17	4000	578.14	100.00	3321.86	605.83
18	3700	0.00	843.22	2856.78	556.38
19	3400	0.00	843.22	2556.78	502.38
20	3200	0.00	843.22	2356.78	466.38
21	3000	0.00	843.22	2156.78	430.38
22	2800	0.00	-643.22	3443.22	651.94
23	2600	0.00	-643.22	3243.22	615.94
24	2400	0.00	100.00	2300.00	419.00

The operation and maintenance cost of a Grid-PV-Battery hybrid system constitutes a pivotal factor in assessing the overall economic feasibility of the energy solution. The systematic of the hybrid cost elements is important for enhancing the efficiency, reliability, and economic sustainability of energy dispatch within grid-connected microgrid frameworks. The optimization process typically involves analyzing PV generation forecasts, battery degradation, Grid exports, and Grid imports, and the sum of all these costs is called the total operating cost of the system, as shown in Table 5.9.

Table 5. 9: Microgrid Operating and Maintenance Cost with PV and Battery using GWO algorithm

Hour	PV Power cost in $	Grid Power Import cost in $	Grid Power Export cost in $	Battery Power degradation cost in $	Total Operating Cost in $
1	0.00	378.00	0.00	5.00	383.00
2	0.00	414.00	0.00	5.00	419.00
3	0.00	486.00	0.00	5.00	491.00
4	0.00	691.78	0.00	32.16	723.94
5	0.00	727.78	0.00	32.16	759.94
6	0.00	799.78	0.00	32.16	831.94
7	0.00	568.22	0.00	42.16	610.38
8	3.80	467.53	0.00	42.16	513.49
9	3.43	552.61	0.00	42.16	598.20
10	4.70	846.49	0.00	32.16	883.36
11	5.47	854.84	0.00	32.16	892.47
12	3.26	970.43	0.00	32.16	1005.85
13	5.28	879.70	0.00	32.16	917.14
14	5.45	855.63	0.00	32.16	893.24
15	3.54	754.62	0.00	5.00	763.16
16	2.30	727.18	0.00	5.00	734.48
17	2.89	597.94	0.00	5.00	605.83
18	0.00	514.22	0.00	42.16	556.38
19	0.00	460.22	0.00	42.16	502.38
20	0.00	424.22	0.00	42.16	466.38
21	0.00	388.22	0.00	42.16	430.38
22	0.00	619.78	0.00	32.16	651.94
23	0.00	583.78	0.00	32.16	615.94
24	0.00	414.00	0.00	5.00	419.00

Since the hybrid system has no grid export at all, the operating and maintenance costs are much higher because PV power generation is only available from hour 8 to hour 17 as depicted in Figure 5.17. Again, the battery charging/discharging pattern is the same as for case study 1 (Figure 5.18); therefore, the system encounters high operating and maintenance costs, especially during high load demand

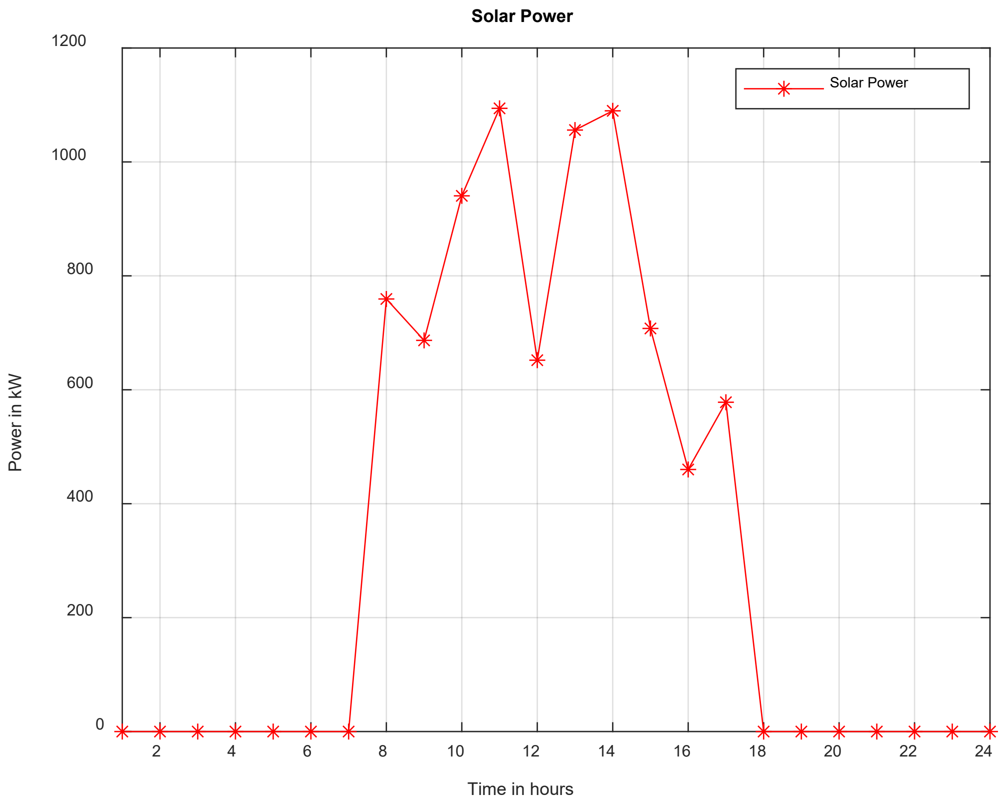

Figure 5. 16: **Solar Power cost for 24 hours using GWO**

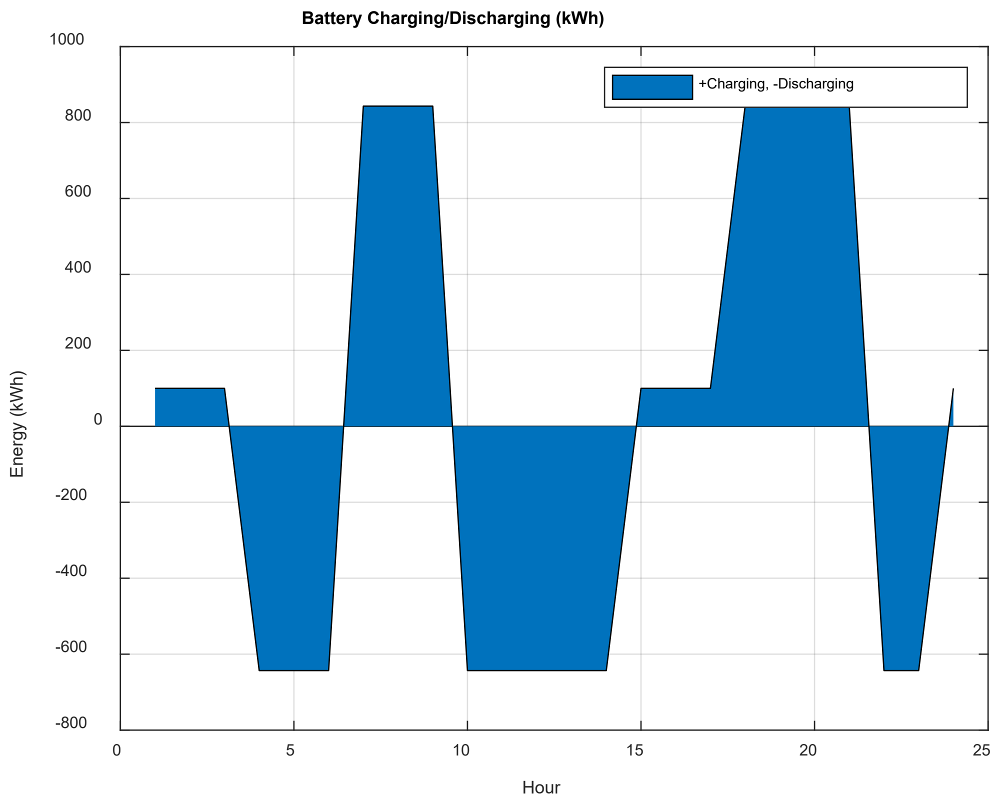

Figure 5. 17: Battery Charging/Discharging of Battery System

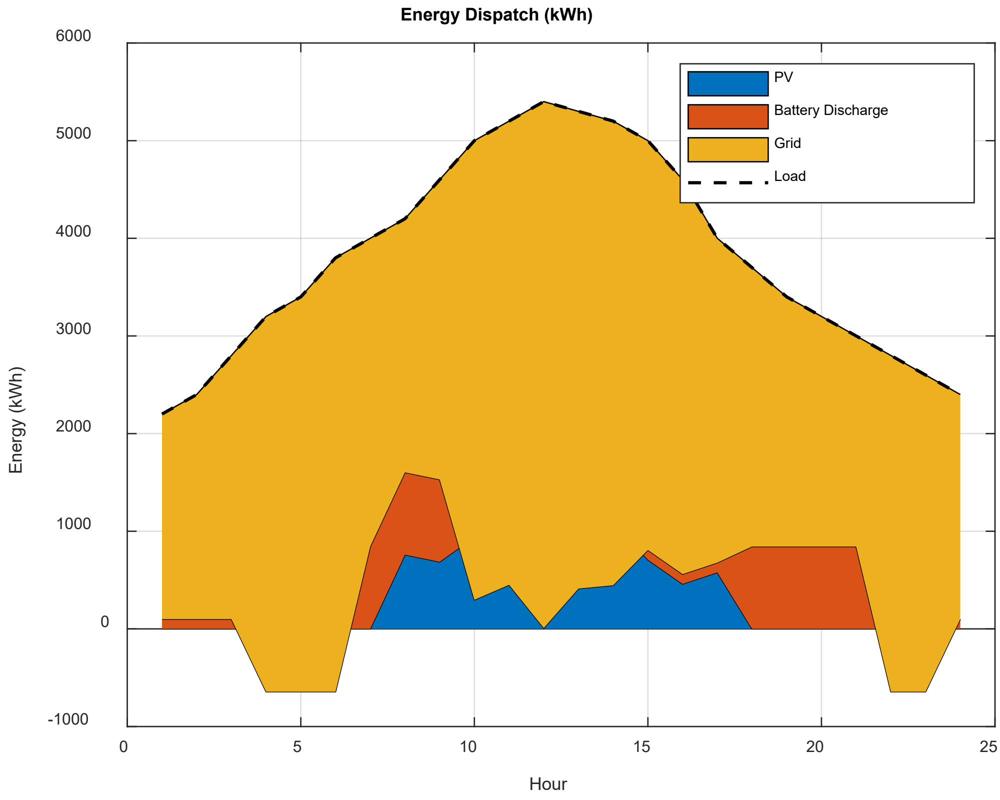

Figure 5. 18: Energy Dispatch for 24 hours using GWO

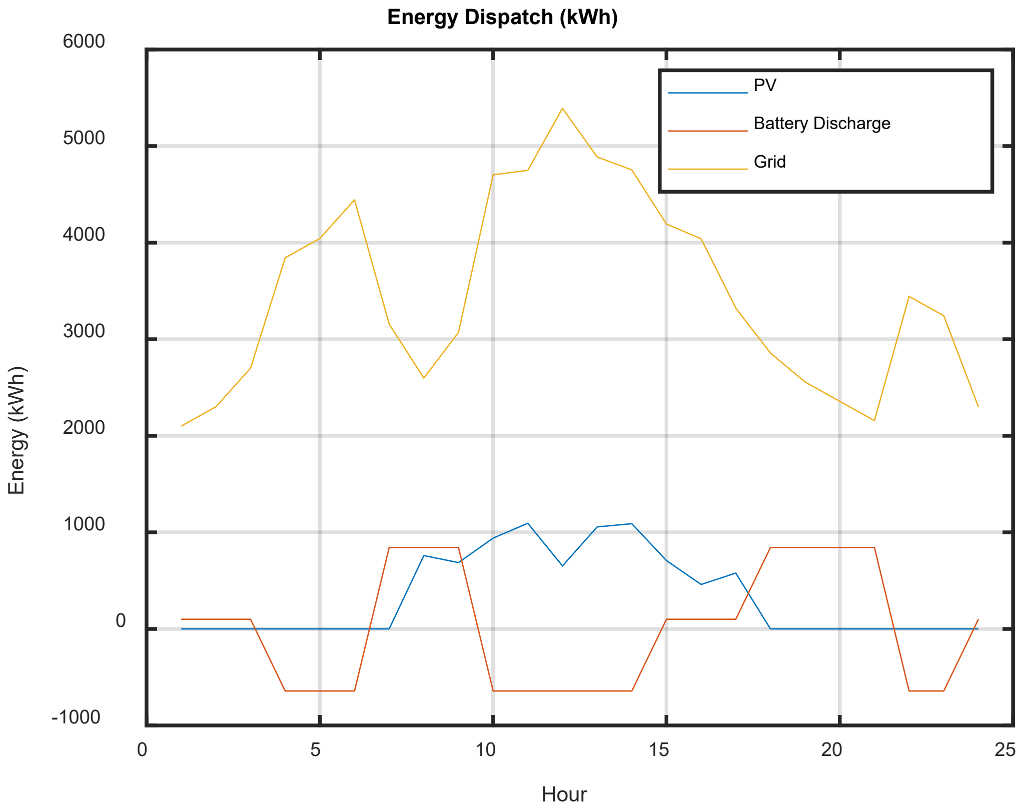

Figure 5. 19: Energy Dispatch cost for 24 hours using GWO

Figure 5.19 shows energy dispatch for the system, with the grid as the main supplier to meet load demand. This implies a high operational and maintenance cost for the grid. PV and Battery systems only supply during their availability. The battery system only stores energy during the off-peak hours by charging the battery until it reaches a maximum of 643.33kWh, as depicted by Figure 5.19.

