ARTIFICIAL INTELLIGENCE-BASED HIERARCHICAL MANAGEMENT FOR OPTIMIZED PERFORMANCE AND ENERGY TRADING IN NETWORKED MICROGRIDS

By

TUKKEE AHMED SAHIB HAMMADI

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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DEDICATION

With heartfelt sincerity, I extend my deepest gratitude to:

My cherished wife, Ph.D. student **Qamar Muhammad Naji,** for her unwavering support, patience, and understanding, and to my beloved children, **Zainulabdeen, Abdullah, Yusur**, and my dear daughter, **Dima**.

I also dedicate this research to the memory of my beloved father, my mother, my siblings, and my friends in Iraq.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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Chairman : Associate Professor Noor Izzri bin Abdul Wahab, PEng, PhD
Faculty : Engineering

With the increasing demand for electrical energy due to population growth and technological advancements, coupled with concerns over fossil fuel prices and environmental impacts, the integration of renewable energy sources like photovoltaic and wind turbines has become imperative. Microgrid offers a solution by efficiently meeting load demands through a combination of renewable energy sources and conventional resources like diesel generators and battery storage systems. For enhanced utility, adjacent microgrid s are interconnected to form Networked Microgrid systems. The optimal integration of networked microgrid systems necessitates addressing three fundamental aspects: optimizing microgrid size, effectively managing diverse microgrid resources, and facilitating energy trading within local energy markets.

This thesis presents a two-level hierarchical strategy based on artificial intelligence methods to address these problems. A hybrid artificial intelligence method is developed by integrating grey wolf optimizer and particle swarm optimization technique called hybrid grey wolf- particle swarm optimization to determine optimal configurations and sizes for microgrid. Multi-objective optimization, considering levelized cost of energy, power losses, and gas emissions, is employed and reliability indicators including losses of power supplied probability, cost benefit index, and participation of renewable index are monitored. The results showed that the configuration that include photovoltaic-wind turbines-diesel generators-battery storage systems delivered highly favorable outcomes. Specifically, it achieved an impressive levelized cost of energy of 0.127 $/kWh, correspondingly, the losses of power supplied probability index was (0.0271). A comparative analysis was conducted with results obtained from the firefly algorithm, particle swarm optimization, and grey wolf optimizer techniques individually, highlighting the superiority of the hybrid grey wolf- particle swarm optimization over the others. Furthermore, this thesis proposes a distributable resource management strategy to reduce gas emissions and minimize levelized cost of energy. Additionally, a demand-side management strategy is introduced to shift non-sensitive loads from periods of energy shortage to surplus. These dual strategies succeeded in diminishing the levelized cost of energy and gas emissions of Microgrids 1, 2, 3, and 4 to (0.125, 0.127, 0.129, 0.128) $/kWh and (5.77, 5.52, 19.98, 14.79) tone/year respectively. Finally, a revised approach for energy trading in the local energy market is presented, encompassing various mechanisms including peer-to-peer, peer-to-grid, and distributed methods. Multi-round energy auctions, considering transmission line capacities and costs, determine energy prices and quantities traded. peer-to-peer yields the highest annual benefit, while distributed trading reduces losses of power supplied probability. Overall, the proposed strategies prove effective in enhancing Networked Microgrid systems performance, showcasing significant improvements in economic, technical, and environmental aspects.

These contributions collectively demonstrate significant improvements in the economic, technical, and environmental performance of Networked Microgrid systems, making them more sustainable and efficient for future energy demands.

Keywords: artificial intelligence, energy management, energy trading market, microgrid, renewable energy.

SDG: GOAL 7: Affordable and Clean Energy, GOAL 9: Industry, Innovation, and Infrastructure, GOAL 13: Climate Action.

Abstrak tesis yang dikemukakan kepada senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazh Doktor Falsafah

PENGURUSAN HIERARKI BERASASKAN KECERDASAN BUATAN UNTUK PENGOPTIMUMAN PRESTASI DAN PERDAGANGAN TENAGA DALAM MIKROGRID BERANGKAIAN

Oleh

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Dengan peningkatan permintaan terhadap tenaga elektrik disebabkan oleh pertumbuhan populasi dan kemajuan teknologi, serta kebimbangan mengenai harga bahan api fosil dan kesan alam sekitar, integrasi sumber tenaga boleh diperbaharui seperti fotovolta dan turbin angin menjadi semakin penting. Mikrogrid menawarkan penyelesaian dengan memenuhi permintaan beban secara efisien melalui gabungan sumber tenaga boleh diperbaharui dan sumber konvensional seperti penjana diesel dan sistem penyimpanan bateri. Untuk kegunaan yang lebih optimum, mikrogrid yang berdekatan saling dihubungkan bagi membentuk sistem Mikrogrid Berjaringan. Integrasi optimum sistem mikrogrid berjaringan memerlukan perhatian kepada tiga aspek utama: pengoptimuman saiz mikrogrid, pengurusan sumber mikrogrid yang pelbagai secara efektif, dan memudahkan perdagangan tenaga dalam pasaran tenaga tempatan.

Tesis ini membentangkan strategi hierarki dua peringkat berasaskan kaedah kecerdasan buatan untuk menangani masalah ini. Kaedah kecerdasan buatan hibrid dibangunkan dengan menggabungkan pengoptimum serigala kelabu dan teknik pengoptimuman kawanan zarah, yang dinamakan hibrid serigala kelabu-kawanan zarah, untuk menentukan konfigurasi dan saiz optimum mikrogrid. Pengoptimuman pelbagai objektif, yang mempertimbangkan kos tenaga tahap, kehilangan tenaga, dan pelepasan gas, diaplikasikan, serta penunjuk kebolehpercayaan seperti indeks kebarangkalian kehilangan tenaga yang dibekalkan, indeks manfaat kos, dan indeks penyertaan sumber boleh diperbaharui dipantau. Hasil menunjukkan bahawa konfigurasi yang merangkumi sistem fotovolta-turbin angin-penjana diesel-sistem penyimpanan bateri memberikan hasil yang sangat baik, dengan kos tenaga tahap sebanyak 0.127 $/kWh dan indeks kebarangkalian kehilangan tenaga yang dibekalkan sebanyak 0.0271. Analisis perbandingan dilakukan dengan keputusan daripada algoritma kelip-kelip, pengoptimuman kawanan zarah, dan pengoptimum serigala kelabu secara individu, menonjolkan keunggulan pengoptimuman hibrid serigala kelabu-kawanan zarah berbanding yang lain.

Tambahan lagi, tesis ini mencadangkan strategi pengurusan sumber teragih untuk mengurangkan pelepasan gas dan meminimumkan kos tenaga tahap. Strategi pengurusan permintaan turut diperkenalkan untuk mengalihkan beban yang tidak sensitif dari tempoh kekurangan tenaga kepada lebihan. Kedua-dua strategi ini berjaya mengurangkan kos tenaga tahap dan pelepasan gas bagi Mikrogrid 1, 2, 3, dan 4 masing-masing kepada (0.125, 0.127, 0.129, 0.128) $/kWh dan (5.77, 5.52, 19.98, 14.79) tan/tahun. Akhir

sekali, pendekatan yang diperbaharui untuk perdagangan tenaga dalam pasaran tenaga tempatan dibentangkan, meliputi pelbagai mekanisme seperti perdagangan rakan-ke-rakan, rakan-ke-grid, dan kaedah teragih. Lelongan tenaga berbilang pusingan, yang mempertimbangkan kapasiti talian penghantaran dan kos, menentukan harga dan kuantiti tenaga yang diperdagangkan. Perdagangan rakan-ke-rakan memberikan manfaat tahunan tertinggi, manakala perdagangan teragih mengurangkan kebarangkalian kehilangan tenaga yang dibekalkan.

Kata Kunci: kecerdasan buatan, pengurusan tenaga, pasaran perdagangan tenaga, mikrogrid, tenaga boleh diperbaharui.

SDG: MATLAMAT 7: Tenaga Bersih dan Berpatutan, MATLAMAT 9: Industri, Inovasi dan Infrastruktur, MATLAMAT 13: Tindakan Memerangi Perobahan Iklim.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and accepted as a fulfilment of the requirements for the degree of Doctor of Philosophy. Members of the Supervisory Committee are as follows:

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Date: 13 January 2025

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AA	Adaptive Aggression
AC	Alternating Current
BS	Bill Sharing
BSA	Backward Search Algorithm
CBI	Cost Benefit Index
C^c	Capital investment cost
C_c	Carbon element's proportion
CDA	Continuous Double Auction
C^f	Cost of fuel
CL	Curtailable Load
C_l	Conductor length connecting two buses
C_{line}	Costs escalate with the trading of energy through the lines
CMP	Capacity Market Programs
CMU	Central Management Units
$C^{o\&m}$	Cost of operation and maintenance
COE	cost of energy
CPP	Critical Peak Pricing
C^r	Cost of replacement
CRF	Capital Recovery Factor
C^s	Cost of salvage
C_{sh}	Cost of load shedding
DA	Double Auction
DC	Direct Current
DER	Distributed Energy Resources
DG	Diesel Generators

DG^{feul}	DG fuel consumption
DG_{max}	DG maximum generated power
DLC	Direct Load Control
DOD_{max}	Maximum battery Depth of Discharge
DRMS	Distributable Resources Management Strategy
DRP	Demand Response Programs
DSMS	Demand Side Management Strategy
DG_{strtup}	DG start-up limit
E^{DG}	The output energy of the DG
E^{load}	The load required
EMS	Energy Management Strategies
E_{net}	Net energy
EP	Equilibrium Point
EPRI	Electric Power Research Institute
E^{PV}	The output energy of PV panels
ESS	Energy Storage Systems
E^{WT}	The output energy of a wind turbine
$E_{MGi}^{BSS,ch}$	BSS output at charging mode
$E_{MGi}^{BSS,dich}$	BSS output at discharging mode
E_{max}^{BSS}	Maximum power for charging and discharging
E_{max}^{DG}	Upper limit of the DG output.
E_{max}^{WT}	Maximum energy output of the wind turbine
E_{max}^{pv}	Maximum output energy of the PV system
E_{min}^{DG}	Lower limit of the DG output.
E_{rate}^{DG}	Rated design power of the DG
$E_{sh,load}$	Shiftable loads

FA	Firefly Algorithm
f_{PV}	PV panels derating factor
$G(t)$	the solar radiation
GA	Genetic Algorithm
gbest	global best
GEM	Gas Emissions
G_{ref}	Standard episode solar radiation
GSO	Group Search Optimizer
GWO	Grey Wolf Optimizer
h	hub height
HGWPSO	Hybrid GWO and PSO
HOMER	Hybrid Optimization of Multiple Energy Resources
hr	Reference height of wind turbine tour
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
I_r	Interesting factor
ISFLA	Improved Shuffled Frog Leaping Algorithm
k	BSS mode
l	The MG component's lifetime
LCOE	Levelized Cost of Energy
LEM	Local Energy Markets
LMU	Local Management Units
LPSP	Loss of Power Supply Potential
l_{ref}	Reference load
LV	Low Voltage
MAQL	Multi-Agent Q-Learning

MG	Microgrid
MG-EMC	Microgrid Energy Management Central
MILP	Mixed Linear Programming
MMR	Mean Market Rate
MT	Microturbines
MV	Medium Voltage
n	Project lifetime
NDER	Non-Distributed Energy Resources
NMG	Networked Microgrid
NMG-MU	NMG Management Units
NOCT	Nominal Operating Temperature of a PV
N^{PV}	Number of PV panels
N^{WT}	Number of WT
$P_{(i,j)}$	Power transmission between bus i and j
P2G	Peer-to-Grid
P2P	Peer-to-Peer
pbest	particle best
PCC	Points of Common Coupling
P_{in}	The input power of inverter
P_{loss}	The power losses
P_{out}	The output power of inverter
PSO	Partial Swarm Optimization
PV	Photovoltaic
PVF	Present Value Factor
REI	Renewable Energy Index
RES	Renewable Energy Resources

