Department of Electrical, Electronic and Computer Engineering
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Optimization method for a hybrid microgrid energy management system with reserve margins

(THESIS)

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Declaration

I, Manduleli Mquqwana, declare that the ideas presented in this thesis are original to me and have not been submitted for review to receive credit towards any degree. Moreover, it expresses my viewpoints rather than those of the Cape Peninsula University of Technology.

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Signed Date

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Abstract

The research study aims to provide an optimization technique for a hybrid microgrid energy management system with reserve margins. The load for the hybrid microgrid under consideration consists of grid-connected photovoltaic, wind, and battery energy storage devices and electric vehicles that may provide grid support.

The recommended solution considers both an isolated mode of operation and a grid-connected operating situation. Isolated microgrids improve system resilience by distributing electricity to nearby loads from locally accessible resources. Furthermore, it is still challenging to govern, run, and protect these systems in grid-connected and islanded modes, cope with dispatch difficulties that decide the DRES's priority, and provide grid support, among other challenges. Furthermore, the BESS charging and discharging strategy should follow the Risk Mitigation Independent Power Producer Procurement Programme (RMIPPP) guidelines, charging predominantly from local renewable energy sources rather than the grid. This ensures that local South African legislation and requirements are observed throughout the investigation.

The study focuses on optimizing and modeling a hybrid microgrid system incorporating different green energy sources, such as grid-tied solar photovoltaic, wind energy, and battery energy storage devices. The study uses sophisticated optimization techniques to increase the microgrid's efficiency and reliability. Specifically, particle swarm optimization and the genetic algorithm are used to solve the system model and address the difficulties of optimal energy generation, storage management, and hybrid integration. The findings illustrate the efficiency of these optimization approaches in improving overall performance, lowering costs, and assuring the microgrid's dispatch strategy under different operational situations.

Keywords

Energy Management Systems, Microgrid Optimization, Distributed Generation, Economic Dispatch, Electric Vehicles, Battery Energy Storage Systems, Power System Optimization.

Mathematical Notations

$\eta_{bat_{char}}$	-	Charging efficiency
$\eta_{bat_{disc}}$	-	Discharging efficiency
η_{cev}	-	Charging efficiency
η_{pv}	-	Efficiency of the solar panel
A_{pv}	-	Area of a solar panel
C_{EV}	-	Total battery capacity (C/kWh)
C_{EV}	-	Battery replacement cost of EV
C_{bat}	-	Battery depreciation cost
C_{grid}	-	Grid interaction cost between microgrid and the grid
$C_{op}(P_{i,t})$	-	Cost of maintenance of the i-th generator in t-cycle
E_{EV}^{PUT}	-	EV's total charging/discharging capacity (kWh)
$E_{pur,t}$	-	Energy purchased in t-cycle (kWh)
$E_{sel,t}$	-	Energy sold in t-cycle (kWh)
N_{pv}	-	Solar panel quantity
N_{wind}	-	Wind turbines quantity
$P_{bat_{char}}$	-	Battery charging power
$P_{bat_{disc}}$	-	Battery discharging power
$P_{grid_{rec}}$	-	Power received from grid
$P_{grid_{sent}}$	-	Power sent grid
$P_{EV(load)}$	-	Total charging load
$P_{EV,t}$	-	Total EV charging/discharging power (kW)

PP_t	-	Buying energy price in t-cycle (ZAR/kWh)
PS_t	-	Selling energy price in t-cycle (ZAR/kWh)
P_{Tpv}	-	Total power generation by solar panels
P_{Twind}	-	Total power generation by wind turbines
P_c	-	Charging power in kW
$P_{i,t}$	-	Generated power of the i-th generator in the t-cycle
P_{pv}	-	Power generation by a solar panel
P_{res}	-	Instantaneous reserve margins
P_{wind}	-	Power generation by a wind turbine
$SOC_{bat}(t)$	-	Total available energy capacity for all batteries
SW_{100}	-	Energy consumption per 100 km (kwh/100km)
$T_{bat}(t+1)$	-	Total energy for all batteries at time interval t + 1
T_{char}	-	Charging duration in hours
T_{maxdis}	-	Maximum EV battery discharging duration
v_{cin}	-	Cut-in wind speed
v_{cout}	-	Cut-out wind speed
v_r	-	Rated wind speed
SOC	-	Battery State of Charge in percentage
v	-	Measured wind speed
Δt	-	Time interval

Definitions

Glossary of items

Algorithm - A step-by-step approach to solving an issue using a computer.

Automatic Generation Control - a system that regulates the output of power generators to maintain a stable system frequency and balance the load and generation in an electric power system.

Demand-side management is a strategy used by electric utilities to persuade users to adjust their electricity consumption patterns.

Economic Dispatch - is the process of running production facilities to produce energy at the lowest possible cost while providing reliable service to customers. It entails assigning generating levels to various units to fulfill the system load while minimizing production costs.

Energy Management System - A set of computer-aided tools used by electric utility grid operators to monitor, regulate, and optimize the operation of the generation and transmission system.

Flexible Alternating Current Transmission Systems – The collection of power electronics-based devices that enhance the regulation and flow of power in an alternating current (AC) transmission system.

Genetic Algorithm is a computational strategy that uses natural evolution to solve optimization issues or produce solutions for search problems.

Global Maximum Power Point - is a function of inverters that allows solar arrays to maximize output power. It accomplishes this by shifting the working point of solar panels versus the maximum power point, even when there is some shade.

Microgrid Centralized Controller - a device that maintains the energy balance in microgrids, with the primary objective of operating the microgrid while minimizing expenses and meeting demand.

Microgrid Controller - is a device that controls and monitors a microgrid's energy sources and loads.

Microgrid - a tiny community of electricity users with their own source of energy that is usually linked to a centralized national grid but may operate independently.

Optimization Method - a mathematical and computational procedure to find the optimum problem solution by maximizing or minimizing an objective function.

Particle Swarm Optimization - a computational technique which leverages a population of potential solutions to minimize or maximize an objective function.

Plugin Hybrid Electric Vehicle - a car that runs on an electric motor and a combustion engine.

Point of Common Coupling - a location where consumer devices can exchange energy with the electrical utility grid.

Renewable Energy - is the energy derived from hydro, solar, and wind sources.

Reserve Margin is a measure of the amount of additional capacity in a power system compared to peak demand.

South African Grid Code - a set of rules that outlines the responsibility of industry participants in operating the interconnected power system (IPS) and using the transmission system (TS).

Static Var Compensator - a device that adjusts voltage and improves the stability of an alternating current power system by absorbing or delivering reactive power.

Vehicle-to-Cloud (V2C) is a technology that allows vehicles to exchange and save data with the cloud via mobile networks and the Internet.

Nomenclature

AC – Alternating Current

AGC – Automatic Generation Control

BESS – Battery Energy Storage System

CIGRE – Council on Large Electric Systems

DC – Direct Current

DCGAN – Deep Convolution Generative Adversal Network

DCRM – DC Ring Microgrid

DG – Distributed Generation

DPMR – Disjoint Multi Path-based Routing

DRES – Distributed Renewable Energy Sources

DSM – Demand Side Management

EA – Evolution Algorithm

ED – Economic Dispatch

EMS – Energy Management System

EV – Electric Vehicles

FACTS – Flexible Alternating Current Transmission Systems

FMCDM – Fuzzy Multi-Criteria Decision Making

FO – Firefly Optimization

FTID – Fuzzy Tilt Integral Derivative

GA – Genetic Algorithm

GMPP – Global Maximum Power Point

GWO – Gray Wolf Optimization

HEMS – Home Energy Management System

HESS – Hybrid Energy Storage Systems

HHO – Harris Hawks Optimization

HRES – Hybrid Renewable Energy Systems

ICT – Information and Communications Technology

IEEE – Institute of Electrical and Electronic Engineers

IHMS – Island-based Hybrid Microgrid Systems

LFC – Load Frequency Control

LP – Linear Programming

MADRC – Modified Active Disturbance Rejection Controller

MC – Microgrid Controller

MCC – Microgrid Centralized Controller

MCTS – Monte Carlo Tree Search

MFO – Moth Flame Optimization

MOST – Metaheuristic Optimization Searching Technique

MSTA – Modified Super Twisting Algorithm

MV – Medium Voltage

NLP – Non-Linear Programming

NN – Neural Network

OEM – Optimal Energy Management

OHPF – Optimal Harmonic Power Flow

PCC – Point of Common Coupling

PHEV – Plugin Hybrid Electric Vehicle

PQ – Power Quality

PSO – Particle Swarm Optimization

PV – Photovoltaic

QP – Quadratic Programming

RES – Renewable Energy Sources

RMIPPPP – Risk Mitigation Independent Power Producer Procurement Program

SAGC – South African Grid Code

SAO – Smel Agent Optimizer

SASOS – Smell Agent Symbiotic Organism Search

SDG 7 – Sustainable Development Goal 7

SFO – Sailfish Optimizer

SHEMS – Smart Home Energy Management System

SOS – Symbiosis Organism Search

SSA – Salp Swarm Optimization

SSPSO – Series Salp Particle Swarm Optimization

STATCOM – Static Var Compensator

THDv – Voltage Total Harmonic Distortion

UCTE – Union for the Coordination of Transmission of Electricity

UNIDO – United Nations Industrial Development Organization

V2C – Vehicle to Cloud

VUF – Voltage Imbalance Factor

WCA – Water Cycle Algorithm

WIPSO-GSA – Weight Improved Particle Swarm Optimization Gravitational Search Algorithm

WNN – Wavelength Neural Network

WOA – Whale Optimization Algorithm

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CHAPTER ONE
INTRODUCTION

1.1 Introduction

As stated in the South African Constitution, everybody has the right to obtain energy. This puts pressure on the government to figure out how to guarantee that everyone, not only the wealthy and/or those who live in large cities, has access to energy. This right is also one of the Sustainable Development Goals (SDGs) of the United Nations, which is to be accomplished by 2030. By that year, SDG7 aims to guarantee that everyone has access to modern, reasonably priced, and environmentally friendly energy resources. The World Bank's collection of development indicators states that 84.39% of South Africans had access to electricity in 2020. This suggests that a sizable portion of the population remains without electricity, so more work needs to be done to raise these figures. A significant portion of this population resides in isolated places that are not connected to the existing electrical grids, indicating that there is still a large population without electricity. As such, more efforts must be put in to improve these numbers. A huge percentage of this number is the population that is in remote areas where the current electricity network does not reach.

The problem presents an opportunity for microgrids, which use renewable resources such as solar, wind, and energy storage devices like batteries to create electricity. Adding renewable energy sources to fossil fuel sources boosts reliability, lowers carbon emissions, increases price competitiveness, and offers clean energy. These align with the aims of the UN SDG 7. Alternative energy sources are required to improve competitiveness, reliability, and availability of electricity and lower carbon emissions, considering the current wave of load shedding and electricity price spikes in South Africa.

An investigation on the deployment of microgrids is conducted considering the recent policy changes made by the South African government, which include the removal of the requirement for a generation license. The study's primary objective is to create energy management systems that regulate hybrid renewable energy sources whilst electric vehicles are present and also take reserve margins into account. The study aims to identify the best energy management practices applicable to isolated and grid-connected microgrid operating modes.

1.2 Awareness of the problem

Energy management systems are crucial to solving the power systems' economic dispatch challenge. Microgrids are low-voltage distribution networks that are located downstream of the distribution substation and can function in grid-connected and islanded modes. The microgrid energy management system, which is a control program that can efficiently dispatch power or energy from several distributed generators to provide loads as needed, was also defined by the authors in the same publication by (Su & Wang, 2012). Additionally, it can handle real-time resynchronization when switching between islanded and grid-connected modes or between grid-connection and islanded modes. Hybrid microgrids are made up of several power generators, including photovoltaic, wind, energy storage systems, and electric vehicles, which can function as both sources and loads based on grid requirements and the battery's SOC. The example in Figure 1 illustrates a microgrid.

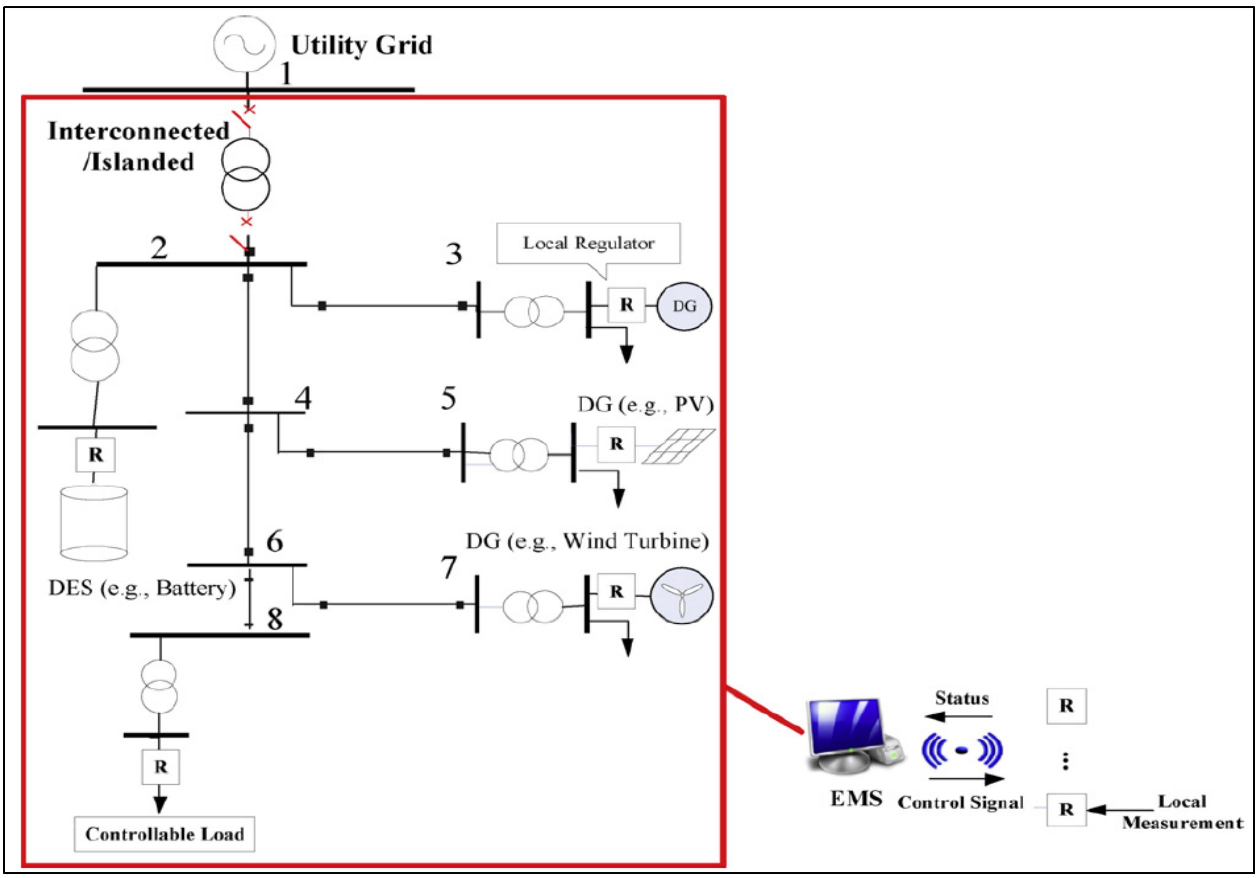

Figure 1. Hybrid Microgrid example (Su and Wang, 2012)

Due to their primary use of renewable energy sources, microgrids help reduce pollution, improve consumer price competitiveness, and improve power system stability. Load forecasting, resource forecasting, electricity market pricing, optimal power flow, real-time control, etc. are among energy management systems' software features. The microgrid EMS ensures the power balance is always maintained by accounting for the unpredictable energy output of renewable energy resources. If energy from renewable sources is insufficient to meet loads, storage systems are either used to supply loads or the grid, if available, based on the market price. Regulations have been implemented within the system to guarantee that loads are supplied from renewable energy when there is enough energy, that excess energy is stored for later use, and even that the grid is supplied. To optimally maintain supply to the loads, the system needs to make these decisions in real time. The study aims to identify and create an optimization strategy for hybrid microgrid energy management systems that consider electric vehicle usage. Genetic algorithms and PSO will be evaluated to attain better microgrid management.

1.3 Problem Statement

Microgrids are crucial to power system networks because they reduce carbon emissions and help to increase system reliability. They also prove to be quite helpful in supplying electricity to loads located in isolated locations away from current power systems, like isolated rural areas and islands. The study considers HRES, which includes photovoltaic, wind, battery storage, electric cars, etc., that may function in islanded and grid-connected settings. To ensure that energy is supplied to loads as efficiently as possible, microgrid energy management systems are essential. These systems must consider various constraints, including power balance, intermittent renewable energy sources, voltage supply violations, and the requirement that battery storage systems only be charged from surplus power generated by green energy sources rather than from the grid, as the RMIPPPP requires in the South African context.

The research problem of a hybrid microgrid consisting of photovoltaic and energy storage systems revolves around optimizing the interaction and operation of these green energy sources to achieve a sustainable, reliable, and cost-effective energy supply while resolving the inherent fluctuation and unpredictability of green energy resources, such as solar energy.

Research Questions:

How can the functioning of a combined microgrid, made up of photovoltaic generation as well as battery energy storage, be optimized to guarantee a consistent and effective energy supply, minimize operational costs, and improve system sustainability while accounting for variability in renewable generation and load demand?

Research Question 1: How can energy dispatch from a hybrid PV-battery microgrid be optimized to minimize operational costs while maintaining a reliable power supply?

Research Question 2: How can hybrid microgrids be integrated with the primary grid to improve energy reliability, reduce reliance on fossil fuels, and lower operational costs?

1.4 Research aims and objectives

Microgrid energy management systems are a crucial component of microgrid operations because they can efficiently distribute generated electricity while conforming to system constraints. The system seeks to determine the most cost-effective producing technique to satisfy load needs while remaining within restrictions.

Aim: The study intends to balance energy output from solar power, battery storage, and customer demand while lowering operational costs, increasing renewable energy use, and enhancing energy security.

Objectives

- Conduct literature review on mathematical structures and models for reserve margins and optimization strategies for hybrid microgrid energy management systems.
- Conduct mathematical formulation of the optimization model for the EMS based on generation, storage, and reserve margins in grid-tied and islanded scenarios.
- Develop the PSO and GA optimization algorithms that effectively handle the uncertainties and variability inherent in green energy sources such as wind and solar. This ensures robust optimization that adapts to fluctuating situations and load demands.

- Investigate how different reserve margin values affect the microgrid's efficiency and dependability.
- Assess the system's performance under different scenarios (e.g., varying weather conditions, grid outages, fluctuating demand) to understand how the hybrid microgrid responds and can be optimized further. Minimize the cost of hybrid microgrid operation by defining the optimal operating parameters.
- Compare the economic feasibility of the suggested optimization technique to standard methods that do not involve reserve margins.
- Implement the developed optimization methods MATLAB environment and evaluate the simulation outcomes.

1.5 Hypothesis

An optimized energy management system of a heterogeneous microgrid, including reserve margins for generation and storage capacity, will improve the system's economic efficiency and reliability under changing load and renewable energy conditions while ensuring resilience against potential system failures and grid stability. The reserve margin improves reliability by ensuring load balance irrespective of demand for power or generation changes. To ensure cost savings, energy management must efficiently deploy reserve margins during times of need.

1.6 Motivation of the research study

The study aims to reduce the adverse effects of load shedding on communities in South Africa by employing microgrids as a clean, dependable, and sustainable energy source. A technical requirement states that a storage system if deployed, cannot be charged from the grid is examined. This requirement was noted in the Risk Mitigation Independent Power Producer Procurement Programme (RMIPPPP). Since the requirements in the tender are for individual projects or plants that do not have local loads to feed, the plant will shut down when removed from the grid. This study applies the criterion to a hybrid microgrid, examining islanded and grid-connected configurations. When coupled to the electric grid, the BESS provides dispatchable reserve margins. It also supplies essential loads when green energy production is inadequate or absent. One notable point about this study is the fact that it has been adapted to the South African context, including regional legislation and standards.

1.7 Delimitation

The research has outlined some areas not considered and excluded from the study, as listed below.

1 The conventional classical techniques have not been considered.
2 Modeling of Fuel Cell renewable energy sources for energy generation has yet to be considered.
3 The research work does not cover the microgrid's protection and control strategies.
4 The sizing and positioning of the distributed energy sources in the mixed microgrid are not part of the scope.
5 Feasibility studies of the microgrid.

1.8 Assumptions

Certain assumptions have been made to lessen the intricate nature of the mixed microgrid's system modeling and simulation.

1) The energy generation from the photovoltaic system is dependent on the quantity of available sunlight, which is often modeled using historical solar irradiance data and may incorporate seasonal or daily oscillations. The effectiveness of solar panels is thought to be constant, however, it may change based on external variables.
2) Wind speed determines the wind turbine's production, which is expected to be estimated using historical data. Wind speed is commonly likely to follow a stochastic distribution.
3) It is assumed that both solar and wind resources are intermittent and changeable but may be modeled with predicted availability patterns.
4) Some models assume that the load demand is unpredictable, and optimization techniques (PSO or GA) are utilized to account for this variation.
5) Both the PSO and GA algorithms are expected to reach an optimal or near-optimal solution within a tolerable time limit. The performance of these algorithms is also

considered to be affected by factors such as population size, iteration limitations, mutation/crossover rates in GA, and particle velocity and position parameters in PSO.

6) The objective functions for PSO and GA methods are assumed to focus on minimizing operational costs, maximizing efficiency, or achieving a balance between price and reliability.

1.9 Research Methodology

The research methodology for hybrid microgrid systems involving photovoltaic systems, wind turbines, and battery storage systems optimized using PSO and GA follows a systematic approach that integrates modeling, simulation, and optimization to achieve optimal microgrid operation. The methodology identifies the most efficient and cost-effective configurations for hybrid microgrid systems through simulation and comparison of both PSO and GA. Figure 2 shows the final implementation of the proposed methodology with the developed optimization methods control and management of the hybrid microgrid system.

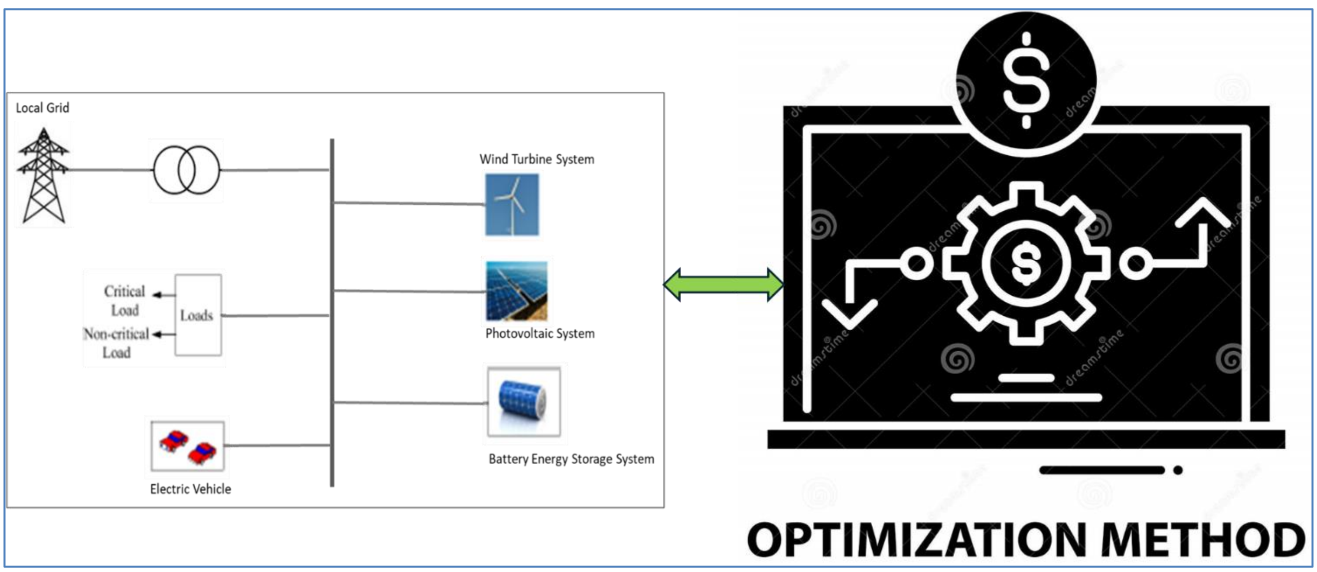

Figure 2. Hybrid Micro Grid System with Optimization Method

- Literature Review: A systematic literature review that investigated the hybrid microgrid model, including the renewable generation profiles, demand patterns, and reserve margins was conducted.

- Mathematical Modeling: A mathematical representation of the mixed microgrid that incorporates reserve margins was developed.
- Optimization Algorithms: The optimization strategies such as genetic algorithms as well as particle swarm optimization were developed to solve the system model.
- Software Development: The system model simulation as well as the optimization strategies were developed in MATLAB environment.
- Simulation: Different system scenarios with varied renewable generation profiles, demand patterns, and reserve margins were tested.
- Performance Evaluation: The performance in terms of cost and dependability under different scenarios was examined.

1.10 Publications

Mquqwana, M.A.; Krishnamurthy, S. Particle Swarm Optimization for an Optimal Hybrid Renewable Energy Microgrid System under Uncertainty. Energies 2024, 17, 422. https://doi.org/10.3390/en17020422.

Mquqwana, M.A.; Krishnamurthy, S. Comparative study of the PSO and GA optimization methods for the Hybrid Microgrid Energy Management System using real-time data. Submitted to the Journal of Electronics and Electrical Engineering.

1.11 Deliverables

1 Conduct a literature search to learn more about the application of optimization methods in energy management systems, discuss current trends in hybrid microgrids, and discuss the opportunities and difficulties.
2 Development of a PSO-based algorithm and its use in the MATLAB software environment to validate its performance in the economic dispatch of hybrid microgrid systems.

3 Development of a GA-based algorithm and its application in the MATLAB software environment to evaluate its effectiveness in economic dispatch in heterogeneous microgrid systems.

4 Develop a charging and discharging strategy that ensures the BESS only charges from excess power generated from renewables.

5 Develop adequate reserve margin management that may reduce the necessity for fossil-fuel backup production from the grid, improving system sustainability and cutting emissions.

6 Analysis of the simulation outcomes for the integrated microgrid for the various use-case scenarios and reporting of the research findings.

1.12 Chapter Breakdown

1. Introduction: The section presents an overview of the research work, indicating the problem and subproblems to be solved. It also includes the aims and objectives, motivation for the research effort, delimitations emphasizing areas not covered in the scope, research technique to be used, and research deliverables.
2. Literature review on microgrids optimization methods and energy management systems: The literature review examines current and published information, compares it based on the various problems it addresses and the strategy it takes, and finds any gaps that may exist, as well as prospects for future additions.
3. Particle Swarm Optimization for Hybrid Renewable Energy Microgrid System under Uncertainty: A background on particle swarm optimization is provided, followed by the basic formulation and application to the microgrid optimization problem. A simulation of the microgrid system, as well as MATLAB test results for the algorithm above, are provided
4. Genetic Algorithm for Hybrid Renewable Energy Microgrid System under Uncertainty: The evolutionary algorithm is provided with a background, followed by its basic formulation and application to the microgrid optimization problem. The GA MATLAB test results for the algorithm above are shown, and a comparison study of the two optimization approaches is performed.
5. Conclusion: A quick examination of what the research effort covered compared to what it aimed to achieve in terms of deliverables, methodology, etc. Noting any

deviations and the causes for such deviations, if any, and proving future recommendations are offered.

6. Appendices: Software program of the developed optimization methods for the microgrid system.
7. Bibliography: A list of references utilized during the investigation

1.13 Research Contributions

1. The optimization research problem considers a hybrid microgrid comprising solar, wind, battery energy storage, and electric vehicles operating in isolated and connected modes.
2. The developed optimization method considers hybrid microgrids with reserve margins for critical loads.
3. The developed optimization method does not allow the battery energy storage system to charge from the grid but only from excess generation from renewable sources.

1.14 Conclusion

Hybrid renewable microgrid systems are an essential power system component since they provide system support functions such as increased reliability, lower carbon footprint, and so on. Because SDG 7 stipulates access to reasonably priced and consistent power for everyone, it is difficult to supply this service to persons who reside in remote areas where the current national grid cannot reach. Deploying islanded microgrids helps in this area by providing much-needed services to those communities. The supply is uncertain because hybrid renewable microgrid energy is derived from unpredictable natural sources. It must be supplemented by a Battery Energy Storage System (BESS), which stores excess generated power for later use when renewable generation is limited.

This method will be managed by the study energy management system, which will also establish the appropriate charging as well as discharging strategy for the battery system for supplying loads. The study's primary goal is to design an optimization approach for the energy management system that results in savings for microgrid owners. The study approach offered outlines a strategy for achieving the desired findings.

The next chapter reviews the literature on microgrid application optimization methods and energy management systems.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

Microgrid optimization, EMS, real-time EMS, load frequency control, power system operation, distributed generation, economic dispatch, electric vehicles, energy storage systems, frequency in microgrids, etc. are some of the keywords used in this section's literature search and literature review of published material, which includes papers, journals, books, and other publications. The literature focuses on microgrid optimization, microgrid energy management systems, and reserve margins, which are discussed further in the following sections.