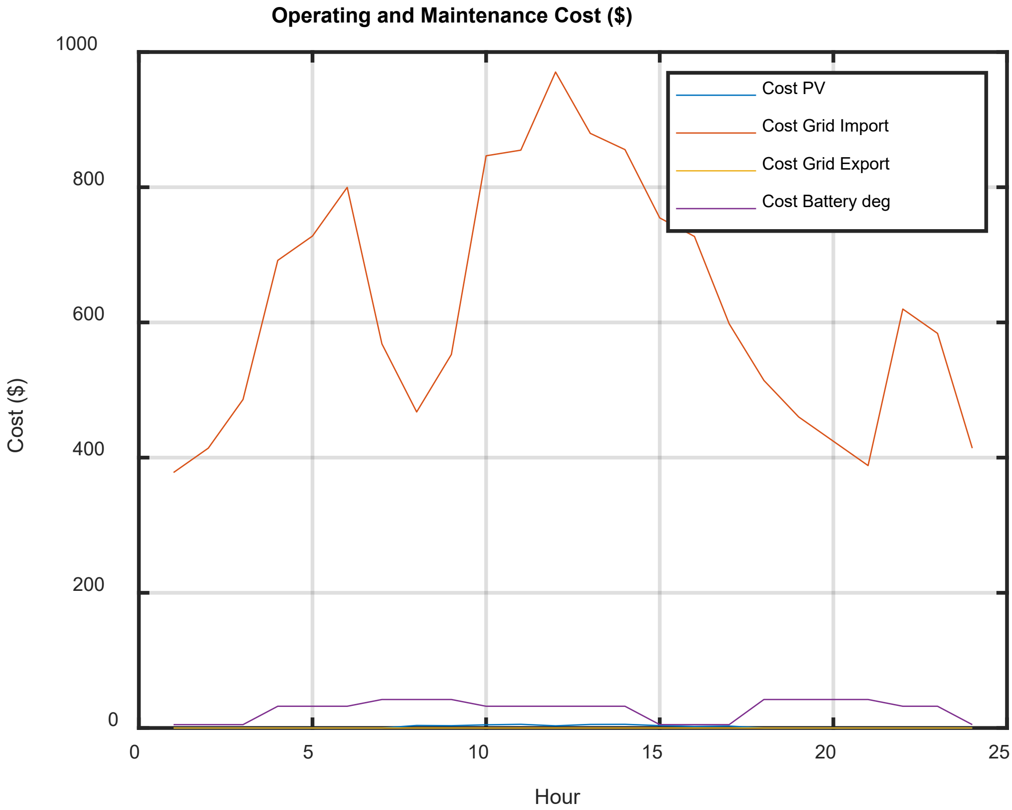

Figure 5. 20: Operating and maintenance cost for 24 hours using GWO

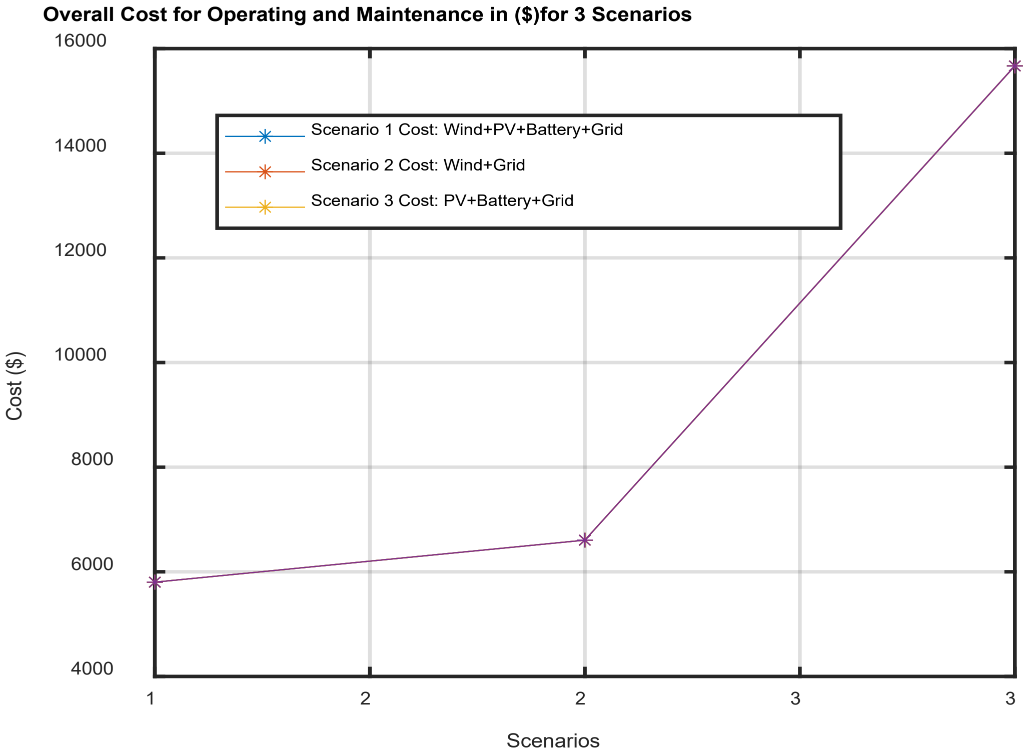

Figure 5. 21: Operating and maintenance cost for 24 hours using GWO

In this case, the elevated operating cost associated with grid power import is depicted in Figure 5.20. This reflects a considerable reliance on the utility to balance energy demand, especially during periods of low PV generation or inadequate battery availability. However, another significant driver of O&M costs is the battery system, due to degradation cost and efficiencies lost through regular charging/discharging. For the contracts, the PV system has lower O&M costs, suggesting either that less solar resource was utilized or that the system was not functioning properly. Furthermore, the lack of grid export suggests that excess PV generation was either limited or insufficiently controlled to prevent it. In general, this cost trend supports further energy management and optimization to increase self-sufficiency, reduce grid reliance, and enable more efficient in-cost generation dispatch throughout the microgrid.

5.8 Discussion of the simulation results

These findings validated a hybrid system of PV, wind, and BSS; LP optimization reduced operating and maintenance (O&M) costs by optimizing each component, since PV does not meet demand on its own and only supplements pre-existing demand. Yet LP and GWO optimization revealed an optimal capacity versus cost, which overproduced to a negligible extent but allowed for more production during the highest demand sun hours.

The differentiation between LP and GWO based on optimal output reveals that many sources and hybridization occur as wind and PV are integrated with BSS for optimal microgrid efficiency. Wind-PV-Battery-Grid-Grid was the least cost for operating scenarios each time. This reveals that hybridization creates a diversified energy portfolio, reducing reliance on the grid (less dependency) despite the variability of renewables. While three scenarios yielded better dispatch decisions, the GWO algorithm outperformed its counterparts because all total operating costs were lower than the equivalent dispatch recommendations. Since GWO attributes greater efficiency to nonlinearities and the variable nature of renewable generation, this results in a more efficient determination of renewable scheduling. These results are substantial, as optimized systems result from hybridized fields operating for longer, which naturally yield more efficient cost and reliability metrics. To note, the LP analysis provided a total operating cost of $9,250.82 to GWO $5,802.44; operating costs were 37.28% lower for GWO, implying the efficiency of dispatch under improved renewable conditions. In general, the LP method's most expensive scenario configuration, PV-Battery-Grid, showed a total of $14,912.15, which is 61% higher than its most economical configuration (wind-PV-Batt-Grid) at $9,250.82 (margin of error). Ultimately, the importance of wind in any scenario is revealed. The GWO algorithm offers lower costs; however, it consistently outperforms LP by increasing the 30th and 40th percentiles. These findings lend credibility to the need for smart dispatching efforts, especially from biologically inspired algorithms such as GWO, which increase renewable energy utilization and improve battery efficiency across multiple demand scenarios, thereby reducing operational costs.

5.9 Comparative Analysis of the Three Case Studies

The simulation outcomes of the three case studies indicate that the (at present) possible operation of microgrid systems consisting of RERs and BESS results in lower total operating costs for these systems. For instance, case study 1 has the lowest total operating cost of $5802.44, with case study 2 next at $6605.37, with case study 3 taking the highest operating cost of $15668.82, all summarized in Table 5.10 and visually represented in Figure 5.21. Furthermore, Figure 5.22 extrapolates the three case studies against the cost obtained for each scenario.

Table 5. 10: Microgrid Operating and Maintenance cost for three scenarios using the GWO algorithm

Hour	Microgrid Dispatch (Wind, PV, Battery, and Grid)	Microgrid Dispatch (Wind and Grid)	Microgrid Dispatch (PV, Battery, and Grid)
1	-14.34	57.05	383.00
2	0.52	-13.41	419.00
3	40.68	16.35	491.00
4	294.83	-5.27	723.94
5	622.52	181.15	759.94
6	275.43	430.85	831.94
7	357.30	168.74	610.38
8	26.74	24.62	513.49
9	3.04	450.00	598.20
10	443.53	629.32	883.36
11	333.26	775.26	892.47
12	164.56	833.01	1005.85
13	71.22	200.47	917.14
14	781.64	380.97	893.24
15	468.35	640.41	763.16
16	116.87	31.76	734.48
17	365.47	2.27	605.83
18	367.20	502.98	556.38
19	41.56	514.02	502.38
20	311.78	13.97	466.38
21	60.89	440.34	430.38
22	405.38	4.07	651.94
23	22.21	389.80	615.94
24	241.80	-63.36	419.00
	Total Operating cost comparison for three scenarios		
	$5802.44	**$6605.37**	**$15668.82**

5.10 Conclusions

This chapter explores the theory and practical application of the Grey Wolf Optimization algorithm for optimizing microgrid systems powered by hybrid renewable energy sources. The section began with the theoretical foundations of GWO, its advantages for microgrid applications, and its advantages and disadvantages compared to more conventional optimization approaches. Subsequently, the general considerations of the GWO algorithm were introduced, along with the mathematical formulation of the objective function and a comprehensive step-by-step formulation that includes computational aspects, such as wolf position shift, encircle, parameter change, and solution stopping point. Cost equations of PV, wind generation, and battery storage systems (BSS) created an optimization problem for which a GWO schematic was created to visually represent the steps taken, both methodologically and mathematically, to arrive at the solution. Chapter 6 concludes the research. Recommendations for further research are also presented in Chapter 6.

CHAPTER 6
CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter concludes the comprehensive research with transferable results, key findings assessed and suggested for application, performances evaluated, and gaps for future research. Future research is a realistic continuation of this dissertation in the relevant fields discussed. This dissertation will provide a basis for similar implementation projects for more operational and cost-effective performance of a renewable energy-based hybrid microgrid system. The renewable energies explored during this project were Photovoltaic (PV), Wind, and Battery Energy Storage System (BESS). The hybrid renewable energy optimization findings of this project are crucial, as they address the problems and needs that many digitized power system networks have faced over recent years.

Microgrid design and optimization with renewable energy for rural electrification is an interesting aspect of power system design, implementation, and evaluation with cost reduction in mind. Therefore, it increases the share of renewables and job market demand while decreasing the carbon footprint. Microgrid design and optimization with renewable energies for rural electrification is of great significance.

The furtherance of this approach is achieved through the application of optimization techniques based on classical and heuristic algorithms. Subsequently, the thesis has applied classical optimization methods, namely Linear Programming (LP), as well as heuristic optimization methods, namely the Dynamic Arithmetic Optimization Algorithm (DAOA), and Grey Wolf Optimization (GWO) algorithm. The development of procedures for implementing the steps of these algorithms is reported in the thesis. MATLAB is used to validate the developed optimization methods and to analyze the simulation results. The optimization techniques were employed to minimize total system operating cost while ensuring reliability and energy balance within the microgrids.

The thesis systematically formulates the daily operational and maintenance costs. The optimized models were validated using realistic hybrid renewable energy and load demand data to analyze system performance for the developed DAOA, LP, and GWO optimization methods.

6.2 Aims and Objectives of the thesis.

Optimization techniques are widely used in hybrid microgrid systems for power system planning and operation. Dynamic Arithmetic Optimization (DAOA) is a family of arithmetic-optimization variants that introduce a dynamic control mechanism to improve the exploration-exploitation balance of the original Arithmetic Optimization Algorithm (AOA). DAOA produces smoother dispatch decisions, improved battery utilization, and lower overall operating costs. Such a flexible parameterization enables it to perform better under personalized load-demand conditions. Linear programming optimization obtains an optimal solution with precision and establishes a definitive solution to a given problem, ensuring that linear constraints and objective functions are satisfied to the greatest degree possible, providing a mathematically based algorithm. However, GWO is a population-based metaheuristic that simulates the social ranking and hunting behaviors of grey wolves. The difference between DAOA, LP, and GWO is that GWO is the newer, more applicable approach.

Thus, enabling the tackling of non-linear and multi-modal problems, which traditional methods might struggle with.

This research aims to systematically formulate cost functions for each energy component, accounting for operational cost. For achieving improvement in utility networks with microgrid-based rural electrification, the following are addressed in this thesis to facilitate proper planning of the integration:

- Develop a microgrid-based-rural electrification model.
- To investigate the effects of the existing optimization methods in a renewable energy microgrid.
- Develop a Dynamic Arithmetic Optimization Algorithm (DAOA) optimization method for a microgrid energy management system and validate the simulation results using MATLAB programming.
- Develop an LP optimization method for a microgrid energy management system and validate the simulation results using MATLAB programming.
- Develop the GWO method for a microgrid energy management system and validate the simulation results using MATLAB programming.
- To observe and compare the developed, planned, and optimal microgrid energy management systems for rural electrification.

6.3 Thesis Deliverables

6.3.1 Review of the planning and optimization of the renewable-energy-based microgrid for rural electrification.

A literature review of existing microgrid systems, microgrid systems for rural electrification, and the optimization methods used in microgrid systems was conducted and reported. A total of 133 papers on microgrid systems for rural electrification are reviewed. A comparison of the existing classical optimization techniques was based on the findings outlined in Figure 2.5 and Table 2.4. For classical optimization methods, 86 papers are reviewed; for heuristic optimization, 133 are reviewed, as depicted in Figure 2.6 and Table 2.5. Thus, 352 total of papers were reviewed for their contribution to the complete thesis. The analysis of the findings leads to the conclusion that a classical optimization algorithm must be developed first, followed by a heuristic optimization algorithm.

6.3.2 Development of a Dynamic Arithmetic Optimization Method for the microgrid system

The DAOA optimization model was successfully developed. The DAOA model was implemented and tested using a series of MATLAB-based simulations to evaluate its performance in solving the microgrid dispatch problem. The MATLAB implementation involved coding for the DAOA framework, system parameters, and objective functions, and running multiple simulations to assess performance in convergence characteristics and solution quality. The results were always stable, fast, and very accurate, no matter how it was implemented, indicating that the DAOA framework is highly adaptable across different operating conditions. Therefore, the MATLAB implementation indicates that the DAOA framework is not only computationally efficient but also exceptionally effective for microgrid operation optimization in renewable energy systems.

6.3.3 Performance of the Dynamic Arithmetic optimization method.

The developed DAOA MATLAB code is presented in Appendix A.

6.3.4 Development of Linear Programming Optimization Method for the microgrid system

The LP optimization model was successfully developed. The LP model was constructed with high computational efficiency, as all solutions were output in the shortest possible execution time. Also, there are constraints within which the microgrid's economic dispatch can be successfully applied.

The LP-based optimization for microgrid energy management follows an eight-step systematic approach. First, the microgrid dispatch problem should be clearly defined, as this exercise aims to establish operational parameters and goals. Second, all necessary input data for this definition should be collected, including load profiles, generation profiles, and costs. Thus, the decision variables will be defined as the controllable parameters of the microgrid, with an objective function that minimizes total operational costs. Constraints will be constructed based on the system's balance of power, generation limits, and the battery's state-of-charge behaviour. The developed LP MATLAB code is presented in Appendix B.

6.3.5 Performance of the LP optimization method.

The resultant LP model is solved with standard LP solvers in MATLAB to obtain an optimal operational cost, accounting for available PV and wind, grid imports, and battery charge/discharge cycles. The ultimate result is a cost-effective dispatch solution that can be practically applied in real-time operational improvements of the microgrid.

LP revealed a lower total cost in static, deterministic conditions, which is sustainable for linear systems with such mathematical properties. It also increases renewable use and decreases conventional production. A high level of reliability is achieved through the BESS component, which reduces fluctuations in operation by properly managing over-generation/under-generation periods.