RL	Reinforcement Learning
RTP	Real-Time Pricing
S_D	Battery autonomy or storage days
SDR	Supply-Demand Ratio
SOC	State of Charge
SOC_{max}	Upper limits of the *SOC*
SOC_{min}	Lower limits of the *SOC*
SSI	System Stability Index
t and t_{max}	Current and maximum iteration
T_{amb}	Ambient temperature
$T_c(t)$	Cell temperature
T_{cf}	Temperature correction factor.
TNPC	Total Net Present Cost
ToU	Time of Use
T_{ref}	Standard cell temperature at test conditions
$v(t)$	Wind speed
VAR	Volt-Ampere Reactive
V_B	Battery voltage
$V_{cut\ out}$	Cut-out speed
v_{cutin},	Cut-in speed
V_i	Distribution voltage at the i^{th} bus
v_r	Rated speed
v_w	Wind speed at the turbine blades
w_1, w_2,w_3	Weighting variables for objective function
WT	Wind turban
WT^{rate}	Output power at the rated speed

ZI	Zero Intelligence
ZIP	Zero Intelligence Plus
α	Power law exponent
α_P	Coefficient of temperature
η_{10}	Efficiency of the inverter at 10%
η_{100}	Efficiency of the inverter at 100%
η^{BSS}	Battery efficiency
η^{inv}	Inverter's efficiency
ρ	Resistivity of the conductor
σ	Self-discharge rate
$\mathfrak{y}$	Generative disturbance coefficient.
ξ	Coefficient of a lump-sum payment
ρ_{fixed}^{sell}	Fixing selling price .
$\vec{X}_p(t)$	Prey position vectors
$\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$	Best three solutions at each iteration
$\vec{A}, \vec{C}$	GWO vectors
$\vec{X}(t)$	Wolfe position vectors
A	Cross-section of the conductor
$f_{sh,load}$,	Factors for load shifting from hour t
$f_{max}^{sh,load}$	Maximum value of factors for load shifting
k_{max}^{DG}	Maximum load rates of the DG
k_{min}^{DG}	Minimum load rates of the DG
pv_{MGi}^{rate}	PV-rated capacity
β_o	FA brightness when the distance is zero

γ_i	Priority factor for each buyer
ρ_G^{sell}	Selling price of the main grid
ρ_{fixed}^{buy}	Fixing buying price.

CHAPTER 1

INTRODUCTION

The escalating global demand for electrical energy, coupled with challenges like soaring fuel prices and environmental constraints, has spurred a growing interest in leveraging renewable energy sources within existing energy frameworks. In response, the concept of microgrids (MG) has emerged, integrating renewable resources alongside traditional ones, and incorporating energy storage systems. These MGs are further interconnected into networked MG (NMG) systems, fostering a more resilient and adaptable energy landscape.

This research delves into contemporary approaches employing artificial intelligence to optimize networked microgrid systems, facilitating the seamless integration of renewable energy resources. The introductory chapter lays the groundwork by outlining the evolution of energy systems toward smarter and more dependable configurations. It also delineates the underlying assumptions and research challenges propelling this investigation forward. Additionally, the chapter delineates primary and secondary research objectives, concluding with a structured overview of the thesis and a simplified breakdown of forthcoming chapters.

1.1 Background

Electricity is widely regarded as the cornerstone of modern civilization and a definitive measure of a nation's progress. Nonetheless, according to the

United Nations (UN), approximately one billion individuals worldwide are still deprived of access to this essential resource (Nti et al., 2020). The demand for electricity on a global scale has surged in recent years, propelled by remarkable technological advancements and rapid population growth, while the capacity of power plants has remained largely unchanged. The International Energy Agency (IEA) predicts that between 2000 and 2040, the average annual growth rate of power consumption will be 66% (Saint Akadiri et al., 2020). According to the "New Energy Policy Scenario," by 2040, the total amount of electricity consumed in the world is expected to increase from 25.679 billion kilowatt hours to 40.443 billion kilowatt hours, with an annual growth rate of 2.0% (Koot & Wijnhoven, 2021). Starting from the 1950s, conventional energy sources, including fossil fuels, have been employed in electricity generation facilities, alongside hydroelectric and nuclear power plants. In 2017, fossil fuels contributed to generating up to 64.5% of the electricity produced around the world, compared to 61.9% in 1990 (Savage, 2023) . It is believed that about 80% of carbon dioxide in the atmosphere is produced by burning fossil fuels, 50% of which typically comes from electricity production plants (Nandimandalam & Gude, 2022).

Present-day worldwide issues, encompassing concerns like climate change, environmental deterioration, and the volatile nature of fossil fuel markets, have motivated operators in the electricity sector to enhance and adapt conventional power grids. This evolution involves the augmented integration of renewable energy sources (RES) (Breyer et al., 2022). Due to its great efficiency, low emission, and low noise levels, there has been a remarkable surge in worldwide enthusiasm for generating electrical energy through RES.

Reports from the United Nations' Intergovernmental Panel on Climate Change (IPCC) indicate that, with sufficient storage capacity, renewable energies have the potential to satisfy the entire global energy demand. Furthermore, RES are projected to account for 50% of the world's total energy supply by the year 2050 (Al-Shetwi, 2022). Figure 1.1 displays the net power production of the world by RES (in trillion kilowatt-hours).

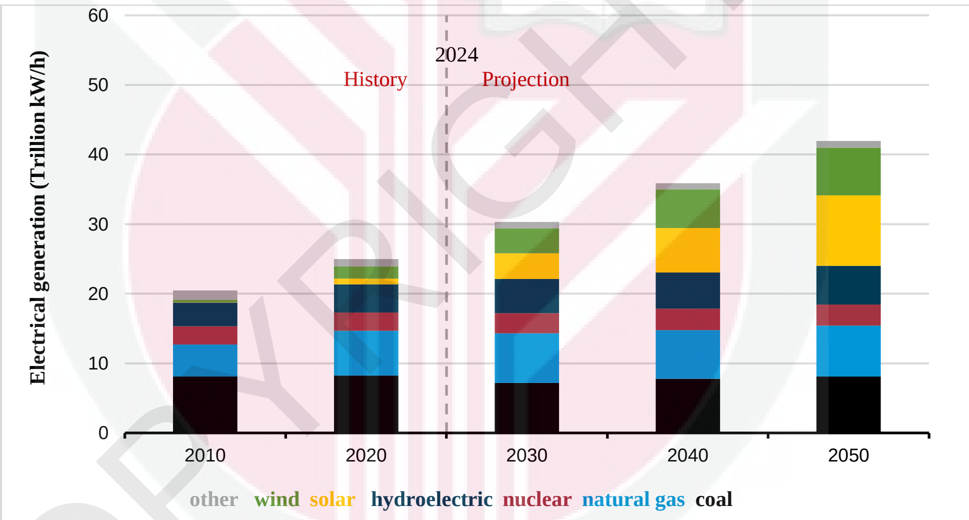

Figure 1.1 : The Net Electricity Generation of the World by Different Distributed Generation Sources

Although RES technology is being rapidly adopted and increasingly integrated into established distribution systems, there are a variety of challenges associated with RES that could negatively impact system performance. Concerns like power quality and discrepancies between energy generation and load demand are included in these problems. The most efficient method for addressing these issues is to move to an MG (Dey et al., 2023).

MGs represent a sophisticated local grid system distinguished by their utilization of low-voltage (LV) or medium-voltage (MV) distribution networks. These grids incorporate a diverse array of generation resources, including RES like photovoltaic (PV) systems, wind turbines (WT), and tidal energy, alongside conventional sources such as diesel generators (DG), microturbines (MT), and energy storage systems like batteries energy storage systems (BSS) and flywheels strategically positioned in proximity to end users (Alzahrani et al., 2022).

The MG resources operate in harmony to meet the varying electrical demands of a diverse range of flexible loads. The MG can operate in tandem with conventional power systems through grid-connected mode or function autonomously in standalone mode. MG stands out predominantly due to its distinctive management and coordination of energy resources, coupled with its exceptional flexibility in transitioning between operational modes (Shahgholian, 2021).

Individual MGs often encounter challenges in meeting full load requirements and may resort to shedding less critical loads during periods of energy scarcity, particularly when operating independently. This energy shortfall stems from the intermittent nature of RES and fluctuations in energy demand, resulting in a noticeable misalignment between energy supply and demand within the system. Conversely, there are instances of energy surplus that cannot be efficiently utilized (Cagnano et al., 2020).

Hence, the necessity arises to interconnect a cluster of neighboring individual MGs to create more sophisticated energy systems known as NMG systems. The establishment of NMG systems facilitates the exchange of energy reserves among MGs, especially when they function autonomously or during emergency scenarios (Chen et al., 2020). Consequently, this enhances the adaptability of power systems and minimizes the likelihood of load shedding. Looking ahead, NMG systems are poised to continually expand to address the ever-growing global energy needs (A. R. Singh et al., 2023).

The heightened integration of NMG systems with distribution networks has resulted in a surge in the complexity of energy systems and the dynamic variation in energy flow within them. Consequently, there is a pressing need to develop efficient and effective Energy Management Systems (EMS) capable of regulating energy flow, optimizing economic returns, and mitigating associated challenges and drawbacks stemming from the integration of these systems (Singh et al., 2023).

Moreover, this heightened integration has unlocked more self-reliant and reliable local energy markets (LEM), propelled by the synergistic utilization of RES. Within the domain of electricity distribution systems, energy trading between NMG systems and the main grid has emerged as a promising LEM strategy aimed at maintaining an efficient energy balance and mitigating escalating retail electricity costs (Trivedi et al., 2022).

The LEM plays a crucial role in maintaining an efficient energy balance and alleviating strain on centralized grids. Among the emerging solutions, peer-to-peer (P2P), peer-to-grid (P2G), and distributed energy trading stand out as prominent methods gaining traction for decentralized energy trading between NMG and centralized energy systems (Zia et al., 2020).

The LEM fosters a culture of innovation and collaboration, encouraging participants to explore new avenues for energy trading. It serves as a horizontal platform for sharing, transferring, and trading energy among peers, who may function as both consumers and producers. Given the pressing need to enhance traditional energy systems and imbue them with greater flexibility through seamless integration with NMG systems, three pivotal dimensions demand attention: strategic planning and design of NMG systems, effective management practices, and efficient organization of energy markets. These pillars encapsulate the primary objectives of our study, which seeks to optimize the performance of NMG systems across economic, technical, and environmental considerations. Through a comprehensive exploration of these aspects, we aim to enhance the overall efficiency and sustainability of NMG systems.

1.2 Problem Statement

The transition from traditional energy systems to intelligent energy systems has been pivotal in elevating the prominence of MGs and advancing towards NMG systems. These NMG systems are adept at efficiently coordinating and managing RES collaboratively. This progress has markedly enhanced the efficiency and reliability of energy systems, serving as a cornerstone for bolstering economic, technical, and environmental aspects (Nardelli et al., 2021). Moreover, it has successfully mitigated the adverse impacts linked with fossil fuels and addressed the mounting global energy demand while aligning with efforts to combat climate change and rising energy costs. Following a comprehensive review of current literature on NMG systems, three key research domains related to design, management, and energy trading have emerged as requiring further investigation and emphasis.

In recent years, the energy industry has increasingly turned its attention to RES for large-scale energy generation. However, these resources are characterized by volatility and unpredictability due to their dependence on weather and climate patterns. This variability can create challenges in aligning energy supply with demand over time (Singh et al., 2023). Designing an economically and technically optimal MG system considering these factors poses a significant challenge. The size of MGs can contribute to surplus energy, which may become underutilized when MGs operate independently or engage in trading with central grids at unfavorable prices, leading to increased production costs. Conversely, small-size MGs may struggle to meet all load requirements, necessitating energy imports to cover shortages (Kumar et al., 2020). Before initiating the design of any MG emphasizing RES, it is essential to calculate the optimal sizes of MG components and select efficient energy management systems.

To address the intermittent nature of RES due to climate conditions, there is a pressing need to integrate more reliable and stable backup energy resources (Muhtadi et al., 2021). Diesel generators are often considered as dependable standby resources, offering swift responses to load demands. However, their integration presents challenges for overall system performance, such as heightened environmental pollution and increased operational and maintenance costs (Ndwali et al., 2020). Achieving optimal performance in NMG systems demands a harmonious balance between energy production from various sources, including RES and DG, while considering economic and environmental factors. This necessitates stringent regulations on DG operation and the ability to control their energy output. Addressing these challenges requires the implementation of efficient collaborative and collective management strategies.