Section 2.2 presents some background on microgrids' role in the electric power system's network. Section 2.3 offers a summary of the academic assessment of smart home energy management systems, and Section 2.4 delivers a summary of the academic analysis of energy management systems utilized in microgrids. Section 2.5 summarizes the scientific assessment of power system modeling and optimization. Section 2.6, on the other hand, provides a review of the literature on optimization strategies for microgrids that function in grid-tied or islanded configurations. The literature review on reserve margins is briefly reviewed in part 2.7; the chapter discussion is offered in section 2.8, and a conclusion is provided in section 2.9.

2.2 Background

A microgrid is a low-voltage distribution system that connects to a point of common coupling located beneath the distribution station (Su & Wang, 2012). As previously stated, microgrids can operate independently or in connected to the grid. The Manhattan Pearl Street Station, Thomas Edison's initial electric station erected in 1882, was a microgrid because a centralized grid had yet to be developed. Direct current (DC) microgrids totaling fifty-eight were installed by Edison's company in 1886. Built in the United States in 1955, the first contemporary microgrid had a 64 MW capacity. Microgrids can be classified into five categories: military, commercial/industrial, institutional/campus, community/utility, and distant off-grid (Asmus, et al., 2009).

Microgrids continue developing and improving to provide reliable electricity using renewable energy resources. This is in line with recent developments in the energy industry policies and the United Nations Sustainable Development Goals (SDG7), which focuses on guaranteeing all people have a means of receiving affordable, environmentally friendly, and clean energy. The intermittent nature of renewable energy sources, control schemes, cyber security risks brought on by system interconnectivity, etc. are some of the microgrids' current research problems. Table 1 depicts the evolution of energy management systems in power systems from the early 1950s.

Table 1. Energy Management System History (Su and Wang, 2012)

1950s	**1960s**	**1970s**	**1980s**	**1980s**	**After 2000s**
Load Frequency Control (LFC)	SCADA-RTU	Network Analysis (State Estimator)	Transmission Security (Optimal Power Flow)	Inter-Control Center Communications Protocol	Demand Side Management (DSM)
	EMS Database	Load Forecast	Generation Control (AGC, ED, ISP)	Open Platform and Distributed Architecture	Multi-directional Power Flow
	Automatic Generation Control (AGC)	Alarm / Event Processor	Operation (Full Graphic and Customized User Interface)	PC-Based Operator Console	Decentralized Control
	Economic Dispatch (ED)	System Redundancy and Backup			Network Management
	Unit Commitment (UC)				Plug and play

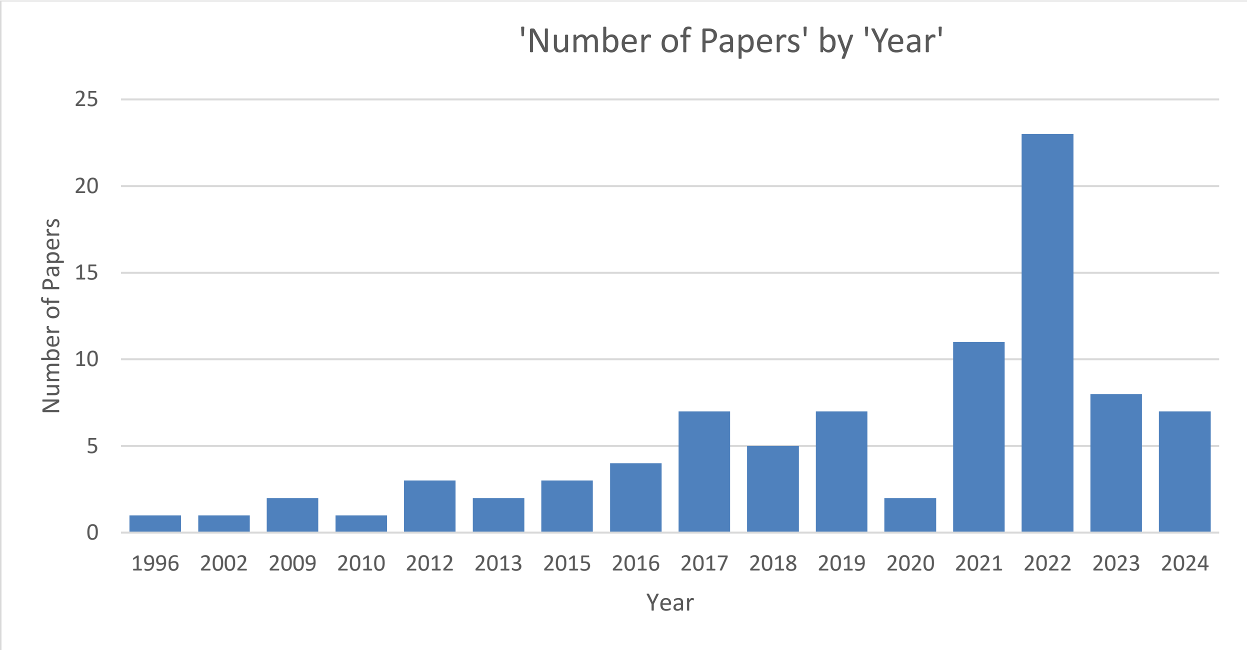

Figure 3. Number of publications per year on microgrids

A literature review has been done to understand the topic better and identify gaps in the research. The materials that have been reviewed are arranged based on the year of publication, as depicted in Figure 3. The literature review is grouped into five categories: review by the smart home energy management system, energy management system, power system modeling and optimization, microgrid optimization methods, and reserve margins. Out of the 83 publications reviewed, as shown in Figure 4, 4 publications are grouped under smart home energy management systems, 29 are grouped under energy management systems, 9 are grouped under power system modeling and optimization, and 37 fall under microgrid optimization. In comparison, 8 publications discuss power system reserves.

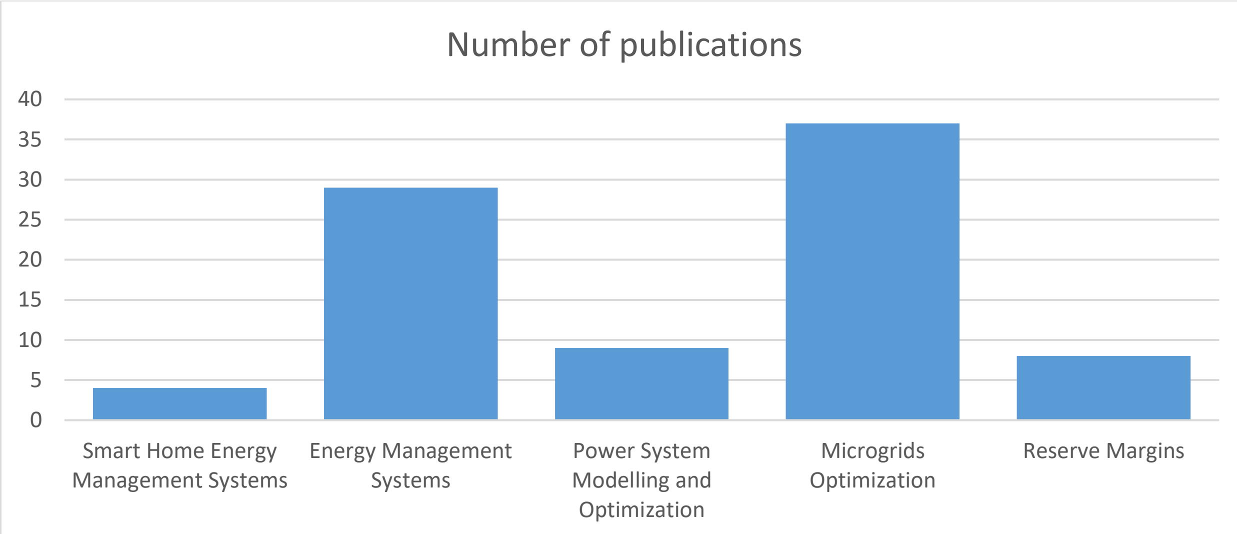

Figure 4. Number of publications per review category

The next section discusses the literature survey on smart home energy management systems and includes their applications in microgrids.

2.3 Smart Home Energy Management System

This section presents an academic assessment of smart home energy management systems. (Han & Lim, 2010) proposed implementing smart home energy management systems using IEEE802.15.4 and ZigBee for wireless communications, which they called the “ZigBee sensor network.” The proposed solution assigns tasks to various network components. A routing protocol called Disjoint Multi Path-based Routing (DPMR) was developed to improve ZigBee performance. (Zhou, et al., 2016) provide a brief discussion on smart home energy management systems, their architecture, and their functional modules. Various green energy resources like wind, solar, biomass, etc., and their impacts are analyzed. (Bisschoff, 2016). The study investigates the effects of installing an energy management system in a real-life system in South Africa, assuming that net-metering rules are not adopted. The EMS was implemented together with a solar system and grid-connected inverter, and the results showed an improvement from 83% to 98% in self-consumption. (Tostado-Véliz, et al., 2022) offered a home energy management system that combines feasible demand response tactics without compromising the end users' financial domain. Table 2 analyzes the literature review of smart home energy management systems.

Table 2. Review summary of Smart Home Energy Management Systems

Author	**Aim**	**Application**	**Hardware/Software used**	**Key Points**
Han, and Lim, 2010	The paper proposed implementing Smart Home Energy Management Systems using IEEE802.15.4 and ZigBee for wireless communications, which they called a "ZigBee sensor network."	Simulation and physical implementation	Simulation software tools	Implementation of the ZigBee sensor network for HEMS
Zhou, et al., 2016.	The paper on smart home energy management systems, their architecture, and their functional modules.	General review and discussion of energy management systems and their applications	A review paper	Demonstrated comparative analytical results of EMS.
Bisschoff, 2016.	The study investigates the effects of installing an energy management system in a real-life system in South Africa, assuming that net-metering rules are not adopted.	Simulation and physical implementation	Simulation software tools, 2 kW Solar System	The EMS is implemented together with a solar system with a grid-tied inverter, and the results showed a huge improvement in self-consumption from 83% to 98%.
Tostado-Véliz, et al., 2022.	Offered a home energy management system that combines feasible demand response tactics without compromising the end users' financial domain.	Simulation	Simulation software tools	The solution results showed improvement when compared with other methods in terms of financial saving.

The next section discusses the literature review on energy management systems in general and includes their applications in microgrids.

2.4 Energy Management System

The section discusses a literature review on energy management systems. (Slutsker, et al., 1996) implemented a method that can estimate the impedance parameters of the network as they fluctuate due to load changes using the Kalman filter and these parameters were. Using a real energy management system, the method was tested on a 100-bus network. (Clarke, et al., 2002) discussed the development of the simulation-assisted controller that has a program running in real time to manage

(Su & Wang, 2012) discussed the operation of microgrid energy management systems, providing opportunities, challenges, etc. Some of the mentioned issues include the intermittency of green energy resources and the influence of electric automobiles on microgrid operation in terms of load or source, dependable communications infrastructure requirements, cyber security requirements, etc. In contrast, some of the opportunities listed include grid reliability improvement, end-user participation in the electricity markets, reduction of emissions due to the implementation of renewable resources, etc. (Aman, et al., 2013) provide a comparative analysis of various energy management systems, their applications, frameworks, etc. United Nations Industrial Development Organization (UNIDO), 2013 developed a guide for implementing energy management systems.

(Shakeri, et al., 2017) suggested an improved design and control mechanism that gets price information from the utility company to decide whether to purchase power from the market, charge batteries, provide the batteries without a solar system supply, etc. A comparative examination of decision-making strategies for energy management systems to handle the inconsistent availability of green energy resources, load demand, market electricity prices, etc. is offered by (Zia, et al., 2018). The book by (Suzuki, et al., 2020) provides a discussion about the inclusion of energy management systems, electric vehicles (EV), and information communications technology (ICT) to form microgrids. (Habib, et al., 2019) discussed energy management techniques on wind, diesel, battery, and inverter mixed energy source systems. The commercial software tool (HOMER) was used to evaluate the ideal size of the various elements of the network according to the actual environmental data and demand profile of an isolated residential area in Pakistan. The suggested energy management system was built in a MATLAB/Simulink environment to regulate the hybrid renewable energy systems.

(Farhangi & Joós, 2019) discussed different topics, including operation, control, protection, disturbance detection, diagnostics, microgrid planning, optimization, microgrid benchmarks, automation, communications infrastructure, real-time operation, testing, etc. Some case studies, challenges, and energy management applications on microgrids are also discussed.

(Patnaik, et al., 2020) presented an overview literature review on the protection of AC microgrids, including protection coordination considering bidirectional power flow scenarios and integration of renewable energy resources. The research discussion included the current, major challenges, and research areas of interest. (Roy, et al., 2021) suggested a two-level optimization strategy for energy management and scaling microgrid components. The optimization method allowed benefits to be maximized while costs were minimized. (Sarda, et al., 2022) discusses the energy management system for battery energy storage systems in microgrids with solar PV systems. Two approaches are evaluated for a cloudy and clear day, and the findings show that the optimization method outperforms the heuristic method.

(Kavitha, et al., 2022) proposed an energy management system based on Mimosa Pudica optimization technique designed for optimal dispatching of the microgrids to improve performance and efficiency, ensuring that power balance is always met. The suggested method showed an 8% improvement in profits versus other methods. (Bukar, et al., 2022) presented a rules-driven approach along with metaheuristic optimization searching techniques (MOST) in energy management systems and microgrid development. The MOSTs were applied to weather data of Maiduguri, Nigeria, and the outcomes showed that the grasshopper optimization technique had better results than the other techniques. (Chopra, et al., 2022) developed an innovative technique for establishing control levels and optimizing the performance of islanded microgrids employing offline, centralized, and power flow-based energy management systems. The approach was evaluated on an updated 14-bus CIGRE medium voltage reference microgrid network. (Lopez-Santiago, et al., 2022) presented a rule-driven energy management system to replace optimization or prediction-based energy management systems on isolated microgrids. The proposed rule-based EMS solution showed better results than optimization-based energy management systems.

(Sanabria-Torres, et al., 2022) presented a paper whereby energy management tasks are based on microgrid analysis, control, and predictions in real-time to improve the reliability and validity of the energy management system. A cloud-based energy management system that involves machine learning to solve economic dispatch problems is tested on an experimental microgrid with the implementation of hardware in the loop philosophy and communications protocols to connect to the on-cloud EMS. (Correia & Aoki, 2022) proposed the method to manage load uncertainties and energy generation intermittencies using energy management systems. Using energy management systems, the method to manage load uncertainties and energy generation intermittencies was proposed. The proposed energy management system monitors, in real time, the difference between the dispatched energy and the prediction with the consideration of renewable resources, battery state of charge, and load curve. (Hassanzadeh & Rahmani, 2022) proposed a real-time energy management system for plug-in hybrid electric vehicles (PHEVs) that integrates battery degradation and fuel consumption optimization.

(Yu, et al., 2022) presented a real-time energy management system based on Monte Carlo Tree Search (MCTS) using vehicle-to-cloud (V2C) connectivity. The outcomes of the suggested approach, using the actual vehicle and hardware in the loop test bench, are compared with the results of the rule-based and online dynamic programming method, and an improvement of above 11% is seen. To meet network restrictions and ensure co-optimization of the energy management system and economic power dispatch (EPD), (Adenuga & Krishnamurthy, 2023) created an optimization strategy that reduces the overall operating expenses of all scheduled units that supply the grid. Although the B coefficient loss formula calculates the transmission losses, the suggested PSO technique approaches the optimization question by characterizing the operational expenses of generating plants employing a piecewise quadratic function. The quantity and ecologically favorable characteristics of renewable energy-based power systems are driving up interest in them globally. A relatively recent innovation in this field, island-based hybrid microgrid systems (IHMS) integrate two or more sustainable energy sources, along with photovoltaic systems, wind turbines, including other green energy sources like geothermal, wave, and ocean energy. The growing population along with the manufacturing industry of Perhentian Island, Malaysia, relies on an uninterrupted power supply, so an energy management system that effectively synchronizes and controls alternative power sources is necessary (Shezan, et al., 2023).

Production of clean energy is becoming more common, which raises the degree of stochasticity and intermittency in energy management. To tackle this problem, an integrated energy management along with a preservation system is presented, which comprises a fuzzy logic-based super-twisting algorithm. The goal is to maximize the efficiency of the microgrid's design and operation, which comprises electrical energy conversion technologies such as fuel cells, tidal energy, solar and wind turbines, charging facilities for electric vehicles, and the main electrical grid. Another objective is to build an energy management system that will optimize power production, ensure service continuity, and smooth out the microgrid's energy output while also providing the best potential outcomes for hybrid energy storage systems (HESS) and renewable energy sources (RESs) (Belkhier & Oubelaid, 2024). Nowadays, an energy management system is important. However, the overreliance on fossil fuels and the expanding gap between electricity use and energy power supply has resulted in various worldwide concerns, including energy shortages, high utility bills, and greenhouse gas emissions (Hou, et al., 2024).

Energy management systems are often either predictive or real-time, but they do assist grid integration by matching the supply and demand of power. As a result, the integration of renewable energy sources into the grid is limited since they are unable to utilize the range of supply and demand responses fully. By using an integrated energy management system, this restriction is removed. From there, a thorough summary of recent findings and advancements in the creation of frameworks for integrated energy management systems with real-time and predictive energy management features is given in (Falope, et al., 2024).

Two main obstacles must be overcome for the DC microgrid to have efficient energy management: minimizing operating costs and balancing power flow. Most benchmarking strategies are employed to demonstrate the availability of power optimization or cost optimization to construct energy management systems (EMS). In contrast, this study introduces a new optimal energy management (OEM) approach in the DC ring microgrid (DCRM) that considers both power flow and operational cost during the grid-connected scenario. A multi-objective optimization model is created using key constraints, such as the reduction of operational expenses and power availability via the use of an enhanced sparrow search algorithm (ISSA) based on a modified active disturbance rejection controller (M-ADRC), to achieve the OEM in the DCRM (Anjaiah, et al., 2024). Three characteristics are used as inputs in the Bayesian inference process: the hybrid system's overall production, the load demand, and the batteries' state of charge, which determines the supply for charge consumption. The technique shifts the task from choosing the best response to drawing optimum predictions about management by defining action and decision-making picking as variational Bayesian Interpretation. A Bayesian inference technique for the new demand management strategy has been developed as a result of the findings, and it may be used to load profiles that are similar to those of commercial and service institutions. (Benallal, et al., 2024).

Table 3 shows the comparisons of various publications on energy management systems for categories as reviewed above.

Table 3. Review summary of energy management systems

Author	**Aim**	**Application**	**Hardware/Software used**	**Key Points**
Slutsker, et al., 1996.	The implemented method is capable of estimating the network's impedance parameters as they fluctuate due to load changes using the Kalman filter.	Simulation and physical implementation	Energy Management System, power system simulation software	The use of the Kalman filter to estimate impedance parameters.
Clarke, et al., 2002.	The paper discusses the development of the simulation-assisted controller, which uses a program running in time with a real-time program to make decisions.	Simulation and physical implementation	Simulation software tools	Development of a simulation system to improve control capabilities of Building Energy Management System
Su, and Wang, 2012	The paper discusses the operation of energy management systems in microgrids, providing opportunities, challenges, etc.	General review and discussion of energy management systems as applied in microgrid operations	A review paper	Provided clear background to microgrids and energy management systems and the definitions used.
Aman, et al., 2013.	The article presents a comparative analysis of energy management systems, their applications, frameworks, etc.	General review and discussion of energy management systems and their applications	A review paper	Provided comparative results of energy management systems and their applications.
UNIDO, 2013.	The United Nations Industrial Development Organization developed a guide for implementing energy management systems.	General guide	General Guide	Developed a guide for implementing management systems.
Shakeri, et al., 2017.	The study offered a novel design and control technique that gets the electrical company's price information to decide whether to purchase electricity from the market, charge batteries, provide utilizing batteries in the absence of solar power, etc.	Simulation and physical implementation	Simulation software tools	Design of the energy management system to determine when to buy/sell from the grid, charge/discharge batteries, etc. depending on the purchase price.

Zia, et al., 2018.	A comparative analysis of decision-making strategies in microgrid energy management systems to handle the unpredictable nature of green energy resources, load demand, and so on is offered.	General review and discussion of energy management systems and their applications	A review paper	Demonstrated comparative analysis of decision-making strategies in energy management systems.
Habib, et al., 2019.	An energy management technique for wind, diesel, battery, and converter hybrid green power systems is suggested.	Not Applicable	MATLAB/Simulink, HOMER	Testing of the proposed optimization method for hybrid microgrid
Farhangi, and Joós, 2019.	The book discusses different topics including operation, control, protection, disturbance detection, diagnostics, microgrid planning, optimization, microgrid benchmarks, automation, communications infrastructure, real-time operation, testing, etc.	Conventional, intelligent search techniques	Theoretical book discussion	Provided clear discussions and definitions, on microgrid planning, operation, protection, etc.
Suzuki, et al., 2020.	The book discusses the integration of energy management systems, electric vehicles, and information and communication technologies to form microgrids	General review and discussion of energy management systems and their applications	Theoretical book discussion	Provided clear discussions of EMS, EVs, and ICT to microgrids.
Patnaik, et al., 2020.	The paper presents an overview literature review on the protection of AC microgrids including coordination considering bidirectional power flow scenarios and integration of distributed renewable resources.	Not Applicable	A review paper	Clear definition of interventions required to mitigate protection issues.
Roy, et al., 2021.	A two-stage optimization method of power management, as well as the capacity of microgrid components, is proposed.	Intelligent search techniques	Simulation software	The results of the optimization method showed an increase in profits due to the sale of hydrogen although the investment cost of the electrolyzer is high.
Sarda, et al., 2022.	The paper discusses the power management system of battery storage systems connected to a microgrid with a solar PV system.	Simulation	Simulation software tools	Demonstrated cost improvement due to the implementation of the proposed solution

Kavitha, et al., 2022.	The article presents the power management system based in Mimosa Pudica, developed to optimally manage microgrid dispatching to improve performance and efficiency and ensure power balance.	Simulation	Simulation software tools	The proposed method showed an 8% increase in profits than other methods.
Bukar, et al., 2022.	A rule-based algorithm and metaheuristic optimization searching techniques (MOST) are presented for energy management and sizing microgrids.	Simulation	Simulation software tools	Provided a comparative analysis of MOST (Meta-heuristic Optimization Techniques).
Chopra, et al., 2022.	A novel approach for implementing hierarchical control in optimizing the operation of islanded microgrids using the offline, centralized, and power flow-based energy management system is presented.	Simulation	Simulation software tools	Demonstrated cost improvement due to the implementation of the hierarchical control in optimization methods.
Lopez-Santiago, et al., 2022.	A rule-based energy management system is proposed instead of an optimization or prediction-based system on isolated microgrids.	Simulation	Simulation software tools	Demonstrated cost improvement due to the implementation of the proposed solution.
Sanabria-Torres, et al., 2022,	In the paper, energy management tasks are based on analysis, control, and predictions in real-time to improve the system's reliability and validity.	Simulation and physical implementation	Simulation software tools, electric vehicles, cloud-based EMS	Demonstrated cost improvement due to the implementation of the proposed solution
Correia, and Aoki, 2022.	The study proposed a method to manage load uncertainties and energy generation intermittency using energy management systems.	Simulation	Simulation software tools	Demonstrated cost improvement due to the implementation of the proposed solution
Hassanzadeh, and Rahmani, 2022.	A real-time energy management system for plugin hybrid electric vehicles (PHEVs) that integrates battery degradation and optimization of fuel consumption.	Simulation	Simulation software tools	Demonstrated cost improvement due to the implementation of the proposed solution

Yu, et al., 2022.	The paper proposed a real-time energy management system based on Monte Carlo Tree Search using vehicle-to-cloud connectivity.	Simulation	Simulation software tools	Demonstrated cost improvement due to the implementation of the proposed solution
Benallal, et al., 2023.	A new techno-economic feasibility analysis of energy management for an autonomous hybrid microgrid using the Homer software v3.14.5 environment is presented.	Simulation	Homer software	successfully lowered the net current cost, initial cost, and energy cost by 37.93%, 41.43%, and 36.71%, respectively, on secondary and tertiary priority charges. The overall unmet load was 1.9%.
Qayyum, et al., 2023.	This study critically looks at how energy management systems are integrated into intelligent residential buildings, which are essential hubs in the network of smart cities.	Not Applicable	A review paper	Highlighted the need for multidisciplinary research and the implementation of comprehensive tactics to maximize energy efficiency, lower carbon footprints, and encourage resilient urban living in the age of smart cities.
Shezan, et al., 2023.	Give a thorough examination of the convergence rate and net present cost (NPC) of different optimization techniques.	Various optimization techniques	Simulation software	The results show how FLC works under different operating conditions to keep the voltage and frequency within allowable bounds.
Hou, et al., 2023.	With several ideal or nearly optimal DSM recommendations, the model hopes to increase users' receptivity to the advice and fully use DSM's advantages.	Indexed-based ring topology PSO	Simulation software	Demonstrated cost improvement due to the implementation of the proposed solution
Adenuga, and Krishnamurthy, 2023.	To minimize the total operating expenses of all scheduled units supplied to the grid while simultaneously guaranteeing improvement of the energy management system and economic power dispatch (EPD) and fulfilling network constraints.	Simulation	Software	The suggested co-optimization methodology greatly improved the self-consumption ratio.

Belkhier, and Oubelaid, 2024.	To provide an energy management system for renewable energy sources (RESs) and hybrid energy storage systems (HESS) to optimize benefits, maintain service continuity, and increase power production in the microgrid.	Simulation	Software	The suggested management unit offers reliable output power and long-term service.
Falope, et al., 2024.	To examine integrated energy management systems, including supply and demand side response types, power system designs, and operations	Not Applicable	A review paper	The results helped guide future research on integrated energy management system design and deployment.
Anjaiah, et al., 2024.	This paper introduces a new optimal energy management (OEM) approach for the DC ring microgrid (DCRM), which takes into account both power flow and operational costs in the grid-connected scenario.	Simulation	Hardware and Software	The suggested method is scalable to large and intricate microgrids and is not just restricted to PV-wind-based DCRM management

2.4.1 Review discussion of energy management systems

Energy management systems have been around for decades, as shown in Table 1, with the first control philosophy being load frequency control. One of the definitions of an energy management system given by (Su & Wang, 2012) is “A microgrid EMS is a control software that can optimally allocate the power output among the DG units, economically serve the load, and automatically enable the system resynchronization response to the operating transition between”. The above definition has been adopted for the research. Two main obstacles to the DC microgrid's optimum energy management are balancing the power flow and minimizing operating costs. By proving either cost optimization or availability of power optimization, the majority of benchmark methodologies are utilized to construct energy management systems (EMS) (Anjaiah, et al., 2024). The goals are to optimize the main grid, solar and wind turbines, fuel cells, tidal energy, electric vehicle charging stations, and other electrical-based energy conversion systems when it comes to microgrid design and operation. (Belkhier & Oubelaid, 2024).

Grid integration of renewable energy sources is limited because energy management systems, which balance power supply and demand, are typically either predictive or real-time. As a result, they cannot fully exploit the range of supply and demand responses. By using an integrated energy management system, this restriction is removed (Falope, et al., 2024). There have been developments throughout the years, as shown in the literature review above. Continuous improvements are ongoing as researchers always look at different, more straightforward, effective, efficient, and accurate etc. ways of solving current and future problems. The correct application of energy management systems has demonstrated system improvements in the efficiency rate of renewable energy resources, increased saving, operation, and control, etc.

2.5 Power System Modelling and Optimization

The section discusses a literature review on microgrid optimization methods. (Parmar, et al., 2012) presented load frequency control (LFC) for a realistic power system network with multi-source generation. The paper's authors proposed using an optimal output feedback controller to solve the LFC problem while considering all the power system state variables. The proposed controller was tested using a power system in Khozestan, Iran. (Kothari, 2012) provided a book that discusses the basics of power system modeling, load flow studies, economic dispatch, multi-objective generation scheduling, and evolution programming for generation scheduling. (Bhutto, et al., 2013) presented the development of photovoltaic and battery energy storage systems controllers using Static Compensator (STATCOM) controllers. The developed controllers were tested on the distribution test network developed by CIGRE, and the outcomes showed good performance by the controllers. (Zhu, 2015) presented a book that covered the basic operation of power systems, from conventional methods to intelligent search techniques. The book addresses subjects such as power flow evaluation, sensitivity calculation, classical economic dispatch, security-constrained economic dispatch, multi-area system economic dispatch, unit commitment, optimal power flow, optimal load shedding, uncertainty analysis, and so on.

(Alzahrani, et al., 2017) discussed different models of electrical components in a microgrid. The models discussed use complex modeling techniques to represent various electrical components. (Madathil, et al., 2018) discussed the creation of the mathematical model dealing with the dependability difficulties of off-grid microgrids for architecture, planning capacity, and management of distributed generators. A rolling horizon algorithm was also developed to solve the model and the proposed solution was tested using the modified IEEE test network and the Alaskan real microgrid. (Dougier, et al., 2021) research presented a method to determine parameters and performances that define a compromise between economic, technical, and environmental objectives. A Genetic Algorithm (GA) optimization method was used to perform the multi-objective non-weighted optimization to find the balance.

(Gadanayak, 2021) discussed protection algorithms for microgrids interfaced with inverter generation units operating in grid-connected mode. The initial power generation system had numerous flaws that eventually came to light from a long-term strategic standpoint. Because those generators are non-renewable resources, the pollution they produce is irreversible, and also they will be gradually depleted. Two significant crises are plaguing the world: the energy and environmental crises, which pose serious threats to humankind's ability to develop sustainably. It's now necessary to find new, environmentally beneficial energy sources (Luo & Mei, 2023). A literature review summary of the power system modeling and optimization is provided in Table 4.