6.3.6 Development of Grey Wolf Optimization Method for the microgrid system

The GWO model was successfully developed. The GWO model has high potential for solving the nonlinearities and uncertainties of a renewable energy microgrid for rural electrification. The GWO method for microgrid energy management operates by having thousands of grey wolves navigate potential solutions, each dispatch solution in a state-space representing the microgrid. A natural method of grey wolf pack hunting relies on alpha, beta, and delta pack members as the top three, ultimately deemed feasible or cost-effective from an operational perspective during their time in the territory. The analysis is transparent and consistently defined, offering critical insight into the financial implications. The developed GWO MATLAB code is presented in Appendix C.

6.3.7 Performance of the GWO method.

GWO can influence all other candidate solutions, enabling it to gradually refine power-scheduling conclusions based on PV generation or wind, battery discharge/charge requests, and the amount of power needed from the grid to support demand and requirements. GWO is a more versatile solution, operating on dynamic input, therefore, even if it goes off course with renewable dispatch through its iterations to find other avenues, it merely takes startup trends as an assumption of the best case scenario to optimize for successful solutions against variances that come from renewables and the uncertainties of rural microgrids which require dynamic parameters that need adjustment over time. The more it converges towards the required iterations, the more the optimized solution will be favoured for reliability, operational expenditures, and improved renewable penetration for rural electrification.

GWO also works more effectively under harsher, nonlinear, or uncertain conditions, as in a hybrid RE microgrid, where incremental improvements to the methodology increase exploration capabilities. GWO has demonstrated system stability with variable renewables, producing these findings with a few more iterations and more exhaustive adjustments. Better energy management was facilitated by reduced reliance on grid power and by managing BESS excess/deficiency, as the implementation relies on stable systems. Furthermore, hybrid optimizations can yield better synergistic solutions that promote flexibility or cost-effectiveness, compared to purely accurate solutions.

6.3.8 Developed a Software program for the DAOA, LP, and GWO optimization methods

The developed software, implemented in MATLAB, meets the project scope and objectives of this study by supporting a microgrid planning and dispatch strategy for renewable-energy-based hybrid microgrid systems using a dynamic arithmetic optimization algorithm, linear programming, and grey wolf optimization, thereby outlining effective and efficient microgrid energy management.

While LP and GWO have their strengths, DAOA constitutes a more flexible optimization dispatch strategy. DAOA does not focus solely on finding candidates for ideal scheduling; instead, a combination of dynamic arithmetic operators adjusts based on solutions learned from one another from iteration to iteration. As such, DAOA can better justify dispatch costs given the nonlinearities of PV and wind generations, load variances, and battery characteristics, and operates better than LP and GWO. As such, the optimized dispatch minimizes operating costs for overall economic feasibility while effectively balancing power. Thus, it is the best comprehensive, more flexible optimization dispatch strategy for microgrid energy management.

The linear programming software microsystem mathematically solves the microgrid dispatch problem to minimize total operational costs while accounting for power balance requirements, generation limits, and battery state-of-charge constraints.

GWO employs a seamless metaheuristic search, inspired by grey wolf hunting, to explore differentiated renewables with varying charging needs and potential grid assistance to manage renewable volatility, given that solar and wind resources are unavailable in this median rural microgrid setting. Ultimately, both types of algorithms, through their smaller microsystems, enable cost-effective, reliable, and renewable-heavy microgrid operation schedules applicable to rural electrification objectives and energy management goals.

The MATLAB software developed for the DAOA, LP, and GWO optimization methods is listed in Table 6.1, and the MATLAB code for each method is provided in Appendices A-C.

Table 6. 1: Developed MATLAB code for the DAOA, LP, and GWO optimal solution for the renewable-based microgrid system

Objective Function	Algorithm	Type of Microgrid system	Appendix Identity	MATLAB Identification
Operating Costs	Dynamic Arithmetic Optimization Algorithm	Grid-connected-PV -Wind-Battery Network	Appendix A	DAOA_Microgrid.m
Operating Costs	Linear Programming	Grid-connected-PV -Wind-Battery Network	Appendix B	LP_Microgrid.m
Operating Costs	Grey Wolf Optimization	Grid-connected-PV -Wind-Battery Network	Appendix C	GWO_Microgrid.m

Table 6.1 presents the MATLAB code appendix for the DAOA, LP, and GWO optimization methods developed in this research work.

6.4 Utility Applications of the developed LP & GWO methods

The main areas of application for the results of this thesis include:

- Planning and optimization of hybrid renewable-energy-based microgrids.
- Control design for the integration and management of Battery Energy Storage Systems (BESS).
- Formulation and validation of comprehensive cost and operational models for PV–Wind–BESS microgrids.
- An ultimate cost and performance model for the PV–Wind–BESS microgrid was established and validated.
- A better understanding of the effects of optimization selection on costs, reliability, and renewable penetration was achieved.
- The use of metaheuristic optimization strategies was applied to enhance the flexibility of these renewable resource control systems.

- The determination of which optimization method was best suited for certain microgrid structures and operational scenarios.
- This research offers a practical and theoretical framework for DAOA, LP, and GWO as a new method of reliably, cost-effectively, and with high renewable penetration.
- A mixed-methods approach to compare DAOA, LP, and GWO as a means of acknowledging the pros and cons of each for microgrid energy management.
- Microgrid energy management training for undergrad/grad students with optimal control techniques.

6.5 Future Research

Hybrid renewable-energy-based microgrid planning and optimization consider solutions that enable reliable optimization and can be useful to engineers, researchers, and public officials. The best solution has been achieved based on the models, but the following limitations are acknowledged:

- The research did not consider the degradation of the battery performance over extended operational periods.
- The future work considers tuning the DAOA's dynamic control parameters (exploration and exploitation factors, adaptive operators). Poor parameter selection can lead to slower convergence or premature stagnation.
- The LP model assumes perfect forecast accuracy; this may not hold in real-world conditions.
- The future work considers tuning the GWO parameters, such as iteration count as well as population size, which influences convergence speed and solution quality.

These specific future scopes must be standardized to enable comparison of the performance of the developed optimal models. Also, the battery dynamic degradation capabilities must be included as a factor in a practical, optimal solution for planning and optimizing hybrid renewable-energy-based microgrid systems.

6.6 Publications

1. N. M. Maletsie and S. Krishnamurthy, "Review of Planning and Optimization of the Renewable-Energy-Based Micro-Grid for Rural Electrification," 2024 32nd Southern African Universities Power Engineering Conference (SAUPEC), Stellenbosch, South Africa, 2024, pp. 1-6, doi: 10.1109/SAUPEC60914.2024.10445088
2. Maletsie Nteka Mojela, Senthil Krishnamurthy. "Energy Management of a Photovoltaic–Wind–Battery Energy Storage Microgrid Using Linear

Programming and Grey Wolf Optimization Techniques" International Journal of Energetica (IJECA), pages 29-48, ISSN: 2543-3717, https://www.ijeca.info/index.php/IJECA/article/view/288/274

3. Maletsie Nteka Mojela and Senthil Krishnamurthy. Performance-Enhanced Dynamic Arithmetic Optimization Algorithm for Energy Management in a Hybrid Renewable Microgrid System. Anticipated submission in Feb 2026 to the Journal of Engineering (JoE) published by the Institution of Engineering and Technology (IET).

6.7 Conclusions

This chapter presents the aims and objectives of the thesis. It details the key deliverables, including the development of three optimization algorithms: Dynamic Arithmetic Optimization Algorithm (DAOA), Linear Programming (LP), and Grey Wolf Optimization (GWO), and a MATLAB-based software program for optimizing hybrid renewable-energy-based microgrid systems for rural electrification. The chapter also outlines practical methods for applying the developed algorithms and software in offline simulations to evaluate microgrid performance. Additionally, it highlights potential directions for future research and provides a list of related publications stemming from this work.

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APPENDICES

APPENDIX A: MATLAB CODE FOR DAOA

Appendix A1: Pseudocode of the Dynamic Arithmetic Optimization Algorithm (DAOA)

```
%% Dynamic Arithmetic Optimization Algorithm (DAOA) pseudocode
Inputs: f, lb, ub, N, K, MOA_min, MOA_max, MOP0, alpha
Initialize X_i(0) ~ U(lb, ub), evaluate F_i(0) = f(X_i(0))
Set X* = argmin_i F_i(0), F* = min_i F_i(0)

for k = 1 to K
    MOA = MOA_min + (MOA_max - MOA_min)*(k/K)^alpha
    MOP = MOP0*(1 - k/K)

    for i = 1 to N
        for d = 1 to dim
            draw r1,r2,r3 ~ U(0,1)
            if rand < MOP
                if rand < 0.5
                    tilde = X_i(d) - MOA * r1 * (ub(d)-lb(d))
                else
                    tilde = X_i(d) + MOA * r2 * (ub(d)-lb(d))
            else
                if rand < 0.5
                    tilde = X*(d) - MOA * r3 * ( X*(d) / (X_i(d) + eps) )
                else
                    tilde = X*(d) + MOA * r3 * ( (X*(d) - X_i(d)) / (1 +
abs(r2)) )
            end
            % small stochastic attractor
            tilde = tilde + 0.05*(rand - 0.5)*( X*(d) - X_i(d) )
            X_i(d) = min( ub(d), max( lb(d), tilde ) )
        end
    end

    preserve best: X(index_of_best,:) = X*
    evaluate F_i for all i
    update (X*,F*) if improvement
end

Output: X*, F*
```