Microgrids participating in the LEM are required to bid, buy, and sell energy every hour to supplement any energy skew. It is common practice for MG to bid to purchase energy from the central grid at high prices close to the retail price and bid to sell energy at a very low price to ensure that these bids are always accepted in the LEM (Zahraoui et al., 2023). This situation creates significant difficulties in the current energy markets, both technically and economically. In the realm of domestic energy markets, a prominent issue arises from existing energy trading strategies that impede the involvement of smaller capacity participants (Dudjak et al., 2021). The predominant focus on executing substantial energy trading contracts overlooks critical factors such as transmission line capacities, typically owned by distribution networks, and the associated costs (Bahmani et al., 2020). This oversight results in distorted data concerning the true costs of energy trading within independent system operators. This misinformation may lead to inefficient allocation of resources, as the system operators base their decisions on inaccurate cost assessments. Furthermore, it can result in congestion on the transmission lines, as the capacity constraints are not properly accounted for, ultimately affecting the stability and reliability of the energy grid. In brief, this study can solve the following research problems:

1) **Intermittency and Optimal Sizing of RES in MGs:** The volatility and unpredictability of RES pose challenges in ensuring a balance between energy supply and demand, necessitating the calculation of optimal sizes for MG components and efficient energy management strategies to address underutilization or shortages.

2) **Environmental and Economic Impacts of Backup Resources:** Integrating diesel generators as backup resources for intermittent RES leads to increased pollution, higher operational costs, and performance challenges, emphasizing the need for balanced energy production and stringent DG operation regulations in NMG systems.

3) **Inefficiencies in Local Energy Markets (LEM):** Current energy trading strategies in local energy markets hinder the participation of small-capacity MGs and fail to account for transmission line capacities and associated costs, leading to inefficiencies in energy flow, increased operational costs, and compromised grid stability.

1.3 Research Objectives

The aim of this study is to develop a two-level, hierarchical management strategy to enhance the economic, technical, and environmental performance of NMG systems and optimize energy trading management through distributed, P2P, and P2G mechanisms, utilizing AI techniques. To achieve this comprehensive goal, the following objectives will be addressed:

1- To determine the optimal configurations and sizing of networked microgrid systems using a hybrid artificial intelligence technique known as Hybrid Grey Wolf Particle Swarm Optimization (HGWPSO), based on a multi-objective function.

2- To develop two energy management strategies called Distributable Resource Management Strategies (DRMS) and Demand Side Management Strategies (DSMS) aimed at reducing costs of energy and minimizing harmful emissions in networked microgrid systems.

3- To develop an efficient collaborative energy trading market based on multi-round energy auctions and artificial intelligence methodologies, considering the costs associated with the use of transmission lines and their design capabilities. This will be achieved by implementing distributed, peer-to-peer (P2P), and peer-to-grid (P2G) energy trading frameworks.

1.4 Organization of Thesis

This research primarily addresses the current challenges associated with the integration of NMG systems into the distribution system and the expansion of energy sharing among them. It investigates these issues from three key perspectives: economic, environmental, and reliability considerations. The research is structured into five chapters to effectively present its findings.

Chapter one serves as a comprehensive introduction, offering insight into established conventional energy systems, the associated challenges, and their evolution towards more adaptable and decentralized systems. This evolution involves the increased integration of RES and the development of MGs, followed by NMG systems. The chapter also outlines the research's underlying motivations, and specific research objectives. To conclude, a summary is provided regarding the thesis's structure and the topics covered in its various chapters.

In the second chapter, a comprehensive review of existing research pertaining to our study's subject matter is conducted. The literature review was structured around three fundamental dimensions. Firstly, it offered a thorough exposition of NMG systems and their components, evaluating the advantages, disadvantages, and challenges encountered during its integration with energy distribution systems. The review also examined the methodologies employed in previous studies to determine optimal MGs sizes. Secondly, the focus shifted to the structures, methods, and management strategies utilized in NMG systems applications, emphasizing their role in enhancing overall system performance. Lastly, the discussion delved into the structures of energy markets and the strategies employed for the implementation of energy contracts.

The emphasis of the third chapter lies in elucidating the research methodology employed to attain the objectives of this study. The chapter is structured into three sections, each addressing specific aspects. The first section pertains to modeling the components of MG to ascertain the optimal configuration and size. The second section focuses on the management strategies applied. The final part of the chapter delves into the design of energy markets and the mechanisms for determining prices and the quantity of energy traded.

In the fourth chapter. The results obtained from using the proposed management strategies were presented, as well as the results of the sensitivity analysis of important parameters related to the subject of which scenarios of shortage and increase in potential energy were studied.

The fifth Chapter presents the conclusions and recommendations for future research where an overall conclusion for the thesis is presented. Figure 1.2 illustrates the overall layout of the chapters in the thesis.

CHAPTER 2

LITERATURE REVIEW

Addressing the formidable challenge of harnessing renewable energy resources and restructuring them within multi-microgrid systems stands as a critical task for contemporary electrical energy systems. This is particularly crucial to meet the escalating energy demand and facilitate the transition towards modern smart grids. To ensure the optimal performance of electrical energy systems and adeptly navigate the burgeoning interconnected multi-microgrid landscape, a thorough investigation into three key facets is imperative. These aspects include the optimal design and planning of individual microgrids, the effective management of their operation within energy systems, and the regulation of local energy markets. This chapter offers a comprehensive overview of prior research efforts dedicated to exploring these foundational aspects, all grounded in pertinent journal papers and a review of conference proceedings aligning with the scope of this dissertation.

2.1 Modern Energy Infrastructures

For many years, consumers of electricity have heavily depended on centralized power systems owned by governments. These traditional systems mainly use large power plants fueled by sources like fossil fuels, nuclear, or hydraulic energy. The power generated is transmitted through high-voltage lines over long distances and then distributed to consumers through medium and low-voltage networks (Judge et al., 2022). The centralized nature of these power systems raises concerns about their reliability and flexibility, especially during unexpected faults. If one part of the network fails, it can have widespread effects, potentially causing localized power outages or even complete blackouts during emergencies (Butt et al., 2021).

Moreover, the dependence on fossil fuels in traditional power networks exacerbates the climate crisis by producing harmful gases through combustion. This reliance also contributes to energy price volatility as these resources deplete with fluctuating prices (Tao et al., 2020).

To address these economic, technical, and environmental challenges, the concept of smart energy networks has emerged as a solution. Smart grids, considered the next generation of electrical power networks, incorporate significant technological upgrades, and leverage smart control technology provided by devices like smart meters. The focus extends to increasing the integration of renewable energy sources and other energy-saving technologies (Panda & Das, 2021). The objective of smart grids is to enhance the technical, economic, and environmental benefits of energy systems. This improvement includes increased integration with smart interconnected microgrids, aligning with the IEEE 1547.4 standard (Alsafran, 2023). Consequently, there has been a notable emphasis on the concept of microgrid operation in recent years. Figure 2.1 showcases the evolution of electrical grids, progressing from conventional to contemporary and ultimately toward futuristic grid systems.

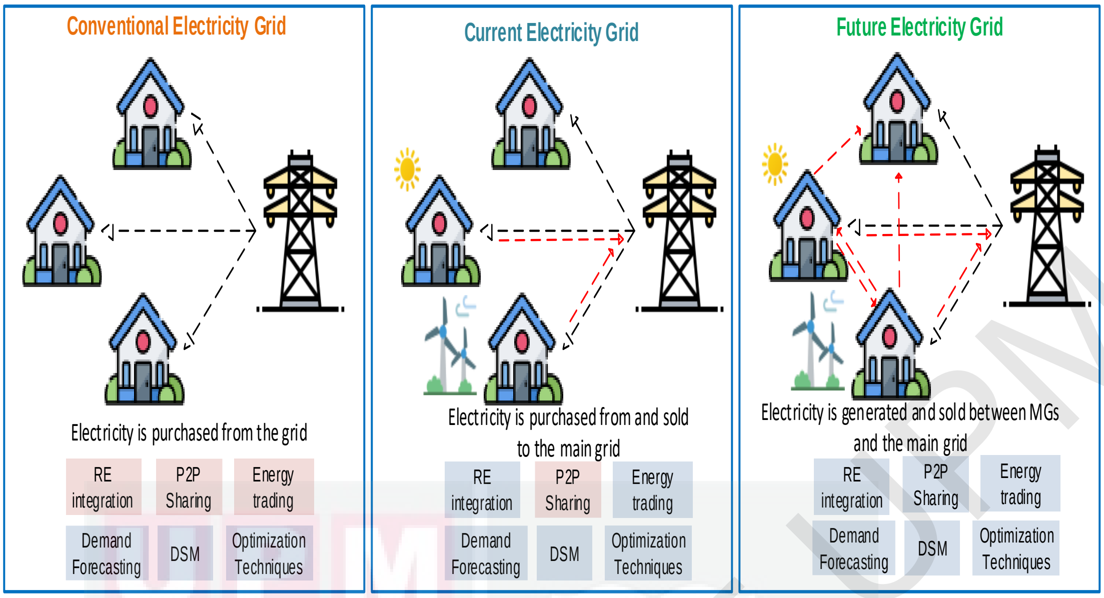

Figure 2.1 : Evolution of the Electricity Grid Infrastructure

2.2 Networked Microgrid Systems

NMG systems are a new concept that effectively coordinates and controls a group of geographically close microgrids. MGs serve as the foundation for NMG systems, enhancing the reliability and flexibility of electrical energy systems. They ensure the optimal utilization of RES and facilitate their increased integration. An MG functions as an interconnected cluster of distributed energy resources (DER) such as DG and MT, non-distributed energy resources (NDER) like RES, and ESS. They operate cohesively to fulfill the electrical load demands of consumers (Choudhury, 2020). Microgrids are typically categorized by their capacity and integration into low-voltage (LV) or medium-voltage (MV) networks. Smaller systems, such as nanogrids (up to a few kilowatts), are integrated into LV networks and serve individual homes or small commercial buildings. Microgrids, ranging from a few kilowatts to megawatts, can connect to both LV and MV networks, powering small communities, campuses, or industrial complexes. Larger microgrids (up to 50 MW) serve towns or industrial zones and are usually integrated into MV networks. Most community or institutional microgrids fall between 50 kW and 5 MW, depending on their energy needs and infrastructure (Khare & Chaturvedi, 2023). MGs offer seamless power exchange with distribution networks through points of common coupling (PCC) during grid-connected mode. They can also transition to standalone mode effortlessly during emergencies, providing a high degree of flexibility for the power system (Hmad et al., 2023). This dual operational mode enhances adaptability, allowing microgrids to efficiently contribute to and draw from the larger grid when needed, while also ensuring autonomous functionality during critical situations. Figure 2.2 illustrates the overall configuration of an ideal microgrid, including generating units, energy storage, and loads.