Table 4. Review Summary of Power System Modelling and Optimization

Author	**Aim**	**Application**	**Hardware/Software used**	**Key Points**
Parmar, et al., 2012.	The paper presented the demand frequency regulation of an actual electrical network with multi-source generation.	Not Applicable	Simulation software, Real Power System	Implementation and testing of load frequency controller.
Kothari, D.P., 2012.	The book provides the basics of power system modeling, load flow studies, economic dispatch, multi-objective generation scheduling, and evolutionary programming for generation scheduling.	Different categories of optimization methods have been defined	Theoretical book discussion	Provided clear definitions of power system modeling, etc.
Bhutto, et al., 2013.	The paper provides the development of Photovoltaic (PV) and battery energy storage system (BESS) controllers using Static Compensator (STATCOM) controllers.	Not Applicable	Simulation software	Implementation and testing of renewable energy controllers.
Zhu, J., 2015.	The book provides the basics of power system operation, from conventional methods to intelligent search techniques.	Conventional, intelligent search techniques	Theoretical book discussion	Provided clear definitions, power system modeling, etc.
Alzahrani, et al., 2017.	The paper discusses the different models of electrical components in a microgrid. The models discussed use complex modeling techniques to represent various electrical components.	Not Applicable	A review paper	Clear definition of the complex models used to represent microgrid components.
Madathil, et al., 2018.	The publication describes the creation of a mathematical framework that addresses the reliability difficulties for off-grid microgrids during architectural design, capacity planning, and distributed generator functioning.	Rolling horizon algorithm	Simulation software, Real Power System	Implementation and testing of the rolling horizon al algorithm method in Alaskan to improve the reliability of microgrids.
Dougier, et al., 2021.	The paper determines parameters and performances that compromise economic, technical, and environmental objectives.	Genetic Algorithm (GA)	Simulation software	Demonstration of the flexibility of the proposed algorithm to find a balance between opposing objectives.

Gadanayak, 2021.	The paper discusses protection strategies for microgrids interfaced using inverter generator devices that operate in grid-connected mode.	Not Applicable	A review paper	Clear definition of interventions required to mitigate protection issues.
Luo, and Mei, 2023.	The use of multi-objective optimization-based microgrid scheduling technique.	PSO	Simulation software	Effectiveness as well as the author's suggested approach's logic and applicability

2.5.1 Review Discussion of Power System Modelling and Optimization

The papers discuss load frequency control (LFC) for a realistic power system network with multi-source generation, proposing an optimal output feedback controller. They also discussed power system modeling, load flow studies, economic dispatch, and generation scheduling. The authors also discuss the development of photovoltaic and battery energy storage systems controllers using Static Compensator (STATCOM) controllers. The book covers basic power system operation, power flow evaluation, sensitivity calculation, classical economic dispatch, security-constrained economic dispatch, multi-area system economic dispatch, unit commitment, optimal power flow, optimal load shedding, uncertainty analysis, and protection algorithms for microgrids. The research also discusses different models of electrical components in a microgrid and a method to determine parameters and performances that balance economic, technical, and environmental objectives using a Genetic Algorithm (GA) optimization method.

In the following section literature review on microgrid optimizations is discussed.

2.6 Microgrids Optimization

The section discusses a literature review on microgrid optimization methods. (Asmus, et al., 2009) presented research that provides a historical background of microgrids dating back to the 1800s. They also offer the expected developments of microgrids, application categories, and the benefits of using microgrids. (Rauf, et al., 2016) discussed the optimal application of intelligent DC grid systems for solar distributed generation to develop reliable infrastructure to fulfill set goals. The authors advocate for implementing the DC distribution grid as it minimizes power losses due to DC to AC conversion with the expectation of having more home appliances, including lights, to use DC supply for the proposal to gain traction.

(Mohanty, et al., 2017) discussed the standalone PV-based microgrid power management system, including its limitations, such as reliability of voltage concerns along with problems with power quality that need interventions. Some of the interventions discussed include diesel generators for the restoration of voltage stability and flexible Alternating Current Transmission Systems (FACTS) devices. (Reddy, et al., 2017) Presented a Fuzzy Multi-Criteria Decision Making (FMCDM) approach to rank load points and locations that would be used to restore distributed generators after natural disasters. Particle Swarm Optimization (PSO) was used to evaluate distributed generators' optimal size and location using the proposed objective function. (Muthuvel, et al., 2017) presented the development of a DC nano grid employing a straightforward and robust evaluation technique. A simple approach was used to determine the PV system sizing utilizing the area of interest's consumption, irradiation, and ambient temperature. In contrast, rigorous Particle Swarm Optimization was used to determine the cost using all design variables, and the proposed solution was tested in the local network in India. (Mumtaz & Bayram, 2017) presented the critical challenges of implementing island microgrids and possible solutions for those challenges in terms of planning, operation, and control, with a focus on power system protection.

(Arulraj & Kumarappan, 2019) presented a study on the optimal planning of distributed generators and capacitor installation using the maximization of total cost benefit as the main objective function. A hybrid optimization method called Weight Improved Particle Swarm Optimization and Gravitational Search Algorithm (WIPSO-GSA) was proposed and tested on a 33-bus test network and the real 85-bus network in India. The results of the proposed algorithm showed improvements when compared to the results of conventional algorithms. (Diab, et al., 2019) offered a simulated technique for operating a mixture of PV, wind, battery, and diesel generator microgrids. Energy costs were reduced, while dependability and efficiency were boosted. Whale Optimization Algorithm (WOA), Water Cycle Algorithm (WCA), Moth-Flame Optimization (MFO), and a hybrid PSO-GSA were all applied to the simulation model. Still, the results indicated the superiority of the WOA.

(Ruiz, et al., 2019) presented a novel design method for hybrid off-grid microgrids considering the integration of electric vehicles operating as both the load when charging and the source for ancillary services support. (Raji & Luta, 2019) explored the mathematical representation as well as the optimization of a communal microgrid (diesel generator and PV rooftop), located in an urban area in Cape Town, South Africa. A commercial software tool, HOMER was used for the optimal design of the system. (Antonanzas-Torres, et al., 2021) research works presented the present status of microgrid installations and the major challenges for future developments and installations of microgrids in West Africa. The research showed that the electrification status was below 40% with many areas being remote areas from the grid. (Mathiesen, et al., 2021) proposed a fast method for optimizing distributed energy resources investments and dispatch planning considering 5-minute intra-hour variability. The proposed method showed improvements to maintain optimality at below 2% while reducing runtime by 98.2%.

(Zhang, et al., 2021) presented a multi-criteria evaluation method to deal with microgrids' peak shaving ability and carbon reduction effects. The research proposed converting peak shaving and emission reduction effects to economical values such as peak load reduction costs and carbon tax. (Mah, et al., 2021) This paper presents the optimization framework for designing and operating the isolated microgrid with electrical and hydrogen loads. Particle Swarm Optimization was used to solve the problem, and two energy management strategies were proposed. (Mah, et al., 2021) also presented his work using a P-graph optimization framework to optimize microgrids with BESS and hydrogen storage and photovoltaic.

(Çetinbaş, et al., 2021) the study proposed applying the Harris Hawks Optimization (HHO) algorithm for the optimization and the design of AC microgrids consisting of photovoltaic, wind turbines, battery energy storage systems, and diesel generators. MATLAB tool was used as a simulation test environment. It demonstrated success by showing savings from just above 1% to just over 18% in comparison to PSO and Firefly Algorithm, Gray Wolf Optimization (GWO), and Salp Swarm Algorithm (SSA). (Yang & Su, 2021) proposed an efficient optimization method for microgrids that takes into account the intermittent nature of green energy sources as well as the microgrid's necessary reliability. A two-stage resilient optimization was defined to strike a balance between cost and reliability. The proposed optimization method was incorporated into the CPLEX solver and evaluated on the IEEE 39 bust test network.

(Shen, et al., 2022) presented research on the energy storage optimization method for the microgrid consisting of wind and solar generation considering multi-energy coupling demand response using electric, heat, and gas loads. (Rai & Das, 2022) presented a load frequency development of multiple-area microgrids consisting of green resources using a Fuzz-based Tilt-integral-derivative (FTID) controller. The FTID controller's settings are adjusted using the Sailfish Optimizer (SFO) to resolve the demand frequency challenge. (Zarate-Perez &

Sebastián, 2022) proposed a model that evaluates photovoltaic microgrid energy autonomy with a battery storage system. The energy consumption of the residential area and the solar irradiation data of the exact location were used for the isolated microgrid. The energy produced is sent towards the residential area for self-utilization, while surplus energy can be preserved in the BESS for future use.

(Soykan, et al., 2022) Served to determine the optimal operation and configuration of islanded microgrids comprising wind and solar renewable resources, batteries, and electric vehicles. A two-level probabilistic programming that is based on multi-objective optimization reduces life cycle expenses while increasing the dependability index. The operation of electric vehicles and their influence on the sizing and operation of microgrids are also discussed. (Chen, et al., 2022) presented the optimal capacity planning model for the grid-connected microgrid, considering renewable energy generation intermittencies. The Deep Convolution Generative Adversarial Network (DCGAN) and an upgraded k-medoids clustering technique were applied, along with a power management strategy. The suggested approach maximizes green energy utilization effectiveness while reducing investment costs as well as carbon emissions.

(Castillo-Calzadilla, et al., 2022) evaluated the feasibility of a low-voltage direct current distribution network, bringing attention to the obstacles that require being solved to make the transition. Grid configurations, distribution, and voltage-level standardization are explored. Some of the highlighted findings include the improved efficiency rate for off-grid microgrids between 15% and 30%. However, grid-connected microgrids are more economically viable. Voltage level standardization between 48V and 380V still needs to be concluded. (Huo, et al., 2022) proposed a chance-constrained convex optimization via second-order cone programming to determine the optimal energy storage system size for an isolated microgrid while also monitoring the reliability. An optimal compromise between reliability and investment cost was achieved with the chance constraints value of 4.8%.

(Kizito, et al., 2022) suggested a numerous phases probabilistic algorithm that evaluates the microgrid investment's techno-economics and processes, optimizing the dependability and robustness of the microgrid for a complete week of an electricity interruption. (Abubakr, et al., 2022) proposed adaptive control utilizing the Harris Hawks Optimizer to keep frequency and voltage within acceptable levels. (Dagal, et al., 2022) proposed a hybrid Series Salp Particle Swarm Optimization (SSPSO) algorithm to track the standalone battery charging station's Global Maximum Power Point (GMPP), considering partly cloudy conditions. The results of using SSPSO compared to conventional methods showed that the proposed method was far superior as it presented an optimum measuring effectiveness of 99.99%. (Li, et al., 2022) This paper discusses a technique to assist grid-connected microgrids with power fluctuation smoothing, thereby minimizing operating costs, including fluctuation penalties. A rolling horizon strategy was proposed, showing better results than conventional strategies, with about 5.67% savings.

(Adineh, et al., 2022) presented research addressing the quality of electricity challenges in isolated microgrids with green energy resources by presenting a cohesive single-end harmonic reduction solution based on a reliable optimization framework. The central controller gets voltage harmonic distortion readings of all buses in the microgrid and then returns the optimized voltage harmonic elements to localized controllers. (Zhang, et al., 2022) recommended creating a charging along with a discharging mechanism for electric automobiles and an objective function optimization strategy for dispatching microgrid loads. A hybrid optimization technique combining an updated Gravitational Search Algorithm, as well as Particle Swarm Optimization, was developed to improve load management in microgrids incorporating electric automobiles. The results demonstrated significant improvements as compared to other optimization methods. The impact of the number of electric automobiles linked to the microgrid along with their charging options is also explored.

When parts of power electronics and irregular loads are integrated into microgrids, difficulties with power quality (PQ) occur. An uneven loading in the microgrid may also be the cause of these problems. Without a doubt, they have an impact on the microgrid's daily operation schedule. Three indices are used in the framework to assess PQ: Voltage magnitude, total harmonic distortion (THD), as well as voltage imbalance factor (VUF). To avoid breaches of PQ indices, a non-iterative mitigation technique based on demand-side management (DSM) is proposed. This method is put onto the optimization derivation section of the OHPF as a collection of demand constraints (Budiman, et al., 2024). Both industry and human growth now place a high priority on the problems of energy scarcity and environmental damage. Therefore, research into green energy sources along with the effective utilization of distributed energy resources (DERs) is crucial and beneficial. Combine these energy resources with networked consumers to create a self-managed microgrid (MG) system. It can work in grid-connected or isolated configurations with flexibility (Tran, et al., 2023).

With a focus on enhancing small-signal stability, an optimization technique enhanced with domain knowledge is created to enhance the adaptive robustness of isolated microgrids. Optimizing the controller settings for the dispersed power electronic interfaces, that are vital to the system's fluctuating adaptability, necessitates the creation of a new eigenvalue-oriented target function with associated restrictions. Utilizing the understanding of the microgrid domain, incorporates an additional loss term a multivariate polynomial in the optimization variables to address the ensuing non-smooth and irregular optimization challenge (Kweon, et al., 2024). The haphazard generation of clean energy, combined with the unorganized network connection of electric automobiles, will make it impossible for the power system to run safely and consistently. To mitigate the influence of sporadic EV entry on electrical system performance, a programmable EV cluster framework is developed utilizing the Minkowski total. The wavelength neural network predicts that the generation of green energy will lessen the impact of output volatility on the smooth functioning of the electrical system (WNN) (Wu, et al., 2023). Renewable energy (RE) deployment is complex due to load demand changes and wind speed unpredictability. On the other hand, installing hybrid energy storage systems (HESS) in islanded microgrids can increase power supply dependability and allow for additional use of excess energy. (Seedahmed, et al., 2023).

Due to issues with power imbalance and peak demand on the grid in recent decades, demand-side management has emerged as a practical means of addressing the power system's and customers' needs. (Attou, et al., 2023). The depletion of non-renewable resources on Earth is leading to an increasing severity of environmental issues. Variations in loads cause instability in line characteristics, like voltage and frequency, which lowers power quality and overall system stability in microgrid operations. To overcome these obstacles, an optimized controller design was developed that incorporates the Smell Agent Symbiotic Organism Search (SASOS) algorithm, which combines the Smell Agent Optimizer (SAO) and Symbiosis Organism Search (SOS) algorithms. The Microgrid's Centralized Controller (MCC) used the SASOS, SAO, and SOS algorithms to control steady-state disturbances. (Mohammed, et al., 2023).

2.6.1 Review discussion of microgrid optimizations

(Asmus, et al., 2009) research provided the historical background of microgrids, expected developments, application categories, and the benefits of microgrids. The research indicates the start of microgrids as early as 1882, during Thomas Edison’s time. Also, in the research, further developments, application categories, and benefits of microgrids are discussed. The following definition of microgrids as given by (Su & Wang, 2012) has been adopted for the research, “A microgrid is a low-voltage distribution network that is located downstream of a distribution substation through a point of common coupling (PCC)”. There have been various implementations of microgrids, including islanded microgrids and grid-connected microgrids. As highlighted in the literature review, some challenges need consideration when designing microgrids, and these can be categorized into economic, technical, and environmental categories.

The optimization method’s role, as discussed in the literature review, is to find a balance between the different categories such as costs, reliability, and environmental friendliness. The concerns of energy shortage and environmental damage are currently critical to industry and human development. Research into renewable energy sources and the appropriate utilization of distributed energy resources (DERs) are vital and helpful in building a self-managed system called a microgrid (MG) by combining these energy resources with networked consumers (Tran, et al., 2023). Optimizing the controller settings for distributed electricity resources power electronic interfaces, considered critical to the system's fluctuating adaptability, necessitates the creation of a new eigenvalue-oriented target function with associated restrictions. They solved the ensuing non-smooth and irregular optimization issue by inserting an extra loss element, a multidimensional polynomial, in the optimization variables, leveraging thier understanding of the microgrid domain (Kweon, et al., 2024). Sustainable energy-based generators are becoming increasingly popular worldwide due to their abundance and environmental benefits.

Isolated hybrid microgrid systems (IHMS), a relatively recent development within this field, integrate multiple renewable energy generators, which include wind turbines, geothermal, wave, ocean energy, and solar photovoltaic (PV) systems. Due to Perhentian Island, Malaysia's growing population, and the industrial sector's reliance on a steady supply of electricity, the island nation needs an energy management system that can efficiently coordinate and regulate several power sources (Shezan, et al., 2023). An energy management system is now necessary. However, an over-reliance on fossil fuels and the growing disparity between the amount of energy consumed and the amount of power produced has led to several worldwide issues, such as high utility bills, greenhouse gas emissions, and energy shortages. (Hou, et al., 2024).

Since it is now well acknowledged that humans and the environment must coexist harmoniously, sustainable development is the most critical factor to consider. Many of the original power generation system's shortcomings were eventually discovered from a long-term strategic perspective. Globally, the former distribution sector has evolved into a twilight industry.

Since they are non-renewable resources, their contamination is irreversible, and their supply will eventually run out. The world faces two major crises threatening humanity's ability to progress sustainably: the energy crisis and the environmental catastrophe. Finding new, ecologically friendly energy sources is increasingly essential (Luo & Mei, 2023). The increasing utilization of intermittent green energy sources like wind, solar, and so on, as well as the expanding use of electric vehicles, has made microgrids and microgrid optimization difficulties more complex to tackle. To address upcoming power system issues, new techniques and combinations of current methods are being developed.

A summary of the microgrids optimization reviewed material may be found in Table 5.

Table 5. Review Summary of Microgrid Optimization

Author	Aim	Optimization Method	Hardware/Software used	Key Points
Asmus, et al., 2009.	The research provided the historical background of microgrids, expected developments, application categories, and benefits.	Not Applicable	A review paper	The historical background of microgrids from Thomas Edison's days has been clearly defined.
Rauf, et al., 2016.	The paper discusses the optimal use of smart grid DC grid technology for photovoltaic distributed generation, building reliable infrastructure to achieve defined goals.	Not Applicable	A review paper	Challenges and opportunities have been clearly defined.
Mohanty, et al., 2017.	The standalone PV-based microgrid power management is discussed, along with voltage stability problems and other power quality issues that need serious intervention.	Not Applicable	Simulation software	A clear definition of interventions is required to curb power quality issues.
Reddy, et al., 2017.	The paper presents the Fuzzy Multi-Criteria Decision-Making (FMCDM) approach to ranking load points and locations that would be used to restore distributed generators after natural disasters.	Fuzzy Multi-Criteria Decision Making (FMCDM), Particle Swarm Optimization (PSO)	Simulation software	Implementation and testing of the proposed optimization methods to rank load and locations to restore distributed generators.
Muthuvel, et al., 2017.	The design of a DC nanogrid using a simple and rigorous analytical approach is discussed.	PSO	Simulation software	Design, implementation, and, testing of the proposed optimization method.

Mumtaz, and Bayram, 2017.	The paper discusses the protection-related critical challenges of implementing islanded microgrids and possible solutions regarding operation, planning, and control.	Not Applicable	Simulation software	Discussion of protection-related challenges of implementing islanded microgrids and the possible solutions.
Arulraj, and Kumarappan, 2019.	The study provides for the optimal planning of distributed generators and capacitor installations, with the maximization of total cost benefit as the main objective function.	Weight Improved Particle Swarm Optimization and Gravitational Search Algorithm (WIPSO-GSA)	Simulation software, Real Power System	Testing of the proposed optimization method in real network and the IEEE test network.
Diab, et al., 2019.	The paper proposed a simulation model for the operation of hybrid PV, wind, battery, and diesel generator microgrid.	Whale Optimization Algorithm (WOA), Water Cycle Algorithm (WCA), Moth-Flame Optimization (MFO), Particle Swarm Optimization-Gravitation Search Algorithm (PSO-GSA)	Simulation software	Demonstration of the cost-saving superiority of WOA in comparison to other optimization methods.
Ruiz, et al., 2019.	A novel design method for integrating hybrid off-grid microgrids, which uses electric vehicles as both load sources, is proposed.	Not Applicable	Simulation software	Demonstration of the advantages of having electric vehicles providing ancillary services.
Raji, and Luta, 2019.	The paper presents the modeling and optimization of a community microgrid (diesel generator and rooftop PV) in an	Not Applicable	HOMER	Modeling and development of optimization method for a community microgrid.

	urban area in Cape Town, South Africa.			
Antonanzas-Torres, et al., 2021.	The research provides the present status of microgrid installations and significant challenges for future developments and installation of microgrids in West Africa.	Not Applicable	A review paper	Highlighted the status of electrification in West Africa and the opportunities and challenges for microgrid development.
Mathiesen, et al., 2021.	The research proposed a fast method for optimizing distributed energy resources investments and dispatch planning, considering 5-minute intra-hour variability.	Intelligent search techniques	Simulation software	The proposed method showed improvements to maintain optimality at below 2% while reducing runtime by 98.2%.
Zhang, et al., 2021.	A multi-criteria evaluation method is proposed to deal with peak shaving ability and carbon reduction effects of microgrids.	Not Applicable	Simulation software	Demonstration of savings achieved with the proposed method.
Mah, et al., 2021.	The research presents an optimization framework for designing and operating an off-grid microgrid with electrical and hydrogen loads.	Particle Swarm Optimization	Simulation software	Demonstration of savings achieved with the proposed method.
Mah, et al., 2021.	A multi-period P-graph optimization framework for microgrids with battery and hydrogen storage along with photovoltaic systems is presented.	Multi-period P-graph	Simulation software	Demonstration of savings achieved with the proposed method.

Çetinbaş, et al., 2021.	The study proposed applying the Harris Hawks Optimization (HHO) algorithm to optimize and design AC microgrids consisting of photovoltaic, wind turbines, battery energy storage, and diesel generators.	Harris Hawks Optimization (HHO), PSO, Firefly Optimization (FO), Gary Wolf Optimization (GWO), Salp Swarm Algorithm (SSA)	MATLAB/Simulink	Demonstration of savings from just over 1% to just over 18% from using HHO in comparison to other optimization methods.
Yang, and Su, 2021.	A robust optimization method for microgrids considering the intermittency of renewable distributed generation and the required reliability of the microgrid.	Intelligent search techniques	Simulation software, CPLEX	Testing of the proposed optimization method on the IEEE 39 bus test network.
Shen, et al., 2022.	The paper presents an energy storage optimization method for the microgrid of wind and solar generation considering multi-energy coupling demand response using electric, heat, and gas loads.	Intelligent search techniques	Simulation software	Demonstration of savings achieved with the proposed method.
Rai, and Das, 2022.	A load frequency control design for multi-area microgrids with renewable resources using a fuzzy-based Tilt-integral-derivative (FTID)controller is presented.	Fuzzy-based Tilt-integral-derivative (FTID), Sailfish Optimizer (SFO)	Simulation software	Demonstration of the proposed method.
Zarate-Perez, and Sebastián, 2022.	The research proposed a model that evaluates photovoltaic microgrid energy autonomy with a battery storage system.	Not Applicable	Simulation software	Demonstration of the proposed method to operate BESS and renewable energy resources.
Soykan, et	The study determines the optimal operation	Intelligent search	Simulation software	Demonstration of the advantages of

al., 2022.	and configuration of off-grid microgrids comprising wind and solar renewable resources, batteries, and electric vehicles.	techniques		having electric vehicles providing ancillary services.
Chen, et al., 2022.	The paper presents a suitable capacity estimation framework for the grid-connected microgrid, incorporating green power intermittencies, using a Deep Convolutional Generative Adversarial Network (DCGAN) with an enhanced k-medoids grouping technique, which includes a power management system technique.	Deep Convolutional Generative Adversal Network (DCGAN), k-medoids clustering algorithm	Simulation software	The proposed solution maximizes renewable energy utilization efficiency while it minimizes investment costs and carbon emissions.
Castillo-Calzadilla, et al., 2022.	The goal of this article is to analyze the practicality of a low voltage direct current distribution network, throwing some light on the problems that must be addressed to transition.	Not Applicable	A review paper	One of the findings of the study includes an improved efficiency rate for off-grid systems of between 15% to 30% however, economically grid-connected microgrids are most suitable.
Huo, et al., 2022.	A chance-constrained convergent optimization using second-order curve coding is suggested to estimate the best capacity for a power storage system for an isolated community grid while analyzing reliability.	Chance-constrained convex optimization	Simulation software	An optimal compromise between reliability and investment cost is achieved when the chance constraint is about 4.8%.

Kizito, et al., 2022.	A numerous phases probabilistic algorithm that analyses the techno-economics of microgrid investment and management by maximizing the microgrid's dependability and robustness throughout a whole week of an electrical failure is proposed.	Intelligent search techniques	Simulation software	Demonstration of the flexibility of the proposed algorithm to find a balance between opposing objectives.
Abubakr, et al., 2022.	The adaptive control using Harris Hawks Optimizer is proposed to maintain frequency and voltage at nominal values.	Harris Hawks Optimization (HHO)	Simulation software	Demonstration of the proposed method to control voltage and frequency at nominal values.
Dagal, et al., 2022.	A hybrid Series Salp Particle Swarm Optimization (SSPSO) algorithm is proposed to track the standalone battery charging station's global maximum power point (GMPP) under partly cloudy conditions.	Series Salp Particle Optimization (SSPSO)	Simulation software	The results showed that the proposed method is performed better, presenting an average tracking efficiency of 99.99%.
Li, et al., 2022.	The purpose of the is to assist grid-connected microgrids with power fluctuation smoothing, thereby minimizing operating costs, including fluctuation penalties.	Rolling horizon algorithm	Simulation software	A rolling horizon optimization strategy has shown better results than conventional strategies, with about 5.67% savings.
Adineh, et al., 2022.	Addresses power quality issues in islanded microgrids with renewable energy resources by introducing a unified single-end harmonic mitigation approach using a robust optimization model.	Not Applicable	Simulation software	Demonstration of the proposed method in mitigating power quality issues.

Zhang, et al., 2022.	The development of the charging-discharging model for electric vehicles and the objective optimization model of dispatching load for the microgrid are presented.	Gravitational Search Algorithm (GSA), PSO	Simulation software	Demonstration of the advantages of having electric vehicles providing ancillary services.
Mohammed, et al., 2023.	Presents an optimal control of steady-state disturbances in the power flow of microgrids.	SASOS, SOS, SAO	Simulation software	The MCC-SASOS strategy demonstrated a leading reduction in VUF of 41.24%,
Attou, et al., 2023.	To offer a practical and optimal management plan to lower power prices, decrease peak demand, and replace costly reserve generation units	Tree-based algorithm	Simulation software	The deployed controller lowers the network's peak demand by up to 54%
Budiman, et al., 2023.	The application of the harmonic power flow (HPF) and optimization formulation in a grid-connected microgrid and the optimal scheduling of that microgrid.	Optimal Harmonic Power Flow (OHPF)	Simulation software	The framework can prevent PQ index limitations from being violated under various events without unduly burdening the original optimization and harmonic load flow.
Tran, et al., 2023.	To create a power management strategy for an MG that works well in both operating modes.	Lagrange Multiplier	Simulation software	Demonstrated cost improvement due to the implementation of the proposed solution
Kweon, et al., 2023.	To resolve the ensuing non-convex and non-smooth optimization problem	Various optimization techniques	Simulation software	Showed significantly faster computing than state-of-the-art alternatives and a noticeable improvement in the objective function of over 1 dB.

Wu, et al. 2023.	To mitigate the effects of erratic EV access on power system performance	Wavelength Neural Network (WNN)	Simulation software	The viability and efficacy were confirmed.
Seedahmed, et al., 2023.	To set up an energy management system for an optimally designed system comprising wind turbines, an electric storage system, a hydrogen storage system, and a diesel generator to meet predetermined technical and financial requirements for a stand-alone microgrid.	Model Predictive Control	Simulation software	The EMS demonstrates that MPC has guaranteed the HRES boundaries to prevent degradation, circumvent weather-related power outages, and lower grid-integration startup costs.
Hou, et al., 2023.	With several ideal or nearly optimal DSM recommendations, the model hopes to increase users' receptivity to the advice and fully use DSM's advantages.	Indexed-based ring topology PSO	Simulation software	Qualifying solutions with better variety and higher accuracy in a single run, are revealed by numerical experiments

2.7 Reserve Margins

The reserve margin, the difference between peak demand and nominal capacity, is widely recognized as a crucial criterion for evaluating the state of a nation's electrical transmission and supply network. (Eskom, 2015). The technical rules for supplemental amenities in South Africa specify the requirements that apply to every spare class, which includes the subsequent five kinds of reserves (Sørensen, et al., 2017):

a. AGC manages regulatory reserves, which are used to reconcile demand and supply in real time.
b. Instant reserves are used to keep frequency inside appropriate limits following an unexpected occurrence.
c. Ten-minute reserves accommodate variations in demand as well as supply between the market for the day ahead along with real-time, incorporating errors in forecasting loads and unit reliability.
d. When slower reserves run out, emergency reserves are called upon to rebuild integrated electrical systems. They are also used when the system is not working properly.
e. Supplemental reserves ensure manageable risk for the day ahead.

Several control mechanisms are in place to balance the grid's supply and demand. The Union for the Coordination of Transmission of Electricity (UCTE) has devised a strategy for its member states that use the European interconnected electrical network. The policies in this document explain temporal control, secondary control, and tertiary control (Frunt, et al., 2009) as presented in Table 6.