Appendix A 2: MATLAB Code for Case 3.1: Grid-connected Microgrid dispatch with Wind, PV, and Battery using Dynamic Arithmetic Optimization Algorithm

```
%% Dynamic Arthimetic Optimization Algorithm DAOA
% DAOA-based sizing and dispatch optimization for Wind+PV+Battery+Grid
% Filename: DAOA_hybrid_optimization.m
clear; close all; clc;

%% === Load input data (24-hour) ===
% Ensure file 'DAOA_data.xlsx' has the same columns used previously.
data = xlsread('DAOA_data');
load_profile      = data(:,1);
solar_irradiance  = data(:,2);
wind_speed        = data(:,3);
grid_price        = data(:,4);
% sell_price = data(:,5); % if needed
```

```
T = length(load_profile);

%% === DAOA parameters ===
nAgents = 24;        % population size (wolves -> agents)
maxIter = 100;       % iterations
dim = 4;             % [wind_cap, pv_cap, batt_cap, grid_cap]

%% === Parameter bounds (design variables) ===
% x = [wind_cap, pv_cap, batt_cap, grid_cap]
lb = [0,    0,  100,  400];
ub = [5000,1000, 500, 4000];

%% === Initialize population (random inside bounds) ===
X = repmat(lb, nAgents, 1) + rand(nAgents, dim) .* repmat((ub - lb), nAgents,
1);

% Ensure feasible initial population
X = max(repmat(lb, nAgents, 1), min(repmat(ub, nAgents, 1), X))

fitness = inf(nAgents,1);

% Best-so-far
[f_best, idx_best] = deal(inf, 1);
X_best = X(1,:);

%% === DAOA control parameters (dynamic) ===
% MOA (Math Optimizer Accelerator) and MOP (Math Optimizer Probability)
MOA_min = 0.2;  MOA_max = 1.0;    % MOA increases -> more exploitation over time
MOP_init = 0.5;                   % baseline probability switching
exploration/exploitation

% Additional dynamic term to help balance exploration/exploitation
dynamic_rate = @(iter) MOA_min + (MOA_max - MOA_min) * (iter / maxIter).^1.5;

%% === Auxiliary generation of hourly PV / wind / battery dispatch templates ===
% Compute instantaneous generation later inside cost function using
% decision variables as capacities.

%% === Main DAOA loop ===
history.best_f = zeros(maxIter,1);
history.best_x = zeros(maxIter, dim);

for iter = 1:maxIter
    MOA = dynamic_rate(iter);
    MOP = MOP_init * (1 - (iter / maxIter)); % probability decays slightly (more
determinism later)

    for i = 1:nAgents
        x = X(i,:);  % current agent

        % Evaluate fitness using user's costHybrid function if available,
        % otherwise use the example cost below.
        % named costHybrid(...) if it exists on the path.
        if exist('costHybrid','file') == 2
            fit = costHybrid(x, wind_speed, solar_irradiance, load_profile,
grid_price);
        else
            fit = costHybrid_example(x, wind_speed, solar_irradiance,
load_profile, grid_price);
        end
```

```
        fitness(i) = fit;

        % Update global best
        if fit < f_best
            f_best = fit;
            X_best = x;
            idx_best = i;
        end
    end

    % Store history
    history.best_f(iter) = f_best;
    history.best_x(iter,:) = X_best;

    % --- Update positions using arithmetic-inspired operations ---
    for i = 1:nAgents
        for d = 1:dim
            r1 = rand;
            r2 = rand;
            r3 = rand;

            if rand < MOP
                % Math-based (Exploration / global search)
                if rand < 0.5
                    % Subtraction-driven exploration
                    new_val = X(i,d) - MOA * ( r1 * (ub(d) - lb(d)) );
                else
                    % Addition-driven exploration
                    new_val = X(i,d) + MOA * ( r2 * (ub(d) - lb(d)) );
                end
            else
                % Exploitation: move toward best with scaled arithmetic
operators
                if rand < 0.5
                    % Multiply move (compress towards best)
                    new_val = X_best(d) - MOA * r3 .* ( X_best(d) ./ (X(i,d) +
1e-6) );
                else
                    % Division-like adjustment (expand/shrink towards best)
                    new_val = X_best(d) + MOA * r3 .* ( (X_best(d) - X(i,d)) ./
(1 + abs(r2)) );
                end
            end

            % Small stochastic attractor toward best (helps fine tune)
            new_val = new_val + 0.05 * (rand - 0.5) * (X_best(d) - X(i,d));

            % Assign
            X(i,d) = new_val;
        end

        % Keep inside bounds
        X(i,:) = max(lb, min(ub, X(i,:)));

    end

    % Optional: elitism — keep best agent in the population
    X(idx_best,:) = X_best

    % Display quick progress every 10 iterations
    if mod(iter,10) == 0 || iter == 1 || iter == maxIter
```

```
        fprintf('Iter %d/%d  BestCost = %.4f\n', iter, maxIter, f_best);
    end

end

%% === Output results ===
optimal = X_best;
disp('Optimal capacities and grid max:');
disp(optimal);
% disp(['Optimal cost: $' num2str(f_best)]);

%% === Plots ADOA visualizations ===
%% Draw Operating Cost Curve
figure;
plot(1:maxIter, history.best_f, 'LineWidth', 2);
grid on;
xlabel('Iteration'); ylabel('Best cost'); title('DAOA Convergence');


figure;
plot(load_profile, '-k*'); xlim([1 T]); grid on;
legend('Load Power consumption'); xlabel('Time (hour)'); ylabel('kW');
title('Load Profile');

figure;
plot(solar_irradiance, '-g*'); xlim([1 T]); grid on;
legend('Solar Irradiance'); xlabel('Time (hour)'); ylabel('kW'); title('Solar
Irradiance');

figure;
plot(wind_speed, '-b*'); xlim([1 T]); grid on;
legend('Wind Speed'); xlabel('Time (hour)'); ylabel('kW'); title('Wind Speed');

% For dispatch stacked area, generate simple profiles from optimal capacities:
% Assume instantaneous generation scales by normalized profiles (simple model)
wind_gen_opt = min(optimal(1) * (wind_speed / max(wind_speed+eps)), optimal(1));
% PV generation with 8-17h mask
pv_hours = 8:17;                  % hours when PV generates
pv_mask  = zeros(T,1);            % initialize mask
pv_mask(pv_hours) = 1;            % set 1 for PV active hours

% Generate PV output
pv_gen_opt = optimal(2) * (solar_irradiance / (max(solar_irradiance)+eps)) .*
pv_mask;

% Ensure PV does not exceed capacity
pv_gen_opt = min(pv_gen_opt, optimal(2));


%% Typical Battery Charging & Discharging Schedule (24-Hour Period)
% Sample Charging/Discharging Timing
% 24-hour classification (example)
% +1 = Charging, -1 = Discharging, 0 = Idle
battery_mode = [...
    0, 0,0 ...     % 00-03   Idle or light charging Low load, low price
    1, 1, 1,...    % 04-06    Charging Preparing for morning peak
    -1, -1, -1,...   % 07-09     Discharging  Morning load peak
    1, 1, 1, 1,1, ...% 10-14     Charging     Solar generation available
    0, 0,0,  ...     % 15-17     Idle or trickle     No major load or price event
    -1, -1, -1,-1, ...% 18-21    Discharging  Evening peak demand
    1, 1,0];          % 22-24    Charging     Off-peak pricing starts
```

```
P_bat_min=100;
P_bat_max=500;
% For battery dispatch values:
bat = P_bat_min + (P_bat_max - P_bat_min).*battery_mode;
bat_gen_opt=bat;

% ================================
% Battery Charging / Discharging Plot
% ================================

t = 1:length(bat_gen_opt);        % Time vector (hours)
battery_power = bat_gen_opt(:);   % Ensure column vector

% Separate charging and discharging
battery_discharge = battery_power;
battery_discharge(battery_discharge < 0) = 0;

battery_charge = battery_power;
battery_charge(battery_charge > 0) = 0;

figure;
hold on; grid on;

% Plot discharging (positive)
bar(t, battery_discharge, 'FaceColor', [0.9 0.4 0.1], 'DisplayName',
'Discharging');

% Plot charging (negative)
bar(t, battery_charge, 'FaceColor', [0.1 0.4 0.9], 'DisplayName', 'Charging');

xlabel('Time (Hour)');
ylabel('Battery Power (kW)');
title('Battery Charging and Discharging Profile');
legend('Location', 'best');
set(gca, 'FontSize', 12);

hold off;


% Power Balance Constraint
grid_power_opt = (load_profile - (wind_gen_opt(:) + pv_gen_opt(:) +
bat_gen_opt(:)));

% Calculate net grid power
% Calculate Separate import/export
Grid_Import_Energy  = max(grid_power_opt, 0);   % positive values
Grid_Export_Energy  = min(grid_power_opt, 0);   % negative values

% Energy calculations
%Grid_Import_Energy = sum(Grid_Import);         % kWh imported
%Grid_Export_Energy = -sum(Grid_Export);        % convert negative sum to
positive value

% Display
% disp(['Total Grid Import Energy: ', num2str(Grid_Import_Energy), ' kWh']);
% disp(['Total Grid Export Energy: ', num2str(Grid_Export_Energy), ' kWh']);

figure;
area(1:T, [wind_gen_opt(:), pv_gen_opt(:), bat_gen_opt(:), grid_power_opt(:)]);
hold on;
plot(1:T, load_profile, 'k--', 'LineWidth', 1.2);
```

```
legend('Wind','PV','Battery Discharge','Grid','Load');
title('Energy Dispatch (approx)'); xlabel('Hour'); ylabel('kW'); grid on;

%% Cost Calculation
%% Energy Operating and Maintanance Costs
C_Grid_import = 0.18;      % $/kWh  - buying from grid
C_Grid_export = 0.04;      % $/kWh  - selling to grid (revenue)
C_Bat_cycle   = 0.05;      % $/kWh  - battery degradation cost
C_PV_OM       = 0.005;     % $/kWh  - PV O&M cost
C_Wind_OM     = 0.01;      % $/kWh  - Wind turbine O&M cost


%% P_PV, P_Wind, P_Bat_Charge, P_Bat_Discharge,
%  P_Grid_Import, and P_Grid_Export must be nWolves × 24 matrices


%% -----------------------------
%   PV OPERATING COST
%% -----------------------------
PV_Energy = sum(pv_gen_opt, 2);                  % kWh/day
Cost_PV_OM = PV_Energy * C_PV_OM;          % daily O&M cost


%% -----------------------------
%   WIND OPERATING COST
%% -----------------------------
Wind_Energy = sum(wind_gen_opt, 2);              % kWh/day
Cost_Wind_OM = Wind_Energy * C_Wind_OM;


%% -----------------------------
%   GRID COST / REVENUE
%% -----------------------------
Cost_Grid_Import = Grid_Import_Energy * C_Grid_import;
Cost_Grid_Export = -Grid_Export_Energy * C_Grid_export;   % revenue (negative
cost)

%% -----------------------------
%   BATTERY DEGRADATION COST
%% -----------------------------
Cost_Battery_deg =  bat_gen_opt'*C_Bat_cycle;

%% -----------------------------
%   TOTAL OPERATING COST (NO CAPITAL COST)
%% -----------------------------
Operating_Cost = Cost_PV_OM + Cost_Wind_OM + ...
                 Cost_Grid_Import + Cost_Grid_Export + ...
                 Cost_Battery_deg
Operating_Cost_Table = [Cost_PV_OM Cost_Wind_OM Cost_Grid_Import
Cost_Grid_Export Cost_Battery_deg];

%% Optimal cost
Total_Operating_Cost = sum(Operating_Cost_Table);
Total_Operating_Cost = sum(Total_Operating_Cost);
format long g          % <-- removes scientific notation
disp(Total_Operating_Cost)


%% Preallocate storage for total operating cost
Total_Operating_Cost_History = zeros(maxIter,1);
```

```
for iter = 1:maxIter
    % --- DAOA update and fitness evaluation code ---
    % After computing Operating_Cost_Table for this iteration:

    Total_Operating_Cost = sum(Operating_Cost_Table);   % Sum individual
components
    Total_Operating_Cost = sum(Total_Operating_Cost);   % Flatten to scalar if
needed
    format long g                                       % Disable scientific
notation
    disp(['Iteration ', num2str(iter), ': Total Operating Cost = ',
num2str(Total_Operating_Cost)]);

    % --- Save to history vector ---
    Total_Operating_Cost_History(iter) = Total_Operating_Cost;

    % --- Continue DAOA updates ---
end

% Optional: plot convergence
figure;
plot(1:maxIter, Total_Operating_Cost_History, 'LineWidth', 1.5);
xlabel('Iteration');
ylabel('Total Operating Cost ($)');
title('DAOA Convergence of Operating Cost');
grid on;

%% Draw Power Dispatch Plot
    figure (12);

    plot(1:T,
[Cost_PV_OM,Cost_Wind_OM,Cost_Grid_Import,Cost_Grid_Export,Cost_Battery_deg]);
    hold on;
    legend('Cost PV','Cost Wind','Cost Grid Import','Cost Grid Export','Cost
Battery deg');
    title('Operating and Maintenance Cost ($)');
    xlabel('Hour');
    ylabel('Cost ($)');
    grid on;
    %ylim([-200 800]);
    % Get current axes handle
    ax = gca;

    % Optional customizations
    ax.FontSize = 12;              % adjust font size
    ax.LineWidth = 1.4;            % make axis lines thicker
    ax.XAxis.Exponent = 0;         % disable scientific notation on X-axis
    ax.YAxis.Exponent = 0;         % disable scientific notation on Y-axis
    ax.Box = 'on';                 % show box around the plot
    xtickformat('%.0f');      % X-axis as normal numbers (no scientific notation)
    ytickformat('%.0f');   % Y-axis: integer values
    %ytickformat('%.6f');      % Y-axis with up to 6 decimal places (adjust as
needed)

%% Print the Solution
X = [wind_gen_opt(:), pv_gen_opt(:), bat_gen_opt(:), grid_power_opt(:)];  % T x
4

% ==========================================
%   Multi-Curve Dispatch Plot from matrix X
% ==========================================
```

```
t = 1:size(X,1);   % Time index (hours)

figure;
plot(t, X(:,1), 'b', 'LineWidth', 1.6); hold on;      % Wind
plot(t, X(:,2), 'g', 'LineWidth', 1.6);               % PV
plot(t, X(:,3), 'm', 'LineWidth', 1.6);               % Battery
(charge/discharge)
plot(t, X(:,4), 'r', 'LineWidth', 1.6);               % Grid import/export

grid on;

xlabel('Time (Hour)');
ylabel('Power (kW)');
title('Power Dispatch of Microgrid Components');

legend('Wind Generation', ...
       'PV Generation', ...
       'Battery (+Discharge / -Charge)', ...
       'Grid Import (+) / Export (-)', ...
       'Location','Best');

set(gca, 'FontSize', 12);


%% Power Balance Constraint Check (hourly)
Power_Balance_Check = [sum(X,2), load_profile(:)];  % T x 2

% Optional: check imbalance
imbalance = Power_Balance_Check(:,1) - Power_Balance_Check(:,2);
disp('Hourly Power Balance Check (Generated vs Load):');
disp(Power_Balance_Check);
disp('Maximum imbalance (kW):');
disp(max(abs(imbalance)));
```

Appendix A3: **MATLAB Code for cost comparison of all 3 case scenarios using Dynamic Arithmetic Optimization Algorithm**

```
clc
clear all
% Case 1:Grid-connected Microgrid dispatch with Wind, PV and Battery using
% DAOA
% Case 2: Grid-connected Microgrid dispatch with Wind using DAOA
% Case 3: Grid-connected Microgrid dispatch with PV and Battery using
% DAOA

    Cost_3Scenarios=[
140.80 153.80 383.00
180.71 193.71 419.00
267.66 280.66 491.00
251.15 316.15 511.00
244.62 309.62 547.00
289.85 354.85 619.00
445.74 406.74 759.00
359.35 362.29 754.83
96.33  114.53 812.22
110.69 50.00  776.57
213.73 351.95 800.89
511.05 652.31 833.96
536.19 675.92 817.43
315.01 456.28 797.96
```

```
221.34 295.36 828.57
107.44 173.83 763.88
68.44  53.55  685.09
213.28 174.28 705.00
339.72 300.72 651.00
66.29  33.39  615.00
49.10  76.10  579.00
150.47 105.47 439.00
120.34 75.34  403.00
168.25 181.25 419.00
];

    %% Draw Operating Cost Curve
    %% Draw Power Dispatch Plot
    figure (13);
    T=size (Cost_3Scenarios);
    plot(1:T, [Cost_3Scenarios]);
    hold on;
    legend('Cost Wind+PV+Battery+Grid','Cost Wind+Grid','Cost PV+Battery+Grid');
    title('DAOA Operating Cost ($) comparsion for 3 Scenarios');
    xlabel('Hour');
    ylabel('Cost ($)');
    grid on;
    % Optional customizations
    ax.FontSize = 12;              % adjust font size
    ax.LineWidth = 2;            % make axis lines thicker

Overall_Cost = [5467.56, 6148.10, 15411.40];

figure(14);
plot(Overall_Cost, '-*', 'LineWidth', 1.5, 'MarkerSize', 8);
hold on;
grid on;

title('DAOA Overall Operating Cost ($) for 3 Scenarios');
xlabel('Scenario');
ylabel('Cost ($)');

% Set x-axis ticks
xticks(1:length(Overall_Cost));
xticklabels({'Scenario 1','Scenario 2','Scenario 3'});

% Show values on the plot
for i = 1:length(Overall_Cost)
    text(i, Overall_Cost(i)+350, num2str(Overall_Cost(i),'%.2f'), ...
         'HorizontalAlignment','center', 'FontSize',10,'FontWeight','bold');
end

    % Get current axes handle
    ax = gca;

    % Optional customizations
    ax.FontSize = 12;              % adjust font size
    ax.LineWidth = 2;            % make axis lines thicker
    ax.XAxis.Exponent = 0;         % disable scientific notation on X-axis
    ax.YAxis.Exponent = 0;         % disable scientific notation on Y-axis
    ax.Box = 'on';                 % show box around the plot
    xtickformat('%.0f');     % X-axis as normal numbers (no scientific notation)
    ytickformat('%.0f');   % Y-axis: integer values
```