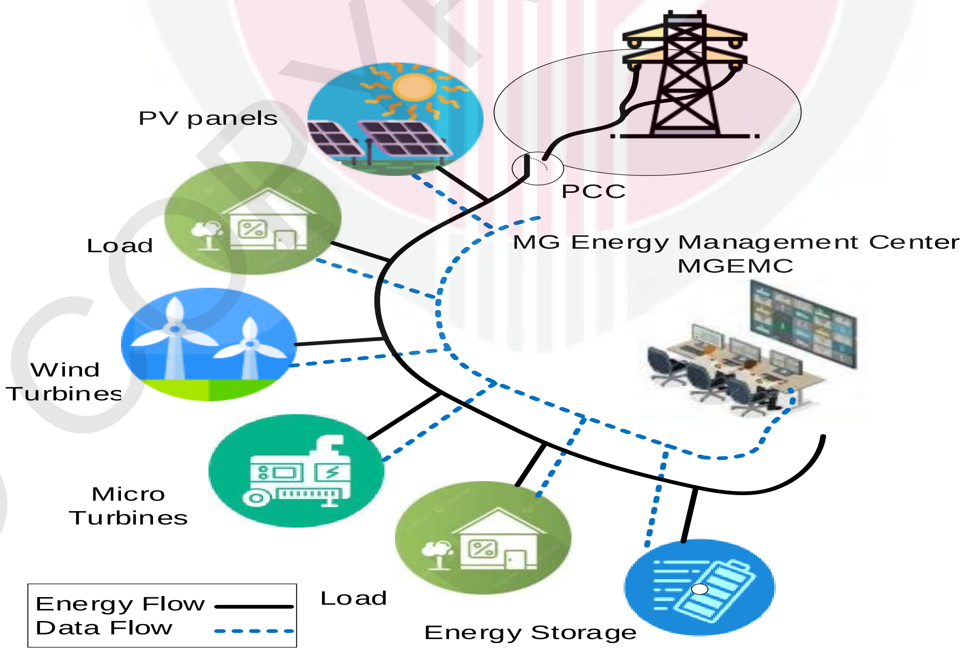

Figure 2.2 : Typical Configuration of Microgrid (Dagar et al., 2021)

It also incorporates essential elements such as the microgrid energy management central (MG-EMC), microgrid communications system, and measuring devices. The MG-EMS governs and orchestrates the activities within the microgrid using specialized programs designed to ensure optimal economic and environmentally sustainable operation with a high level of reliability (Ahmad et al., 2023). Various MG configurations incorporate different distributed generation technologies to meet specific load requirements. The generation of these resources is influenced by external factors such as climate conditions (temperature, solar radiation, wind speed, water flow, etc.) and the availability of conventional fuel resources like oil, gas, and coal (Shi et al., 2022). The interaction of these factors presents challenges in determining the optimal sizes of microgrid components. Figure 2.3. demonstrates the range of technologies used to provide energy within an MG.

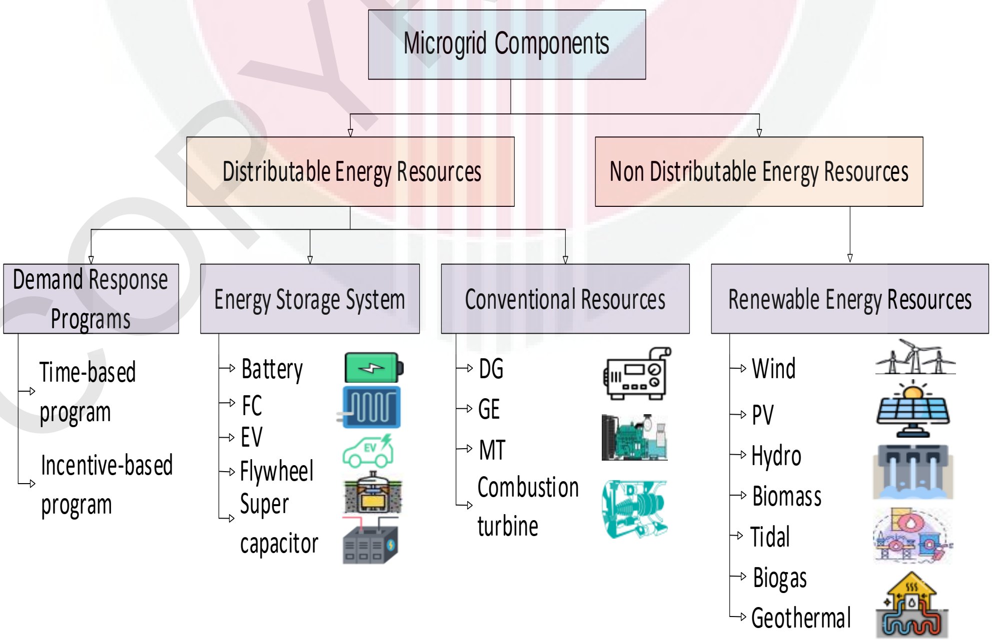

Figure 2.3 : Varieties of Technologies Employed for Energy Supply in MG, (https://www.google.com/ renewable energy storage microgrid resources)

The optimal functioning of NMG systems can bring various technical, economic, and environmental benefits to everyone involved in the electrical system, including consumers, suppliers, and grid operators. According to IEEE 1547.4 standards, improvements in the stability and reliability of distribution systems can be seen, and these advantages are evident in the following areas:

i. The possibility of sharing surplus energy within NMG systems motivates power system operators to increase their reliance on RES. This allows them to take advantage of the numerous benefits, such as lower energy generation costs and reduced harmful emissions (Yassim et al., 2024).

ii. Increasing the penetration of NMG systems reduces dependence on central grids, resulting in decreased energy demand. This, in turn, improves the reliability and stability of power systems (Pires et al., 2023).

iii. NMG systems are highly flexible and capable of meeting the requirements of individual MGs, whether the system is operating in autonomous mode or during emergencies. This is accomplished by exchanging excess energy between microgrids to create an energy balance (Kamal et al., 2023).

iv. NMG systems can mutually support one another, minimizing total generation or load curtailment. This collaborative approach enhances the performance of the electrical system and improves overall reliability (Wang et al., 2021).

2.2.1 Architectures of Networked Microgrid Systems

NMG systems have a crucial role in addressing energy demand challenges in major electricity grids and reducing strain on transmission lines. The ability for energy exchange among neighboring MGs is vital in lowering costs and minimizing energy losses associated with long-distance transportation. NMG systems can exchange energy not only with distribution networks but also with each other thanks to various connectivity topologies. This improves the flexibility of existing power systems but also adds complexity. Generally, the interconnection between NMGs is characterized by three fundamental trends:

i. **Radial architecture:** The radial or star structure involves MGs establishing direct connections to the main grids via buses. This connection allows for the exchange of energy and data only with distribution systems, without direct interactions between individual MGs. Within this framework, distribution network operators act as the highest controller of the system, issuing directives for energy and data transmission. MG operators, on the other hand, function as the lowest-level controllers, primarily receiving and executing orders. The radial interconnection of MGs is characterized by lower complexity and easier management due to the transmission of energy through shared buses. However, this configuration becomes less reliable in scenarios where the central system experiences sudden malfunctions or congestion caused by power transmission through specific buses (Gray et al., 2021).

ii. **Mesh architecture:** The individual MGs are connected to the distribution networks and each other in the mesh architectures through specialized power transmission lines and expanded communication systems. This allows for direct energy exchange with the main grids and local neighboring MGs. Mesh connections improve system flexibility and reliability, and greatly reduce energy costs. The more advanced management system in this interconnection considers the loading characteristics of the MGs that are part of the NMG systems, as well as the management decisions made by each MG (Aghmadi et al., 2023).

iii. **Daisy-chain architecture:** The NMG system utilizes individual MGs arranged in a daisy-chain configuration, connecting them not only to the main grids but also exclusively to their neighboring MGs (Syed & Morrison, 2021). This creates a two-way power and data exchange mechanism. This innovative architecture combines the benefits of both radial and mesh interconnection, enabling seamless power exchange and providing extensive operational and economic advantages. Unlike traditional radial connections, the sequential chain formation enhances connectivity, resembling a mesh interaction. However, effectively managing this configuration requires a sophisticated system to efficiently coordinate energy and data exchange between adjacent MGs and central grids. This management system must maintain the operational privacy of each MG while ensuring an optimal energy balance between supply and demand.

Table 2.1 illustrates the advantages and disadvantages of each type of NMG system architecture.

Table 2.1 : The Advantages and Drawbacks of Various Interconnection Architectures of NMG Systems

Architecture	Advantages	Disadvantages
Radial	• Easy and strong interconnection of MG. • Does not require a complex communication system. • It can be easily expanded.	• Needs a central entity for coordination. • Low privacy. • Low reliability.
Mesh	• Easily solve power flow congestion problems. • Reliable and robust system. • It requires strict security measures because there are multiple connections between the MGs. • The ability to easily detect errors.	• Problems with scalability. • It requires an expensive and complex communications infrastructure. • The I/O ports for connectivity and power are very large. • The complexity increases as the network increases.
Daisy Chin	• Easy to install and create. • Better scalability and reliability.	• One point of failure. • Power congestion problems.

(Aghmadi et al., 2023) and (Davison et al., 2017)

2.2.2 Techno, Economic, and Environmental Aspects of Networked Microgrid Systems

NMG systems play a crucial role in modernizing power systems to meet the evolving needs of society. These systems are designed with the overarching goal of enhancing stability, reliability, and user satisfaction in the realm of energy management. Over the years, numerous studies have delved into the multifaceted benefits of NMG systems, focusing on three fundamental pillars: economic, technical, and environmental aspects (Shayeghi & Alilou, 2021).

Economically, NMG systems offer a pathway towards cost reduction and maximizing returns for investors in the energy sector. By optimizing energy production, distribution, and consumption, these systems streamline operations, minimize wastage, and improve overall efficiency (Hu et al., 2023). From a technical standpoint, NMG systems facilitate the integration of RES into the power grid, thereby promoting sustainability and reducing dependence on fossil fuels enhancing energy efficiency, and mitigating transmission losses (Charadi et al., 2021).

Furthermore, NMG systems play a pivotal role in addressing environmental concerns by minimizing harmful emissions and promoting cleaner energy alternatives (Roslan et al., 2021). Previous studies have underscored the significant benefits of NMG systems across these key areas, highlighting their potential to drive positive outcomes for stakeholders and society at large as displayed in the following sections.

i. **Economic aspects:** The main objective of the majority of NMG systems is to minimize energy production costs, enhance annual profits, and fulfill load requirements through reliable and cost-effective sources. To achieve these goals, NMG systems employ various strategies, including an increased reliance on RES, engaging in energy trading with the central grid and other MGs, and diminishing the cost of energy derived from traditional sources to minimize the cost of fossil fuels (Ghadimi & Moghaddas-Tafreshi, 2023). Numerous factors and indicators associated with economic aspects, such as the cost of energy (COE), total net present cost (TNPC), levelized cost of energy (LCOE), annual profit rate (AP), and others, have been systematically calculated and evaluated in this context (Malik et al., 2022) and (Chaurasia et al., 2022).

ii. **Technical and welfare aspects:** The energy sector and MG operators strive to provide customers with cost-effective and reliable energy tailored to their needs, ensuring customer satisfaction. Achieving optimal technical performance involves monitoring and analyzing numerous factors and employing different approaches. For instance, one approach involves controlling adjustable or fixed loads, prioritizing essential loads, and minimizing less critical ones to enhance reliability and maximize social welfare (Mansouri et al., 2022) and (Dey et al., 2024). Another approach involves scheduling energy production, managing energy demand and supply, and implementing combined heat and power (CHP) systems to simultaneously handle electrical and thermal energy (Mianaei et al., 2022). Emphasizing reliance on RES becomes crucial for enhancing the resilience of power systems by maximizing the utilization of RES and distributing surplus energy to clusters with high demand (Eskandari et al., 2022). Additionally, addressing energy loss during transmission between clusters and the main network is a key consideration for achieving both efficient economic and technical operations (Ashok Babu et al., 2024) and (Riaz et al., 2023).

iii. **Environmental aspects:** Assessing the performance of NMG systems involves crucial considerations of environmental aspects, particularly in the context of mitigating greenhouse gas emissions (Jirdehi et al., 2020). Various strategies are employed to fulfill this objective, including a heightened emphasis on leveraging RES and curbing the utilization of conventional energy sources and fuel combustion (Zhong et al., 2022) and (Karimi et al., 2023). Stringent regulations are often imposed to restrict their usage. Table 2.2 succinctly outlines prior studies that have delved into these significant aspects and the strategies employed to enhance NMG systems' performance.