Table 6. UCTE Reserve Capacity Characteristics

	Main Control	Backup Control
Time	30 seconds	15 minutes
UCTE Size	3000 MW	5700 MW
Ramp Rate	200 %/minute	7 %/minute
Duration	<15 minutes	Not Specified

Grid-forming controls enable fast inverters to respond quickly to disturbances and prevent traditional system oscillations, as is well-established. When there is a disturbance, power must be injected. There must be energy headroom in a PV system to allow dynamic control or services comparable to spinning reserve. Low energy costs can allow the value of additional services to more than balance out the production losses associated with energy headroom, which suggests lower PV system output (Krein & Jason, 2021). Adequate reserve capacity is necessary to compensate for inaccuracies in demand and renewable forecasts, as well as unplanned generator failures, in order to ensure safe and stable system operation. It is necessary to draw on fast-acting-up reserves when renewable resources fall short of projected production levels. However, a separate issue with decreasing conventional generators occurs when the actual wind generation exceeds the estimated value. An operator may be mandated to utilize all available wind power in specific networks.

Even in unregulated networks, the truly delivered wind surpasses the cleared amount because of the low instantaneous fashion wind price and the absence of an oversupply punishment. As a result, a significant amount of standby reserve is necessary to compensate for these erratic supplies. (Hedayati-Mehdiabadi, et al., 2015). Operating reserve is considered in Photovoltaic/Diesel Generator (PV/DG) hybrid systems since solar radiation and electrical load might fluctuate rapidly. This ensures a steady supply of power regardless of the load or solar radiation unexpectedly rises or drops. The regulating reserve addresses the quick, frequent, and continuous variations in load along with production that causes power imbalance (Movahediyan & Askarzadeh, 2018). Power system security can be preserved by using the proper hourly reserve margins to maintain equilibrium between demand alongside supply in the event of generation outages, inaccuracies in wind power generation forecasts, or errors in demand forecasting. Cost assessment to select the most affordable buffer margin is a critical component of electrical system operations because the cost of unit commitment rises with more excellent, more significant reserve margins (Kwon, et al., 2016).

The greater the quantity of green energy included in the electrical network, the greater the degree of unpredictability that power system operators need to consider. Reliability requires scheduling more operating reserves within the security-constrained economic dispatch. Current methods depend on traditional power plants to provide the functional versatility needed to mitigate the volatility of renewable energy sources. However, given the rising presence of green resources in the power mix, such unpredictable resources will be expected to participate in the balancing responsibilities. Wind turbines can mitigate against unpredictability by offering a reserve buffer (Hedayati-Mehdiabadi, et al., 2018). Constraints on the maintenance window guarantee that every unit is maintained within a predetermined time window, neither earlier nor later. Usually, operational service levels or yearly generating unit service frequencies enforced by power company policies set these time limits. Load limitations guarantee that each period over the planning horizon satisfies the load demand. Naturally, units that are not planned for repair during the pertinent times must be generated to meet this need. Dependability limitations can be included by specifying a backup or security buffer in addition to the demand restrictions. Operational continuity constraints are put in place to guarantee that the periods that occur when a certain generator component is serviced, operate continuously (that is, without disruption) (Lindner, et al., 2018).

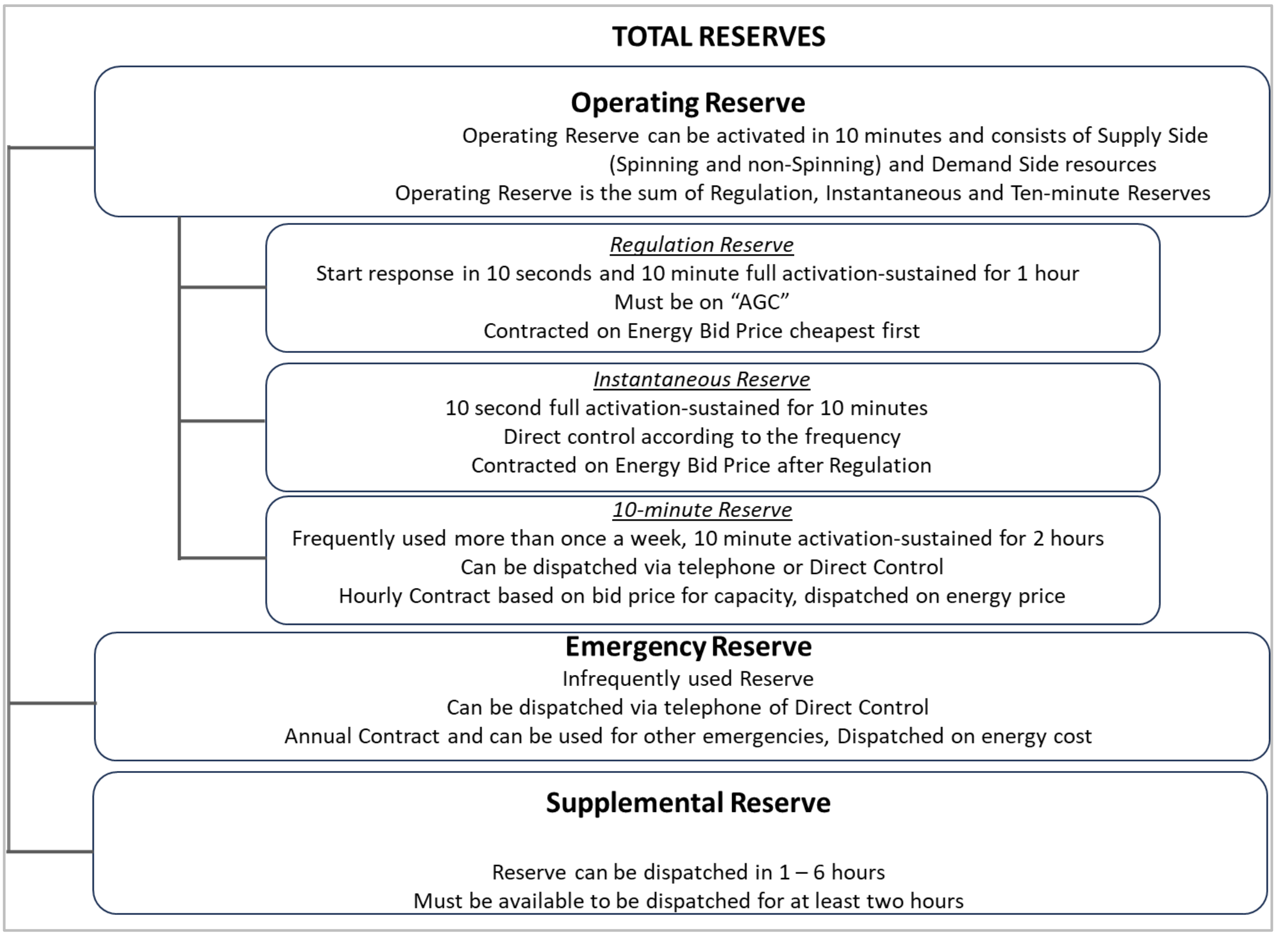

Figure 5. Reserve Margins as defined by SAGC System Operation Code

As stated in (Eskom System Operator, 2019), Figure 5 displays the overall reserves, which include operating reserves, emergency reserves, and supplemental reserves. However, the analysis only looks at operational reserves.

2.7.1 Review summary and discussion of reserve margins.

It is commonly acknowledged that one of the most important metrics for assessing the condition of a country's electrical transmission and supply network is the reserve margin, which is the difference between peak demand and nominal capacity. To guarantee safe and reliable system operation, sufficient reserve capacity is required to account for errors in demand and renewables projections and unforeseen generator breakdowns. When expected output levels of renewable resources are not met, fast-acting-up reserves must be accessed. Nevertheless, there is another problem with fewer conventional generators when real wind generation is higher than predicted.

Power system operators must account for an increasing degree of unpredictability as the amount of renewable energy increases. Adding extra operating reserves to the security-constrained economic dispatch schedule is necessary for reliability. Current technologies use conventional generators to give the operational flexibility required to mitigate the uncertainty arising from renewable energy sources. However, these sporadic resources would have to participate in the balancing chores as the percentage of green energy in the overall mix of sources increased. By providing a reserve buffer, wind turbines can help reduce unpredictability.

2.8 Discussion

Energy management systems have been around for decades, as shown in Figure 2, with the first control philosophy being load frequency control. One of the definitions of an energy management system is given by (Su & Wang, 2012) is “A microgrid EMS is a control software that can optimally allocate the power output among the DG units, economically serve the load, and automatically enable the system resynchronization response to the operating transition between”.

The above definition has been adopted for the research. (Asmus, et al., 2009) research provided the historical background of microgrids, expected developments, application categories, and the benefits of microgrids. The research indicates the start of microgrids as early as 1882, during Thomas Edison’s time. Also, and benefits of microgrids are discussed. The following definition of microgrids given by (Su & Wang, 2012) has been adopted for the research, “A microgrid is a low-voltage distribution network that is located downstream of a distribution substation through a point of common coupling (PCC).”

2.9 Conclusion

The definition mentioned above has been used in the study. The literature analysis above demonstrates the changes that have occurred over time. The researchers looking; they always look for new, easier, more accurate, efficient, effective, and so on methods to solve problems that arise now and towards the foreseeable future. The effective utilization of power management systems has shown benefits in the system's operation, control, and efficiency rate of renewable energy supplies, among other areas.

Microgrids have been implemented in various ways, such as islanded and grid-connected microgrids. Microgrid design involves several considerations, some of which are technical, environmental, and economical, as the literature study makes clear. The literature study highlights that the optimization method's function is to among many factors, including budgetary constraints, dependability, and ecological sustainability. The assessment of existing literature has demonstrated the significance and added value of integrating microgrids with energy management systems. Communities in rural places gain access to electricity, maximizing profits, increasing self-consumption, and reducing carbon emissions.

2.9.1 Research Contributions

1) The study considers a hybrid microgrid (solar, wind, BESS, and EVs) that operates both in connected and islanded modes.
2) Development of an optimization method for a microgrid that maintains reserve margins for critical loads.
3) Development of an optimization method that doesn't allow BESS charging from the grid but only from excess renewable energy generation.

Genetic algorithms and Particle Swarm Optimization (PSO) are powerful tools for solving various optimization problems. Genetic algorithms handle complex search spaces, find near-global optima, work with diverse problem types, are robust to noise, and can parallelize computations, making them ideal for complex optimization problems. PSO has several key advantages, including its simplicity in implementation, ease of parameter tuning, fast convergence, ability to handle high-dimensional problems, and good balance between exploration and exploitation.

The following chapter presents a theoretical overview of the optimization techniques chosen for use in the research study.

CHAPTER THREE

PSO FOR HYBRID RENEWABLE ENERGY MICROGRID SYSTEM UNDER UNCERTAINTY

3.1 Introduction

The topic of power system optimization has been around for decades. It continues to be improved throughout time by advances in computing and programming mathematics approaches. However, it precedes the introduction of digital computers, which completely revolutionized numerical optimization and computation in general. The strategies developed to address power system operation issues, including conventional and contemporary optimization techniques, can be categorized into three classes based on optimization theory as below. (Zhu, 2015).

1. Conventional optimization techniques, such as unrestricted optimization, nonlinear programming (NLP), linear programming (LP), quadratic programming (QP), etc.
2. Intelligent Search Techniques like neural networks (NN), evolution algorithms (EA), Tabu Search (TS), Particle Swarm Optimization, etc.
3. Nonquantitative Techniques such as probabilistic optimization, fuzzy set, etc.

The study focuses on two types of intelligent search optimization algorithms: Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) and explored in the subsequent sections. Genetic algorithms and Particle Swarm Optimization (PSO) are powerful tools for solving various optimization problems. Genetic algorithms handle complex search spaces, find near-global optima, work with diverse problem types, are robust to noise, and can parallelize computations, making them ideal for complex optimization problems. PSO has several key advantages, including its simplicity in implementation, ease of parameter tuning, fast convergence, ability to handle high-dimensional problems, and good balance between exploration and exploitation.

3.2 Theory of Particle Swarm Optimization

Particle swarm optimization is an algorithmic method in the field of computers that optimizes a challenge by constantly striving to enhance the potential remedy based on a predefined quality criterion. It solves a challenge by using a collection of probable answers, referred to as particles in this case, and altering their velocity and position within the search space using a straightforward mathematical equation. A particle's motion is propelled to the most recognized locations in the search space, which gets modified when other particles find superior locations and are influenced by their local best-known position. As a result, the swarm should be directed toward the optimal solutions.

Kennedy and Eberhart initially presented Particle Swarm Optimization (PSO) in 1995. The approach is modeled after the natural procedure that flocks of birds or schools of fish use to find food. When flocks of birds look for food in the sky at random, the birds in the flock communicate their finds and work together to find the best hunt, increasing the efficiency of the flock's search. PSO is a population-centered search strategy in which particles gradually modify their position based on their own and other particles' experiences. The ideal application of a multifaceted vector space is to find the highest or lowest value of a given function. PSO is a metaheuristic algorithm because it may search vast spaces of potential solutions and make little or no preconceptions regarding the problem being optimized. Furthermore, PSO is not dependent on the slope of the challenge under optimization. This implies that contrary to traditional optimization methodologies like slope decline and Quasi-Newton approaches, PSO lacks the need for the optimization problem to be differentiable. Metaheuristic algorithms like PSO, however, do not ensure that an ideal solution will ever be discovered. PSO is unique because it proposes searching for better answers by flying candidate solutions through hyperspace. The algorithm's stability and simplicity are its defining features. Few lines of code are needed to implement it, and it only uses simple mathematical operators with low memory needs and a small number of parameters that must be set for each problem.

This "natural simplicity," based on mimicking nature, gives rise to a potent algorithm that has been useful for various tasks, most notably the weight training of artificial neural networks. (Hu, et al., 2004). The PSO algorithm is an unpredictable multiple-agent parallel search approach in which the distinct elements within a group represent potential solutions to an optimization problem. According to its personal as well as the swarm's cohesive action flying encounters, particles might be considered self-sufficient smart agents that "fly" within a multidimensional problem space in search of the best possible solution to the optimization challenge. Every particle i in the group is made up of 3 n-dimensional vectors (n represents the dimensions of the searchable area, R^n), which can be represented at time t as the current location, X_i^k, the previous best position, p_i^{best} and the velocity, V_i^k (Mataifa, et al., 2023). Each particle's current position denoted as X_i^k, Serves as the decision vector. The decision vector is assessed for "fitness" at each iteration using the optimization problem's objective function. A particle's position is updated to move it towards a "better" position based on its improved fitness evaluation.

The particle velocity, V_i^k, represents the combined flight experiences of the particular particle and the remainder of the swarm. p_i^{best} is the greatest degree of fitness that a particle achieved up to the most recent repetition that each particle records. This location is changed to reflect the current position when the current position achieves a higher fitness value than the previous highest value. The swarm, resembling a group of birds hunting for a meal, will most probably move to the best position in the area of search as repetitions continue. One key characteristic of particle swarm optimization is the interpersonal relationships along with data exchange that occurs among the elements in the cluster. The group's cohesive behavior enables the algorithm to seek as efficiently as feasible (Tam, 2021).

Consider having *P* particles and denote the position of particle *i* at iteration t as $X^i(t)$ which can be represented in coordinates form as shown in Equation 3-1.

$$X^i(t) = (x^i(t), y^i(t)) \tag{3-1}$$

The exact representation is applied in the velocity of each particle as denoted in Equation 3-2.

$$V^i(t) = (v_x^i(t), v_y^i(t)) \tag{3-2}$$

At the next iteration, the position of each particle is updated using Equations (3-3) to (3-5).

$$X^i(t+1) = X^i(t), V^i(t+1) \tag{3-3}$$

$$x^i(t+1) = x^i(t), v_x^i(t+1) \tag{3-4}$$

$$y^i(t+1) = y^i(t), v_y^i(t+1) \tag{3-5}$$

Particle velocities are updated for each iteration using Equation 3-6.

$$V^i(t+1) = wV^i(t) + c1r1(pbest^i - X^i(t)) + c2r2(gbest^i - X^i(t)) \tag{3-6}$$

Where r1 and r2 are random numbers between 0 and 1, while constants w, c1 and c2 are the PSO parameters. $pbest^i$ is the best position of particle *i* and $gbest^i$ is the best position considering the complete particle swarm. Figure 8's flowchart presents the standard PSO algorithm. Table 7 summarizes the PSO algorithm's distinguishing properties compared to other heuristic optimization strategies.

Table 7. Parameters of PSO Technique

Name	Details
Population Size	The particle group's population size, or the overall amount of elements. The larger group sizes suggest greater processing power and a bigger search area. Swarm sizes ranging from 20 to 60 are suitable for a variety of applications.
Iterations	When there are several options, it is easier to find the best one. A vast number may result in expensive computing costs. The nature of the task may determine the proper maximum number of iterations.
Velocity	The corresponding values of the accelerating constants determine how each element contributes towards a total velocity adjustment. The right mix of intellectual and social elements can assist solve a range of challenges.

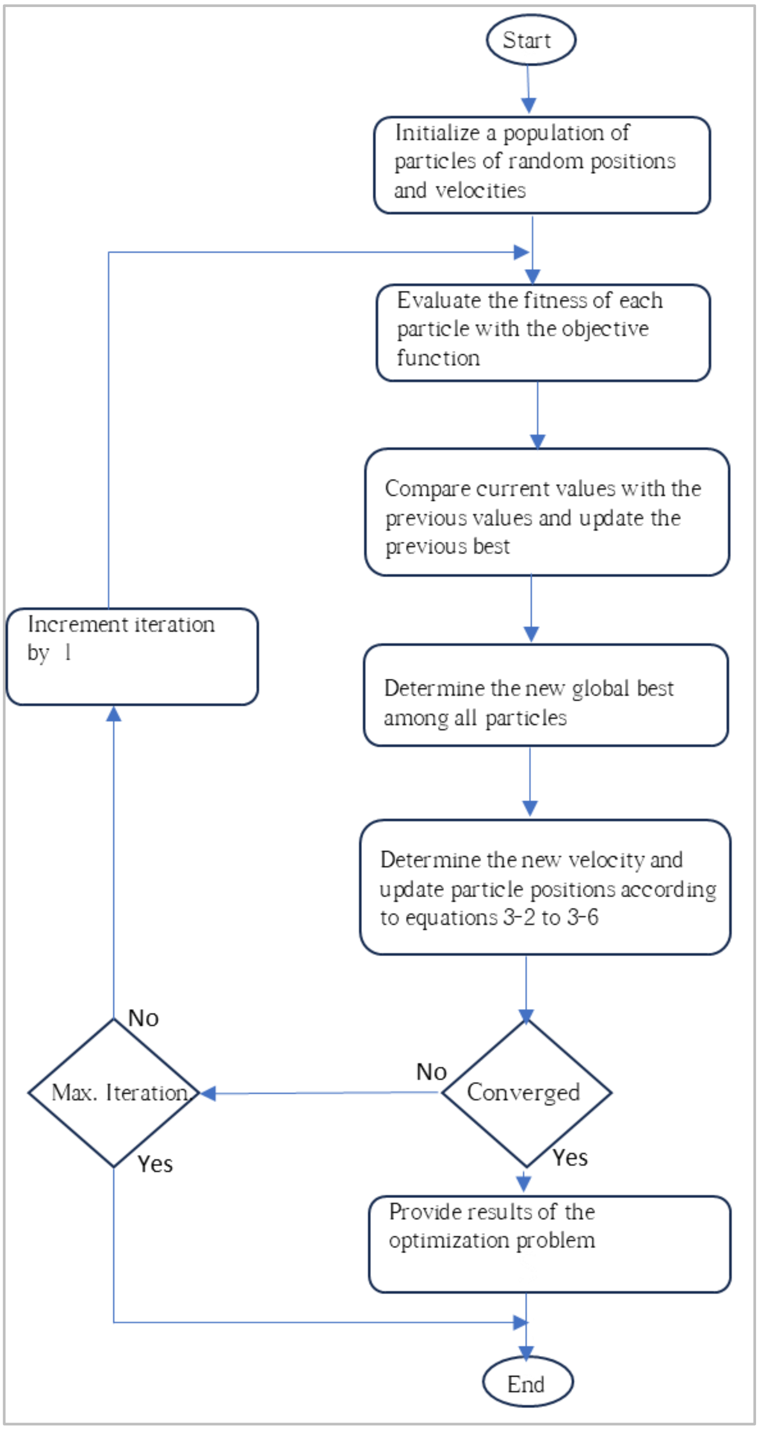

Figure 6. PSO Algorithm Flow Diagram

Figure 7 illustrates a microgrid that integrates wind, photovoltaic, BESS, and EVs. The microgrid system's modelling takes into consideration the unpredictability associated with clean energy sources along with electric vehicle behaviours. The next sections address the modelling of individual systems.

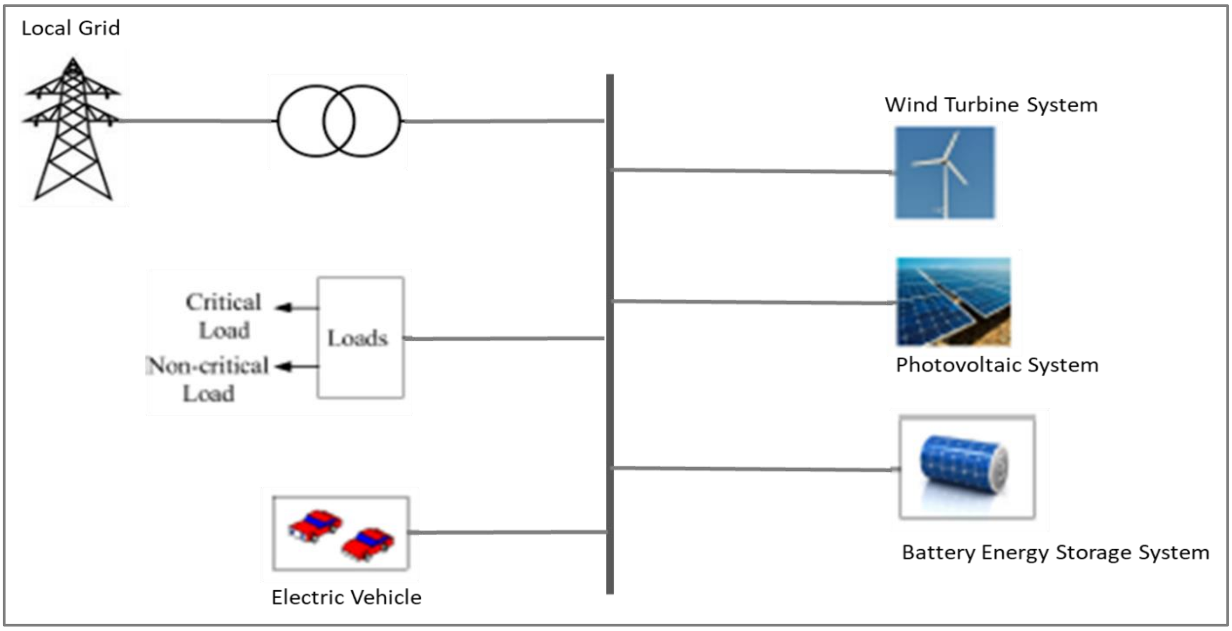

Figure 7. Grid-integrated Microgrid

3.3 Electric Vehicle Modelling

Environmental concerns, such as carbon emissions, drove the development of electric vehicles. The electric vehicle's batteries serve as a load (the system needs to charge them) and an electricity source (they provide electricity to the microgrid network).

$$T_{maxdis} = \frac{0.5(SOC_{max} - SOC_{min})\,\mathrm{Cev}}{P_{dis}} - \frac{SW_{100}}{100P_{dis}} \tag{3-7}$$

Whereby,

T_{maxdis} = Maximum EV battery discharging duration

S = Daily driving distance in km

SW_{100} = energy consumption per 100 km (kWh/100km)

SOC = Battery State of Charge in percentage

C_{EV} = Total battery capacity (C/kWh)

The charging duration is defined as follows.

$$T_{char} = \frac{\left(P_{dis} \times T_{maxdis} + \frac{SW_{100}}{100}\right)}{P_c * P\eta_{cev}} \tag{3-8}$$

Whereby,

T_{char} = Charging duration in hours

η_{cev} = Charging efficiency

P_c = Charging power in kW

The total charging load for all the electric vehicles is defined as follows.

$$P_{EV(load)} = \sum_{j}^{M} P_j(t)M \tag{3-9}$$

Whereby,

$P_{EV(load)}$ = Total charging load

t = 1, 2, 3, …,24

M = number of electric vehicles connected

$P_j(t)$ = power rating of the EV battery

The simulation includes ten electric vehicles with 60 kWh battery capacity.

3.4 Photovoltaic Modelling

Energy production from a single solar panel is given using the following equation:

$$P_{pv} = \mathrm{SI} * A_{pv} * \eta_{pv} \tag{3-10}$$

Whereby,

SI = Solar Irradiance of the area in W/m^2

A_{pv} = Solar panel area

η_{pv} = Solar panel efficiency

The following Equation gives the overall power generated from all connected solar panels.

$$P_{Tpv} = N_{pv} * P_{pv} \tag{3-11}$$

Whereby,

P_{Tpv} = Total Power Output Generated

N_{pv} = Amount of PV panels

It was presumed the converter was equipped with DC/AC ratio of 1 with no power losses being considered. For simplicity, the temperature influence was ignored in the computation. The solar panel utilized in the study has a size of $2100m^2$ and an efficiency of 30%.

3.5 Wind Turbine Modelling

Power generation from a single wind turbine is calculated using the following formula.

$$P_{wind} = \begin{cases} 0 & v \leq v_{cin} \\ 0 & v \geq v_{cout} \\ P_r \frac{v^k - v_{cin}{}^k}{v_r{}^k - v_{cin}{}^k} & v_{cin} < v < v_r \\ P_r & v_r < v < v_{cout} \end{cases} \tag{3-12}$$

Whereby,

v = Current wind speed

v_{cin} = Cutin wind speed (wind speed for the turbine to start producing)

v_{cout} = Cutout wind speed (wind speed for the turbine to stop producing)

v_r = Rated wind speed at which the turbine produces rated power

The overall electrical power produced by all wind turbines connected is provided by the following Equation.

$$P_{Twind} = N_{wind} * P_{wind} \tag{3-13}$$

Whereby,

P_{Twind} = Total Power Output Generated from wind turbines

N_{wind} = Wind turbine number

The estimate disregarded the effect of air density. The wind turbine has a cutin wind speed of 5 m/s, a cutout wind speed of 25 m/s, a rated wind speed of 11 m/s, and a total power output of 5.8 MW of all the wind turbines.

3.6 Battery Storage System Modelling

The battery energy storage technology is critical in renewable microgrids because it improves reliability. An energy preservation technology is needed to increase system resilience. The battery energy preservation technology has a capacity of 100 kWh and can charge and discharge at a maximum of 100 kW. The power system equation below is used for battery simulation.

$$P_{bat_{disc}}(t)\frac{\Delta t}{\eta_{bat_{disc}}} + T_{bat}(\mathrm{t}) + (P_{bat_{char}}(t) * \eta_{bat_{char}}\Delta t = T_{bat}(\mathrm{t}+1) \tag{3-14}$$

Whereby,

$P_{bat_{disc}}$ = Power flow for battery discharging

$\eta_{bat_{disc}}$ = Discharging efficiency

Δt = Time interval

$T_{bat}(\mathrm{t})$ = Total energy for all batteries at time interval t

$P_{bat_{char}}$ = Power flow for battery charging

$\eta_{bat_{char}}$ = Charging efficiency

$T_{bat}(\mathrm{t}+1)$ = Total energy for all batteries at time interval t + 1

The following formula gives the total available energy capacity of the batteries.

$$SOC_{bat}(t) = \frac{T_{bat}(t)}{E_{bat} * N_{bat}} \tag{3-15}$$

Whereby,

E_{bat} = Maximum available energy capacity of the batteries

N_{bat} = Number of batteries in the microgrid

3.7 Battery Storage System Degradation Modelling

Battery degradation expenses are an important part of the overall microgrid operating costs. As a result, a reliable deterioration expense simulation is required, and it should be shown as an accurate representation of the BESS fundamental parameters (Zhang, et al., 2022). The battery degradation costs are given by,

$$C_{bat} = \sum_{i \in T} E_{bat} * \int_{SOC_0}^{SOC_T} w(s)|ds| \tag{3-16}$$

Whereby,

SOC_T = State of Charge (SOC) at a time interval T

SOC_0 = initial State of Charge (SOC)

$w(s)$ = Wear density function

The formula to calculate the wear density function is given by,

$$w(s) = \frac{C_{batrepl}}{2 * \eta_{bat}^2} * \frac{B(1 - SOC)^{B-1}}{A} \tag{3-17}$$

Whereby,

$C_{batrepl}$ = Battery replacement costs

A & B = Battery-specific parameters as given by the manufactures

3.8 Grid Energy Exchange Costing Model

Grid energy exchange costs are the expenses incurred when purchasing energy from the utility power network during periods of little or no output and selling surplus energy back into the utility power network. Purchasing as well as selling prices commonly differ. The equation defining this phenomenon is shown below.

$$C_{grid} = \sum_{t=1}^{T} PP_t * E_{pur,t} - \sum_{t=1}^{T} PS_t * E_{sel,t} \tag{3-18}$$

Whereby,

PP_t = Electricity purchase price in t-cycle (ZAR/kWh)

$E_{pur,t}$ = Quantity of electricity purchased in t-cycle (kWh)

PS_t = Electricity sell price in t-cycle (ZAR/kWh)

$E_{sel,t}$ = Quantity of electricity sold in t-cycle (kWh)

3.9 Optimization Method Formulation

The objective function used to minimize the cost of operating a grid-connected hybrid microgrid is defined as follows. It should be emphasized that microgrid operating costs only comprise battery operation or degradation expenses and grid interface costs, maximizing the use of renewable energy resources.

$$C_{mg} = C_{bat} + C_{grid} \tag{3-19}$$

Whereby,

C_{bat} = Cost of battery energy system operation and maintenance

C_{grid} = Net cost of microgrid power exchange with grid

C_{mg} = Microgrid operation costs

Subject to,

1. Power balance constraint

$P_{Tpv} + P_{Twind} + P_{bat_{disc}} + P_{grid_{rec}} + P_{EV(load)} - P_{EV(load)} - P_{bat_{char}} - P_{load} - P_{grid_{sent}} - P_{res} = 0$ (3-20)

Whereby,

P_{load} = Microgrid load demand (kW)

$P_{grid_{rec}}$ = Power from grid (kW)

$P_{grid_{sent}}$ = Power to grid (kW)

P_{res} = Instantaneous reserve margins (kW)

2. Grid power constraint.

$$P_{grid_{rec}} \leq P_{load} + P_{EV(load)} \quad (3\text{-}21)$$

3. Generation limit constraint

$$P_{Tpvmin} < P_{Tpv} < P_{Tpvmax} \quad (3\text{-}22)$$

$$P_{Twindmin} < P_{Twind} < P_{Twindmax} \quad (3\text{-}23)$$

$$P_{bat_{discmin}} < P_{bat} < P_{bat_{charmax}} \quad (3\text{-}24)$$

4. Battery charging constraint.

$$P_{Tpv} + P_{Twind} + P_{res} > P_{load} + P_{EV(load)} \quad (3\text{-}25)$$

5. Reserve margins constraint.

$$(P_{load} + P_{EV(load)}) * \frac{10}{100} = P_{res} \quad (3\text{-}26)$$

3.10 PSO Application

To apply the particle swarm optimization method to any problem, the structure of the algorithm must be transferred to the mechanics of the problem. Whenever searching for the optimum answer to the challenge, an association connecting particle locations and motions and the optimization problem's deciding matrix must be developed, along with a mechanism for making adjustments to the deciding matrix. The particle swarm optimization method addresses the mixed microgrid optimization problem presented in Equation (3-19), according to limitations specified in Equations (3-20) – (3-26).