APPENDIX B: MATLAB CODE FOR LINEAR PROGRAMMING ALGORITHM

Appendix B1: MATLAB Code for Case 4.1: Grid-connected Microgrid dispatch with Wind, PV, and Battery using LP algorithm

```
%% Microgrid dispatch LP: Wind + PV + Battery + Grid (24-hour)
clear; clc;

%% --------------------------
% User inputs / data
%% --------------------------
% Load data: columns [load_kW, solar_irradiance (0..1 or W/m2),
wind_speed(optional), grid_price(optional)]
data = xlsread('GWO_data');   % change filename if needed
load_profile = data(:,1);     % 24x1
if size(data,2) >= 2
    solar_irr = data(:,2);
else
    solar_irr = ones(24,1);   % fallback
end
if size(data,2) >= 3
    wind_speed = data(:,3);

else
    wind_speed = [];          % will synthesize
end
if size(data,2) >= 4
    grid_price = data(:,4);
else
    grid_price = 0.18*ones(24,1);  % $/kWh default
end

T = length(load_profile);
assert(T==24, 'This script expects 24 hourly rows.');

%% --------------------------
% Fixed capacities (dispatch-only)
% (set these to your system capacities)
%% --------------------------
wind_cap = 5000;   % kW
pv_cap   = 1000;    % kW
batt_cap = 500;    % kWh
grid_cap = 4000;   % kW

% Initial battery SOC (kWh)
SOC0 = 0.5 * batt_cap;

%% --------------------------
% Technical parameters
%% --------------------------
eta_ch = 0.95;      % battery charge efficiency
eta_dis = 0.90;     % discharge efficiency
SOC_min_frac = 0.20;
SOC_max_frac = 0.95;
P_ch_rate = 0.5;    % max charge power per kWh battery capacity (kW per kWh)
P_dis_rate = 0.5;

% PV hours mask (only produce between 08:00 - 17:00)
hours = (1:T)';
```

```
pv_mask = double(hours >= 8 & hours <= 17);  % 24x1 (0/1)

% Convert solar_irr to PV capacity factor (CF). If solar_irr already 0..1, scale
by max:
if max(solar_irr) > 1  % likely irradiance in W/m2
    PV_CF = solar_irr ./ max(solar_irr);    % normalize 0..1
else
    PV_CF = solar_irr;                      % already 0..1
end
PV_CF = PV_CF .* pv_mask;  % zero out night hours

% Wind fraction WF from speed -> use simple cubic region or normalized input
if isempty(wind_speed)
    % synthesize diurnal wind fraction (example)
    daily_variation = 1 + 0.10*sin(2*pi*(hours-12)/24);
    baseWF = 0.5 * ones(T,1);         % base fraction (tune for site)
    WF = min(max(baseWF .* daily_variation, 0), 1);
else
    % convert wind_speed to WF using a simple cubic ramp (cut-in v_in, rated
v_r)
    v_in = 3; v_r = 12; v_out = 25;
    WF = zeros(T,1);
    for t=1:T
        v = wind_speed(t);
        if v < v_in
            WF(t)=0;
        elseif v < v_r
            WF(t) = ((v - v_in)/(v_r - v_in))^3;
        elseif v <= v_out
            WF(t) = 1;
        else
            WF(t) = 0;
        end
    end
end

%% --------------------------
% Cost parameters ($/kWh)
%% --------------------------
C_Grid_import = 0.18;    % buying price (can be hourly via grid_price)
C_Grid_export = 0.04;    % feed-in tariff
C_Bat_cycle   = 0.05;    % battery degradation cost per kWh cycled
C_PV_OM       = 0.005;
C_Wind_OM     = 0.01;
Unserved_penalty = 1e5;  % very large to avoid unserved unless infeasible
otherwise

%% --------------------------
% Decision variable ordering (for linprog)
% x = [ P_PV(1..T);
%       P_Wind(1..T);
%       P_ch(1..T);
%       P_dis(1..T);
%       P_imp(1..T);
%       P_exp(1..T);
%       SOC(1..T);
%       P_unserved(1..T) ]
%% --------------------------
nBlocks = 8;
nVar = nBlocks * T;
```

```
idx = @(block,t) (block-1)*T + t;  % block=1..8, t=1..T

%% --------------------------
% Objective vector c (linear)
%% --------------------------
c = zeros(nVar,1);

% PV O&M
c(idx(1,1):idx(1,T)) = C_PV_OM;
% Wind O&M
c(idx(2,1):idx(2,T)) = C_Wind_OM;
% Battery degradation (charge+discharge)
c(idx(3,1):idx(3,T)) = C_Bat_cycle;
c(idx(4,1):idx(4,T)) = C_Bat_cycle;
% Grid import (hourly price available)
for t=1:T
    c(idx(5,t)) = grid_price(t);
end
% Grid export (negative cost = revenue)
c(idx(6,1):idx(6,T)) = -C_Grid_export;
% SOC block has zero cost
% Unserved load penalty
c(idx(8,1):idx(8,T)) = Unserved_penalty;

%% --------------------------
% Equality constraints Aeq x = beq (power balance and SOC dynamics)
% - power balance: P_PV + P_Wind + P_dis + P_imp - P_ch - P_exp + P_unserved =
Load
% - SOC dynamics: SOC(t) - SOC(t-1) - eta_ch*P_ch(t) + (1/eta_dis)*P_dis(t) = 0
%% --------------------------
Aeq = zeros(2*T, nVar);
beq = zeros(2*T,1);

% Power balance rows
for t=1:T
    Aeq(t, idx(1,t)) = 1;   % P_PV
    Aeq(t, idx(2,t)) = 1;   % P_Wind
    Aeq(t, idx(4,t)) = 1;   % P_dis
    Aeq(t, idx(5,t)) = 1;   % P_imp
    Aeq(t, idx(3,t)) = -1;  % -P_ch
    Aeq(t, idx(6,t)) = -1;  % -P_exp
    Aeq(t, idx(8,t)) = 1;   % +P_unserved
    beq(t) = load_profile(t);
end

% SOC dynamics rows
for t=1:T
    row = T + t;
    Aeq(row, idx(7,t)) = 1;    % SOC_t
    if t == 1
        % SOC1 - eta_ch*P_ch1 + (1/eta_dis)*P_dis1 - SOC0 = 0
        Aeq(row, idx(3,t)) = -eta_ch;
        Aeq(row, idx(4,t)) = 1/eta_dis;
        beq(row) = SOC0;
    else
        Aeq(row, idx(7,t-1)) = -1;   % -SOC_{t-1}
        Aeq(row, idx(3,t)) = -eta_ch;
        Aeq(row, idx(4,t)) = 1/eta_dis;
        beq(row) = 0;
    end
end
```

```
%% --------------------------
% Inequality constraints A x <= b
% PV/Wind availability, SOC bounds linked to batt_cap, C-rate limits, grid cap
limits
%% --------------------------
A = []; b = [];

% 1) PV availability: P_PV_t <= pv_cap * PV_CF(t)
A_pv = zeros(T, nVar); b_pv = zeros(T,1);
for t=1:T
    A_pv(t, idx(1,t)) = 1;
    A_pv(t, idx(1,t)) = 1;
    b_pv(t) = pv_cap * PV_CF(t);   % right-hand side constant because we fixed
pv_cap
end
% We will implement PV limits as simple upper bounds on P_PV via ub (preferred),
% but for clarity keep A_pv here as alternative (not appended).
% Append if you prefer matrix form: A=[A;A_pv]; b=[b;b_pv];

% 2) Wind availability: P_Wind_t <= wind_cap * WF(t)
A_w = zeros(T, nVar); b_w = zeros(T,1);
for t=1:T
    A_w(t, idx(2,t)) = 1;
    b_w(t) = wind_cap * WF(t);   % RHS constant
end
% (We'll set ub directly instead of A matrix)

% 3) SOC bounds: SOC_min <= SOC(t) <= SOC_max
SOC_min = SOC_min_frac * batt_cap;
SOC_max = SOC_max_frac * batt_cap;
A_soc = zeros(2*T, nVar); b_soc = zeros(2*T,1);
for t=1:T
    A_soc(t, idx(7,t)) = 1;          b_soc(t) = SOC_max;
    A_soc(T+t, idx(7,t)) = -1;       b_soc(T+t) = -SOC_min;
end
A = [A; A_soc]; b = [b; b_soc];

% 4) C-rate limits: P_ch_t <= P_ch_rate*batt_cap, P_dis_t <= P_dis_rate*batt_cap
A_ch = zeros(2*T, nVar); b_ch = zeros(2*T,1);
for t=1:T
    A_ch(t, idx(3,t)) = 1;         b_ch(t) = P_ch_rate * batt_cap;
    A_ch(T+t, idx(4,t)) = 1;       b_ch(T+t) = P_dis_rate * batt_cap;
end
A = [A; A_ch]; b = [b; b_ch];

% 5) Grid import/export limits: P_imp <= grid_cap, P_exp <= grid_cap
A_grid = zeros(2*T, nVar); b_grid = zeros(2*T,1);
for t=1:T
    A_grid(t, idx(5,t)) = 1;       b_grid(t) = grid_cap;
    A_grid(T+t, idx(6,t)) = 1;     b_grid(T+t) = grid_cap;
end
A = [A; A_grid]; b = [b; b_grid];

%% --------------------------
% Variable bounds (lb_var <= x <= ub_var)
%% --------------------------
lb_var = zeros(nVar,1);
ub_var = inf(nVar,1);

% P_PV upper bounds = pv_cap * PV_CF(t)
```

```
for t=1:T
    ub_var(idx(1,t)) = pv_cap * PV_CF(t);
end

% P_Wind ub = wind_cap * WF(t)
for t=1:T
    ub_var(idx(2,t)) = wind_cap * WF(t);
end

% P_ch and P_dis ub from C-rate (already in A_ch but also set numeric ub)
for t=1:T
    ub_var(idx(3,t)) = P_ch_rate * batt_cap;
    ub_var(idx(4,t)) = P_dis_rate * batt_cap;
end

% Grid ub
for t=1:T
    ub_var(idx(5,t)) = grid_cap;
    ub_var(idx(6,t)) = grid_cap;
end

% SOC numeric bounds
for t=1:T
    lb_var(idx(7,t)) = SOC_min;
    ub_var(idx(7,t)) = SOC_max;
end

% Unserved >= 0
for t=1:T
    lb_var(idx(8,t)) = 0;
    ub_var(idx(8,t)) = Inf;
end

%% --------------------------
% Solve LP
%% --------------------------
options = optimoptions('linprog','Algorithm','dual-
simplex','Display','iter','MaxIterations',10000);
[x, fval, exitflag, output, lambda] = linprog(c, A, b, Aeq, beq, lb_var, ub_var,
options);

if exitflag ~= 1
    warning('linprog did not find optimal solution (exitflag=%d). Message: %s',
exitflag, output.message);
end

%% --------------------------
% Extract and report results
%% --------------------------
P_PV   = x(idx(1,1):idx(1,T))';
P_Wind = x(idx(2,1):idx(2,T))';
P_ch   = x(idx(3,1):idx(3,T))';
P_dis  = x(idx(4,1):idx(4,T))';
P_imp  = x(idx(5,1):idx(5,T))';
P_exp  = x(idx(6,1):idx(6,T))';
SOC    = x(idx(7,1):idx(7,T))';
P_unserved = x(idx(8,1):idx(8,T))';
P_all_sources=[P_PV; P_Wind;P_ch; P_dis; P_imp; P_exp; SOC; P_unserved]';

% Sanity: reconstructed supply balance
recon_load = P_PV + P_Wind + P_dis + P_imp - P_ch - P_exp + P_unserved;
```

```
max_abs_diff = max(abs(recon_load - load_profile'));
fprintf('Max power-balance mismatch after solution: %.6f kW\n', max_abs_diff);

% Daily Operating cost breakdown
Cost_PV_OM_Hourly = (P_PV) * C_PV_OM;
Cost_Wind_OM_Hourly = (P_Wind) * C_Wind_OM;
Cost_Grid_Import_Hourly = (P_imp) * C_Grid_import;
Cost_Grid_Export_Hourly = (P_exp) * C_Grid_export;
Battery_Throughput_Hourly = (P_ch + P_dis);
Daily_Operation_Cost_Hourly=[Cost_PV_OM_Hourly; Cost_Wind_OM_Hourly;
Cost_Grid_Import_Hourly; Cost_Grid_Export_Hourly;Battery_Throughput_Hourly]';
% Sum each row
Daily_Operation_Cost_Hourly_Each_loads = sum(Daily_Operation_Cost_Hourly, 2);

% Display results
disp(Daily_Operation_Cost_Hourly_Each_loads)

%Daily_Operation_Cost_hour1=sum(Daily_Operation_Cost_Hourly (1,:));
% Overall Operating cost breakdown
Cost_PV_OM = sum(P_PV) * C_PV_OM;
Cost_Wind_OM = sum(P_Wind) * C_Wind_OM;
Cost_Grid_Import = sum(P_imp) * C_Grid_import;
Cost_Grid_Export = sum(P_exp) * C_Grid_export;
Battery_Throughput = sum(P_ch + P_dis);
Cost_Battery_deg = Battery_Throughput * C_Bat_cycle;

Operating_Cost = Cost_PV_OM + Cost_Wind_OM + Cost_Grid_Import + Cost_Grid_Export
+ Cost_Battery_deg;

fprintf('\nOperating cost breakdown ($/day):\n');
fprintf(' PV O&M:      %.2f\n', Cost_PV_OM);
fprintf(' Wind O&M:    %.2f\n', Cost_Wind_OM);
fprintf(' Grid import: %.2f\n', Cost_Grid_Import);
fprintf(' Grid export: %.2f\n', Cost_Grid_Export);
fprintf(' Battery deg: %.2f\n', Cost_Battery_deg);
fprintf(' Total:       %.2f\n', Operating_Cost);
fprintf(' Total objective fval: %.2f\n', fval);
fprintf(' Total unserved energy (kWh/day): %.4f\n', sum(P_unserved));

%% --------------------------
% Plots
%% --------------------------
h = 1:T;
figure('Name','Dispatch Stack');
area(h, [P_Wind; P_PV; P_dis; P_imp]');
hold on; plot(h, load_profile,'k--','LineWidth',1.5);
legend('Wind','PV','Battery Discharge','Grid Import','Load');
xlabel('Hour'); ylabel('Power (kW)'); title('Dispatch Stack vs Load'); grid on;

figure('Name','Battery & Grid');
subplot(2,1,1); plot(h, P_ch,'r-',h,P_dis,'m-'); ylabel('kW');
legend('P_{ch}','P_{dis}'); title('Battery Charge/Discharge');
subplot(2,1,2); plot(h, P_imp,'b-',h,P_exp,'c-'); ylabel('kW'); legend('Grid
Import','Grid Export'); title('Grid Import/Export'); xlabel('Hour');

figure('Name','SOC & Unserved');
subplot(2,1,1); plot(h, SOC,'k-'); ylabel('kWh'); title('Battery SOC'); ylim([0
batt_cap]);
subplot(2,1,2); stem(h, P_unserved,'k'); ylabel('kW'); xlabel('Hour');
title('Unserved Load (if any)');
```

APPENDIX C: MATLAB CODE FOR GREY WOLF OPTIMIZATION

This appendix presents a MATLAB code for the GWO algorithm, which was tested across three different microgrid scenarios to demonstrate its adaptability to various renewable setups. **Appendix C1** examines Case Study 1, which features a microgrid comprising wind, PV, and battery storage, providing a comprehensive view of how GWO integrates multiple energy sources. **Appendix C2** then focuses on Case Study 2, which looks only at wind-based generation, allowing us to see how the algorithm handles a single but highly unpredictable renewable resource. Finally, **Appendix C3** presents Case Study 3, where dispatch decisions rely on just PV and battery systems, highlighting GWO's ability to balance solar output with stored energy. Together, these appendices offer a clear and practical view of how GWO performs under different operating conditions and energy mixes.