Table 2.2 : Various Performance Aspects of NMG Systems Have Been Addressed in Previous Studies

Objective	The approach	Ref.
Economic aspects	Maximize the use of renewable energy resources with increasing penetration of all types of RES.	(Y. Zheng et al., 2024) (Anaadumba et al., 2021)
	Selling the surplus energy to the main grid at a high price and buying shortage energy from the main grid at a low price	(Nunna et al., 2020) (H. Liu, Li, et al., 2020) (D. Xu et al., 2020)
	Minimize the expenses brought on by fuel-fired generators	(Dejamkhooy et al., 2020)
Technical and welfare aspects	A scheduling technique designed to sacrifice or postpone the elastic loads.	(Menos-Aikateriniadis et al., 2022).
	Install a combined heat and power (CHP) system to control the thermal and electrical energy.	(Jordehi, 2021) (D. Zhu et al., 2020)
	Distributing the extra energy to the MGs with the greatest demand.	(Zargar & Yaghmaee, 2021)
	Reduce power transmission losses.	(Mehraban & Eslami, 2023), (Nawaz et al., 2022)
Environmental aspects	Greenhouse gas emissions are typically used to quantify environmental benefits.	(A. Xu et al., 2023) (Grisales-Noreña et al., 2022)

2.2.3 Techniques Used to Obtain the Optimal Size of Microgrids

MG based on RES are considered a promising solution for current energy systems. In these systems, RES generation is unpredictable due to its reliance on climatic conditions. Therefore, it is necessary to incorporate additional energy resources like BSS and DG to ensure a reliable and stable energy supply. This complexity increases the need to determine the optimal sizes of each component in MG systems, ensuring their efficiency in terms of economics, technology, and the environment. The determination of optimal component sizes is a crucial factor that can significantly impact the success or failure of a project (Goh et al., 2022).

Numerous studies have addressed the task of determining optimal component sizes for microgrid systems. Generally, three main approaches have been recognized in this field. These approaches include the use of software and simulation tools, deterministic methods, and optimization algorithms based on artificial intelligence methods such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Firefly, Gray Wolf Optimizer (GWO), etc. (Mohammadi et al., 2022).

2.2.3.1 Software and Simulation Tools

Although software methodologies and simulation tools like IHOGA, HOGA, and HOMER (Hoarcă et al., 2023) offer user-friendly interfaces that don't require extensive calculation and programming skills, they have limitations. Users are unable to actively select system parameters, participate in installation strategy creation, or intuitively identify system components. Moreover, users are often restricted from accessing, viewing, or modifying the underlying programs and algorithms. These tools are primarily used to determine optimal sizes for MGs by making specific assumptions and employing predefined sequences. As a result, simulation tools are mainly used as comparative instruments to assess the sensitivity of sizing outcomes (Hannan et al., 2020).

Software and simulation tools like IHOGA, HOGA, and HOMER, while user-friendly, limit customization and user control over key parameters and system strategies. They operate with fixed assumptions and predefined algorithms, restricting users from modifying underlying models or installation plans. As a result, these tools are mainly suited for comparative analyses rather than flexible optimization, making them less effective for complex or dynamic microgrid scenarios

2.2.3.2 Deterministic Methods

On the other hand, deterministic algorithms like numerical, analytical, iterative, and graphical techniques engage users more actively in the preparation and design of computational algorithms compared to software and simulation tools (Gamil et al., 2021). Deterministic algorithms are notable for their high precision in dealing with single and straightforward objective functions (Salehi et al., 2022). However, they become more complex when applied to intricate large MG structures or situations involving overlapping objectives and constraints. Consequently, deterministic sizing algorithms have significant drawbacks, such as considerable complexity, extended simulation time, and lengthy calculations required to attain the optimal solution (Worku et al., 2021).

Deterministic methods, while precise and effective for simple, well-defined objective functions, encounter notable limitations when applied to complex microgrid systems or scenarios with multiple overlapping objectives and constraints. As deterministic algorithms rely on exact calculations and fixed-step processes, they can become computationally intensive and time-consuming, especially when handling the high-dimensional, nonlinear optimization problems typical of modern energy systems. In these cases, deterministic approaches may struggle to achieve timely solutions due to their extensive calculation requirements and the need for prolonged simulation times. Additionally, deterministic methods often lack the flexibility to adapt to dynamic conditions, making them less suited for real-time energy management in microgrids, which often face fluctuations in energy demand, generation, and pricing. These limitations hinder the scalability and practicality of deterministic algorithms in large or dynamic MG applications, where more adaptive, efficient, and robust optimization techniques may be required.

2.2.3.3 Artificial Intelligence Techniques

The most promising and efficient approaches for determining optimal sizes of NMGs involve the application of artificial intelligence techniques. AI methods are widely used to address the challenges of calculating optimal sizes for microgrids, regardless of the complexity of the system's structures or the diversity and complexity of its goals and constraints (Mohammadi et al., 2022).

AI techniques like GWO, PSO, and FA are useful for optimizing multi-objective microgrid sizing but have limitations. They often risk premature convergence to local optima, especially in complex problems with conflicting objectives, which reduces solution accuracy. Additionally, these methods can be computationally demanding and require careful parameter tuning, making them less effective and more challenging to implement in dynamic or large-scale MG systems. The following section reviews the most important and widely used AI methods which are GWO, FA, and PSO, recognized for their high reliability.

i. Grey Wolf Optimizer

The Grey wolf optimizer (GWO) is introduced to emulate the social structure and predation of grey wolves, with streamlined operation, fewer parameter modifications, and understandable and obvious principles (Miao & Hossain, 2020). In the GWO approach, the wolves were divided into four levels: level 1 is the present best individual wolf (leader), established by the letter α, levels 2 and 3 reflect the suboptimal second and third-best alternatives and indicated by the letters β and δ, and level 4 corresponds to the ordinary alternative, represented by the letters σ (Almani et al., 2022).

The main phases of the GWO strategy are surroundings, hunting, and attacking prey. Grey wolves follow the following strategies to achieve the goal:

Step 1: Surrounding The prey is surrounded by GWs from all sides, and the location of the wolves and prey can be determined according to the equations (2-1) and (2-2).

$$\vec{D} = \left|\vec{C} \times \vec{X}_p - \vec{X}(t)\right| \tag{2-1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \times \vec{D} \quad (2\text{-}2)$$

Where, $\vec{X(t)}$, and $\vec{X}_p(t)$ is the Wolfe and prey position vectors respectively, and $\vec{A}$, $\vec{C}$ represent the vector evaluated in (2-3).

$$\vec{A} = 2\vec{a}\,\vec{r}_1, \quad \vec{C} = 2\vec{r}_2 \quad (2\text{-}3)$$

Where r_1, *and* r_2 are random number range from 0 - 1.

The components of $\vec{a}$ linearly decrease from 2 to 0 over time as in (2-4).

$$\vec{a} = 2 - \frac{2 \times t}{t_{max}} \quad (2\text{-}4)$$

Where t and t_{max} are the current and maximum iteration respectively.

Step 2: Hunting. In a hunting activity, α, β, and δ are thought to have a clearer view of the prey's location. The other wolves σ are consequently compelled to find a, b, and d. This hunting activity is modeled by equation (2-5).

$$\left.\begin{aligned} \vec{D}_\alpha &= \left|\vec{C}_1 \times \vec{X}_\alpha - \vec{X(t)}\right| \\ \vec{D}_\beta &= \left|\vec{C}_2 \times \vec{X}_\beta - \vec{X}(t)\right| \\ \vec{D}_\delta &= \left|\vec{C}_3 \times \vec{X}_\delta - \vec{X}(t)\right| \end{aligned}\right\} \quad (2\text{-}5)$$

Where $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ are the best three solutions at each iteration, C_1, C_2, *and* C_3 can be calculated as in (2-3).

The new location of the three best wolves can be calculated (2-6).

$$\left.\begin{array}{l} \vec{X}_{i1} = \vec{X}_{\alpha} - \vec{A}_{1} \times (\vec{D}_{\alpha}), \\ \vec{X}_{i2} = \vec{X}_{\beta} - \vec{A}_{2} \times (\vec{D}_{\beta}) \\ \vec{X}_{i3} = \vec{X}_{\delta} - \vec{A}_{3} \times (\vec{D}_{\delta}) \end{array}\right\} \tag{2-6}$$

Then the new location of the best wolf is calculated according to the (2-7).

$$\vec{X}(t+1) = \frac{\vec{X}_{i1}(t) + \vec{X}_{i2}(t) + \vec{X}_{i3}(t)}{3} \tag{2-7}$$

Step 3: Attacking. The wolves begin attacking the prey after they stop moving and the hunt is over. For an in-depth exploration of the GWO technique, consult reference (Al-Tashi et al., 2020).

ii. Firefly Algorithm

The origins of the firefly algorithm were developed by Xin-She Yang in the laboratories of the University of Cambridge, and it was approved as one of the most accurate and efficient AI methods for solving complex optimization problems (Yang et al., 2021). It simulated the behaviour of firefly swarms through the concept of the intensity of brightness of individual fireflies moving randomly and the distance between two adjacent fireflies to explore the solution space. This algorithm is based on three basic principles:

1. Fireflies can be attracted to each other regardless of gender, whether male or female.
2. Fireflies move among themselves according to gravity and brightness, as their value decreases as the distance between them increases.

The firefly with lower brightness moves towards the firefly with higher brightness; while their movement is random if their brightness is equal.

3. The ratio of the brightness of the firefly is obtained by calculating the objective function.

The determination of the optimal solution in FA relies on two fundamental variables: the intensity of light emitted by the caterpillar (brightness β) and the gravitational effect it exerts (γ). Following the three essential rules of FA, the overall procedure can be succinctly outlined as follows (Dey, 2020):

Step 1: Attractiveness. In FA, the attractiveness among fireflies diminishes monotonically as a function of distance. Specifically, the attractiveness decreases as the distance between fireflies increases as in (2-8).

$$\beta(r) = \beta_o e^{-\gamma^m}, (m \geq 1) \tag{2-8}$$

where, *r* denotes the distance between fireflies, and β_o represents the brightness when the distance is zero (r=0).

Step 2: Distance and Movement. The calculation of the distance between two fireflies, denoted as *i* and *j*, positioned at locations x_i and x_j, respectively, is determined using the Cartesian function, expressed by (2-9):

$$r_{i,j} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k}\right)^2} \tag{2-9}$$

In this context, $x_{i,k}$ represents the *kth* component of the spatial coordinate of the *ith* firefly, $x_{j,k}$ represents the kth component of the spatial coordinate of the *jth* firefly, and (d) denotes the number of problem variables or dimensions. To find the new position of the fireflies (candidate solution), the brightness of each firefly is determined according to the objective function f(x). The new location x_i *(t+1)* of the fireflies can be determined based on their old location *(t)* strength of brightness, and the distance between them (x_i-x_j) as shown in equation (2-10) (Sibtain & Saleem, 2022).

$$x_i(t+1) = x_i(t) + \beta 0 e^{(-\gamma r^2)} * \left(x_i - x_j\right) + \alpha \varepsilon i \tag{2-10}$$

Where $\alpha\varepsilon i$ is a randomization parameter.

iii. Particle Swarm Optimization

The inception of the Particle Swarm Optimization (PSO) algorithm traces back to 1995, drawing inspiration from the collective behavior observed in living organisms such as birds, fish, and insects, harmoniously moving towards a common objective (Shami et al., 2022). In adherence to the PSO strategy, a group of particles, representing potential solutions, traverse the problem space—defined by the problem boundaries—in a randomized manner, aiming to uncover the most optimal solution. Throughout the quest for the optimal solution, each particle dynamically adjusts its position based on two critical factors: its locally determined particle best(*pbest*) and the globally superior solution discovered by the other particles within the group, global best (*gbest*). This cooperative movement enables the particles to converge over a series of iterations, gradually homing in on the ideal solution. The PSO algorithm stands out as one of the foremost and most potent artificial intelligence algorithms. It has found widespread applications across diverse fields, efficiently tackling optimization problems, and delivering optimal results.

All particles in motion within space are characterized by two fundamental variables: position and speed (Karim et al., 2020). As they navigate the space in pursuit of their optimal positions and strive to identify the overall best location within the flock, the term "best" refers to the location associated with the most favorable objective value. In their collaborative pursuit of optimal solutions, swarm particles engage in communication to ascertain new locations and modify their speeds based on these identified favorable locations (Li et al., 2020). The optimal *gbest* is achieved through a sequence of consecutive stages.