The mechanics of the position and speed Equation (3-6) have to be converted into the framework of the mixed microgrid optimization challenge. The following steps are taken:

- The quantity of producing units determines how many individuals are assigned to each particle inside the swarm. The locations of element members indicate the real power produced by the units of the optimization challenge.
- Accelerations represent parameters utilized for searching in the constraint's realm, even though they carry identical definitions as real power.
- The swarm is assumed to have Np particles in total.

The following procedures are used to construct the PSO algorithm for the ideal hybrid renewable energy microgrid (Krishnamurthy, et al., 2017). The critical steps needed to implement the PSO algorithm are to map the algorithm parameters to problem parameters as defined in steps 2 -4 and the quantities limits are based on system constraints defined previously. The initial parameter sizes are random guesses that should be with the defined limits.

Step1: Configure the starting quantities for the particle swarm optimization settings, comprising the highest possible number of repetitions (MaxIt), homogeneous randomized quantities (r1, r2), acceleration coefficients (c1, c2), and momentum component (ω) as per Equation 3-27.

$$V^i(t+1) = wV^i(t) + c1r1(pbest^i - X^i(t)) + c2r2(gbest^i - X^i(t)) \tag{3-27}$$

Step 2. Apply generator limit restriction to find the initial velocity's minimum as well as the highest possible number, as shown below.

$$-0.5X_t^{min} \leq V^i(t) \leq 0.5X_t^{max} \tag{3-28}$$

$X = 1, Np \; i = 1, n-1$

Np represents the quantity of elements in a group, while n represents the quantity of members in a single element, equivalent to the quantity of producing units.

Step 3: Define each particle's initial velocities, as shown in Equation (3-29).

$$V^i(t) = V_t^{min} + r(V_t^{max} - V_t^{min}) \tag{3-29}$$

V_t^{min} and V_t^{max} represent the preceding minimum as well as the highest possible number of velocities, respectively.

Step 4: Define the element members' initial location consequently, assuring all limitations are respected.

$$X^i(t) = X_t^{min} + r(X_t^{max} - X_t^{min}) \tag{3-30}$$

In the power system, there are three types of buses: slack bus, generator (PV), and load (PQ). Slack buses, referred to as swing buses, are used in power systems to maintain the equilibrium of the real and reactive powers for load flow calculations. The swing bus makes up for system losses by sending and receiving real and reactive powers from the network when the load is higher than production and to the network when the generation is higher than the load. Two buses are considered swing buses in the microgrid simulation (the grid bus and the BESS bus) but not simultaneously; grid bus is the main priority slack bus while BESS bus takes over when the grid is not available. The slack bus in the particle swarm optimization technique fulfills the power equilibrium restriction in Equation (3-20).

Step 5: Determine the objective function for the element starting locations as described in Equation (3-19).

Step 6: Select the optimum and overall ideal initial points as outlined below.

i. The particles' original placements inside the group are considered to represent their ideal locations.

ii. The overall best is the ideal location among all optimum element locations.

Step 7: Determine the new velocities utilizing Equation (3-27) as well as verify the limits established in Equations (3-20) - (3-26).

Step 8: Calculate the generating unit's new position in the elements utilizing the equation below as well as verify the restrictions.

$$X^{inew} = X_t^{i-1} + X_t^{inew} \quad (3\text{-}31)$$

Step 9: Define the revised active power of the generating units as well as utilize the constraints to confirm the generating unit's new position among the elements.

Step 10: Verify the goal function (microgrid cost minimization as defined in Equation 3-19) outcomes specified in the particle swarm optimization flow chart.

$$If\ F^{inew} < F^{ibest-1}\ then\ F^{ibest} = F^{inew} and\ X^{ibest} = X^{inew}$$

$$Else\ F^{ibest} = F^{ibest-1}\ and\ X^{ibest} = X^{ibest-1}, G^{ibest} = X^{ibest-1}$$

Step 11: Keep going through steps 5-10 till the highest possible number of repetitions has been achieved or the technique has been completed.

In the following section, microgrid simulation results are obtained using particle swarm optimization to determine optimal operation parameters.

3.11 PSO Simulation Results

The network specified in the above sections has been modeled and simulated with MATLAB R2024b utilizing a laptop running Microsoft Windows 11 Enterprise, with an i5-8365 CPU at 1.6 GHz and four cores. Meteorological data of a PV system (solar irradiance) as well as wind speed data for a wind turbine system are utilized to simulate renewable energy's intermittent nature. Irradiance data for a PV system under clear and hazy conditions are supplied. The WindPvLoadPriceData file contains a load profile and energy price data for buying and selling electricity with the grid operator, which is based on MTALAB examples and has been updated to include all essential data. The data presented covers a whole day, 24 hours, with an average of 1 minute. The data was further divided into 1-hour average samples for simulation to facilitate computation, as shown in Table 8. To generate the simulation results, the PSO algorithm ran for 48 seconds.

3.11.1 Data Management

Data Collection: The simulation data was taken from several secondary sources, mainly MATLAB examples for renewable energy weather-related data and load. In contrast, the price data is the modified data of the (City of Ekurhuleni, 2024).

Data Processing: MATLAB altered data from one minute to an hour for 24 hours.

Data Security and Privacy: The data used is public data, which is accessible to everyone on public platforms

Data Sharing and Reuse: The data will be made available via the Cape Peninsula University of Technology database to anyone accessing it.

Table 8. Hourly Simulation Data

Time (Hour)	Wind (kW)	Solar Clear Day (kW)	Solar Cloudy Day (kW)	Load Demand (kW)	Electricity Price (ZAR/kWh)
1	580	0	0	457.64	2.89
2	472.7	0	0	270.058	2.89
3	507.5	0	0	200.831	2.89
4	580	0	0	177.178	2.89
5	580	0	0	153.659	2.89
6	580	28.95	12.6678	180.346	2.89
7	580	173.977	161.195	277.195	4.35
8	402.133	329.009	231.785	374.076	9.82
9	170.133	473.41	496.415	518.656	9.82
10	14.5	601.353	627.65	611.138	9.82
11	0	701.604	742.695	610.077	4.35
12	0	768.139	655.762	635.033	4.35
13	0	789.5	186.89	658.591	4.35
14	0	768.331	819.016	683.404	4.35
15	0	698.673	87.787	731.073	4.35
16	0	593.808	598.137	755.427	4.35
17	0	464.902	51.0998	828.978	4.35
18	95	322.406	321.417	899.059	4.35
19	236.83	175.628	184.584	897.749	9.82
20	208.8	33.4198	32.8875	897.945	9.82
21	479.467	0	0	897.621	4.35
22	580	0	0	773.862	4.35
23	580	0	0	654.885	2.89
24	580	0	0	583.556	2.89

3.11.2 Grid Interaction Costs

Figure 8 depicts three pricing ranges for the grid integration costs, including selling energy to the system as well as purchasing energy from the grid. During off-peak hours energy rate is ZAR 2.89/kWh, the ordinary rate is ZAR 4.35/kWh, and the highest possible rate is ZAR 9.82. The different pricing periods are off-peak between 22:00 and 06:00, standard between 06:00 and 07:00, 10:00 and 18:00, and peak hours between 08:00 and 10:00, 18:00 and 22:00.

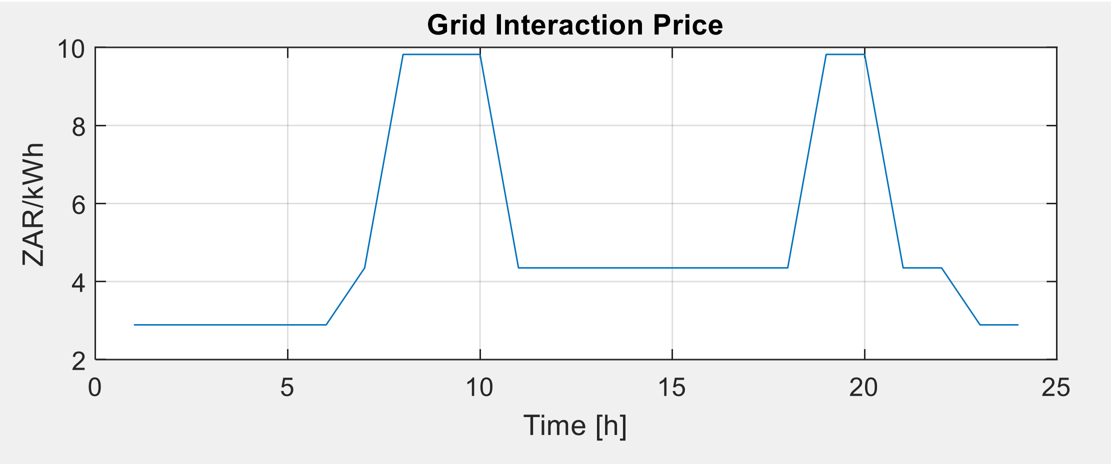

Figure 8. Grid Energy Exchange Costs

3.11.3 Photovoltaic System

Figure 9 depicts a photovoltaic system's behavior on a clear sky day. The system is presented to generate energy exclusively during daytime, between sunrise and dusk. Peak power is obtained between 11:00 and 15:00, after which power diminishes. Figure 10 depicts a photovoltaic system simulation based on partly cloudy day irradiance data. In contrast to a clear day simulation graph in Figure 9, which is more predictable, unpredictable behavior is observed as clouds come by, resulting in unexpected decreases in production.

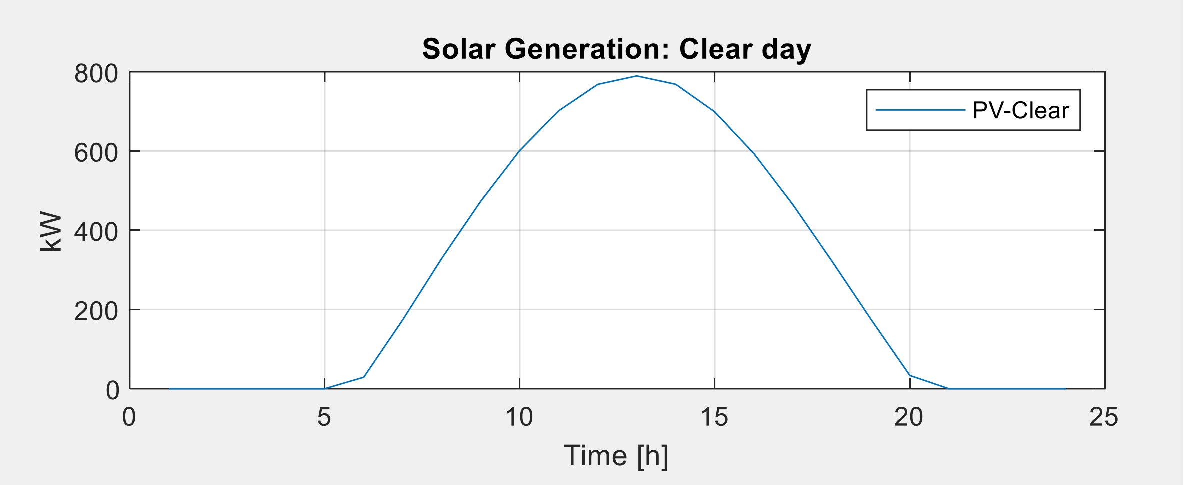

Figure 9. Solar Energy Generation Profile: Clear Day

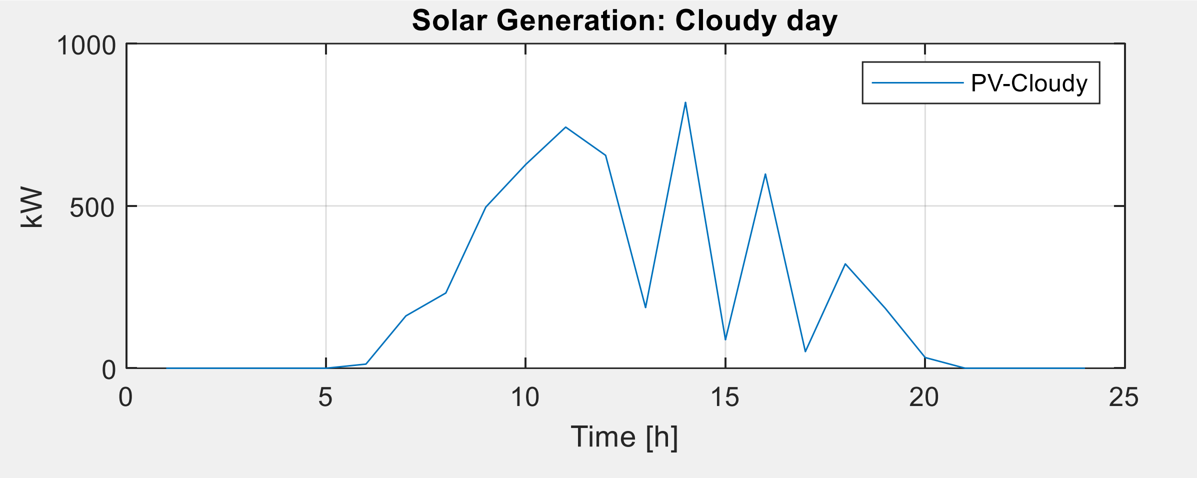

Figure 10. Solar Energy Generation Profile: Partly Cloudy Day

3.11.4 Wind Turbine Generation System

The meteorological data containing wind speed in the WindPvLoadPriceData file represents the generation profile of a wind turbine system as shown in Figure 11. As previously stated in (Livermore, 2012), wind turbine generators create electricity at night when wind speeds are often higher. Figure 11 displays this understanding, which seems to demonstrate the opposite of what the photovoltaic system is accomplishing, with generation only visible through the course of the day, as illustrated in Figures 9 and 10.

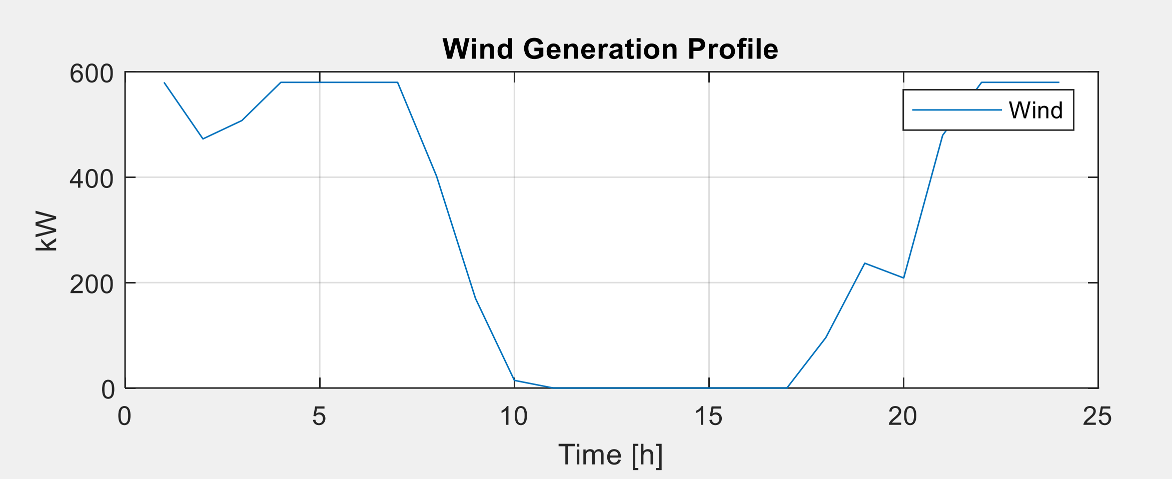

Figure 11. Generation Profile of a Wind Turbine

3.11.5 Microgrid Load Demand Profile

Figure 12 displays the microgrid load profile based on data from the WindPvLoadPriceData file.

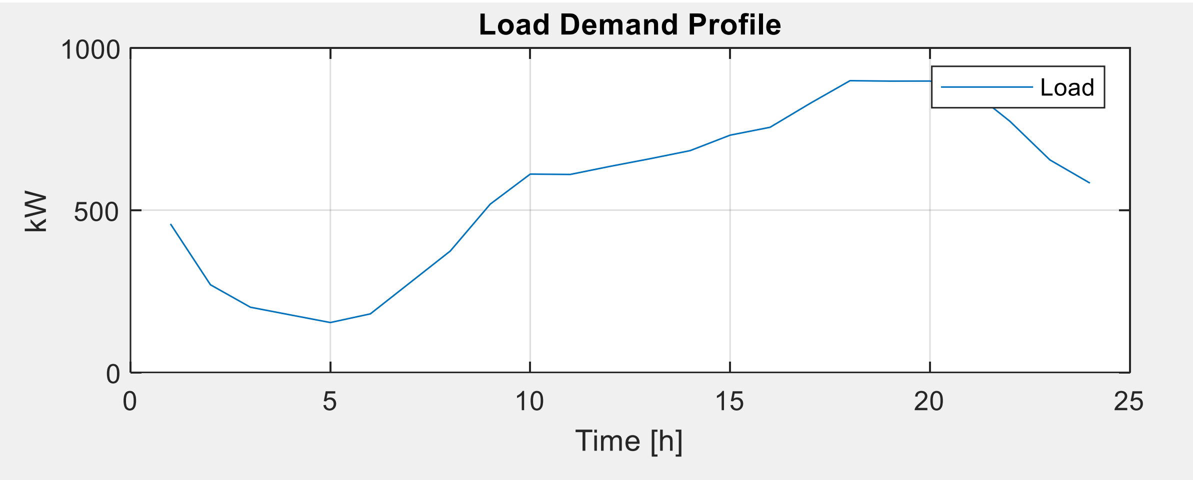

Figure 12. Microgrid Load Demand Profile

3.11.6 Microgrid Operation without BESS

3.11.6.1 MG Operation: Clear Day

Figure 13 depicts microgrid operation in the absence of BESS. The microgrid demand frequently gets power from green power resources (wind and solar), and in the event the load demand is not met, more electricity is obtained through the national grid. The diagram illustrates that electricity is purchased off the electrical system from around 14:30 to 23:30. Whenever the consumption is less than the energy generated from renewable sources, any extra power goes out to the network operator. The energy was offered for sale to the electrical system administrator between 23:30 and around 14:30. Throughout the early hours, the microgrid delivers expensive power to the national grid, and extra renewable energy is sold during conventional pricing periods. Nevertheless, throughout the nighttime peak, before the wind turbine generating unit reaches its maximum production, an additional energy supply is required to meet load demand, which is obtained from the electricity company at a high cost.

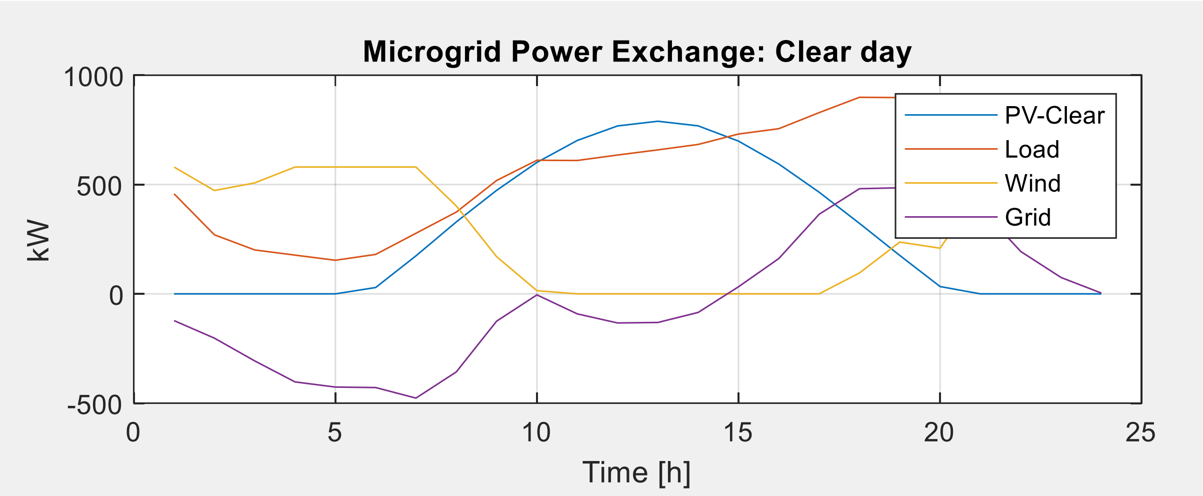

Figure 13. MG Energy Exchange on a clear sky day

3.11.6.2 MG Operation: Partly Cloudy Day

Figure 14 depicts a microgrid operating without BESS on a partially overcast day. During off-peak periods, the microgrid load is provided by renewable energy sources, and when demand is not fulfilled, additional electricity is obtained from the grid. With unreliable renewable generation, more energy is acquired from the grid, even during peak periods, resulting in high prices for the microgrid operator. As described in Section 5.2.6, the adoption of BESS has been beneficial in lowering the microgrid's operating expenses.

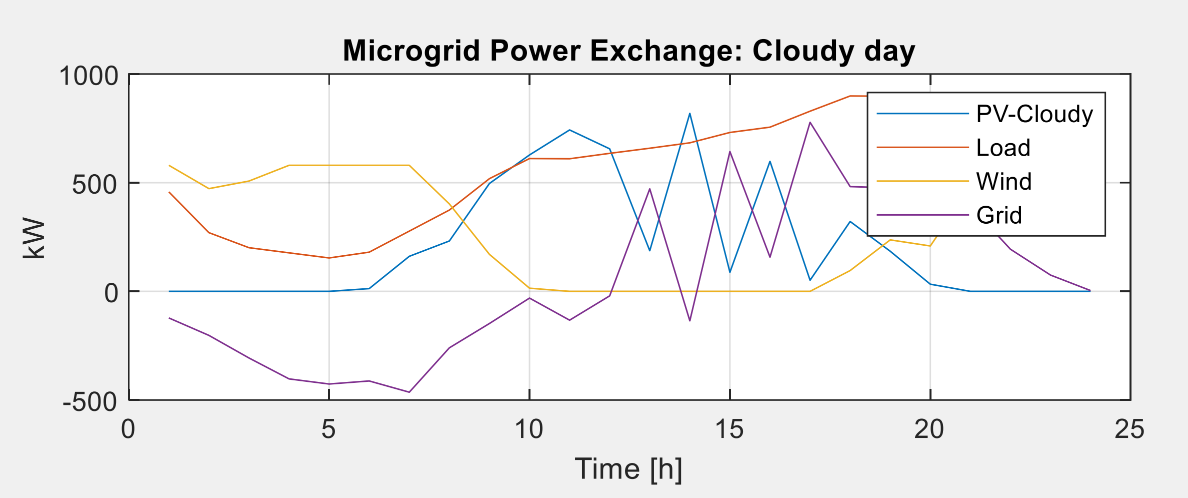

Figure 14. MG Energy Exchange on a partly cloudy day

3.11.7 Microgrid Operation with BESS

3.11.7.1 MG Operation: Clear Day

It is well-recognized that renewable energy supplies are stochastic, and so energy generation is intermittent. Battery Energy Storage Systems are consequently required to supplement renewable energy sources while eliminating the use of diesel generators to reduce carbon emissions. Figure 15 depicts the microgrid operating with the BESS connected and operational on a clear day. The graph indicates that the BESS charges during off-peak hours, from late night to early morning, using excess energy from renewable sources. When the BESS is completely charged, approximately 6 or 7 AM, excess renewable energy is sold to the grid operator during the peak hour at a premium price.

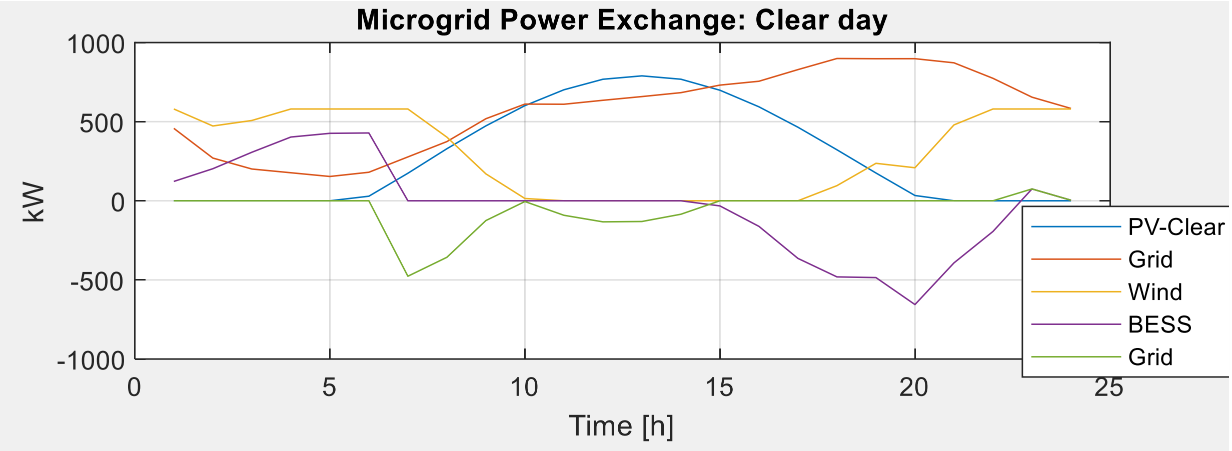

Figure 15. MG Energy Exchange with BESS on a clear sky day

Furthermore, during the day, for clear day predictions, when the solar system's peak generation exceeds load demand and the battery is fully charged, extra energy is sold to the grid at the standard price. In the afternoon, load demand peaks, solar system production decreases, and wind energy remains zero. As a result, the battery system discharges to supply the load, while wind turbine power gradually ramps up to help with energy supply and lessen the burden on the BESS. Also, this is the peak period, and the microgrid avoids pulling energy from the grid because it is quite expensive.

3.11.7.2 MG Operation: Partly Cloudy Day

Figure 16 depicts the microgrid operation with BESS connected and operational on a partly overcast day. Similarly, the graph illustrates that the BESS is charged during off-peak hours, from late at night to early in the morning, using excess energy provided by renewable sources. When the BESS is completely charged, about 6 or 7 AM, excess renewable energy is sold to the grid operator during peak hours at a high price. During partly cloudy days, when the solar system is unpredictable, the BESS is used to supplement energy generation during energy dips and sell excess energy to the grid during overgeneration. Load demand begins to peak in the afternoon, and solar system production decreases, but wind energy is zero, and the BESS is used more, while wind turbine generation gradually increases to assist in energy supply and alleviate the burden of the BESS. Also, this is the peak period, and the microgrid avoids drawing energy from the grid because it is quite expensive.

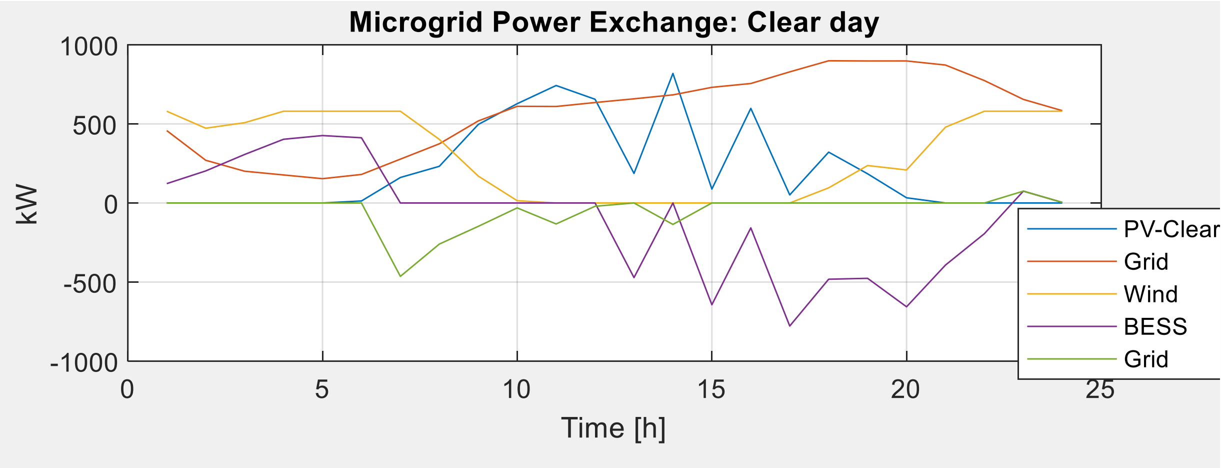

Figure 16. MG Energy Exchange with BESS on a partly cloudy day

3.11.8 MG Reserve Margins using BESS

Figure 17 displays the microgrid during a clear sky day with BESS reserve margins. South Africa's technical requirements for extra services describe the conditions for each reserve category and define the five types of reserves (Sørensen, et al., 2017):

I. AGC supervises the use of regulatory reserves for real-time supply and demand balancing.

II. Following a contingency, instantaneous reserves are used to keep the frequency within acceptable levels.

III. Ten-minute reserves balance supply and demand in reaction to variations between the day-ahead market and real-time, such as load estimate errors and unreliability of units.