Appendix C1: MATLAB Code for Case 5.1: Grid-connected Microgrid dispatch with Wind, PV, and Battery

```
% GWO-based sizing and dispatch optimization for Wind+PV+Battery+Grid
clear; clc;

%% === Input Data (hourly over 24-hr period) ===
data=xlsread('GWO_data');
load_profile=data(:,1);
grid_price=data(:,4);
%sell_price=data(:,5);

%% GWO input parameters
nWolves = 1;
maxIter = 100;
T = length(load_profile);

%% === Parameter bounds (design variables) ===
% x = [wind_cap, pv_cap, batt_cap, grid_cap]
lb = [0, 0, 50, 400];
ub = [5000, 1000, 500, 4000];
dim = length(lb);


%% Typical Battery Charging & Discharging Schedule (24-Hour Period)
% Sample Charging/Discharging Timing
% 24-hour classification (example)
% +1 = Charging, -1 = Discharging, 0 = Idle
battery_mode = [...
    0, 0,0 ...     % 00-03   Idle or light charging Low load, low price
    1, 1, 1,...    % 04-06    Charging Preparing for morning peak
    -1, -1, -1,...  % 07-09     Discharging  Morning load peak
    1, 1, 1, 1,1, ...% 10-14     Charging     Solar generation available
    0, 0,0, ...     % 15-17     Idle or trickle     No major load or price event
    -1, -1, -1,-1, ...% 18-21    Discharging  Evening peak demand
    1, 1,0];          % 22-24    Charging     Off-peak pricing starts
P_bat_min=100;
P_bat_max=1000;
% For battery dispatch values:
%bat = P_bat_min + rand(nWolves,1).* (P_bat_max - P_bat_min).*battery_mode
```

```
bat =repmat(P_bat_min, nWolves,1) + rand(nWolves,1).* (repmat((P_bat_min -
P_bat_max), nWolves,1)).*battery_mode;
bat=bat'
%% Hourly PV Generation Profile (in kW)
solar_irradiance=data(:,2);
PV_min=300;
PV_max=1000;
t = (1:24)';            % 24x1
pv_mask = (t>=8 & t<=17)';
PV = repmat(PV_min, nWolves, 24) + rand(nWolves, 24) .*
repmat(solar_irradiance', nWolves,1);
PV = PV .* repmat(pv_mask, nWolves, 1);
PV=PV'

%% For battery SoC, simulate updates
% SoC(t+1) = SoC(t) + (bat(t) > 0)*eta_ch*bat(t) + (bat(t) < 0)/eta_dis*bat(t);

%% For Wind dispatch values:
%% 24-Hour Wind Speed Data for 5 MW Wind Plant
n_hours = 24;           % 24-hour period
rated_power = 5000;     % kW

% Weibull parameters for typical site
k = 2.0;                % shape
c = 8.5;                % scale (m/s)

% --- Generate baseline Weibull wind speeds ---
wind_speed = wblrnd(c, k, [n_hours, 1]);

% --- Add diurnal variation: peak at afternoon ---
hours = (1:n_hours)';
daily_variation = 1 + 0.15 * sin(2*pi*(hours-6)/24);   % shifted to peak mid-day
wind_speed = wind_speed .* daily_variation;

% --- Add random turbulence noise ---
wind_speed = wind_speed + 0.3*randn(n_hours,1);

% --- Remove negatives ---
wind_speed(wind_speed < 0) = 0;

% --- Plot ---
figure(1);
plot(hours, wind_speed, '-o','LineWidth',1.5);
xlabel('Hour');
ylabel('Wind Speed (m/s)');
title('24-Hour Wind Speed Data');
grid on;

% --- Export (optional) ---
writematrix(wind_speed,'wind_speed_24hr.csv');
disp("24-hour wind speed generated.");

%% Convert Wind Speed to Power (kW)
v_in  = 3;      % cut-in
v_r   = 12;     % rated speed
v_out = 25;     % cut-out
n_hours=24;
P_wind = zeros(n_hours,1);

for t = 1:n_hours
    v = wind_speed(t);
```

```
    if v < v_in
        P = 0;
    elseif v >= v_in && v < v_r
        P = rated_power * ((v - v_in) / (v_r - v_in))^3;
    elseif v >= v_r && v <= v_out
        P = rated_power;
    else
        P = 0;
    end

    wind(t) = P;
end

figure(2);
plot(hours, wind, '-s','LineWidth',1.5);
xlabel('Hour'); ylabel('Wind Power (kW)');
title('24-Hour Wind Power Output using Weibull function');
grid on;

% wind_speed=data(:,3);
% wind_min=min(wind);
% wind_max=max(wind);
wind_min=400;
wind_max=5000;
nWolves=24;
wind =repmat(wind_min, nWolves,1) + rand(nWolves,1).* (repmat((wind_max),
nWolves,1));
%wind=wind';

%% Total power generated from Wind, PV and Battery
PG=wind+PV+bat;
%% Grid Power
grid_min=400;
grid_max=4000;

%grid_power=rand(nWolves,1).* (repmat(load_profile-PG,nWolves,1));
grid_power=load_profile-PG;

%% === Initialize wolves (population) ===
%X = repmat(lb, nWolves,1) + rand(nWolves,dim) .* (repmat(ub-lb,nWolves,1))
X=[wind PV bat grid_power]
Powerbalance=[(wind+PV+bat+grid_power) load_profile]

% if X<=lb
% X=lb;
% elseif X>=ub
% X=ub;
% end
 % X=[load_profile-X]
fitness = inf(nWolves,1);
% Define placeholders for alpha, beta, delta positions
X_alpha = zeros(1,dim); f_alpha = inf;
X_beta  = zeros(1,dim);  f_beta  = inf;
X_delta = zeros(1,dim);  f_delta = inf;

%% === GWO Main Loop ===
for iter = 1:maxIter
    for i = 1:nWolves
        x = X(i,:);
        % Evaluate cost function for design x
```

```
        fitnes(i) = costHybrid(x, wind_speed, solar_irradiance, load_profile,
grid_price);
        % Update alpha, beta, delta
        if fitnes(i) < f_alpha
            f_delta = f_beta;
            X_delta = X_beta;
            f_beta = f_alpha;
            X_beta = X_alpha;
            f_alpha = fitnes(i);
            X_alpha = x;
        elseif fitnes(i) < f_beta
            f_delta = f_beta;
            X_delta = X_beta;
            f_beta = fitnes(i);
            X_beta = x;
        elseif fitnes(i) < f_delta
            f_delta = fitnes(i);
            X_delta = x;
        end
    end

    % Update positions
a = 0.2 * (1 - iter/maxIter); %% a=0.2 optimal results and a=2 non-optimal
results
    for i = 1:nWolves
        for d = 1:dim
            %Each search agent updates its position based on α
            r1 = rand; r2 = rand;
            A1 = 2*a*r1 - a;  C1 = 2*r2;
            D_alpha = abs(C1*X_alpha(d) - X(i,d));
            X1 = X_alpha(d) - A1*D_alpha;

            %Each search agent updates its position based on β
            r1 = rand; r2 = rand;
            A2 = 2*a*r1 - a;  C2 = 2*r2;
            D_beta = abs(C2*X_beta(d) - X(i,d));
            X2 = X_beta(d) - A2*D_beta;

            %Each search agent updates its position based on δ:
            r1 = rand; r2 = rand;
            A3 = 2*a*r1 - a;  C3 = 2*r2;
            D_delta = abs(C3*X_delta(d) - X(i,d));
            X3 = X_delta(d) - A3*D_delta;

% Wolf's new position is averaged from the influences of α, β, and δ:
            X(i,d) = (X1 + X2 + X3)/3;
        end
        % Keep within bounds
        X(i,:) = max(lb, min(ub, X(i,:)));
    end

end

%% === Output Optimal Design ===
% optimal = X_alpha;
% disp('Optimal capacities and grid max:');
% disp(optimal);
% disp(['Optimal cost: $' num2str(f_alpha)]);


%% Draw Load profile
```

```
figure(6)
plot(load_profile,'-k*')
xlim([1 24])
grid
legend('Load Power consumption');
xlabel('Time in hours');
ylabel('Power in kW');
title('Load Power')
%hold on

%% Draw solar_irradiance
figure(7)
plot(PV,'-r*')
xlim([1 24])
grid
legend('Solar Power');
xlabel('Time in hours');
ylabel('Power in kW');
title('Solar Power')

%% Draw Wind power penetration
figure(8)
plot(wind,'-b*')
xlim([1 24])
grid
legend('Wind Power');
xlabel('Time in hours');
ylabel('Power in kW');
title('Wind Power using GWO')

%% Draw Battery Charing and Discharing
    figure (9);
    area(1:T, [bat]);
    hold on;
    legend('+Charging, -Discharging');
    title('Battery Charging/Discharging (kWh)');
    xlabel('Hour');
    ylabel('Energy (kWh)');
    grid on;
%% Draw Power Dispatch Area Curve
    figure (10);
    area(1:T, [wind, PV, bat, grid_power]);
    hold on;
    plot(1:T, load_profile, 'k--', 'LineWidth', 1.2);
    legend('Wind','PV','Battery Discharge','Grid','Load');
    title('Energy Dispatch (kWh)');
    xlabel('Hour');
    ylabel('Energy (kWh)');
    grid on;

    %% Draw Power Dispatch Plot
    figure (11);
    plot(1:T, [wind, PV, bat, grid_power]);
    hold on;
    legend('Wind','PV','Battery Discharge','Grid','Load');
    title('Energy Dispatch (kWh)');
    xlabel('Hour');
    ylabel('Energy (kWh)');
    grid on;

    % Get current axes handle
```

```
ax = gca;

% Optional customizations
ax.FontSize = 12;              % adjust font size
ax.LineWidth = 1.4;            % make axis lines thicker
ax.XAxis.Exponent = 0;         % disable scientific notation on X-axis
ax.YAxis.Exponent = 0;         % disable scientific notation on Y-axis
ax.Box = 'on';                 % show box around the plot
xtickformat('%.0f');     % X-axis as normal numbers (no scientific notation)
ytickformat('%.0f');   % Y-axis: integer values
%ytickformat('%.6f');     % Y-axis with up to 6 decimal places (adjust as
needed)

%% ------  OPERATING COST PARAMETERS --------
%% -----------------------------
X=[wind PV bat grid_power]; % Dispatch Power results using GWO algorithm
P_Wind=wind;
P_PV=PV;

% bat is nWolves × 24
% bat > 0  → Charging
% bat < 0  → Discharging

% Charging power (positive only)
P_Bat_Charge = max(bat, 0);

% Discharging power (convert negative to positive magnitude)
P_Bat_Discharge = max(-bat, 0);


% grid_power is nWolves × 24
% grid_power > 0   → Importing from grid
% grid_power < 0   → Exporting to grid

% Grid Import (positive values only)
P_Grid_Import = max(grid_power, 0);

% Grid Export (convert negative to positive magnitude)
P_Grid_Export = max(-grid_power, 0);

%% Energy Operating and Maintanance Costs
C_Grid_import = 0.18;      % $/kWh  - buying from grid
C_Grid_export = 0.04;      % $/kWh  - selling to grid (revenue)
C_Bat_cycle   = 0.05;      % $/kWh  - battery degradation cost
C_PV_OM       = 0.005;     % $/kWh  - PV O&M cost
C_Wind_OM     = 0.01;      % $/kWh  - Wind turbine O&M cost


%% P_PV, P_Wind, P_Bat_Charge, P_Bat_Discharge,
%  P_Grid_Import, and P_Grid_Export must be nWolves × 24 matrices


%% -----------------------------
%   PV OPERATING COST
%% -----------------------------
PV_Energy = sum(P_PV, 2);                % kWh/day
Cost_PV_OM = PV_Energy * C_PV_OM;        % daily O&M cost


%% -----------------------------
%   WIND OPERATING COST
```

```
%% ----------------------------
Wind_Energy = sum(P_Wind, 2);               % kWh/day
Cost_Wind_OM = Wind_Energy * C_Wind_OM;


%% ----------------------------
%   GRID COST / REVENUE
%% ----------------------------
Grid_Import_Energy = sum(P_Grid_Import, 2);
Grid_Export_Energy = sum(P_Grid_Export, 2);

Cost_Grid_Import = Grid_Import_Energy * C_Grid_import;
Cost_Grid_Export = -Grid_Export_Energy * C_Grid_export;   % revenue (negative
cost)


%% ----------------------------
%   BATTERY DEGRADATION COST
%% ----------------------------
Battery_Throughput = sum(P_Bat_Charge + P_Bat_Discharge, 2);  % total cycled
energy
Cost_Battery_deg = Battery_Throughput * C_Bat_cycle;


%% ----------------------------
%   TOTAL OPERATING COST (NO CAPITAL COST)
%% ----------------------------
Operating_Cost = Cost_PV_OM + Cost_Wind_OM + ...
                 Cost_Grid_Import + Cost_Grid_Export + ...
                 Cost_Battery_deg
Operating_Cost_Table = [Cost_PV_OM, Cost_Wind_OM,Cost_Grid_Import,
Cost_Grid_Export, Cost_Battery_deg];
%% Draw Operating Cost Curve
    %% Draw Power Dispatch Plot
    figure (12);

    plot(1:T,
[Cost_PV_OM,Cost_Wind_OM,Cost_Grid_Import,Cost_Grid_Export,Cost_Battery_deg]);
    hold on;
    legend('Cost PV','Cost Wind','Cost Grid Import','Cost Grid Export','Cost
Battery deg');
    title('Operating and Maintenance Cost ($)');
    xlabel('Hour');
    ylabel('Cost ($)');
    grid on;
    %ylim([-200 800]);
    % Get current axes handle
    ax = gca;

    % Optional customizations
    ax.FontSize = 12;              % adjust font size
    ax.LineWidth = 1.4;            % make axis lines thicker
    ax.XAxis.Exponent = 0;         % disable scientific notation on X-axis
    ax.YAxis.Exponent = 0;         % disable scientific notation on Y-axis
    ax.Box = 'on';                 % show box around the plot
    xtickformat('%.0f');     % X-axis as normal numbers (no scientific notation)
    ytickformat('%.0f');   % Y-axis: integer values
    %ytickformat('%.6f');     % Y-axis with up to 6 decimal places (adjust as
needed)
```

```
 %% Cost Comparsion plot
    Cost_3Scenarios=[-14.3400000000000  57.0500000000000    383
0.520000000000000   -13.4100000000000   419
40.6800000000000    16.3500000000000    491
294.830000000000    -5.27000000000000   723.940000000000
622.520000000000    181.150000000000    759.940000000000
275.430000000000    430.850000000000    831.940000000000
357.300000000000    168.740000000000    610.380000000000
26.7400000000000    24.6200000000000    513.490000000000
3.04000000000000    450    598.200000000000
443.530000000000    629.320000000000    883.360000000000
333.260000000000    775.260000000000    892.470000000000
164.560000000000    833.010000000000    1005.85000000000
71.2200000000000    200.470000000000    917.140000000000
781.640000000000    380.970000000000    893.240000000000
468.350000000000    640.410000000000    763.160000000000
116.870000000000    31.7600000000000    734.480000000000
365.470000000000    2.27000000000000    605.830000000000
367.200000000000    502.980000000000    556.380000000000
41.5600000000000    514.020000000000    502.380000000000
311.780000000000    13.9700000000000    466.380000000000
60.8900000000000    440.340000000000    430.380000000000
405.380000000000    4.07000000000000    651.940000000000
22.2100000000000    389.800000000000    615.940000000000
241.800000000000    -63.3600000000000   419];

    %% Draw Operating Cost Curve
    %% Draw Power Dispatch Plot
    figure (13);

    plot(1:T, [Cost_3Scenarios]);
    hold on;
    legend('Cost Wind+PV+Battery+Grid','Cost Wind+Grid','Cost PV+Battery+Grid');
    title('Operating and Maintenance Cost ($) comparsion for 3 Scenarios');
    xlabel('Hour');
    ylabel('Cost ($)');
    grid on;

    Overall_Cost =[5802.44;      6605.37; 15668.82];
    figure (14);

    plot(Overall_Cost,'-*' );
    hold on;
    legend('Scenario 1 Cost: Wind+PV+Battery+Grid','Scenario 2 Cost:
Wind+Grid','Scenario 3 Cost: PV+Battery+Grid');
    title('Overall Cost for Operating and Maintenance in ($)for 3 Scenarios');
    xlabel('Scenarios');
    ylabel('Cost ($)');
    grid on;

    % Get current axes handle
    ax = gca;

    % Optional customizations
    ax.FontSize = 12;              % adjust font size
    ax.LineWidth = 1.4;            % make axis lines thicker
    ax.XAxis.Exponent = 0;         % disable scientific notation on X-axis
    ax.YAxis.Exponent = 0;         % disable scientific notation on Y-axis
    ax.Box = 'on';                 % show box around the plot
    xtickformat('%.0f');      % X-axis as normal numbers (no scientific notation)
    ytickformat('%.0f');    % Y-axis: integer values
```