Step 1: Initialization During this step, two random matrices are created within the specified upper and lower bounds. The first matrix signifies the particles' positions (*X*), while the second matrix represents their velocity (*v*), as described in equations (2-11) and (2-12).

$$x_i(t) = \begin{cases} x_{1,1} & \cdots & x_{1,i} \\ \cdots & \cdots & \cdots \\ x_{j,1} & \cdots & x_{j,i} \end{cases} \tag{2-11}$$

$$v_i(t) = \begin{cases} v_{1,1} & \cdots & v_{1,i} \\ \cdots & \cdots & \cdots \\ v_{j,1} & \cdots & v_{j,i} \end{cases} \tag{2-12}$$

Step 2: Evaluation. Assess the position of each particle by considering the objective function.

Step 3: Update velocities and position In the pursuit of the optimal solution, each particle computes its local best (*pbest*) and is aware of the global best solutions (*gbest*) for the other particles. Subsequently, the particle's velocity is updated by the formula outlined (2-13).

$$v_i(t+1) = \alpha v_i + C_1 \times rand \times \left(pbest(t) - x_i(t)\right) + C_2 \times rand \times (gbest(t) - x_i(t) \qquad \text{(2-13)}$$

Identify the superior particles based on their last-best positions. If a particle's current position surpasses its previously recorded best position, then update the latter as shown by (2-14).

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad \text{(2-14)}$$

2.2.4 Optimizing Networked Microgrid Performance Using AI

AI techniques have been employed in a wide range of research covering technical, economic, and environmental issues. In terms of economics, Momen et al. (2023) utilized the improved shuffled frog leaping algorithm (ISFLA) to reduce energy costs and pollution through combined heat and power (CHP). Kharrich et al., (2021) analyzed a hybrid grid system along with the development of various control strategies using the Backward Search Algorithm (BSA) to find the optimal size of MGs. The optimal size of MGs, including PV/biomass and three alternative energy storage units, was calculated using intelligent strategies in (Alshammari & Asumadu, 2020). The objective function considered by Lyu et al., (2024) was the optimal levelized cost of energy and annual levelized cost. AI technologies were employed to minimize the cost of energy and loss of power supply potential (LPSP) for MGs consisting of PV/WT and energy storage systems. Batista et al., (2023) devised a multi-objective function to calculate the cost of energy and gas emissions for a PV/WT/ESS-based hydroponic pump system (PHS) operating in grid-connected mode. Cosic et al., (2021) determined the optimal size of MGs consisting of PV, WT, and BSS, and a turbine engine using the mixed linear programming (MILP) technique. Lastly, Zhu et al., (2021) presented a multi-objective function to determine the optimal size of an MG consisting of PV, WT, DG, and BSS.

To address environmental concerns and decrease emissions, Torkan et al., (2022) utilized a genetic algorithm (GA) to lower operational costs and carbon emissions. They investigated how optimal energy storage sizes and properties can impact carbon reduction. Parvin et al. (2023), examined a hybrid MG system composed of PV, WT, DG, and BSS to determine the technical and environmental advantages and identify the best performance using Partial Swarm optimization (PSO). Monte-Carlo Simulation (MCS) was used to schedule the output of microgrids for the following day In (KK et al., 2023). The system, which incorporates both conventional and RES, operates in an uncertain environment. They validated their methodology using a customized version of the IEEE 33-bus test system. Mosa (2021) presented a power management system based on Mixed Linear Programming (MILP) to investigate the operational behavior of MGs and reduce power losses. The authors suggested a two-stage MG scheduling mechanism, using the group search optimizer (GSO) algorithm, to determine the optimal size of MG a (Taghizadegan et al., 2022). Das et al., (2022), determined the optimal size of a PV/WT/Biomass-based system with an energy storage system, using the generalized reduced gradient algorithm to maximize the demand-supply fraction and minimize power losses. A multi-objective crow search technique was introduced for designing PV/FC/Diesel-based hybrid microgrids (HMGs) with objective functions including net present cost and losses of power supply probability (Das et al., 2022). The researchers concluded that optimized hybrid MGs are a cost-effective and reliable power source for remote applications.

While AI methods have been widely applied to determine the optimal size of MG systems, much of the existing research focuses on single-objective optimization, typically addressing only one aspect, such as economic, technical, or environmental criteria. However, relying on single-objective function limits the comprehensive analysis needed to achieve balanced MG performance, especially in complex, real-world scenarios where trade-offs between cost, reliability, and environmental impact are critical. There is a need for further research utilizing multi-objective optimization approaches that can simultaneously consider economic, technical, and environmental objectives. By expanding AI-based optimization techniques to multi-objective frameworks, future studies could provide more holistic solutions that better support sustainable and resilient MG system designs.

2.3 Networked Microgrids Energy Management Strategies

The widespread implementation of NMG systems, capitalizing on the numerous advantages offered by RES, has introduced a higher level of complexity in the management of modern energy systems. This complexity is further compounded by the unpredictable generation of RES and the fluctuation in energy demand throughout the day. To overcome these challenges, it is essential to develop robust energy system management strategies that prioritize enhancing the reliability and stability of energy systems while aligning with the interests of all stakeholders (Rangu et al., 2020). Within this context, Energy Management Strategies (EMS) emerge as the primary facilitator for achieving economically, technically, and environmentally sustainable operation of energy systems. Optimal EMS consists of three fundamental tiers responsible for collecting and processing diverse information and data regarding system equipment and energy markets (Querini et al., 2020). The physical layer encompasses the tangible components of the MGs, such as generation and energy storage units. The information layer involves the gathering and storage of data related to the condition of system equipment and energy market information. Finally, the application layer encompasses the strategies, mechanisms, and software used for the effective management of the system (A. R. Singh et al., 2023). To coordinate the operation of these three levels, there are three basic units: local management units (LMU), NMG management units (NMG-MU), and central management units (CMU). Figure 2.4 illustrates the comprehensive structure of the distinct layers within the EMS.

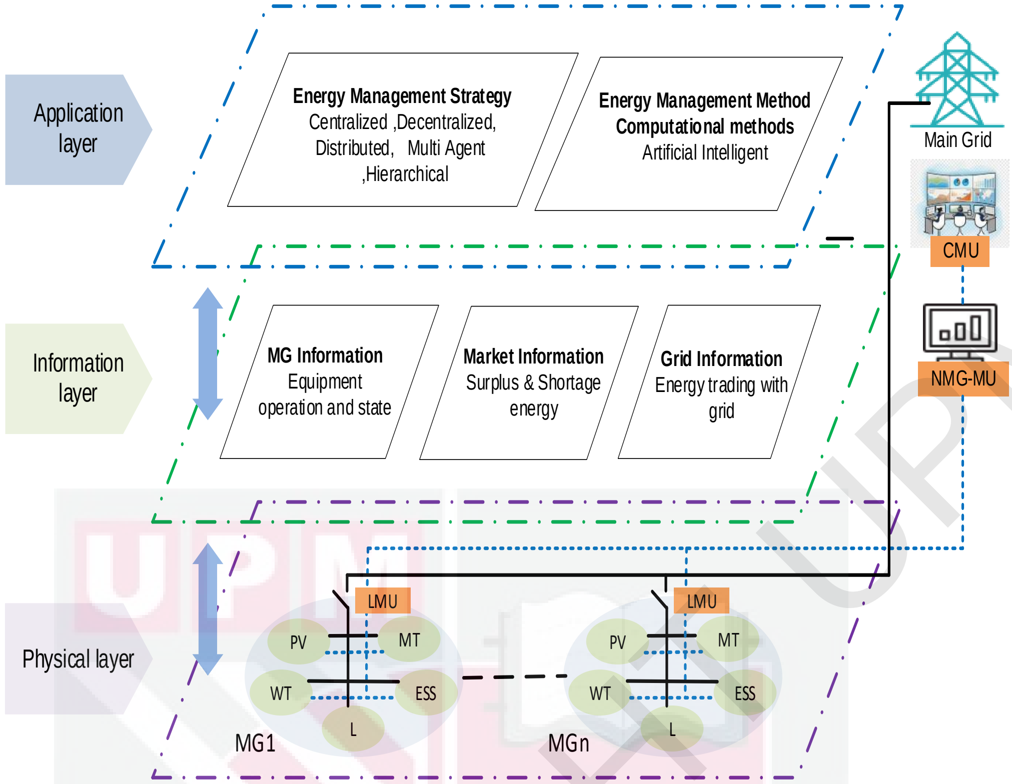

Figure 2.4 : Overview of NMG System Multiple Levels of Energy Management Approaches (L. Chen et al., 2019)

2.3.1 Energy Management Topologies

The effectiveness of EMS hinges significantly on the infrastructure of the system. This includes factors such as the number of components, the array of energy resources, and the technological framework. Equally crucial is the system's capability for swift stabilization and recovery in the face of disturbances affecting any of its components. EMS needs to be efficient, possessing the flexibility to expand and incorporate new components into the system. This includes diverse energy resources, as well as the capacity to accommodate potential increases in loads and the growing intricacies of communication systems. Furthermore, EMS can be broadly categorized into central, decentralized, distributed, multi-agent, and hierarchical energy management strategies (Zheng et al., 2023).

i. Centralized Management Systems

In centralized management systems, energy production and trading in each MG are supervised and managed by a strong CMU. The LMU functions in the MG to receive instructions and communicate with the CMU to exchange data (Bhattar & Chaudhari, 2023). In this scenario, individual MGs are unable to directly exchange energy and data with each other. Instead, all MGs provide basic information to the CMU, which uses that data to make decisions about energy scheduling, energy trading quantity, and so on. The CMU then forwards these decisions to the LMU of each MG. CMUs have a clear design structure and centralized decision-making, ensuring that decisions are smoothly transmitted to all MGs. However, as the number of MGs grows excessively, decision making becomes more difficult. Additionally, in the event of a communication system failure or emergency, CMUs face significant challenges in maintaining the system (Wang et al., 2022).

ii. Decentralized Management Strategies

In decentralized management strategies, LMU manages the independent operations of each MG according to their objectives. These objectives include energy scheduling, energy production cost, amount of energy trading, and so on. The decentralized management approach allows for the direct sharing of energy and data between MGs and main grids based on their specific requirements, without considering the needs of other MGs (Zhou & Erol-

Kantarci, 2020). The role of the CEU in this approach is to manage the energy trading solely with the main grid, without controlling the operation of individual MGs. Decentralized management systems maintain customer confidentiality and promptly meet their needs through a strong management framework. However, the lack of information about nearby MGs may hinder the finding of optimal solutions or prevent the system from achieving the greatest possible economic gain (Zhou & Erol-Kantarci, 2020). Additionally, when the connection to the main grid is lost, the reliability of the MG is compromised as it will switch to operating in standalone mode.

iii. Distributed Management Strategies

In distributed management strategies, LMU are dedicated to overseeing energy management within an MG based on its specific needs. Concurrently, CEU focuses on regulating energy trading activities with central grids (Zhou et al., 2020). This approach also allows for the potential of energy trading with neighboring MGs. NMGs leverage distributed management solutions to facilitate energy and data exchange between adjacent clusters of MGs and the main grids (Muhtadi et al., 2021). The incorporation of these distributed management strategies markedly enhances the flexibility and reliability of power systems. In the event of a specific operational disruption in any MG, the implementation of distributed energy management provides a range of options for compensating energy shortages. While distributed management strategies offer numerous advantages, their complexity grows, demanding more intricate computations. This increased complexity raises the probability of not achieving an optimal global solution, thereby prolonging the time required to identify the best energy trading alternatives.

iv. Multi-Agent Energy Management Strategies

Multi-agent energy management strategies involve independent decision-making for all components of the system, removing the need to rely on decisions made by other entities. In this context, each entity within the energy system is considered an autonomous agent. For instance, there are agents for MG operators, agents for energy market operators, and agents representing energy distribution system operators (Fang et al., 2021). The autonomy given to these agents plays a crucial role in addressing complex optimization problems and allows for the flexibility to incorporate new components into interconnected energy systems. However, the effectiveness of multi-agent management strategies is hindered by the requirement for sophisticated communication systems. The demand for complex communication structures poses a significant challenge in the implementation of these strategies (Fang et al., 2021).

v. Hierarchical Management Strategies

Hierarchical management strategies are used to oversee energy systems by dividing the system into different levels, each with specific goals and tasks. In the lower layers, the focus is on managing and coordinating the operations of MGs through the LMU. This includes meeting load requirements and addressing surplus and shortage energy during different periods through distinct operations (Hong & Alano, 2022). Individual MG data is transmitted to the NMG-MU at intermediate levels. Here, the data is processed, and challenges related to energy sharing are resolved within local energy markets. In the upper layers, coordination takes place between the NMG-MU and CMU. Furthermore, energy sharing with central grids is managed at this level. A crucial aspect of the hierarchical management approach is the need for strong coordination across the upper, middle, and lower layers through a central hierarchy. The upper layers have control over the adjacent lower layers, enabling the exchange of data and commands. Importantly, the management decisions made in the upper layers are directly influenced by those made in the lower layers. This dependency ensures a cohesive and integrated approach to NMG system management (Yassim et al., 2024).