IV. Emergency reserves are utilized to restore normalcy to the interconnected power system, whereas slower reserves are relied on. They are also utilized when the system doesn't work properly.

V. Supplemental reserves are intended to provide a realistic risk for the day ahead.

The study focuses on operating reserves which are made up of regulatory, instantaneous, and ten-minute reserves. The graph illustrates the BESS charge at a minimum of 50%. The discharge depth is 50% when operating normally (with grid and renewable energy available).

When the grid and renewable energy sources are unavailable, the minimum depth of discharge is 30%, with the BESS supplying just critical loads.

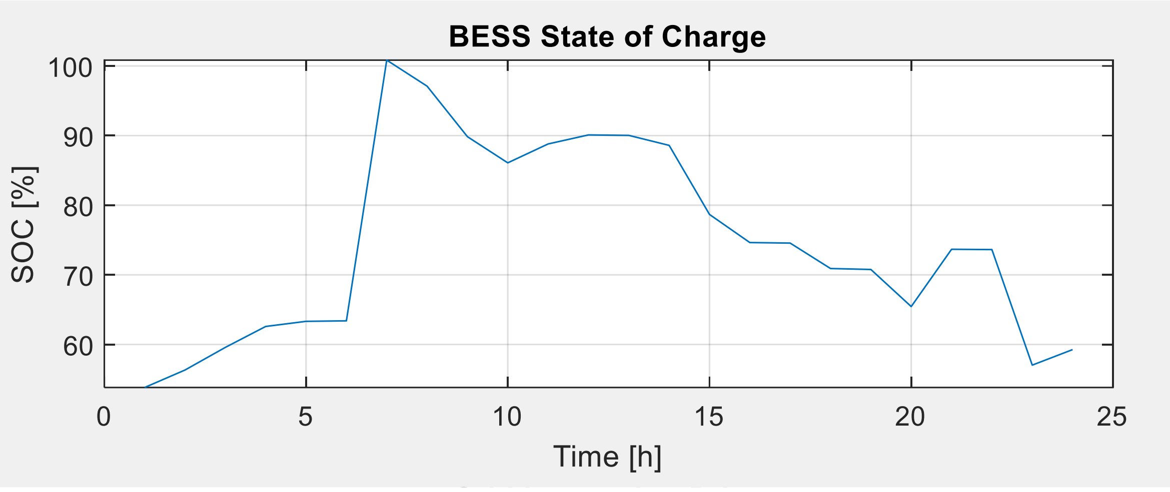

Figure 17. MG BESS reserve margins on a clear sky day

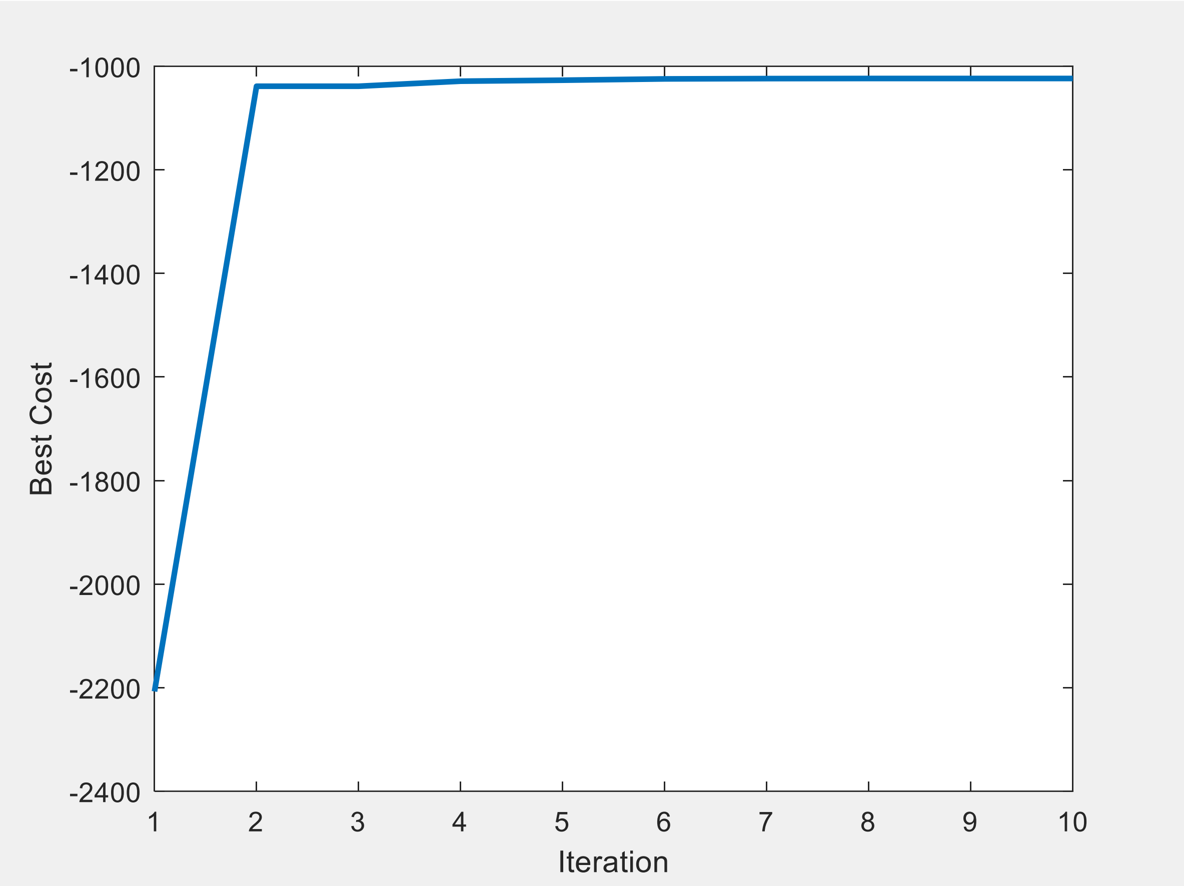

Figure 18. Particle Swarm Optimization Performance

Figure 18 shows the particle swarm optimization performance relative to iteration and solution provided.

3.12 Conclusion

The microgrid system was modeled and simulated. The system simulates the intermittent nature of renewable energy by using meteorological, solar irradiance, and wind speed data. The WindPvLoadPriceData file contains load profile and energy pricing information for purchasing and selling grid electricity. The simulation results were created with the PSO algorithm. The system offers three pricing options for grid interaction costs: off-peak, regular, and peak. Renewable energy suppliers are stochastic, resulting in intermittent energy generation. Battery energy storage Systems are required to supplement renewable energy sources and decrease dependency on diesel generators. Reduce carbon footprint. Figure 15 depicts the microgrid on a clear day, with the BESS connected and working. The graph depicts how the BESS charges during off-peak hours (late night to early morning) by drawing on excess renewable electricity. When the BESS reaches full charge (6 or 7 AM), excess renewable energy is sold to the grid operator at a higher price during peak hours. The graph demonstrates how the BESS is charged during off-peak hours using excess renewable energy. When completely charged, any remaining renewable energy is sold to the grid operator during peak hours. During partially overcast days, the BESS boosts energy generation and sells excess electricity to the grid. The microgrid eliminates costly grid energy disadvantages at peak hours.

CHAPTER FOUR

GA FOR HYBRID RENEWABLE ENERGY MICROGRID SYSTEM UNDER UNCERTAINTY

4.1 Introduction

The hybrid microgrid under study consists of photovoltaic, wind, battery storage, and electric vehicles, and their mathematical models have been discussed previous chapter. Genetic algorithms are an effective method for modeling and simulating the optimization of microgrids that combine PV, wind, and BESS. GAs can build efficient, cost-effective, and sustainable energy systems by successfully managing complicated, nonlinear interactions and including various optimization targets and constraints. Despite convergence and computational complexity issues, GA remains a popular alternative for microgrid optimization, especially when dealing with dynamic, real-time energy management and renewable energy source integration. A random set of probable solutions is produced. Each member of the population represents a unique scheduling strategy for the microgrid's operation, including decisions about how much power to create from each source and how much energy to store or dispatch from the BESS. Each solution is assessed using a fitness function, which computes the overall cost (or other goals, such as emissions reduction) depending on scheduling decisions.

4.2 Genetic Algorithm

The Genetic Algorithm (GA) is a global search method for solving constrained and unconstrained optimization problems by mimicking biological evolution. The algorithm uses natural evolution techniques like inheritance, mutation, selection, and crossover to solve optimization problems. Evolution normally begins with a population of randomly generated individuals and develops over generations. In each generation, the fitness of each person in the population is evaluated, and some individuals are selected from the current population (based on fitness) and modified to create a new population. The freshly generated population is used in the algorithm's subsequent iteration. The process is completed when the maximum number of generations are produced, or the population has reached a satisfactory fitness level. The Genetic Algorithm follows Darwin's survival of the fittest principle of natural evolution, which is characterized by the following principles (Deb, 1998).

1) If an above-average offspring is formed through genetic processing, it will live longer than the average individual and have more possibilities to produce children with some of its characteristics than the typical individual.
2) If, on the other hand, below-average offspring are produced, they do not survive long and are hence eliminated from the population.

A simple GA flowchart is shown in Figure 19 (Deb, 1998). The GA begins its search from a random set of solutions. If the termination requirement is unmet, three alternative operators (reproduction, crossover, and mutation) are used to update population strings.

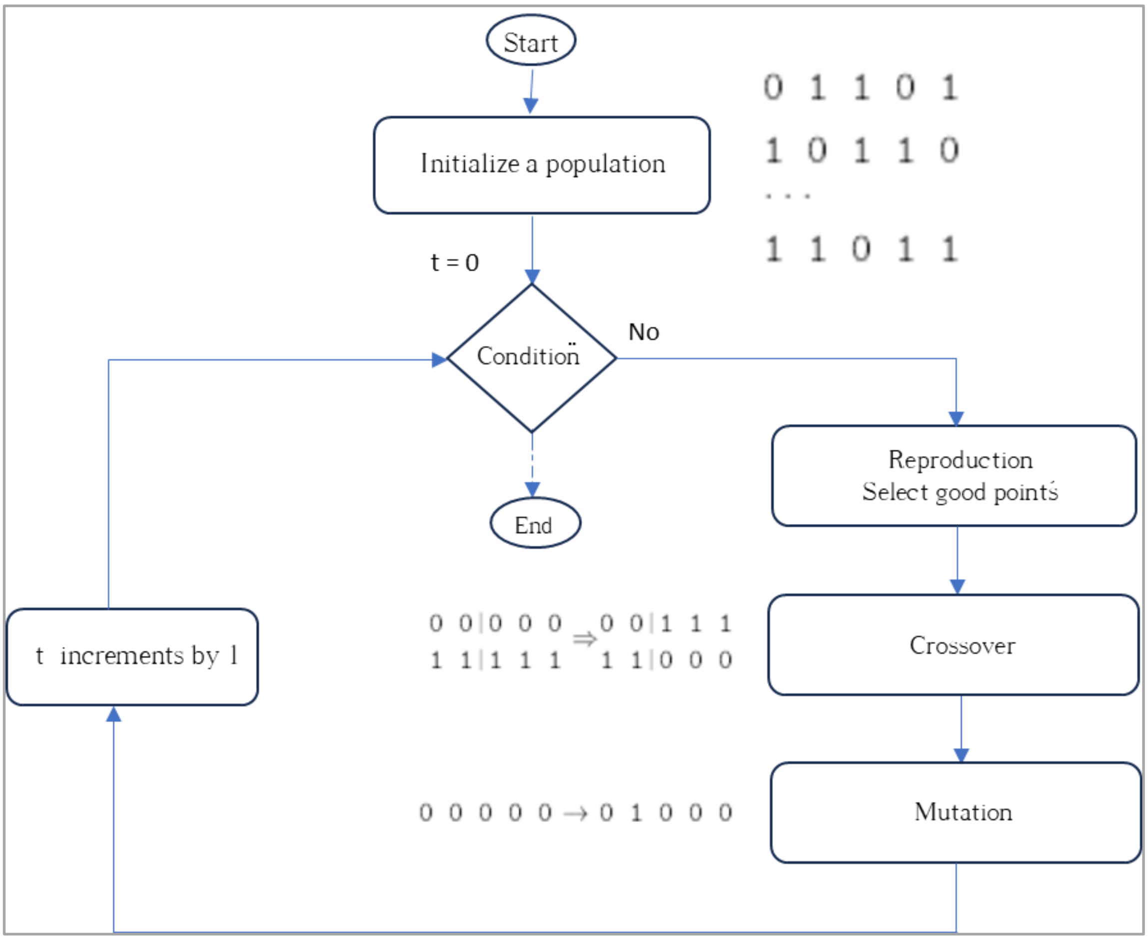

Figure 19. Simple Genetic Algorithm Flowchart

In a binary-coded GA, every variable is first coded in a fixed-length binary string, as demonstrated in the example below. The GA formulation technique, as explained below, has been derived from (Deb, 1998).

$$\underbrace{11010}_{x_1}\ \underbrace{1001001}_{x_2}\ \underbrace{010}_{x_3}\ \ldots\ \underbrace{0010}_{x_N}$$

The i-th problem variable is coded in a binary substring of length, l_i, such that the total number of alternatives allowed in that variable is 2^{l_i}. The lower-bound solution x_i^{min} is represented by solution (0000….0), while the upper-bound solution x_i^{max} is represented by solution (1111…1) any other substring x_i is calculated as shown in Equation 4-1.

$$x_i = x_i^{min} + \frac{x_i^{max} - x_i^{min}}{2^{l_i.} - 1} DV(s_i) \tag{4-1}$$

Where $DV(s_i)$ is the decoded value of the substring s_i. The length of a substring is decided by the accuracy needed in a variable. If, for example, 4 decimal places of accuracy are needed in the i-th variable, the total number of possible solutions in the variable must be $\frac{x_i^{max} - x_i^{min}}{0.0001}$, which can be set to 2^{l_i} and l_i is calculated using Equation 4-2.

$$l_i = log_2(\frac{x_i^{max} - x_i^{min}}{e_i}) \tag{4-2}$$

Where e_i is the desired precision in the i-th variable. The total string length of the N-variable is given by equation 4-3.

$$l = \sum_{i=1}^{N} l_i \tag{4-3}$$

In the Genetic Algorithm, each string generated in the initial population or subsequent generations must be assigned a fitness value based on the objective function value. In maximization problems, a string's fitness value can be the same as the string's aim function value. In minimization problems, the goal is to find a solution with the lowest objective function value. Therefore, the fitness value can be calculated using the reciprocal of the objective function value as given in Equation (4-4).

$$Fitness = \frac{1}{1 + f(x_{i,\ldots,}x_N)} \tag{4-4}$$

4.2.1 Reproduction

The first operation to be performed on the original random population is reproduction. Reproduction aims to pick good strings in a population to establish a mating pool that will carry progeny. The proportionate selection operator, which selects a string in the current population with a probability proportional to the string's fitness, is the most widely used reproduction. As a result, the likelihood of selecting the i-th string in the population is proportional to f_i. Because the population size is held constant, the cumulative probability for all strings in the population is equal to **one**. Therefore, the likelihood of selecting the i-th string ${f_i}\big/{\sum_{j=1}^{N} f_j}$, where N is the population size. One method for achieving proportionate selection is to utilize a roulette wheel with a circumference marked for each string proportional to its fitness.

The roulette wheel is spun N times, with each spin storing an instance of the string selected by the roulette wheel pointer in the mating pool. The roulette wheel mechanism generates f sub 1 slash f bar copies of the i-th string based on its fitness, where the f bar represents the population's average fitness. Due to the roulette wheel's limitations, alternative selection criteria, such as the ranking and tournament selection schemes, are applied.

4.2.2 Crossover

The mating pool's newly created strings are subject to the Crossover operator. Several crossover operators, similar to the reproduction operator, exist in the Genetic Algorithm literature. In each, two strings are chosen at random from the mating pool, and a fraction of the strings are swapped between them. In a single-point crossover operator, both strings are cut at an arbitrary place, and the right-hand component of both strings is exchanged among themselves to generate two new strings, as shown below.

$$\begin{array}{lcc|ccc} \text{Parent1} & 0 & 0 & 0 & 0 & 0 \\ \text{Parent2} & 1 & 1 & 1 & 1 & 1 \end{array} \Rightarrow \begin{array}{cc|cccl} 0 & 0 & 1 & 1 & 1 & \text{Child1} \\ 1 & 1 & 0 & 0 & 0 & \text{Child2} \end{array}$$

It is worth noting from the construction that good strings from either parent string can be combined to form a better child string if the appropriate place is chosen. Because the ideal location is often uncertain, a random selection is made. However, it is critical to realize that selecting a random site does not make the search activity random. With a single-point crossover between two l-bit parent strings, the search can only locate up to $2(l-1)$ different strings in each space. With a random site, the children's strings generated may or may not contain a combination of suitable substrings from the parent strings, depending on whether the crossover site is located in the appropriate position. A two-point crossover operator selects two random sites, and the contents between these sites are transmitted between the two parents.

The purpose of crossover is twofold. The primary purpose of the crossover operator is to search the parameter space, while the secondary is to preserve the parent string's information.

4.2.3 Mutation

Although the mutation operator is sometimes used to explore the parameter space, its main purpose is to change 1 to 0 and vice versa using the mutation probability, p_m as shown below.

$$00000 \quad \Rightarrow \quad 00010$$

Including mutation introduces some probability of turning 0 to 1 or vice versa thereby providing local improvement. One generation of GA is complete once the reproduction, crossover, and mutation processes have been applied to the entire population. The reproduction operator chooses good strings, the crossover operator recombines suitable substrings from two good strings, hoping to produce better ones, and the mutation operator changes strings locally to create better strings. There is no guarantee that these operators will produce better strings in each generation. Still, it is assumed that if faulty strings are formed, the reproduction operator will erase them in the next generation. If good strings are formed, they will be highlighted.

4.3 GA Simulation

As discussed in section 3.2, genetic algorithms simulate the process of selective breeding, indicating only those species that are capable of handling developments in the surroundings will survive, evolve, and proceed on to the next cycle. Simply put, they address a problem by simulating "survival of the fittest" among individuals from successive generations. Every phase consists of a group of individuals indicating a location in the field of exploration and a possible solution. Each individual is represented by a string of letters, integers, floating-point values, and bits. The string in question is identical to chromosomes. The cornerstone of GAs constructed around this juxtaposition is the following (Kumar, 2024):

I. Members within the community fought for commodities as well as mates.

II. Those that are competent will mate to create more children versus competitors.

III. The genetic factors of the "fittest" parent are transmitted across generations; that is, parents can generate children that exceed either one of them.

IV. As consequently, each era is more suited to their surroundings.

The method aims to optimize a "fitness" function. The term "fitness" originates from the concept of evolution. The fitness attribute evaluates and quantifies the fit of potential solutions which is a crucial component of the algorithm. Chromosomes are numerical values that reflect potential solutions to a genetic algorithm's challenge (Carr, 2014).

4.4 GA Simulation Results

The genetic algorithm was implemented using the same microgrid data, grid interaction cost, solar generation profiles, wind turbine generation profiles, and load profile as in particle swarm optimization applications. GA can effectively deal with the complexities of microgrid optimization, such as the nonlinear relationship between generation, storage, and demand.

4.4.1 Microgrid Operation without BESS

Figure 20 displays total microgrid generation during a clear day, with solar and wind generation profiles and their totals as well as the total load profile on the graph. As previously said, solar generation is far more predictable during a clear day. In contrast, wind remains unpredictable—the total generation peaks between mid-day and early afternoon, when solar generation is at its highest. Total load demand is higher than the renewable energy generation from around 15:00 to about midnight. During this period the microgrid is importing power from the grid to supplement its generation to ensure load demand is met. The periods between 18:00 to about 21:00 and between 07:00 and 10:00 are the peak periods and have the highest electricity prices of ZAR 9.82. The morning peak renewable generation is higher than the total load demand and excess energy is sold to the grid operator however, the evening peak period has a load demand greater than renewable energy generation and additional power to meet the load demand is purchased from the grid operator.

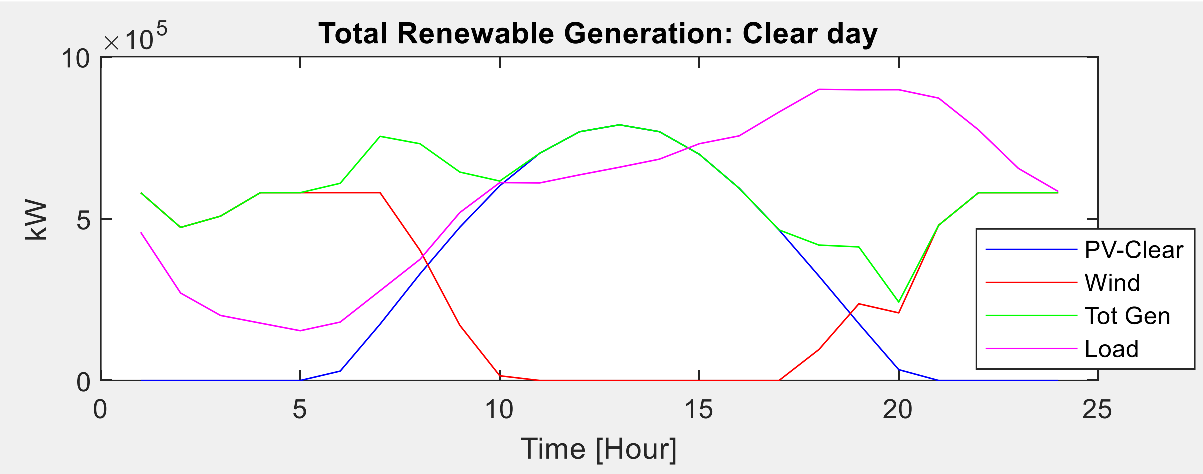

Figure 20. Total Microgrid Generation during a clear day

Shown in Figure 21 is the graph of the total renewable energy generation profile during a clear day, the load demand profile, the power difference for either exporting excess power or importing required power from the grid, and net costs (scaled by 10) considering power purchased from the grid subtracting power sold to the grid. The blue graph in the Figure shows positive costs from early morning till around 14:30 whereby energy export is happening while negative costs start from around 14:30 to midnight whereby energy is imported due to insufficient renewable power generation. The net costs (difference between export and import) during a clear day total **4.274** million ZAR that the microgrid owners need to pay to the grid operator daily.

Figure 22 displays total microgrid generation during a partly cloudy day, with solar and wind generation profiles and their totals as well as the total load profile on the graph. Solar generation is unpredictable on a partially cloudy day so is wind generation, resulting in unpredictable overall generation. The load profiles are similar to those of Figure 20 from midnight till around 10:00 and thereafter the solar profile behaves unpredictably due to cloud cover movements. Power is imported from the grid from just after midday till around midnight with only about an hour around 14:00 of power export to the grid.

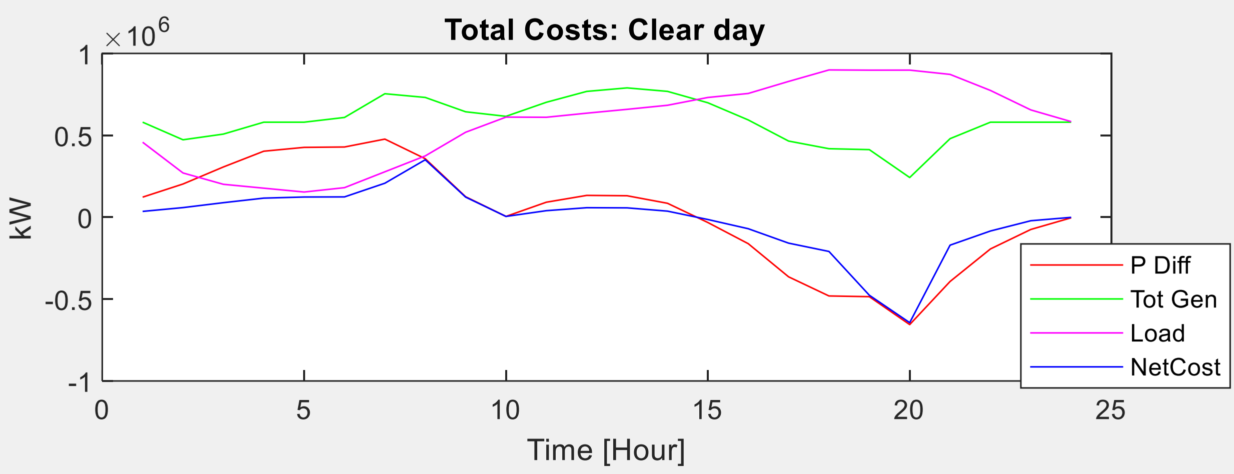

Figure 21. Total Energy Cost: Clear Day

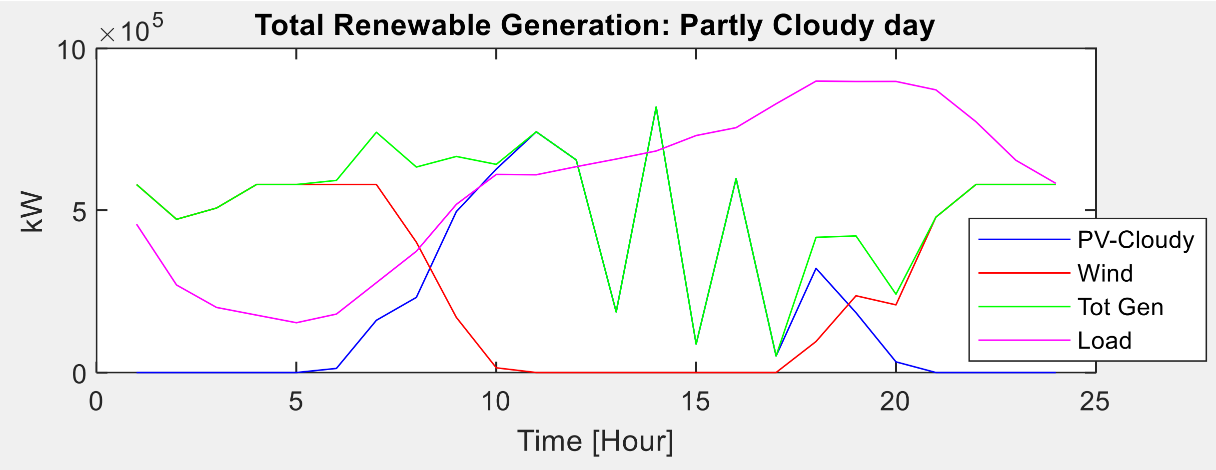

Figure 22. Total Microgrid Generation during a partly cloudy day

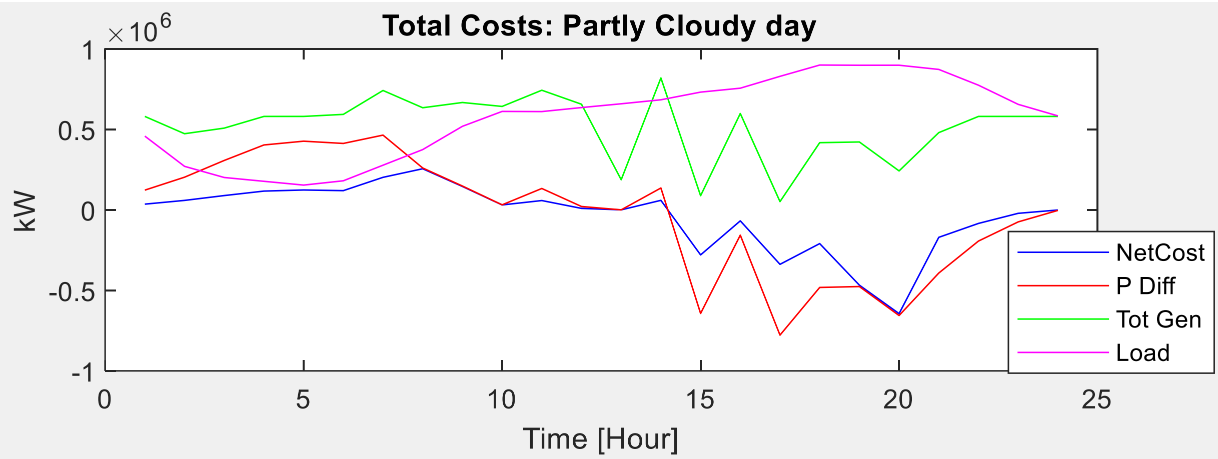

Figure 23. Total Microgrid Generation during a partly cloudy day

Figure 23 is the graph of the total renewable energy generation profile during a partly cloudy day, the load demand profile, the power difference for either exporting excess power or importing required power from the grid, and net costs (scaled by 10) considering power purchased from the grid subtracting power sold to the grid. The blue graph in the Figure shows positive costs from early morning till around 14:00 whereby energy export is happening while negative costs start from around 14:30 to midnight whereby energy is imported due to insufficient renewable power generation. The net costs (difference between export and import) during a partly cloudy day total **9.865** million ZAR that the microgrid owners need to pay to the grid operator daily.