Appendix C2: MATLAB Code for Case 5.2: Grid-connected Microgrid dispatch with Wind

```
% GWO-based sizing and dispatch optimization for Wind+Grid
clear; clc;

%% === Input Data (hourly over 24-hr period) ===
data=xlsread('GWO_data');
load_profile=data(:,1);
grid_price=data(:,4);
%sell_price=data(:,5);

%% GWO input parameters
nWolves = 1;
maxIter = 100;
T = length(load_profile);

%% === Parameter bounds (design variables) ===
% x = [wind_cap, pv_cap, batt_cap, grid_cap]
lb = [0, 0, 50, 400];
ub = [5000, 1000, 500, 4000];
dim = length(lb);


%% Typical Battery Charging & Discharging Schedule (24-Hour Period)
% Sample Charging/Discharging Timing
% 24-hour classification (example)
% +1 = Charging, -1 = Discharging, 0 = Idle
battery_mode = [...
    0, 0,0 ...     % 00-03   Idle or light charging Low load, low price
    1, 1, 1,...    % 04-06    Charging Preparing for morning peak
    -1, -1, -1,...   % 07-09     Discharging  Morning load peak
    1, 1, 1, 1,1, ...% 10-14     Charging     Solar generation available
    0, 0,0, ...      % 15-17     Idle or trickle     No major load or price event
    -1, -1, -1,-1, ...% 18-21    Discharging  Evening peak demand
    1, 1,0];           % 22-24    Charging     Off-peak pricing starts
P_bat_min=100;
P_bat_max=1000;
% For battery dispatch values:
%bat = P_bat_min + rand(nWolves,1).* (P_bat_max - P_bat_min).*battery_mode
bat =repmat(P_bat_min, nWolves,1) + rand(nWolves,1).* (repmat((P_bat_min -
P_bat_max), nWolves,1)).*battery_mode;
bat=bat'
bat=zeros(1,24)';
%% Hourly PV Generation Profile (in kW)
solar_irradiance=data(:,2);
PV_min=300;
PV_max=1000;
t = (1:24)';               % 24x1
pv_mask = (t>=8 & t<=17)';
PV = repmat(PV_min, nWolves, 24) + rand(nWolves, 24) .*
repmat(solar_irradiance', nWolves,1);
PV = PV .* repmat(pv_mask, nWolves, 1);
PV=PV'
PV=zeros(1,24)';
%% For battery SoC, simulate updates
% SoC(t+1) = SoC(t) + (bat(t) > 0)*eta_ch*bat(t) + (bat(t) < 0)/eta_dis*bat(t);

%% For Wind dispatch values:
%% 24-Hour Wind Speed Data for 5 MW Wind Plant
```

```
n_hours = 24;           % 24-hour period
rated_power = 5000;     % kW

% Weibull parameters for typical site
k = 2.0;                % shape
c = 8.5;                % scale (m/s)

% --- Generate baseline Weibull wind speeds ---
wind_speed = wblrnd(c, k, [n_hours, 1]);

% --- Add diurnal variation: peak at afternoon ---
hours = (1:n_hours)';
daily_variation = 1 + 0.15 * sin(2*pi*(hours-6)/24);   % shifted to peak mid-day
wind_speed = wind_speed .* daily_variation;

% --- Add random turbulence noise ---
wind_speed = wind_speed + 0.3*randn(n_hours,1);

% --- Remove negatives ---
wind_speed(wind_speed < 0) = 0;

% --- Plot ---
figure(1);
plot(hours, wind_speed, '-o','LineWidth',1.5);
xlabel('Hour');
ylabel('Wind Speed (m/s)');
title('24-Hour Wind Speed Data');
grid on;

% --- Export (optional) ---
writematrix(wind_speed,'wind_speed_24hr.csv');
disp("24-hour wind speed generated.");

%% Convert Wind Speed to Power (kW)
v_in  = 3;     % cut-in
v_r   = 12;    % rated speed
v_out = 25;    % cut-out
n_hours=24;
P_wind = zeros(n_hours,1);

for t = 1:n_hours
    v = wind_speed(t);

    if v < v_in
        P = 0;
    elseif v >= v_in && v < v_r
        P = rated_power * ((v - v_in) / (v_r - v_in))^3;
    elseif v >= v_r && v <= v_out
        P = rated_power;
    else
        P = 0;
    end

    wind(t) = P;
end

figure(2);
plot(hours, wind, '-s','LineWidth',1.5);
xlabel('Hour'); ylabel('Wind Power (kW)');
title('24-Hour Wind Power Output using Weibull function');
grid on;
```

```
% wind_speed=data(:,3);
% wind_min=min(wind);
% wind_max=max(wind);
wind_min=400;
wind_max=5000;
nWolves=24;
wind =repmat(wind_min, nWolves,1) + rand(nWolves,1).* (repmat((wind_max),
nWolves,1));
%wind=wind';

%% Total power generated from Wind, PV and Battery
PG=wind+PV+bat;
%% Grid Power
grid_min=400;
grid_max=4000;

%grid_power=rand(nWolves,1).* (repmat(load_profile-PG,nWolves,1));
grid_power=load_profile-PG;

%% === Initialize wolves (population) ===
%X = repmat(lb, nWolves,1) + rand(nWolves,dim) .* (repmat(ub-lb,nWolves,1))
X=[wind PV bat grid_power]
Powerbalance=[(wind+PV+bat+grid_power) load_profile]

% if X<=lb
% X=lb;
% elseif X>=ub
% X=ub;
% end
 % X=[load_profile-X]
fitness = inf(nWolves,1);
% Define placeholders for alpha, beta, delta positions
X_alpha = zeros(1,dim); f_alpha = inf;
X_beta  = zeros(1,dim);  f_beta  = inf;
X_delta = zeros(1,dim);  f_delta = inf;

%% === GWO Main Loop ===
for iter = 1:maxIter
    for i = 1:nWolves
        x = X(i,:);
        % Evaluate cost function for design x
        fitnes(i) = costHybrid(x, wind_speed, solar_irradiance, load_profile,
grid_price);
        % Update alpha, beta, delta
        if fitnes(i) < f_alpha
            f_delta = f_beta;
            X_delta = X_beta;
            f_beta = f_alpha;
            X_beta = X_alpha;
            f_alpha = fitnes(i);
            X_alpha = x;
        elseif fitnes(i) < f_beta
            f_delta = f_beta;
            X_delta = X_beta;
            f_beta = fitnes(i);
            X_beta = x;
        elseif fitnes(i) < f_delta
            f_delta = fitnes(i);
            X_delta = x;
        end
```

```
    end

    % Update positions
a = 0.2 * (1 - iter/maxIter); %% a=0.2 optimal results and a=2 non-optimal
results
    for i = 1:nWolves
        for d = 1:dim
            %Each search agent updates its position based on α
            r1 = rand; r2 = rand;
            A1 = 2*a*r1 - a;  C1 = 2*r2;
            D_alpha = abs(C1*X_alpha(d) - X(i,d));
            X1 = X_alpha(d) - A1*D_alpha;

            %Each search agent updates its position based on β
            r1 = rand; r2 = rand;
            A2 = 2*a*r1 - a;  C2 = 2*r2;
            D_beta = abs(C2*X_beta(d) - X(i,d));
            X2 = X_beta(d) - A2*D_beta;

            %Each search agent updates its position based on δ:
            r1 = rand; r2 = rand;
            A3 = 2*a*r1 - a;  C3 = 2*r2;
            D_delta = abs(C3*X_delta(d) - X(i,d));
            X3 = X_delta(d) - A3*D_delta;

% Wolf's new position is averaged from the influences of α, β, and δ:
            X(i,d) = (X1 + X2 + X3)/3;
        end
        % Keep within bounds
        X(i,:) = max(lb, min(ub, X(i,:)));
    end

end

%% === Output Optimal Design ===
% optimal = X_alpha;
% disp('Optimal capacities and grid max:');
% disp(optimal);
% disp(['Optimal cost: $' num2str(f_alpha)]);


%% Draw Load profile
figure(6)
plot(load_profile,'-k*')
xlim([1 24])
grid
legend('Load Power consumption');
xlabel('Time in hours');
ylabel('Power in kW');
title('Load Power')
%hold on

%% Draw solar_irradiance
figure(7)
plot(PV,'-r*')
xlim([1 24])
grid
legend('Solar Power');
xlabel('Time in hours');
ylabel('Power in kW');
title('Solar Power')
```

```
%% Draw Wind power penetration
figure(8)
plot(wind,'-b*')
xlim([1 24])
grid
legend('Wind Power');
xlabel('Time in hours');
ylabel('Power in kW');
title('Wind Power using GWO')

%% Draw Battery Charging and Discharging
    figure (9);
    area(1:T, [bat]);
    hold on;
    legend('+Charging, -Discharging');
    title('Battery Charging/Discharging (kWh)');
    xlabel('Hour');
    ylabel('Energy (kWh)');
    grid on;
%% Draw Power Dispatch Area Curve
    figure (10);
    area(1:T, [wind,grid_power]);
    hold on;
    %plot(1:T, load_profile, 'k--', 'LineWidth', 1.2);
    legend('Wind','Grid');
    title('Energy Dispatch (kWh)');
    xlabel('Hour');
    ylabel('Energy (kWh)');
    grid on;

    %% Draw Power Dispatch Plot
    figure (11);
    plot(1:T, [load_profile, wind,grid_power]);
    hold on;
    legend('load','Wind','Grid','Load');
    title('Energy Dispatch (kWh)');
    xlabel('Hour');
    ylabel('Energy (kWh)');
    grid on;

    % Get current axes handle
ax = gca;

% Optional customizations
ax.FontSize = 12;              % adjust font size
ax.LineWidth = 1.4;            % make axis lines thicker
ax.XAxis.Exponent = 0;         % disable scientific notation on X-axis
ax.YAxis.Exponent = 0;         % disable scientific notation on Y-axis
ax.Box = 'on';                 % show box around the plot
xtickformat('%.0f');     % X-axis as normal numbers (no scientific notation)
ytickformat('%.0f');   % Y-axis: integer values
%ytickformat('%.6f');     % Y-axis with up to 6 decimal places (adjust as
needed)

%% ------  OPERATING COST PARAMETERS --------
%% ----------------------------
X=[wind PV bat grid_power] % Dispatch Power results using GWO algorithm
P_Wind=wind;
P_PV=PV;
```

```
% bat is nWolves × 24
% bat > 0  → Charging
% bat < 0  → Discharging

% Charging power (positive only)
P_Bat_Charge = max(bat, 0);

% Discharging power (convert negative to positive magnitude)
P_Bat_Discharge = max(-bat, 0);


% grid_power is nWolves × 24
% grid_power > 0   → Importing from grid
% grid_power < 0   → Exporting to grid

% Grid Import (positive values only)
P_Grid_Import = max(grid_power, 0);

% Grid Export (convert negative to positive magnitude)
P_Grid_Export = max(-grid_power, 0);

%% Energy Operating and Maintanance Costs
C_Grid_import = 0.18;      % $/kWh  - buying from grid
C_Grid_export = 0.04;      % $/kWh  - selling to grid (revenue)
C_Bat_cycle   = 0.05;      % $/kWh  - battery degradation cost
C_PV_OM       = 0.005;     % $/kWh  - PV O&M cost
C_Wind_OM     = 0.01;      % $/kWh  - Wind turbine O&M cost


%% P_PV, P_Wind, P_Bat_Charge, P_Bat_Discharge,
%  P_Grid_Import, and P_Grid_Export must be nWolves × 24 matrices


%% -----------------------------
%   PV OPERATING COST
%% -----------------------------
PV_Energy = sum(P_PV, 2);                   % kWh/day
Cost_PV_OM = PV_Energy * C_PV_OM;           % daily O&M cost


%% -----------------------------
%   WIND OPERATING COST
%% -----------------------------
Wind_Energy = sum(P_Wind, 2);               % kWh/day
Cost_Wind_OM = Wind_Energy * C_Wind_OM;


%% -----------------------------
%   GRID COST / REVENUE
%% -----------------------------
Grid_Import_Energy = sum(P_Grid_Import, 2);
Grid_Export_Energy = sum(P_Grid_Export, 2);

Cost_Grid_Import = Grid_Import_Energy * C_Grid_import;
Cost_Grid_Export = -Grid_Export_Energy * C_Grid_export;   % revenue (negative
cost)


%% -----------------------------
%   BATTERY DEGRADATION COST
%% -----------------------------
```

```
Battery_Throughput = sum(P_Bat_Charge + P_Bat_Discharge, 2);  % total cycled
energy
Cost_Battery_deg = Battery_Throughput * C_Bat_cycle;


%% ----------------------------
%   TOTAL OPERATING COST (NO CAPITAL COST)
%% ----------------------------
Operating_Cost = Cost_PV_OM + Cost_Wind_OM + ...
                 Cost_Grid_Import + Cost_Grid_Export + ...
                 Cost_Battery_deg
Operating_Cost_Table = [Cost_PV_OM, Cost_Wind_OM,Cost_Grid_Import,
Cost_Grid_Export, Cost_Battery_deg];
%% Draw Operating Cost Curve
    %% Draw Power Dispatch Plot
    figure (12);

    plot(1:T, [Cost_Wind_OM,Cost_Grid_Import,Cost_Grid_Export]);
    hold on;
    legend('Cost Wind','Cost Grid Import','Cost Grid Export');
    title('Operating and Maintenance Cost ($)');
    xlabel('Hour');
    ylabel('Cost ($)');
    grid on;
    %ylim([-200 800]);
    % Get current axes handle
    ax = gca;

    % Optional customizations
    ax.FontSize = 12;              % adjust font size
    ax.LineWidth = 1.4;            % make axis lines thicker
    ax.XAxis.Exponent = 0;         % disable scientific notation on X-axis
    ax.YAxis.Exponent = 0;         % disable scientific notation on Y-axis
    ax.Box = 'on';                 % show box around the plot
    xtickformat('%.0f');     % X-axis as normal numbers (no scientific notation)
    ytickformat('%.0f');   % Y-axis: integer values
    %ytickformat('%.6f');     % Y-axis with up to 6 decimal places (adjust as
needed)
```

APPENDIX C2: **MATLAB code for cost calculation**

```
%% GWO Cost function
%% === Example cost function ===
function cost = costHybrid(x, wind_speed, solar_irradiance, load_profile,
grid_price)
    % Unpack design
    wind_cap = x(1);
    pv_cap   = x(2);
    batt_cap = x(3);
    batt_power = x(4);
    grid_cap = x(5);

    eta = 0.9; SoC = 0.3*batt_cap;
    cost = 0; penalty = 1e4; unmet = 0;
    for t = 1:length(load_profile)
        % generation
        gen_w = wind_cap * windPowerFraction(wind_speed(t));
```

```
        gen_p = pv_cap   * solar_irradiance(t);
        available = gen_w + gen_p;
        % dispatch logic: renewables, battery, grid
        net = available - load_profile(t);
        if net >= 0
            % charge
            ch = min(net, batt_power);
            SoC = min(batt_cap, SoC + eta*ch);
            grid_draw = 0;
        else
            need = -net;
            discharge = min(need/eta, min(SoC, batt_power));
            SoC = SoC - discharge;
            short = need - discharge*eta;
            grid_draw = min(short, grid_cap);
            unmet = unmet + max(0, short - grid_draw);
        end
        cost = cost + grid_draw * grid_price(t);
    end
   cost = cost + penalty * unmet;
end
```