Hierarchical energy management strategies are widely regarded as effective because they combine the benefits of various strategies. These strategies have been extensively used in previous studies to address optimization challenges in NMG systems. For example, Elkazaz et al. (2020), a hierarchical management approach was deployed to efficiently oversee the functioning of NMG systems. The lower level of the hierarchy focuses on the individual management of MGs to minimize operational costs. On the other hand, the upper level oversees the entire system, facilitating energy exchange with distribution networks while adhering to operational constraints and ensuring the mutual interests of both MGs and distribution networks. Alhasnawi & Jasim, (2020), proposed two-level hierarchical management strategy was incorporated to orchestrate the operation of an NMG system capable of exchanging power with the central grid. At the lower level, individual MGs are autonomously managed to optimize the utilization of RES. Simultaneously, the upper level oversees the energy exchange with the central grid, with a focus on minimizing energy losses and enhancing voltage levels. It's important to note that this strategy does not explicitly address the management of energy trade between different MGs. Saki et al., (2022), suggested two-tier hierarchical EMS and a multi-agent EMS were introduced, incorporating Demand Response Programs (DRP) to minimize energy costs and reduce the overall energy demand of the system. A new three-stage hierarchical management strategy has been presented in (Kaysal et al., 2022) to manage the reactive energy of the NMG system. The first stage focuses on reducing the energy cost of the MG, and the data is then sent to the second stage, where it is analyzed, and global optimization is calculated. Finally, the commands and data are returned to the local MG in the third stage. Some studies have focused on modifying energy scheduling and the amount of energy produced to improve system performance. A hierarchical optimization approach was suggested to address power, voltage, and VAR (Volt-Ampere Reactive) transfer challenges within an interconnected system comprising three autonomously functioning MGs in (Yin, 2023). The management tasks are distributed across two levels: first, the scheduling of active energy for each MG is tackled based on generation and energy consumption rates. Then, in the second stage, independent control over voltage and VAR is implemented. Dey et al., (2020), employed a hierarchical management framework to optimize energy and enhance the reliability of MG systems. At the lower level, economic performance is improved, and the economic benefits of individual MGs are maximized using the Crow Search Algorithm (CSA). Simultaneously, at the highest level, system test functions and evaluation indicators are assessed to guide decision-making processes aimed at achieving optimal operation of the energy management model. Table 2.3 provides an overview of the advantages and disadvantages of different EMS.

Existing EMS solutions often face limitations in seamlessly integrating diverse and RES, handling substantial load increases, and adapting to complex communication needs in real-time. Many systems lack the flexibility to support expansion without major reconfigurations, especially under the dynamic and fluctuating conditions of modern energy grids. Additionally, there is a need for more research on the interoperability of these systems within smart grid frameworks, particularly regarding hierarchical strategies that enable coordinated decision-making across distributed components.

Table 2.3 : Advantages and Disadvantages of Different Management Strategies

EMS strategy	Advantages	Disadvantages
Centralized	Low operating costs. Central controller. Reducing the number of disputes. Making use of effective parts. There is little trading in energy abroad. High dependability when operating on an island. Simple implementation and standardization. Low communication bandwidth.	Not able to grow to bigger and more intricate networks. Hefty computational expenses. Sensitive to a single malfunction Poor plug-and-play performance Neglecting to protect client confidentiality. Sensitive to minor changes made to the system. Absence of flexibility and adaptation
Decentralized	Robust privacy safeguards. Robust plug-and-play capabilities. High efficiency of computation. High ability to overlook communication errors. Resilient to single-point errors. Low communication bandwidth.	Reaching a consensus for every MG is challenging. Elevated operating costs and ignorance of resources of MG. Low resilience in the island mode. High-energy exchange between the main grid and NMG. Costly peer-to-peer energy trading.
Distributed	Effects on the overall performance are considered, and each system's shared tasks are managed. Encourages collaboration between different systems.	The sharing of data among individual systems can compromise security. Communication linkages between neighboring systems are required. High communication bandwidth.
Multi-agent	Uses autonomous and intelligent entities to solve coordinated control challenges. Provides plug-and-play functionality and network scalability.	Employ several scattered agents that must communicate with one another to engage. High communication bandwidth.
Hierarchical	Allows for adaptable layered control over networks that contain several systems. Provides an affordable solution that is simple to adopt and has little running costs. Low communication bandwidth.	Susceptibility to failure because of a strong connection between the lower and higher control levels

Figure 2.5 illustrates the overall structure of hierarchical EMS, with individual MGs autonomously managed at the lower level and the upper level overseeing the entire system.

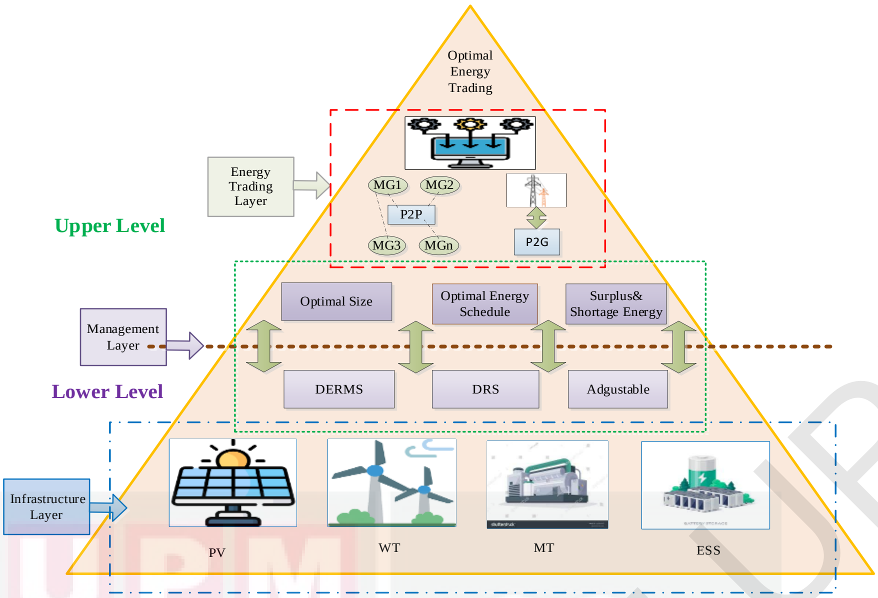

Figure 2.5 : The General Appearance of Two-Level Hierarchical Management Strategies

2.3.2 Demand Side Management Strategies

NMG systems aim to ensure the provision of adequate energy to meet load requirements and establish equilibrium between supply and demand. Demand-side management strategies (DSMS) are designed to achieve a balance in scheduling energy demand. According to the Electric Power Research Institute (EPRI), DSMS can be defined as the planning, monitoring, and implementation strategies used by end consumers to control and manage energy demand (Shalaby, 2021). This includes changing the time pattern of electrical loads and transferring loads from high peak periods to low peak periods, which ultimately improves energy management. Various DSMS, such as peak load reduction, valley filling, load shifting, strategic load growth, strategic conservation, and flexible load shaping, are employed to modify the load profiles of end consumers (Nasir et al., 2021). In recent years, the practical application of smart grid systems has gained more attention. Demand response (DR) programs based on load management have become increasingly popular due to their potential advantages in adapting consumer load profiles and achieving cost-effective energy scheduling (B. Dey et al., 2023). DR programs can be categorized into two fundamental types: time-based programs and incentive-based programs.

i- Time-Based Demand Response Programs

In time-based DR programs, consumers are provided with dynamic and variable energy prices for different periods based on the cost of energy production. When electricity prices are high, consumers are encouraged to reduce their energy usage to mitigate economic losses. On the other hand, when energy costs are low, consumers can take advantage of the opportunity to meet their energy needs at a more affordable price. However, it’s important to note that in these DSMS, customers are not given any incentives to lower their electricity consumption, nor do they have any say in determining these pricing structures (Pan & Shittu, 2023). In fact, these techniques are implemented in three different ways in the time-of-use method. In the Time of Use (TOU) approach, a fixed daily profile is created to depict average energy prices across various periods, regardless of the actual cost of energy production (NAZAR, 2020). The price profile is categorized into two primary levels: the peak rate level and the off-peak level, as shown in Figure 2.6-a. Under TOU, consumers are charged a higher price for energy during peak periods and a relatively lower price during off-peak periods. The intention is to incentivize consumers to adjust their energy consumption patterns. However, this approach is considered less effective because it lacks incentives that actively encourage consumers to optimize and manage their daily energy loads. The Critical Peak Pricing (CPP) approach, like TOU, aims to regulate energy prices across various daily periods (Ghasemi et al., 2021). However, CPP differs by linking pricing adjustments to sudden occurrences that cause prices to rise to predetermined levels. In Figure 2.4-b, the load profile allocation illustrates that energy prices increase in response to events such as energy shortages caused by weather conditions or unforeseen fluctuations in demand. Real-time pricing (RTP) in the energy sector involves variable pricing based on regional energy distribution network rates, resulting in a lack of a consistent behavioral pattern as shown in Figure 2.4-c, (Nourollahi et al., 2020). This pricing model requires bi-directional information exchange before each period to communicate energy prices to end consumers. While RTP aims to ensure fairness in end-consumer prices by relying on the actual energy prices in each period, it presents challenges for consumers in tracking the fluctuating energy prices and adjusting their daily energy consumption. To address these challenges, end consumers are provided with information on the real energy price forecast for the next day in advance.

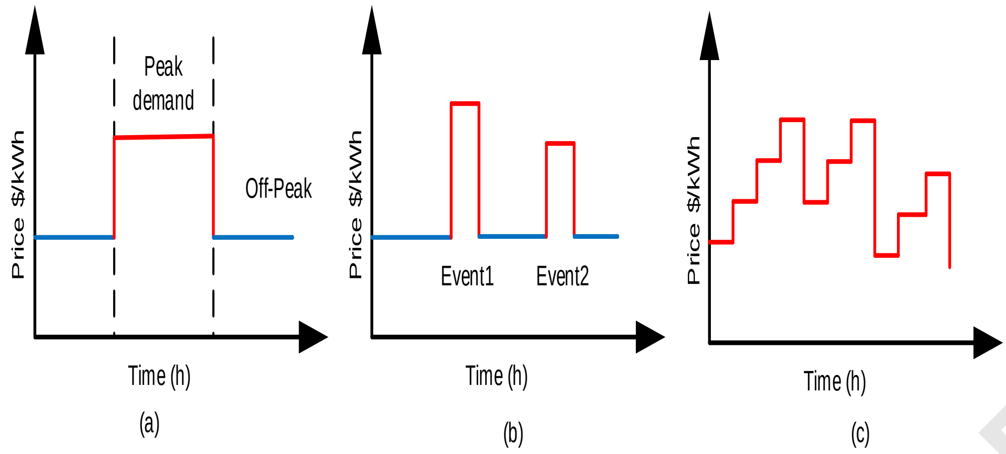

Figure 2.6 : Demand Response Mechanisms according to Time-Based Programs. a) Time of Use, b) Critical Peak Pricing, and c) Real-Time Pricing

ii. Incentive-Based Demand Response

DR schemes that provide users with rewards, remuneration, or lower billing in exchange for their participation in load reduction efforts are known as incentive-based programs. The literature shows a wide range of incentive-based DR models. For example, Direct Load Control (DLC) programs allow end consumers to manage various electrical loads, such as lighting, heating, cooling, and pumps, using downloadable programs. In return, consumers receive rewards in the form of discounted electricity rates (Mansouri et al., 2021). Another type of program is Curtailable Load (CL), which incentivizes consumers to immediately reduce specific loads in response to utility network calls (Swami & Gupta, 2024). Emergency Disaster Response Programs (EDRPs) are a hybrid approach that combines elements of DLC and CL programs (Tahmasebi et al., 2021). These programs offer incentives to end consumers to reduce energy consumption during emergency events that may impact system reliability. Lastly, Capacity Market Programs (CMPs) enable consumers with pre-determined load reductions to actively participate in the energy market as either generation or power delivery resources, contributing to overall power reduction efforts (Akbari-Dibavar et al., 2020). Figure 2.7 provides a visual representation of the fundamental classification of demand response programs.