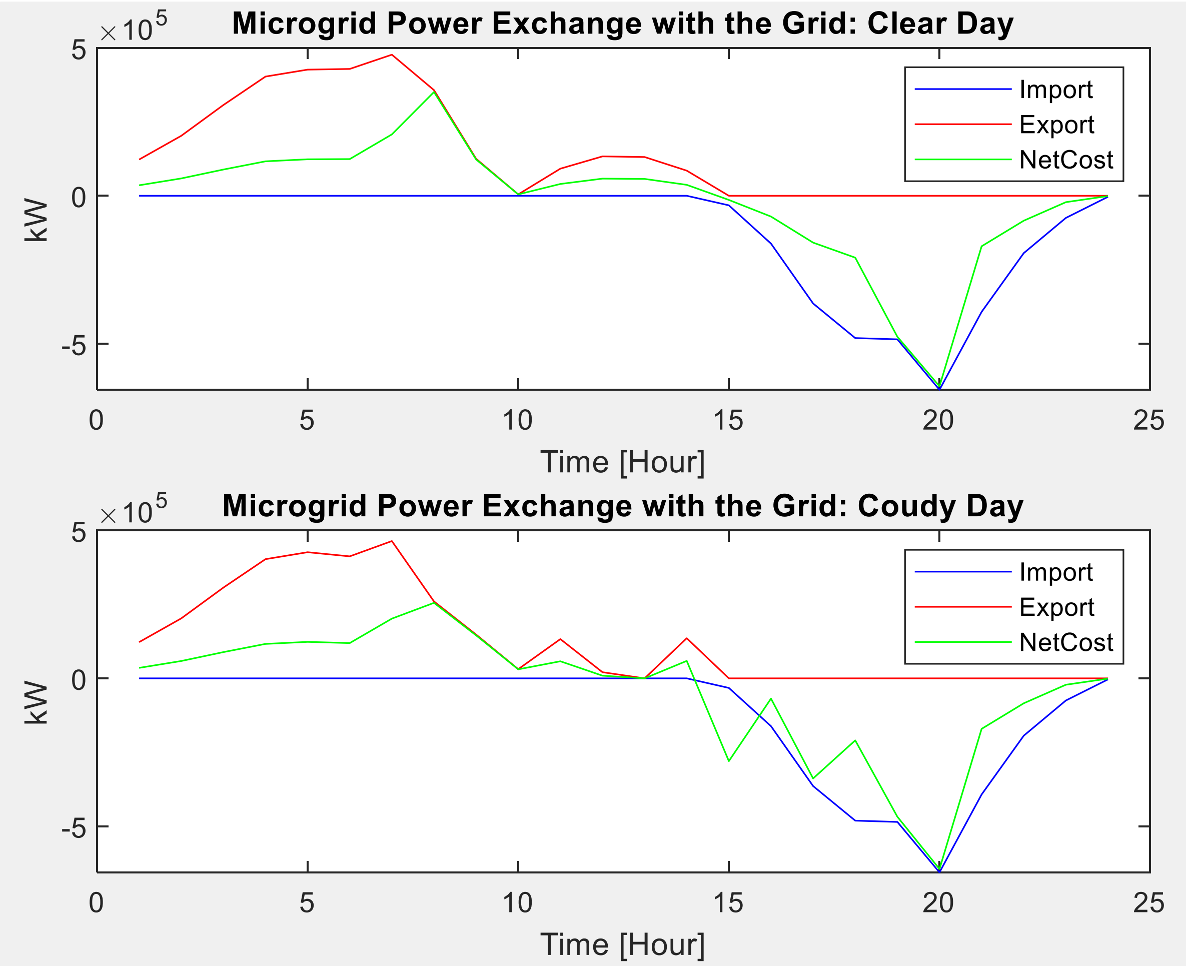

Figure 24. Microgrid and Grid Power Exchange

Figure 24 shows power exchange graphs between the microgrid and the national grid for both clear and partly cloudy days together with the relevant costs (scaled by 10). As discussed in previous sections, power is exported (red graph) to the grid from midnight till about 14:30 and imported (blue graph) from the grid from there onwards until midnight.

4.4.2 Microgrid Operation with BESS

As discussed in section 4.4.1, the microgrid operation with only renewable energy distributed generators including electric vehicles results in just over **4.2** million and just below **10** million ZARs daily costs for clear and cloudy days, respectively. This section analyzes the impact of BESS on microgrid operations considering reserve margins necessary to supply critical loads during less renewable energy production and/or unavailability of the grid. The four unknown variables to be determined are import power, export power, BESS discharge, and charging power. A BESS SOC of 50% is set aside as a reserve margin to supply essential loads during unanticipated outages.

Figure 25 shows microgrid power exchange with the national grid in the presence of a Battery Energy Storage System (BESS). The Figure shows that between midnight and 06:00 there is no export or import of power and the BESS system is charged. When the BESS is fully charged, and the electricity price is high, power is exported to the grid between 06:00 and 15:00 with different variations. Thereafter, as the load demand is higher than renewable energy generation, the BESS supplies the load with the required power to ensure that when the electricity prices are high importing from the grid is avoided as much as possible. Both graphs in Figure 25 for clear and cloudy days show similar behavior with slight differences due to solar irradiation variations during the movement of the clouds.

In Figure 26 the BESS profile is shown whereby charging from around midnight till around 6 in the morning is taking place as also shown in Figure 25. BESS discharging takes place in the afternoon when the load demand is higher than the renewable energy generation when electricity prices are higher. Also in Figure 26, the Battery State of Charge (SOC) in percentage is shown. It can be seen that SOC is kept above 50% which is the reserve margin set for the study to allow for supply of critical loads during emergencies. The costs of operating the microgrid with BESS have decreased tremendously from **4.274** million ZAR owed to the grid operator to **1.472** million ZAR, owed to the microgrid operator by the grid operator, during clear days. For a cloudy day, costs have dropped from **9.865** million ZAR, owed to the grid operator, to **6.210** million ZAR owed by the microgrid operator.

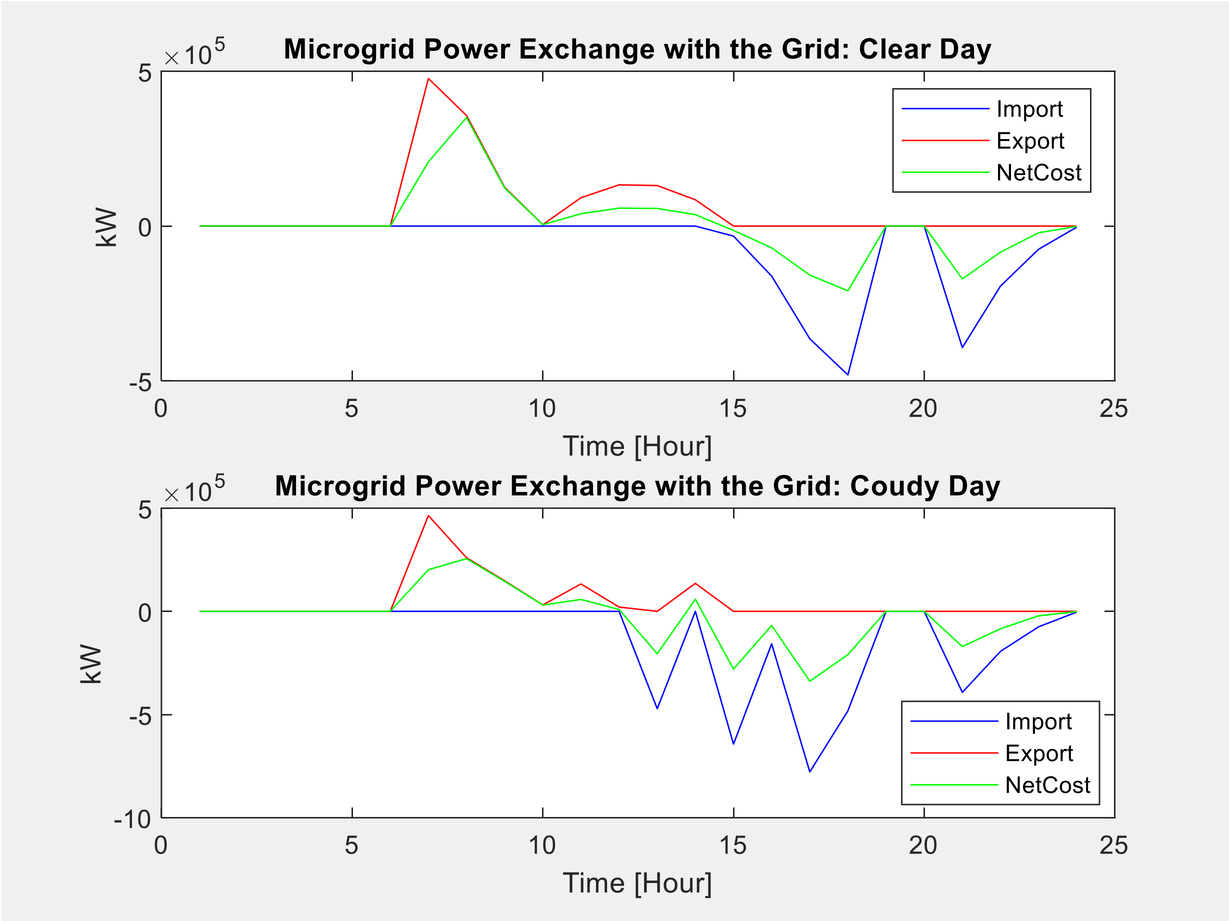

Figure 25. Microgrid Power Exchange with BESS

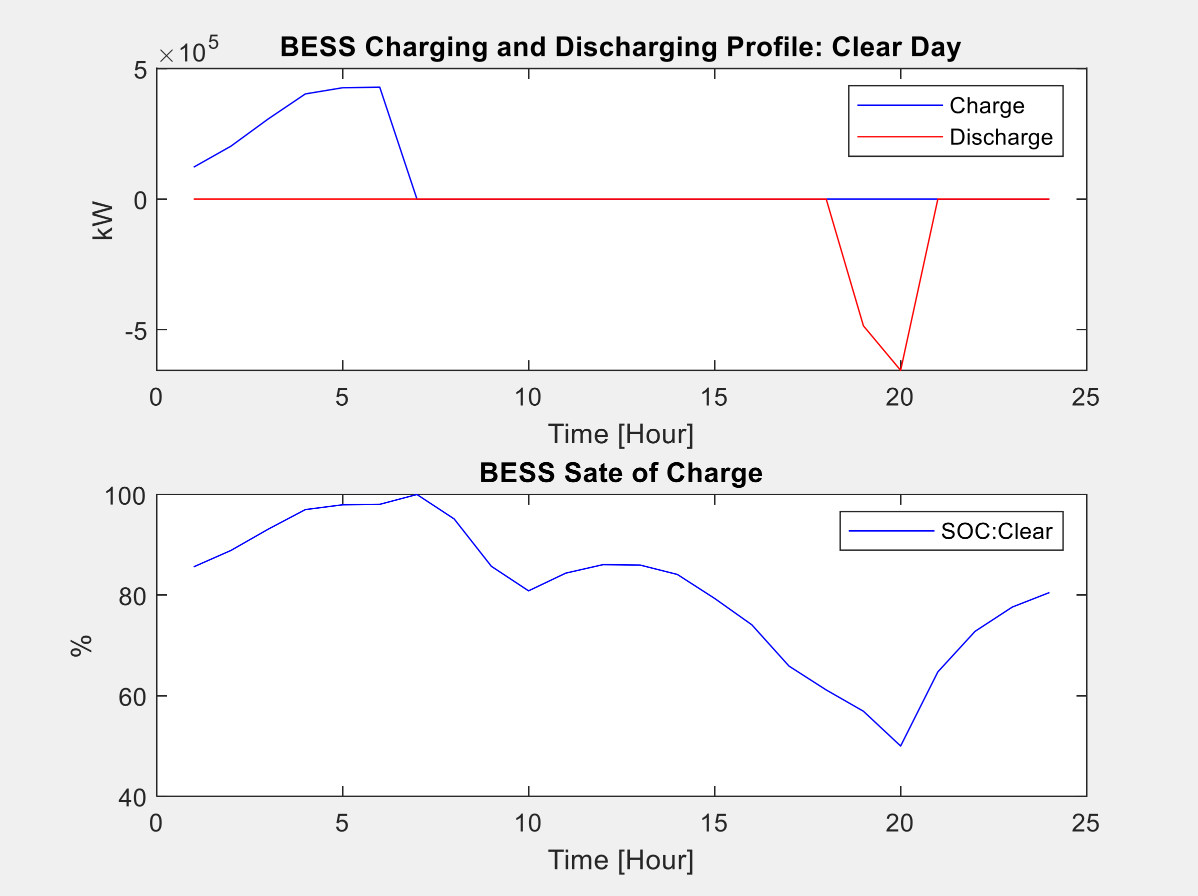

Figure 26. Microgrid Battery Energy Storage System Profile

In section 4.4.2 the impact of operating a hybrid microgrid with a battery storage system has positive outcomes but the operational parameters that result in maximum cost savings should be determined and applied to enjoy the benefits of renewable energy resources. The next section provides a comparative analysis of the results of the proposed optimization methods.

4.5 Comparative analysis of the Optimization methods for Hybrid Renewable Energy Microgrid Systems under Uncertainty

PSO and GA are famous metaheuristic methods that rely on natural processes. They are commonly utilized in optimization issues; however, their mechanisms and performance characteristics vary. Chapter 3 covered the PSO approach from its inception to its implementation in MATLAB software and the results of testing it on a hybrid renewable energy microgrid. In Chapter 4, the Genetic Algorithm is discussed, along with its implementation in MATLAB for testing in the same microgrid simulation. Chapter 5 seeks to analyze the results presented in the preceding chapters. The same hybrid microgrid settings were utilized to test the optimization method, ensuring a fair comparison. Table 9 displays theoretical comparative analyses of the optimization parameters between the particle swarm optimization method and the genetic algorithm.

Table 9. Basic Comparison of PSO and GA

Point	Particle Swarm Optimization	Genetic Algorithm
Inspiration	Inspired by the social habits of birds and fish	Inspired by natural selection and genetics
Representation	The solutions are represented as particles in a continuous or discrete search space	Solutions are encoded as chromosomes, frequently in binary or real-valued form.
Search Mechanism	Updates velocity and position based on individual and swarm experience (personal and global best).	It uses operators like selection, crossover, and mutation to evolve the population
Exploration vs. Exploitation	Its exploitation-oriented behavior causes it to converge faster, sometimes leading to premature convergence.	Better for sustaining variation in the population, which aids exploration but may result in delayed convergence
Parameters	Requires fewer factors (e.g., inertia weight, cognitive and social coefficients)	while requiring tweaking of many parameters
Convergence Speed	Generally faster because of its more straightforward update process	It is slower because it depends on stochastic processes such as crossover and mutation.
Ease of Implementation	Simpler to implement with fewer steps	Multiple operators and encodings make the system more complex
Optimization Type	Designed for continuous	Effectively solves both

	optimization issues	continuous and discrete optimization problems
Advantages	Simple, rapid convergence with fewer parameters.	Robust to local minima, ideal for complicated landscapes
Disadvantages	prone to early convergence; less effective in highly multimodal settings	Computationally expensive and sluggish convergence

To summarize the comparison in Table 9, it is better to choose PSO for issues that require rapid convergence and fewer tuning parameters and GA for complicated problems that require robust exploration and various solutions.

4.6 Simulation Results Comparison

Figure 27 depicts the hybrid microgrid under test (data provided in Excel format), load demand, and renewable energy generation (excluding BESS). Because there is less load demand at night and wind farms typically generate mainly at night, generation has been higher than load demand since in the wee morning hours. However, as the day passes, wind speeds decrease, and load demand rises. Solar generation begins as wind turbine generation decreases and load begins to peak. The solar generation profile is predictable on clear days but unexpected on partly overcast days. The solar system simulation of the hybrid microgrid employs two scenarios:

1. Clear day with a known generation profile.
2. Partly cloudy day with an unstable generation profile.

The operating scenarios have been tested in both optimization methods, particle swarm optimization and genetic algorithm.

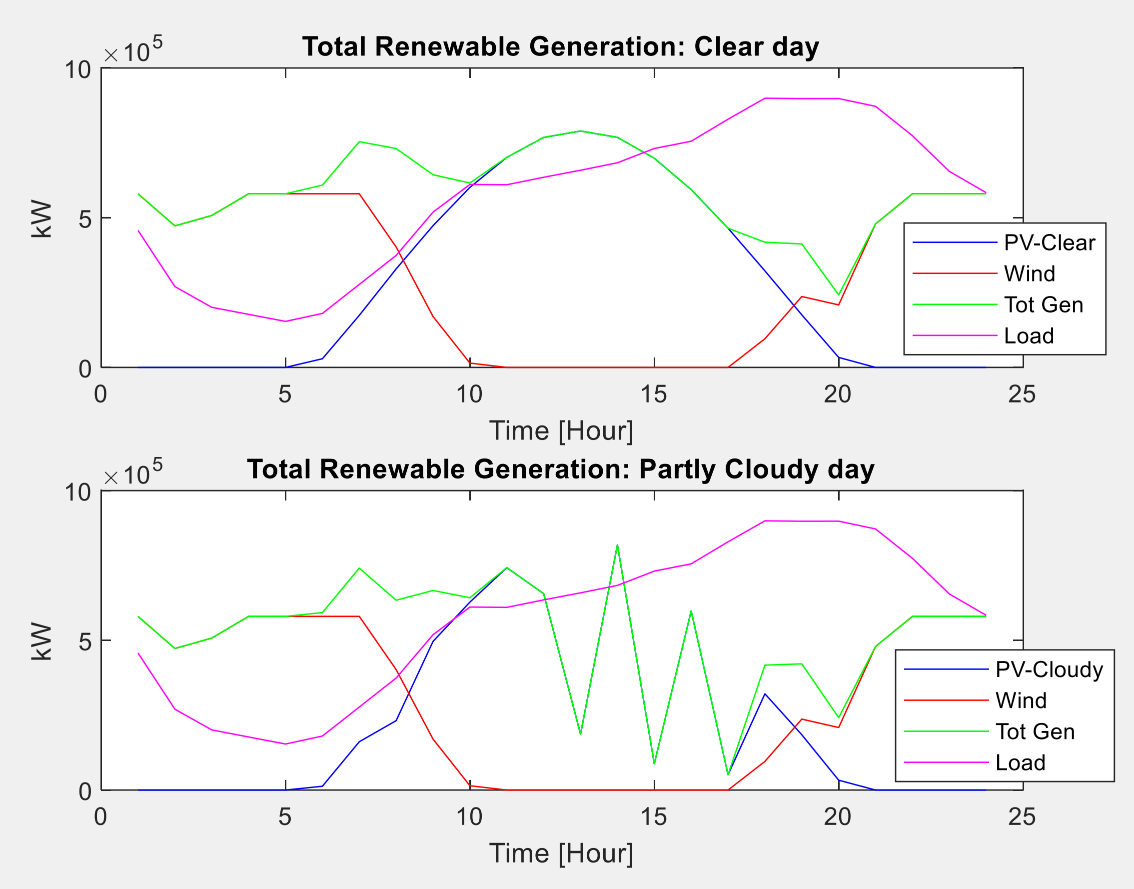

Figure 27. Hybrid Microgrid Generation Profiles

Weather data, such as wind velocity as well as solar irradiation are provided in Excel and utilized as inputs to compute electricity generation using the formulas defined in Chapter 3. Both optimization methods have been subjected to similar system restrictions, such as power balance, reserve margins, and generation limits. The hybrid microgrid system is simulated in MATLAB utilizing weather data for both solar as well as wind while the battery parameters are established in the MATLAB script, as indicated in the appendices. The load profile is supplied in the same file as the meteorological data and the energy pricing information. The data is in a one-minute sampling rate and spans 24 hours. Sampling was done every hour for the simulation to ensure clear visibility, resulting in 24 samples daily in a single day.

Table 10 shows the results of the genetic algorithm of optimizing the operation of a hybrid microgrid with BESS providing 50% SOC reserves. The sign convention uses negative for power import costs and positive for power export costs. The net costs (difference between import and export) are shown at the bottom of the table.

Table 10. Genetic Algorithm Simulation Results

Genetic Algorithm				
	Clear Day		Cloudy Day	
Time	**Import Costs**	**Export Costs**	**Import Costs**	**Export Costs**
1	R0.00	R0.00	R0.00	R0.00
2	R0.00	R0.00	R0.00	R0.00
3	R0.00	R0.00	R0.00	R0.00
4	R0.00	R0.00	R0.00	R0.00
5	R0.00	R0.00	R0.00	R0.00
6	R0.00	R0.00	R0.00	R0.00
7	R0.00	R2,074,004.05	R0.00	R2,018,399.56
8	R0.00	R3,506,392.12	R0.00	R2,551,645.96
9	R0.00	R1,226,394.41	R0.00	R1,452,299.00
10	R0.00	R46,307.57	R0.00	R304,535.66
11	R0.00	R398,141.06	R0.00	R576,887.70
12	R0.00	R579,009.30	R0.00	R90,169.61
13	R0.00	R569,455.42	-R2,051,898.34	R0.00
14	R0.00	R369,435.46	R0.00	R589,912.60
15	-R140,942.46	R0.00	-R2,798,292.56	R0.00
16	-R703,042.89	R0.00	-R684,211.74	R0.00
17	-R1,583,730.75	R0.00	-R3,383,769.50	R0.00
18	-R2,092,145.72	R0.00	-R2,096,448.05	R0.00
19	R0.00	R0.00	R0.00	R0.00
20	R0.00	R0.00	R0.00	R0.00
21	-R1,707,470.15	R0.00	-R1,707,470.15	R0.00
22	-R843,301.32	R0.00	-R843,301.32	R0.00
23	-R216,416.60	R0.00	-R216,416.60	R0.00
24	-R10,275.48	R0.00	-R10,275.48	R0.00
Total	**-R7,287,049.89**	**R8,769,139.39**	**-R13,781,808.26**	**R7,583,850.08**
Net Total	**R1,482,089.50**		**-R6,197,958.17**	

Table 11 shows the comparative results of particle swarm optimization and genetic algorithms in determining optimal microgrid operational parameters. The table compares the results data of both optimization methods for both clear and cloudy days. Based on the results genetic algorithms performed better than the particle swarm optimization method during a clear day, although the values are quite similar. The genetic algorithm has a net value of positive **1.472** million ZAR on a clear day, while the particle swarm optimization has a net value of positive **1.662** million ZAR. The cloudy day results remain negative with values of **6.208** and **6.203** million ZARs for genetic algorithm and particle swarm optimization, respectively.

Table 11. GA and PSO Results Comparison

	Clear Day		Cloudy Day	
Time	**GA**	**PSO**	**GA**	**PSO**
1	R0.00	R0.00	R0.00	R0.00
2	R0.00	R0.00	R0.00	R0.00
3	R0.00	R0.00	R0.00	R0.00
4	R0.00	R0.00	R0.00	R0.00
5	R0.00	R0.00	R0.00	R0.00
6	R0.00	R0.00	R0.00	R0.00
7	R2,074,004.05	-R2,074,004.05	R2,018,399.56	-R2,018,399.56
8	R3,506,392.12	R3,506,392.12	R2,551,645.96	-R2,551,645.96
9	R1,226,394.41	R1,226,394.41	R1,452,299.00	-R1,452,299.00
10	R46,307.57	-R46,307.57	R304,535.66	-R304,535.66
11	R398,141.06	-R398,141.06	R576,887.70	R576,887.70
12	R579,009.30	-R579,009.30	R90,169.61	-R90,169.61
13	R569,455.42	-R569,455.42	-R2,051,898.34	R0.00
14	R369,435.46	R369,435.46	R589,912.60	-R589,912.60
15	-R140,942.46	R0.00	-R2,798,292.56	R0.00
16	-R703,042.89	R0.00	-R684,211.74	R0.00
17	-R1,583,730.75	R0.00	-R3,383,769.50	R0.00
18	-R2,092,145.72	R0.00	-R2,096,448.05	R0.00
19	R0.00	R0.00	R0.00	R0.00
20	R0.00	R0.00	R0.00	R0.00
21	-R1,707,470.15	R0.00	-R1,707,470.15	R0.00
22	-R843,301.32	R0.00	-R843,301.32	R0.00
23	-R216,416.60	R216,416.60	-R216,416.60	R216,416.60
24	-R10,275.48	R10,275.48	-R10,275.48	R10,275.48
Total	**R1,471,814.01**	**R1,661,996.67**	**-R6,208,233.65**	**R6,203,382.62**

Table 12 shows details of the MATLAB code developed for particle swarm optimization and the genetic algorithm that forms part of the appendix Chapter.

Table 12. Appendices List

Appendix	Description

A	Single-Objective PSO MATLAB Code
B	Single-Objective Genetic Algorithm MATLAB Code

4.7 Discussion

As proposed, a literature assessment of current information was conducted to better understand the topic, identify gaps, and potentially uncover better ways to tackle the problem. Particle Swarm Optimization (PSO) and the Genetic Algorithm (GA) are two popular metaheuristic algorithms based on natural phenomena. They are frequently used in optimization problems; nevertheless, their mechanisms and performance characteristics differ. Chapter 3 described the PSO approach from its conception to its implementation in MATLAB software and the results of testing it on a hybrid renewable energy microgrid. Chapter 4 discusses the Genetic Algorithm, as well as its MATLAB implementation for testing in the same microgrid simulation. The solar system simulation of the hybrid microgrid employs two scenarios:

1 Clear day with a known generation profile.
2 Partly cloudy day with an unstable generation profile.

Weather data, such as wind velocity for wind power systems, sun irradiation for photovoltaic systems, are provided in Excel format and used as inputs to calculate power generation using the methods described in previous chapters. Both optimization approaches were exposed to identical system constraints, including power balance, reserve margins, and generating limits. The hybrid microgrid system is simulated in MATLAB using weather data for photovoltaic and wind systems while the battery parameters are defined in the MATLAB script, as shown in the appendices. The load profile includes the weather data and energy pricing details in the same file. The data is collected at one-minute intervals for 24 hours. Sampling was done every hour for the simulation and to ensure clear visibility, totaling 24 samples daily.

The results analysis showed better performance from the genetic algorithm during clear day compared to particle swarm optimization in terms of cost savings while particle swarm optimization had better results in a cloudy day. The PSO microgrid simulation in MATLAB took 40 seconds on average, while the GA MATLAB simulation took over 75 seconds. PSO has advantages like rapid convergence due to fewer parameters and a straightforward update process, while GA has slower convergence due to sporadic processes. The genetic algorithm and particle swarm optimization techniques in hybrid renewable microgrids showed cost savings in both clear and cloudy scenarios. The genetic algorithm showed 25% and 10% cost improvements, respectively.

4.8 Conclusion

The simulation focuses on four unknown variables: import power, export power, BESS discharge, and charging power. A 50% BESS SOC is set aside for unanticipated outages. The simulation results showed that the optimization methods managed to maintain the 50% reserve margin from the BESS while ensuring the charging and discharging philosophy was optimized based on system conditions and electricity prices. The minimum allowable discharge value of 50% under normal conditions assists in improving battery life. The BESS charges around low-demand times using surplus green power in addition to when completely charged, selling surplus power to the electrical utility operator during times of high demand. This microgrid optimization avoids the costly disadvantages of grid energy during peak hours. The PSO microgrid simulation in MATLAB took about 40 seconds on average to run and provide the solution while the GA MATLAB simulation took over 75 seconds to provide the solution. This confirms the advantages of PSO such as rapid convergence due to fewer parameters and its straightforward update process while GA has slower convergence due to sporadic processes such as mutation and crossover. Table 11 illustrates the effectiveness of optimization strategies created and evaluated in the MATLAB environment.

The next Chapter provides the conclusion and future research work on microgrid energy management systems.

CHAPTER FIVE
CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The South African Constitution guarantees everyone the right to energy, crucial for achieving the United Nations' Sustainable Development Goals (SDGs) by 2030. However, 84.39% of South Africans had access to electricity in 2020, indicating a significant portion of the population is still without power. This presents an opportunity for microgrids, which generate electricity from clean energy sources such as solar, wind, including battery energy storage devices, improving reliability, reducing carbon emissions, and providing clean energy.

The study investigated an optimization technique of a mixed microgrid energy management system with reserve margins in South Africa's renewable industry. The research aimed to localize the implementation of rules, including avoiding BESS charging from the grid during load shedding. The hybrid microgrid applied local regulations and local weather data.

5.2 Aim and Objectives of the Research

5.2.1 Research Aim

The goal is to provide a dependable optimization technique for a hybrid microgrid energy management system that takes electric vehicle operation as both a load and a source and to simulate and verify performance using MATLAB software. The research has shown that the goal has been met by developing PSO and GA and implementing and evaluating microgrid simulation in MATLAB.

5.2.2 Research Objectives

According to the research objectives, Chapter 2 includes a literature assessment of mathematical models on reserve margins, optimization methods used in microgrids, and energy management systems. Chapters 3 and 4 present the successful development of the optimization technique for energy management systems as applied of hybrid microgrid systems. The modeling and test findings demonstrated the benefit of using development optimization approaches in hybrid microgrids, resulting in lower operation costs.