APPENDIX C3: **MATLAB code for Wind Power Forecasting Calculation**

```
%% GWO wind power fraction calculation using cutin & cut-0ff wind speeds
%% === Example generation functions ===
function frac = windPowerFraction(v)
    % simplified cubic curve normalized to capacity factor ~0.35
    if v<3 || v>25, frac = 0;
    elseif v<=12, frac = ((v-3)/(12-3))^3;
    else frac = 1;
    end
end
```

Appendix C 3: MATLAB Code for Case 5.3: Grid-connected Microgrid dispatch with PV, and Battery

```
% GWO-based sizing and dispatch optimization for PV+Battery+Grid
clear; clc;

%% === Input Data (hourly over 24-hr period) ===
data=xlsread('GWO_data');
load_profile=data(:,1);
grid_price=data(:,4);
%sell_price=data(:,5);

%% GWO input parameters
nWolves = 1;
maxIter = 100;
T = length(load_profile);

%% === Parameter bounds (design variables) ===
% x = [wind_cap, pv_cap, batt_cap, grid_cap]
lb = [0, 0, 50, 400];
ub = [5000, 1000, 500, 4000];
dim = length(lb);
```

```
%% Typical Battery Charging & Discharging Schedule (24-Hour Period)
% Sample Charging/Discharging Timing
% 24-hour classification (example)
% +1 = Charging, -1 = Discharging, 0 = Idle
battery_mode = [...
    0, 0,0 ...      % 00-03   Idle or light charging Low load, low price
    1, 1, 1,...     % 04-06    Charging Preparing for morning peak
    -1, -1, -1,...    % 07-09     Discharging  Morning load peak
    1, 1, 1, 1,1, ...% 10-14     Charging     Solar generation available
    0, 0,0, ...       % 15-17     Idle or trickle     No major load or price event
    -1, -1, -1,-1, ...% 18-21    Discharging  Evening peak demand
    1, 1,0];           % 22-24    Charging     Off-peak pricing starts
P_bat_min=100;
P_bat_max=1000;
% For battery dispatch values:
%bat = P_bat_min + rand(nWolves,1).* (P_bat_max - P_bat_min).*battery_mode
bat =repmat(P_bat_min, nWolves,1) + rand(nWolves,1).* (repmat((P_bat_min -
P_bat_max), nWolves,1)).*battery_mode;
bat=bat'
%% Hourly PV Generation Profile (in kW)
solar_irradiance=data(:,2);
PV_min=300;
PV_max=1000;
t = (1:24)';                % 24x1
pv_mask = (t>=8 & t<=17)';
PV = repmat(PV_min, nWolves, 24) + rand(nWolves, 24) .*
repmat(solar_irradiance', nWolves,1);
PV = PV .* repmat(pv_mask, nWolves, 1);
PV=PV'

%% For battery SoC, simulate updates
% SoC(t+1) = SoC(t) + (bat(t) > 0)*eta_ch*bat(t) + (bat(t) < 0)/eta_dis*bat(t);

%% For Wind dispatch values:
%% 24-Hour Wind Speed Data for 5 MW Wind Plant
n_hours = 24;           % 24-hour period
rated_power = 5000;     % kW

% Weibull parameters for typical site
k = 2.0;                % shape
c = 8.5;                % scale (m/s)

% --- Generate baseline Weibull wind speeds ---
wind_speed = wblrnd(c, k, [n_hours, 1]);

% --- Add diurnal variation: peak at afternoon ---
hours = (1:n_hours)';
daily_variation = 1 + 0.15 * sin(2*pi*(hours-6)/24);   % shifted to peak mid-day
wind_speed = wind_speed .* daily_variation;

% --- Add random turbulence noise ---
wind_speed = wind_speed + 0.3*randn(n_hours,1);

% --- Remove negatives ---
wind_speed(wind_speed < 0) = 0;

% --- Plot ---
figure(1);
plot(hours, wind_speed, '-o','LineWidth',1.5);
xlabel('Hour');
```

```
ylabel('Wind Speed (m/s)');
title('24-Hour Wind Speed Data');
grid on;

% --- Export (optional) ---
writematrix(wind_speed,'wind_speed_24hr.csv');
disp("24-hour wind speed generated.");

%% Convert Wind Speed to Power (kW)
v_in  = 3;      % cut-in
v_r   = 12;     % rated speed
v_out = 25;     % cut-out
n_hours=24;
P_wind = zeros(n_hours,1);

for t = 1:n_hours
    v = wind_speed(t);

    if v < v_in
        P = 0;
    elseif v >= v_in && v < v_r
        P = rated_power * ((v - v_in) / (v_r - v_in))^3;
    elseif v >= v_r && v <= v_out
        P = rated_power;
    else
        P = 0;
    end

    wind(t) = P;
end

figure(2);
plot(hours, wind, '-s','LineWidth',1.5);
xlabel('Hour'); ylabel('Wind Power (kW)');
title('24-Hour Wind Power Output using Weibull function');
grid on;

% wind_speed=data(:,3);
% wind_min=min(wind);
% wind_max=max(wind);
wind_min=400;
wind_max=5000;
nWolves=24;
wind =repmat(wind_min, nWolves,1) + rand(nWolves,1).* (repmat((wind_max),
nWolves,1));
wind=zeros(1,24)';

%% Total power generated from Wind, PV and Battery
PG=wind+PV+bat;
%% Grid Power
grid_min=400;
grid_max=4000;

%grid_power=rand(nWolves,1).* (repmat(load_profile-PG,nWolves,1));
grid_power=load_profile-PG;

%% === Initialize wolves (population) ===
%X = repmat(lb, nWolves,1) + rand(nWolves,dim) .* (repmat(ub-lb,nWolves,1))
X=[wind PV bat grid_power]
Powerbalance=[(wind+PV+bat+grid_power) load_profile]
```

```
% if X<=lb
% X=lb;
% elseif X>=ub
% X=ub;
% end
 % X=[load_profile-X]
fitness = inf(nWolves,1);
% Define placeholders for alpha, beta, delta positions
X_alpha = zeros(1,dim); f_alpha = inf;
X_beta  = zeros(1,dim);  f_beta  = inf;
X_delta = zeros(1,dim);  f_delta = inf;

%% === GWO Main Loop ===
for iter = 1:maxIter
    for i = 1:nWolves
        x = X(i,:);
        % Evaluate cost function for design x
        fitnes(i) = costHybrid(x, wind_speed, solar_irradiance, load_profile,
grid_price);
        % Update alpha, beta, delta
        if fitnes(i) < f_alpha
            f_delta = f_beta;
            X_delta = X_beta;
            f_beta = f_alpha;
            X_beta = X_alpha;
            f_alpha = fitnes(i);
            X_alpha = x;
        elseif fitnes(i) < f_beta
            f_delta = f_beta;
            X_delta = X_beta;
            f_beta = fitnes(i);
            X_beta = x;
        elseif fitnes(i) < f_delta
            f_delta = fitnes(i);
            X_delta = x;
        end
    end

    % Update positions
a = 0.2 * (1 - iter/maxIter); %% a=0.2 optimal results and a=2 non-optimal
results
    for i = 1:nWolves
        for d = 1:dim
            %Each search agent updates its position based on α
            r1 = rand; r2 = rand;
            A1 = 2*a*r1 - a;  C1 = 2*r2;
            D_alpha = abs(C1*X_alpha(d) - X(i,d));
            X1 = X_alpha(d) - A1*D_alpha;

            %Each search agent updates its position based on β
            r1 = rand; r2 = rand;
            A2 = 2*a*r1 - a;  C2 = 2*r2;
            D_beta = abs(C2*X_beta(d) - X(i,d));
            X2 = X_beta(d) - A2*D_beta;

            %Each search agent updates its position based on δ:
            r1 = rand; r2 = rand;
            A3 = 2*a*r1 - a;  C3 = 2*r2;
            D_delta = abs(C3*X_delta(d) - X(i,d));
            X3 = X_delta(d) - A3*D_delta;
```

```
% Wolf’s new position is averaged from the influences of α, β, and δ:
            X(i,d) = (X1 + X2 + X3)/3;
        end
        % Keep within bounds
        X(i,:) = max(lb, min(ub, X(i,:)));
    end

end

%% === Output Optimal Design ===
% optimal = X_alpha;
% disp('Optimal capacities and grid max:');
% disp(optimal);
% disp(['Optimal cost: $' num2str(f_alpha)]);


%% Draw Load profile
figure(6)
plot(load_profile,'-k*')
xlim([1 24])
grid
legend('Load Power consumption');
xlabel('Time in hours');
ylabel('Power in kW');
title('Load Power')
%hold on

%% Draw solar_irradiance
figure(7)
plot(PV,'-r*')
xlim([1 24])
grid
legend('Solar Power');
xlabel('Time in hours');
ylabel('Power in kW');
title('Solar Power')

%% Draw Wind power penetration
figure(8)
plot(wind,'-b*')
xlim([1 24])
grid
legend('Wind Power');
xlabel('Time in hours');
ylabel('Power in kW');
title('Wind Power using GWO')

%% Draw Battery Charing and Discharing
    figure (9);
    area(1:T, [bat]);
    hold on;
    legend('+Charging, -Discharging');
    title('Battery Charging/Discharging (kWh)');
    xlabel('Hour');
    ylabel('Energy (kWh)');
    grid on;
%% Draw Power Dispatch Area Curve
    figure (10);
    area(1:T, [PV, bat, grid_power]);
    hold on;
    plot(1:T, load_profile, 'k--', 'LineWidth', 1.2);
```

```
    legend('PV','Battery Discharge','Grid','Load');
    title('Energy Dispatch (kWh)');
    xlabel('Hour');
    ylabel('Energy (kWh)');
    grid on;

    %% Draw Power Dispatch Plot
    figure (11);
    plot(1:T, [PV, bat, grid_power]);
    hold on;
    legend('PV','Battery Discharge','Grid','Load');
    title('Energy Dispatch (kWh)');
    xlabel('Hour');
    ylabel('Energy (kWh)');
    grid on;

    % Get current axes handle
ax = gca;

% Optional customizations
ax.FontSize = 12;              % adjust font size
ax.LineWidth = 1.4;            % make axis lines thicker
ax.XAxis.Exponent = 0;         % disable scientific notation on X-axis
ax.YAxis.Exponent = 0;         % disable scientific notation on Y-axis
ax.Box = 'on';                 % show box around the plot
xtickformat('%.0f');      % X-axis as normal numbers (no scientific notation)
ytickformat('%.0f');    % Y-axis: integer values
%ytickformat('%.6f');     % Y-axis with up to 6 decimal places (adjust as
needed)

%% ------  OPERATING COST PARAMETERS --------
%% -----------------------------
X=[wind PV bat grid_power]; % Dispatch Power results using GWO algorithm
P_Wind=wind;
P_PV=PV;

% bat is nWolves × 24
% bat > 0  → Charging
% bat < 0  → Discharging

% Charging power (positive only)
P_Bat_Charge = max(bat, 0);

% Discharging power (convert negative to positive magnitude)
P_Bat_Discharge = max(-bat, 0);


% grid_power is nWolves × 24
% grid_power > 0   → Importing from grid
% grid_power < 0   → Exporting to grid

% Grid Import (positive values only)
P_Grid_Import = max(grid_power, 0);

% Grid Export (convert negative to positive magnitude)
P_Grid_Export = max(-grid_power, 0);

%% Energy Operating and Maintanance Costs
C_Grid_import = 0.18;      % $/kWh  - buying from grid
C_Grid_export = 0.04;      % $/kWh  - selling to grid (revenue)
C_Bat_cycle   = 0.05;      % $/kWh  - battery degradation cost
```

```
C_PV_OM       = 0.005;     % $/kWh  - PV O&M cost
C_Wind_OM     = 0.01;      % $/kWh  - Wind turbine O&M cost


%% P_PV, P_Wind, P_Bat_Charge, P_Bat_Discharge,
%  P_Grid_Import, and P_Grid_Export must be nWolves × 24 matrices


%% ----------------------------
%   PV OPERATING COST
%% ----------------------------
PV_Energy = sum(P_PV, 2);                  % kWh/day
Cost_PV_OM = PV_Energy * C_PV_OM;          % daily O&M cost


%% ----------------------------
%   WIND OPERATING COST
%% ----------------------------
Wind_Energy = sum(P_Wind, 2);              % kWh/day
Cost_Wind_OM = Wind_Energy * C_Wind_OM;


%% ----------------------------
%   GRID COST / REVENUE
%% ----------------------------
Grid_Import_Energy = sum(P_Grid_Import, 2);
Grid_Export_Energy = sum(P_Grid_Export, 2);

Cost_Grid_Import = Grid_Import_Energy * C_Grid_import;
Cost_Grid_Export = -Grid_Export_Energy * C_Grid_export;   % revenue (negative
cost)


%% ----------------------------
%   BATTERY DEGRADATION COST
%% ----------------------------
Battery_Throughput = sum(P_Bat_Charge + P_Bat_Discharge, 2);  % total cycled
energy
Cost_Battery_deg = Battery_Throughput * C_Bat_cycle;


%% ----------------------------
%   TOTAL OPERATING COST (NO CAPITAL COST)
%% ----------------------------
Operating_Cost = Cost_PV_OM + Cost_Wind_OM + ...
                 Cost_Grid_Import + Cost_Grid_Export + ...
                 Cost_Battery_deg
Operating_Cost_Table = [Cost_PV_OM, Cost_Wind_OM,Cost_Grid_Import,
Cost_Grid_Export, Cost_Battery_deg];
%% Draw Operating Cost Curve
    %% Draw Power Dispatch Plot
    figure (12);

    plot(1:T, [Cost_PV_OM,Cost_Grid_Import,Cost_Grid_Export,Cost_Battery_deg]);
    hold on;
    legend('Cost PV','Cost Grid Import','Cost Grid Export','Cost Battery deg');
    title('Operating and Maintenance Cost ($)');
    xlabel('Hour');
    ylabel('Cost ($)');
    grid on;
    %ylim([-200 800]);
```

```
    % Get current axes handle
    ax = gca;

    % Optional customizations
    ax.FontSize = 12;                % adjust font size
    ax.LineWidth = 1.4;              % make axis lines thicker
    ax.XAxis.Exponent = 0;           % disable scientific notation on X-axis
    ax.YAxis.Exponent = 0;           % disable scientific notation on Y-axis
    ax.Box = 'on';                   % show box around the plot
    xtickformat('%.0f');      % X-axis as normal numbers (no scientific notation)
    ytickformat('%.0f');    % Y-axis: integer values
    %ytickformat('%.6f');     % Y-axis with up to 6 decimal places (adjust as
needed)
```