5.3 Deliverables

5.3.1 Comprehensive Literature Study

A literature review on optimization strategies used in microgrid energy management systems was undertaken. Most optimization methods reported in the literature utilized heuristic approaches and provided validation of the simulation outcomes of the considered use case circumstances in the literature.

5.3.2 Development of the PSO Method

The backdrop of the particle swarm optimization approach has been described, as has the application and mapping of the particle swarm optimization, along with step-by-step guidance to the hybrid microgrid's energy management system optimization problem. The optimization approach sought to establish the ideal BESS charging and discharging strategy, as well as the import and export strategy, considering the time of utilization of the electricity price and ensuring that restrictions such as power balance were always met. The created algorithm was tested in the MATLAB software environment alongside the hybrid microgrid to determine its performance. The created approach produced some promising results, but additional fine-tuning is necessary to improve its efficacy.

5.3.3 Development of the GA Method

The genetic algorithm's background has been described, as has the application and mapping of the genetic algorithm, along with step-by-step guidance to the hybrid microgrid's energy management system optimization challenge. The optimization approach sought to identify the ideal BESS charging and discharging strategy, as well as the import and export strategy, while considering the time of use of electricity prices and ensuring that restrictions such as power balance were always met. The created algorithm was tested in the MATLAB software environment alongside the hybrid microgrid to ensure its effectiveness. The developed method produced some positive results, while further fine-tuning is necessary to improve its performance.

5.3.4 Development of the charging and discharging technique

The charging as well as discharging approach have been defined by the constraints outlined in the Risk Mitigation Independent Power Producer Procurement Programme, which states that no BESS charging from the grid supply is permitted and that BESS charging is only permitted when there is excess renewable energy generation. The optimization method proposed considers the criteria while guaranteeing that all other restrictions are met.

5.3.5 Development of reserve margins strategy

The charging and discharging approach ensure that a sufficient amount of BESS energy is always saved for subsequent use to supply vital loads when the national electrical system is unavailable, as well as clean energy generation is insufficient. The optimization method developed considers BESS's 50% minimum reserve margin to ensure critical loads are supplied for up to 4 hours. This BESS 50% minimum constraint increases the BESS life span, while the minimum permissible BESS SOC is barely met at 20%.

5.3.6 Deliverables on Research Findings to Address Community Microgrid System and Publications

The outcomes of this study will be critical in furthering our knowledge and use of hybrid microgrids in communities, particularly in terms of maximizing energy generation, storage, and distribution. The outputs, which include simulation models, case studies, publications, and optimization software, will be critical tools and insights for installing more efficient, sustainable, and resilient microgrid systems at the community level.

5.4 Application

Microgrid optimization aims to improve microgrid operations' efficiency, dependability, and sustainability. Its application spans multiple dimensions and is motivated by maximizing resource utilization, reducing costs, and improving system performance. This is how microgrid optimization is implemented:

Academic: The study intends to share expertise with other academics while also filling gaps identified during the literature survey. Fellow researchers are expected to use the information for future studies and improvements, as it can be used for benchmarking.

Industry: The implementation of industry needs, such as those mentioned for the BESS pricing strategy, in the academic environment strives to bridge the gap between industry and academia. This guarantees that academics focus on industrial requirements rather than the other way around.

5.5 Recommendations for Future Work

The following steps provide a proposal for continued work required to improve the existing research work:

- Future studies might look at enhanced probabilistic or stochastic models to better capture the variability in green energy supply (solar, wind) and demand for power. This will aid in developing more robust solutions for real-world unpredictability.
- To increase flexibility and scalability in simulation models, future research might look at integrating new system components such as hybrid storage systems with supercapacitors, hydrogen fuel cells, smart inverters, and demand response technologies.
- Research can be dedicated toward improving battery management systems (BMS) to better handle charging/discharging faults, taking into account aspects such as battery deterioration, temperature impacts, and quick charging cycles. Machine learning techniques might be used to anticipate and prevent probable problems during the charging and discharging processes.
- Scalable optimization approaches, such as Artificial Neural Networks (ANNs) or Model Predictive Control (MPC), will be used in future research to speed up the

optimization process. These strategies can enhance convergence rates and allow the microgrid to operate in real-time.

- Develop a hybrid framework that uses projected data to drive decision-making, allowing the system to predict future energy generation and load needs and optimize operations appropriately. This might include using projected solar radiation and wind speeds to optimize battery storage scheduling and grid interaction.
- Create novel real-time optimization frameworks based on data-driven models that can be continually updated with live data from sensors, weather predictions, and grid conditions. Real-time optimization can be accelerated using techniques such as fuzzy logic controllers and genetic programming.

5.6 Conclusion

The performance of genetic algorithm and particle swarm optimization techniques in hybrid renewable microgrids has shown cost savings in both simulation scenarios of clear day and cloudy day. The particle swarm optimization performed slightly better on a cloudy day while the genetic algorithm showed better results on a clear day. The genetic algorithm showed cost improvement of about 25% savings during a clear day and about 10% savings on a cloudy day. Similar results have been experienced while using the particle swarm optimization methods. The PSO microgrid simulation in MATLAB took about 40 seconds on average to run and provide the solution, while the GA MATLAB simulation took over 75 seconds to provide the solution. This confirms the advantages of PSO, such as rapid convergence due to fewer parameters and its straightforward update process while GA has slower convergence due to sporadic processes such as mutation and crossover.

As much the optimization methods have shown good performance and allow microgrid operators to enjoy the benefits of renewable energy generation, these methods require a fair amount of training as they are not intuitive. However, a good application, design, and tuning results in the optimal performance of the microgrid, which results in maximal usage of renewable energy, optimal charging, and discharging strategies, and management of reserve margins to ensure critical loads are catered during times of need.

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Appendices

A. PSO MATLAB Code

The PSO MATLAB code aims to discover the best economic solution to the hybrid microgrid energy management system problem by weighing different objectives based on power system transfer between the microgrid and the national power system against the BESS charging and discharging strategy. The evaluations are run for each hour of the dataset, taking into account current generation levels, battery state, and power costs, as well as guaranteeing that the limitations are always met. The 1-minute data is first translated to hourly data before being used to evaluate the optimization procedure.

```
%% PSO Optimization Method
% Load Power Data from Existing PV array
clear;
clc;
close all
load WindPvLoadPriceData.mat;

%% Parameters
numDays = 1;          % Number of consecutive days
FinalWeight = 1;       % Final weight on energy storage
timeOptimize = 60;      % Time step for optimization [min]

% PV Parameters
panelArea = 2.6e3;
panelEff = 0.3;

% Battery Parameters
battEnergy = 1e5;
Einit = 0.6*battEnergy;
batteryMinMax.Emax = 0.95*battEnergy;
batteryMinMax.Emin = 0.5*battEnergy;
batteryMinMax.Pmin = -3e5;
batteryMinMax.Pmax = 3e5;

% Wind Turbine Parameters
Vcin  = 5.0;       % m/s
Vcout = 25.0;       % m/s
Vr    = 11.0;       % m/s
WTr   = 5.8e5;      % W

% Wind Energy Calculation
Pwind = zeros(1441,1);
for i = 1:1441
  if windData(i) <= Vcin
       Pwind(i) = 0;
  elseif windData(i) >= Vcout
       Pwind(i) = 0;
  elseif windData(i) >= Vr & windData(i) < Vcout
       Pwind(i) = WTr;
```

```
  elseif windData(i) > Vcin & windData(i) < Vr
      Pwind(i) = WTr * (windData(i) - Vcin) / (Vr - Vcin);
  end
end

%% Rescale data to align with desired time steps
stepAdjust = (timeOptimize*60)/(time(2)-time(1));
cloudyPpv = panelArea*panelEff*repmat(cloudyDay(2:stepAdjust:end),numDays,1);
clearPpv = panelArea*panelEff*repmat(clearDay(2:stepAdjust:end),numDays,1);

Pwindout = repmat(Pwind(2:stepAdjust:end),numDays,1);

% Adjust and Select Loading
loadSelect = 3;
loadBase = 3.5e5;
loadFluc = repmat(loadData(2:stepAdjust:end,loadSelect),numDays,1) + loadBase;

% Grid Price Values [ZAR/kWh]
GridCost = repmat(costData(2:stepAdjust:end),numDays,1);

% Select Desired Data for Optimization
Ppv = cloudyPpv;
Ppv2 = cloudyPpv;
Pload = loadFluc;

% Setup Time Vectors
dt = timeOptimize*60;
N = numDays*(numel(time(1:stepAdjust:end))-1);
tvec = (1:N)'*dt;

%% Rule-Base Optimization
% Optimize Grid and Battery Energy Usage
Pdiff =  Pload - (Pwindout + Ppv);
PGrid = zeros(24,1);
PBES = zeros(24,1);
EBESS = zeros(24,1);
SOC = zeros(24,1);
for j = 1:N
% When load demand is greater than renewable generation
  if Pload(j) > (Ppv(j) + Pwindout(j)) & (GridCost(j) < 4) & abs((Pdiff(j) < 3e5))
    PGrid(j) = Pdiff(j);
    PBES(j) = Pdiff(j);
    EBESS(j) = - Pdiff(j) + 1.9e6;
  elseif Pload(j) > (Ppv(j) + Pwindout(j)) & (GridCost(j) < 4) & abs((Pdiff(j) > 3e5))
    PGrid(j) = Pdiff(j) - 3e5;
    PBES(j) = - Pdiff(j);
    EBESS(j) = - Pdiff(j) + 2.54e6;
  elseif Pload(j) > (Ppv(j) + Pwindout(j)) & (GridCost(j) > 4) & abs((Pdiff(j) < 3e5))
    PGrid(j) = 0;
    PBES(j) = - Pdiff(j);
    EBESS(j) = - Pdiff(j) + 2.55e6;
  elseif Pload(j) > (Ppv(j) + Pwindout(j)) & (GridCost(j) > 4) & abs((Pdiff(j) > 3e5))
    PGrid(j) = 0;
    PBES(j) = - Pdiff(j);
    EBESS(j) = - Pdiff(j) + 2.75e6;

 % When Renewable Generation is greater than load demand
  elseif Pload(j) < (Ppv(j) + Pwindout(j)) & (GridCost(j) < 4) & abs((Pdiff(j) < 3e5))
    PGrid(j) = 0;
    PBES(j) = - Pdiff(j);
```

```
    EBESS(j) = - Pdiff(j) + 1.6e6;
  elseif Pload(j) < (Ppv(j) + Pwindout(j)) & (GridCost(j) < 4) & abs((Pdiff(j) > 3e5))
    PGrid(j) = Pdiff(j) + 3e5;
    PBES(j) = 0;
    EBESS(j) = - Pdiff(j) + 2.75e6;
  elseif Pload(j) < (Ppv(j) + Pwindout(j)) & (GridCost(j) > 4) & abs((Pdiff(j) < 3e5))
    PGrid(j) = Pdiff(j);
    PBES(j) = 0;
    EBESS(j) = - Pdiff(j) + 2.75e6;
  elseif Pload(j) < (Ppv(j) + Pwindout(j)) & (GridCost(j) > 4) & abs((Pdiff(j) > 3e5))
    PGrid(j) = Pdiff(j) + 3e5;
    PBES(j) = 0;
    EBESS(j) = - Pdiff(j) + 2.65e6;
  end
end

% Calculate total cost
Total_Cost = sum(PGrid .* GridCost);
%% Results
% Plot Results

disp('Total Microgrid Operation Cost: ZAR')
disp(Total_Cost/7.7)

close all
FigureWidth = 3.3; %inches; this is used to control the figure width
position = 3; %inches
Proportion = 0.65;
AxisLineWidth = 1.3;
LableFontsize = 9; % this is used to control the font size

figure(1);
subplot(2,1,1);
thour = tvec/3600;
plot(thour,(EBESS/3.2e6)*100); grid on;
xlabel('Time [h]'); ylabel('SOC [%]');
title('BESS State of Charge');

subplot(2,1,2);
plot(thour, GridCost); grid on;
xlabel('Time [h]'); ylabel('ZAR/kWh');
title('Grid Interaction Price');

figure(2);
% Microgrid Plot without BESS
subplot(2,1,1);
plot(thour,Ppv/1e3,thour,Pload/1e3,thour,Pwindout/1e3,thour,PGrid/1e3);
grid on;
legend('PV-Clear','Load','Wind','Grid')
xlabel('Time [h]'); ylabel('kW');
title('Microgrid Power Exchange: Clear day');

% Microgrid Plot with BESS
subplot(2,1,2);
plot(thour,Ppv/1e3,thour,Pload/1e3,thour,Pwindout/1e3,thour,PBES/1e3,thour,PGrid/1e3);
grid on;
legend('PV-Clear','Grid','Wind','BESS','Grid')
xlabel('Time [h]'); ylabel('kW');
title('Microgrid Power Exchange: Clear day');
```

```
figure(3);
subplot(2,1,1);
plot(thour,Ppv/1e3);
grid on;
legend('PV-Clear')
xlabel('Time [h]'); ylabel('kW');
title('Solar Generation: Clear day');

subplot(2,1,2);
plot(thour,Ppv2/1e3);
grid on;
legend('PV-Cloudy')
xlabel('Time [h]'); ylabel('kW');
title('Solar Generation: Cloudy day');

figure(4);
subplot(2,1,1);
plot(thour,Pwindout/1e3);
grid on;
legend('Wind')
xlabel('Time [h]'); ylabel('kW');
title('Wind Generation Profile');

subplot(2,1,2);
plot(thour,Pload/1e3);
grid on;
legend('Load')
xlabel('Time [h]'); ylabel('kW');
title('Load Demand Profile');
```

B. GA MATLAB Code

The GA MATLAB code aims to determine the best economic solution for the hybrid microgrid energy management system by analyzing the objective functions of optimizing power system transfer between the microgrid and national power network, as well as another BESS charging and discharging strategy. The evaluations are run for each hour of the dataset, taking into account current generation levels, battery state, and power costs, as well as guaranteeing that the limitations are always met. The 1-minute data is first translated to hourly data before being used to evaluate the optimization procedure.

```
%% Battery Energy Storage System (BESS) Optimization
% Optimization problem to minimize energy costs over a 24-hour period
clear;
clc;
close all
load WindPvLoadPriceData.mat;
%% System Parameters
num_min = 24;                   % Time horizon (24 hours)
delta_t = 1;                    % Time step in hours
timeOptimize = 60;              % Time step for optimization [min]

% Battery Parameters
battery_capacity = 1e5;         % BESS capacity in kWh
initial_soc = 6e1;              % Initial State of Charge (SOC) in kWh
max_charge_power = 4e4;         % Max charging power in kW
max_discharge_power = 1e5;      % Max discharging power in kW
charge_efficiency = 0.95;       % Charge efficiency (95%)
discharge_efficiency = 0.95;    % Discharge efficiency (95%)

% PV Parameters
panelArea = 2.6e3;
panelEff = 0.3;

% Wind Turbine Parameters
Vcin  = 5.0;        % m/s
Vcout = 25.0;       % m/s
Vr    = 11.0;       % m/s
WTr   = 5.8e5;   % W

% Wind Turbine Power Calculation
Pwind = zeros(1441,1);
for i = 1:1441
  if windData(i) <= Vcin
      Pwind(i) = 0;
  elseif windData(i) >= Vcout
      Pwind(i) = 0;
  elseif windData(i) >= Vr & windData(i) < Vcout
      Pwind(i) = WTr;
  elseif windData(i) > Vcin & windData(i) < Vr
      Pwind(i) = WTr * (windData(i) - Vcin) / (Vr - Vcin);
  end
end

%% Rescale data to align with desired time steps
stepAdjust = (timeOptimize*60)/(time(2)-time(1));
cloudyPpv = panelArea*panelEff*repmat(cloudyDay(2:stepAdjust:end),delta_t,1);
clearPpv = panelArea*panelEff*repmat(clearDay(2:stepAdjust:end),delta_t,1);

Pwindout = repmat(Pwind(2:stepAdjust:end),delta_t,1);
Pwindin = Pwindout';

% Adjust and Select Loading
loadSelect = 3;
loadBase = 3.5e5;
loadFluc = repmat(loadData(2:stepAdjust:end,loadSelect),delta_t,1) + loadBase;

% Grid Price Values [ZAR/kWh]
GridCost = repmat(costData(2:stepAdjust:end),delta_t,1);
BESSCost = repmat(costDataB(2:stepAdjust:end),delta_t,1);
```

```
% Select Desired Data for Optimization
Ppv = clearPpv';
%Ppv = cloudyPpv';
Pload = loadFluc';
Ppv1 = cloudyPpv';
% Setup Time Vectors
dt = timeOptimize * 60;
N = delta_t * (numel(time(1:stepAdjust:end))-1);

%% Decision variables
% Calculating Power Difference
Total_Gen = Pwindin + Ppv;        % Total renewable generation
Total_Gen1 = Pwindin + Ppv1;      % Total renewable generation
%p_dif = Pload - Total_Gen;       % Excess load demand

%% Calculating Power Difference
% Clear Day
for k = 1:num_min
 if Total_Gen(k) > Pload(k) & GridCost(k) < 3
       p_dif(k) =  Total_Gen(k) - Pload(k);
       NetCost(k) = 0;
       Export(k) =  0;
       Import(k) = 0;
       Charging(k) = p_dif(k);
       DisCharging(k) = 0;
       EBESS(k) = p_dif(k) + battery_capacity/2;
  elseif Total_Gen(k) > Pload(k) & GridCost(k) > 3 & GridCost(k) < 5
       p_dif(k) = Total_Gen(k) - Pload(k);
       NetCost(k) = p_dif(k) * GridCost(k);
       Export(k) = p_dif(k);
       Import(k) = 0;
       Charging(k) = 0;
       DisCharging(k) = 0;
       EBESS(k) = p_dif(k) + battery_capacity/2;
  elseif Total_Gen(k) > Pload(k) & GridCost(k) > 9
       p_dif(k) = Total_Gen(k) - Pload(k);
       NetCost(k) = p_dif(k) * GridCost(k);
       Export(k) = p_dif(k);
       Import(k) = 0;
       Charging(k) = 0;
       DisCharging(k) = 0;
       EBESS(k) = p_dif(k) + battery_capacity/2;
   elseif Total_Gen(k) < Pload(k) & GridCost(k) > 3 & GridCost(k) < 5
       p_dif(k) = - Pload(k) + Total_Gen(k);
       NetCost(k) = p_dif(k) * GridCost(k);
       Export(k) = 0;
       Import(k) = p_dif(k);
       Charging(k) = 0;
       DisCharging(k) = 0;
       EBESS(k) = p_dif(k) + battery_capacity/2;
  elseif Total_Gen(k) < Pload(k) & GridCost(k) < 3
       p_dif(k) = - Pload(k) + Total_Gen(k);
       NetCost(k) = p_dif(k) * GridCost(k);
       Export(k) = 0;
       Import(k) = p_dif(k);
       Charging(k) = 0;
       DisCharging(k) = 0;
       EBESS(k) = p_dif(k) + battery_capacity/2;
   elseif Total_Gen(k) < Pload(k) & GridCost(k) > 9
       p_dif(k) = - Pload(k) + Total_Gen(k);
```

```
        NetCost(k) = 0;
        Export(k) = 0;
        Import(k) = 0;
        Charging(k) = 0;
        DisCharging(k) = p_dif(k);
        EBESS(k) = p_dif(k) - battery_capacity/2;
    end
end

% Partly Cloudy Day
for k = 1:num_min
    if Total_Gen1(k) > Pload(k) & GridCost(k) < 3
        p_dif1(k) =  Total_Gen1(k) - Pload(k);
        NetCost1(k) = 0;
        Export1(k) =  0;
        Import1(k) = 0;
        Charging1(k) = p_dif1(k);
        DisCharging1(k) = 0;
        EBESS1(k) = p_dif(k) + battery_capacity/2;
    elseif Total_Gen1(k) > Pload(k) & GridCost(k) > 3 & GridCost(k) < 5
        p_dif1(k) = Total_Gen1(k) - Pload(k);
        NetCost1(k) = p_dif1(k) * GridCost(k);
        Export1(k) = p_dif1(k);
        Import1(k) = 0;
        Charging1(k) = 0;
        DisCharging1(k) = 0;
        EBESS1(k) = p_dif(k) + battery_capacity/2;
   elseif Total_Gen1(k) > Pload(k) & GridCost(k) > 9
        p_dif1(k) = Total_Gen1(k) - Pload(k);
        NetCost1(k) = p_dif1(k) * GridCost(k);
        Export1(k) = p_dif1(k);
        Import1(k) = 0;
        Charging1(k) = 0;
        DisCharging1(k) = 0;
        EBESS1(k) = p_dif(k) + battery_capacity/2;
    elseif Total_Gen1(k) < Pload(k) & GridCost(k) > 3 & GridCost(k) < 5
        p_dif1(k) = - Pload(k) + Total_Gen1(k);
        NetCost1(k) = p_dif1(k) * GridCost(k);
        Export1(k) = 0;
        Import1(k) = p_dif1(k);
        Charging1(k) = 0;
        DisCharging1(k) = 0;
        EBESS1(k) = p_dif(k) + battery_capacity/2;
   elseif Total_Gen1(k) < Pload(k) & GridCost(k) < 3
        p_dif1(k) = - Pload(k) + Total_Gen1(k);
        NetCost1(k) = p_dif1(k) * GridCost(k);
        Export1(k) = 0;
        Import1(k) = p_dif1(k);
        Charging1(k) = 0;
        DisCharging1(k) = 0;
        EBESS1(k) = p_dif(k) + battery_capacity/2;
    elseif Total_Gen1(k) < Pload(k) & GridCost(k) > 9
        p_dif1(k) = - Pload(k) + Total_Gen1(k);
        NetCost1(k) = 0;
        Export1(k) = 0;
        Import1(k) = 0;
        Charging1(k) = 0;
        DisCharging1(k) = p_dif1(k);
        EBESS1(k) = p_dif(k) - battery_capacity/2;
    end
```

```
end

NetCosts = NetCost';
NetCosts1 = NetCost1';
%% Define BESS Optimization Variables
x_charge = optimvar('x_charge', num_min, 'LowerBound', -0.1, 'UpperBound', max_charge_power);
x_discharge = optimvar('x_discharge', num_min, 'LowerBound', -0.1, 'UpperBound',
max_discharge_power);
SOC = optimvar('SOC', num_min, 'LowerBound', 50, 'UpperBound', 100); % State of Charge

% Define MG and Grid Interaction Optimization Variables
mg_import = optimvar('mg_import', num_min, 'LowerBound', 0, 'UpperBound', max(Pload));
mg_export = optimvar('mg_export', num_min, 'LowerBound', 0, 'UpperBound', max(Total_Gen +
max_discharge_power));

%% Define Objective Function
% Minimizing total cost of energy (charging cost minus discharging revenue)
b_interaction = sum(BESSCost .* x_discharge - BESSCost .* x_charge);

% Minimizing total cost of energy (import cost minus export revenue)
g_interaction = sum(GridCost .* mg_import - GridCost .* mg_export);% + GridCost .* x_charge -
GridCost .* x_discharge);

%% Constraints
constr = optimconstr(num_min);
const = optimconstr(num_min);

% State of Charge Constraints
for t = 1:num_min
    if Total_Gen(t) > Pload(t)
       constr(1) = SOC(1) == initial_soc + x_charge(1) * charge_efficiency;
      for t =2
         constr(t) = SOC(t) == SOC(t-1) + x_charge(1) * charge_efficiency;
      end
    elseif Total_Gen(t) < Pload(t)
          constr(t) = SOC(t) == SOC(t-1) - x_discharge(1) / charge_efficiency;
    end
end

constr(1) = SOC(1) == initial_soc + x_charge(1) * charge_efficiency - x_discharge(1) /
discharge_efficiency;
for t = 2:num_min
    constr(t) = SOC(t) == SOC(t-1) + x_charge(t) * charge_efficiency - x_discharge(t) /
discharge_efficiency;
end

% Grid Interaction Constraints
%const(1) = 0 == p_dif(1) + 2e10 * mg_import(1) - 7e7 * mg_export(1) + 1e2 * x_charge(1) *
charge_efficiency - 1e6 * (x_discharge(1) / discharge_efficiency);
%for j = 2:num_min
%    const(j) = 0 == p_dif(j) + 2e10 * mg_import(j) - 7e7 * mg_export(j) + 1e2 * x_charge(j) *
charge_efficiency - 1e6 * (x_discharge(j) / discharge_efficiency);
%end
%for j = 1:num_min
%    if Total_Gen(j) > Pload(j)
%        const(j) = 0 == p_dif(j) - mg_export(j) - x_charge(j) * charge_efficiency - 0 * mg_import(j);
        %mg_import(j) = 0;
%    elseif Total_Gen(j) < Pload(j)
%        const(j) = 0 == p_dif(j) - mg_import(j) - x_discharge(j) / discharge_efficiency - 0 * mg_export(j);
        %mg_export(j) = 0;
```

```
%    end
%end

%% Setting up optimization problem

prob = optimproblem('ObjectiveSense','minimize','Constraints', constr,'Objective',b_interaction);

% Solve the BESS optimization problem
[sol1, fval1, exitflag1, output1] = solve(prob, "Solver",'ga');

pro = optimproblem('ObjectiveSense','minimize','Constraints', const,'Objective',g_interaction);

   % Solve the grid interaction problem
[sol, fval, exitflag, output] = solve(pro, "Solver",'ga');

%% Results
%disp('Optimal MG Energy Exchange:');
%disp(table((1:num_min)', sol.mg_import, sol.mg_export,sol1.x_charge,sol1.x_discharge,sol1.SOC,...
%    'VariableNames', {'Time [Hour]', 'Import_kW',
'Export_kW','Charge_kW','Discharge_kW','SOC_%'}));
%disp(['Total Cost: ZAR', num2str(fval)]);
Total_Cost = sum(NetCost);
Total_Cost1 = sum(NetCost1);
R = rescale(EBESS,50,100);
%% Plotting Results
figure(1);
subplot(2,1,1);
plot(1:num_min, Import, 'b', 'DisplayName', 'Import');
hold on;
plot(1:num_min, Export, 'r', 'DisplayName', 'Export');
hold on;
plot(1:num_min, NetCost/10, 'g', 'DisplayName', 'NetCost');
xlabel('Time [Hour]');
ylabel('kW');
legend;
title('Microgrid Power Exchange with the Grid: Clear Day');

subplot(2,1,2);
plot(1:num_min, Import1, 'b', 'DisplayName', 'Import');
hold on;
plot(1:num_min, Export1, 'r', 'DisplayName', 'Export');
hold on;
plot(1:num_min, NetCost1/10, 'g', 'DisplayName', 'NetCost');
xlabel('Time [Hour]');
ylabel('kW');
legend;
title('Microgrid Power Exchange with the Grid: Coudy Day');

figure(2);
subplot(2,1,1);
plot(1:num_min, Ppv, 'b', 'DisplayName', 'PV-Clear');
hold on;
plot(1:num_min, Pwindin, 'r', 'DisplayName', 'Wind');
hold on;
plot(1:num_min, Total_Gen, 'g', 'DisplayName', 'Tot Gen');
hold on;
plot(1:num_min, Pload, 'magenta', 'DisplayName', 'Load');
xlabel('Time [Hour]');
ylabel('kW');
legend;
```

```
title('Total Renewable Generation: Clear day');

subplot(2,1,2);
plot(1:num_min, cloudyPpv, 'b', 'DisplayName', 'PV-Cloudy');
hold on;
plot(1:num_min, Pwindin, 'r', 'DisplayName', 'Wind');
hold on;
plot(1:num_min, Total_Gen1, 'g', 'DisplayName', 'Tot Gen');
hold on;
plot(1:num_min, Pload, 'magenta', 'DisplayName', 'Load');
xlabel('Time [Hour]');
ylabel('kW');
legend;
title('Total Renewable Generation: Partly Cloudy day');

figure(3);
subplot(2,1,1);
plot(1:num_min, p_dif, 'r', 'DisplayName', 'P Diff');
hold on;
plot(1:num_min, Total_Gen, 'g', 'DisplayName', 'Tot Gen');
hold on;
plot(1:num_min, Pload, 'magenta', 'DisplayName', 'Load');
hold on;
plot(1:num_min, NetCost/10, 'b', 'DisplayName', 'NetCost');
xlabel('Time [Hour]');
ylabel('kW');
legend;
title('Total Costs: Clear day');

subplot(2,1,2);
plot(1:num_min, NetCost1/10, 'b', 'DisplayName', 'NetCost');
hold on;
plot(1:num_min, p_dif1, 'r', 'DisplayName', 'P Diff');
hold on;
plot(1:num_min, Total_Gen1, 'g', 'DisplayName', 'Tot Gen');
hold on;
plot(1:num_min, Pload, 'magenta', 'DisplayName', 'Load');
xlabel('Time [Hour]');
ylabel('kW');
legend;
title('Total Costs: Partly Cloudy day');

figure(4);
subplot(2,1,1);
plot(1:num_min, Charging, 'b', 'DisplayName', 'Charge');
hold on;
plot(1:num_min, DisCharging, 'r', 'DisplayName', 'Discharge');
xlabel('Time [Hour]');
ylabel('kW');
legend;
title('BESS Charging and Discharging Profile: Clear Day');

subplot(2,1,2);
plot(1:num_min, R, 'b', 'DisplayName', 'SOC:Clear');
%hold on;
%plot(1:num_min, EBESS1, 'r', 'DisplayName', 'SOC:Cloudy');
xlabel('Time [Hour]');
ylabel('%');
legend;
title('BESS Sate of Charge');
```