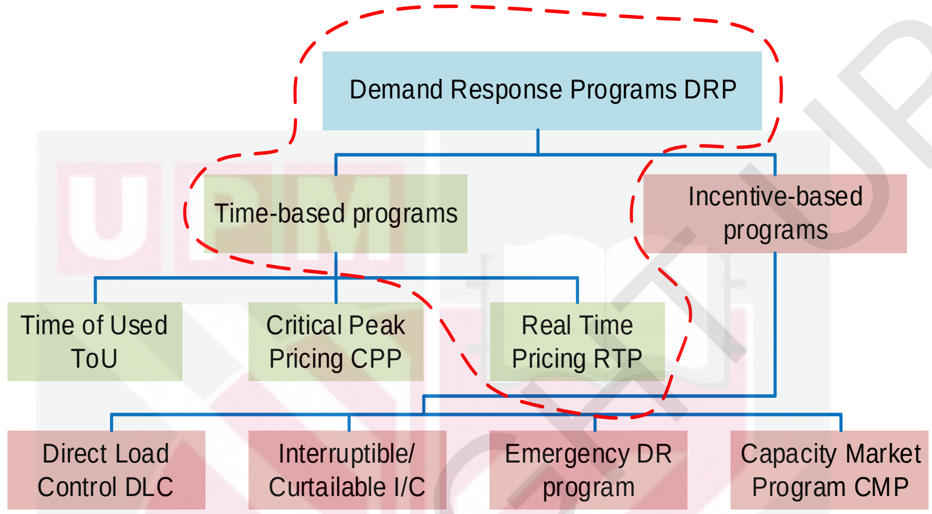

Figure 2.7 : Classification of Demand Response Programs

2.4 Local Energy Trading Markets for Networked Microgrids

The energy landscape is rapidly changing to include the increasing presence of NMG systems, which leverage the benefits of RES. The integration of NMG systems into energy distribution networks opens opportunities for the establishment of LEM (Zahraoui et al., 2023). LEM enables energy trading and offers economic and technical advantages for both energy distribution system operators and NMG systems stakeholders. By enabling energy trade between NMG systems and distribution networks, flexibility is provided to enhance performance for all participants in the energy market (Trivedi et al., 2022). This flexibility addresses performance issues, reduces energy costs, and generates revenue through the sharing of excess energy. However, to achieve the envisioned advantages for all participants in the energy market through LEM, specialized standards and strategies must be implemented to independently regulate energy trade. This entails establishing mechanisms for determining the quantity of exchanged energy, defining prices for energy units, and implementing other essential protocols. In this context, energy trading mechanisms have emerged as a practical management and control approach to assist decision-making processes in energy trading within LEM. These mechanisms empower energy market participants to autonomously determine the volume of energy traded, set buying, and selling prices, and choose collaborators for energy sharing, all without relying on a third party to regulate LEM. Additionally, they aid in achieving energy balance, facilitating consumer access to energy at reasonable prices, and offering the potential to reduce harmful emissions while enhancing system flexibility (Sahebi et al., 2023). The following section explains the fundamental concepts and mechanisms underlying energy trading within local energy markets.

2.4.1 Patterns of Energy Trading in Local Markets

Traditional LEM has undergone significant transformations in recent years, driven by a surge in MG penetration, increased energy exchange among participants and central grids, and a shift towards decentralized or distributed frameworks to fulfill security and reliability requirements while enhancing participant satisfaction. Broadly, LEM can be classified into three basic frameworks according to the path of energy trading among energy market participants:

i. Peer-to-Grid Energy Trading Markets

P2G or centralized energy markets provide participants with the opportunity to engage in energy trading exclusively with the central grid. These markets are overseen and regulated by distribution network operators. P2G energy trading mechanisms are particularly useful when NMG systems operate in grid-connected mode (Rodrigues & Garcia, 2023). Within this framework, participants, or MGs within the LEM who generate surplus energy beyond their consumption requirements can sell this excess energy back to the central grid. On the other hand, participants facing energy shortages can procure energy from the central grid to meet their needs, thus fostering energy equilibrium. P2G energy trading markets typically use digital platforms or centralized energy market infrastructures to facilitate energy exchange between MGs and central grid operators. This arrangement enhances flexibility and efficiency in managing energy resources, as surplus renewable energy can be efficiently utilized instead of being wasted (Bandeiras et al., 2020).

ii. Peer to Peer Energy Trading Markets

Decentralized energy trading systems have emerged as a response to the shortcomings of centralized systems. These shortcomings include security vulnerabilities and the risk of energy loss during malfunctions in the central system (D. Xu et al., 2020). Additionally, centralized systems struggle to accommodate the increasing number of participants in the energy market. In contrast, decentralized P2P energy trading systems enable direct trading between participants, thus addressing these limitations. P2P energy trading allows MGs to exchange energy with their peers to overcome shortages or redistribute surplus energy, ensuring efficient energy balance and operations. This approach has gained popularity, especially when NMG systems operate in standalone modes. In the P2P energy trading model, clusters function as both consumers and producers, engaging in energy exchange with neighboring entities to minimize discrepancies between energy demand and generation. By enabling entities to buy and sell energy directly in a decentralized manner, P2P energy trading enhances system flexibility and efficiency (Ullah & Park, 2021).

iii. Distributed Energy Trading Markets

Distributed energy markets integrate the advantages of both P2G and P2P energy markets within a unified organizational framework. Within distributed energy market mechanisms, participants can engage in bilateral energy trading either directly with their peers or with central grids, all without requiring coordination from a third party. This model affords peers the flexibility to choose whether they want to trade energy directly with neighboring peers or participate in commercial transactions with the central grid (Zia et al., 2020).

Numerous prior studies have extensively investigated the advantages and drawbacks of different energy market structures. The consistent findings highlight that centralized markets or P2G offer enhanced reliability and contribute to a decrease in uncertainty regarding energy demand in local peer markets. This can be attributed to the high operational capacity of centralized grids. However, P2P energy trading mechanisms outshine P2G energy trading mechanisms in terms of flexibility, scalability, privacy maintenance, and the ability to freely contact other peers. Distributed market mechanisms surpass both previous market designs by combining their advantages and overcoming the drawbacks, making them more suitable for local energy markets (Mensin et al., 2022). This setup offers more scalable energy markets with reduced reliance on communication systems compared to the other two types. Figure 2.8 illustrates the different patterns of the energy trading market: (a) P2G energy trading market, (b) P2P energy trading market, and (c) distributed energy trading market.

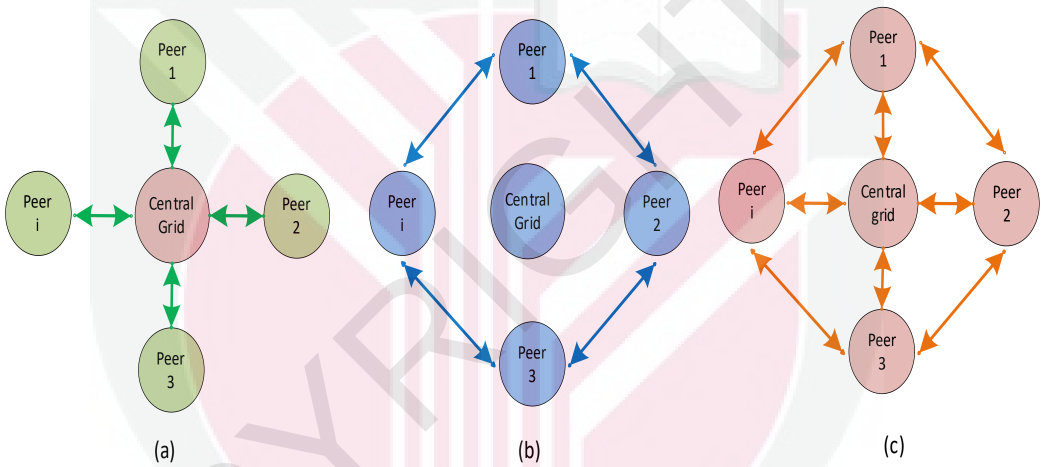

Figure 2.8 : The Various Structures of Local Energy Markets for Smart Energy Systems

2.4.2 Energy Trading Mechanisms in Networked Microgrid Systems

Algorithms used to manage LEM have the goal of encouraging active participation from participants. This is done by optimizing their profits and ensuring a balanced supply and demand for energy within the market. To achieve these objectives, different strategies have been explored in the literature, including the design of energy markets, negotiation mechanisms, and the establishment of energy trading agreements. Previous research has looked at various methods such as bidding strategies, market clearing mechanisms, game theories, and auction strategies to address these challenges (Zahraoui et al., 2023). The following sections will provide concise insights into these strategies, with a particular focus on the prevalence of auction strategies as the primary method used in this investigation.

i. Bidding Strategies

Various bidding strategies have been proposed for the management of energy trading markets, with notable examples being Comparable Bidding Methods and Learning-Based Bidding Methods (B. Hu et al., 2021). Incomparable bidding methods, energy contract prices are determined by analyzing historical energy trading data and assessing the ratio of energy supply to demand. Within Continuous Double Auction (CDA) mechanisms, different techniques like Zero Intelligence (ZI) are employed, where random prices are generated (Angaphiwatchawal et al., 2020). Another approach is Zero Intelligence Plus (ZIP), allowing participants to adjust their profit margins based on previous orders (Cheaib, 2021). Adaptive Aggression (AA) is another method where agents automatically adapt their prices in response to market price variations, enhancing customer bidding in energy markets (Cheng et al., 2021). While AA strategies outperform ZI and ZIP in terms of adaptability and trading efficiency, CDA bidding strategies, in general, lack the flexibility for clients to modify bid amounts. This limitation results in fewer rational options for participants.

Bidding strategies grounded in learning afford agents increased flexibility to dynamically engage in the bidding process, enabling them to adjust prices iteratively in response to fluctuations in energy prices as well as shifts in local market supply and demand. Learning-based strategies not only enhance the likelihood of successful negotiations but also diminish the risk of agreement breakdown. This is achieved through the introduction of a negotiation agent capable of intelligent bidding decisions, as exemplified in (Chang et al., 2023), or the utilization of negotiation agents based on artificial intelligence, as demonstrated in (Fan et al., 2022), to facilitate financial transaction procedures. Certain bidding investigations have employed reinforcement learning (RL) for bidding decisions instead of human input, aiming to tackle stochastic tasks and amplify the cumulative profits in the context of P2P energy trading (Harrold et al., 2022). Additionally, an energy market bidding algorithm grounded in multi-agent Q-learning (MAQL) was introduced to enhance bidding practices, aiming to offer more realistic prices and minimize time-related expenses (Chiu et al., 2021). Bidding strategies based on the MAQL algorithm outperform previously examined approaches by effectively managing production uncertainty in renewable energy generators and optimizing profits for both end users and aggregators. Nevertheless, it involves a time cost during the learning process. Moreover, to ensure the sensitivity of these bidding strategies to the learning rate, the rate mustn't fall below a reasonable threshold.

ii. Market Clearing Strategies

Energy market management methodologies based on market clearing are influenced by several factors, such as the number and behavior of participants and the scale of the network. There are differences between distributed approaches commonly used in large-scale markets and methods focused on auctions and speculation among participants (Hamouda et al., 2021). Demand ratio liveness of three P2P trading mechanisms, namely Double Auction (DA), Mean Market Rate (MMR), and Supply-Demand Ratio (SDR), was evaluated (L. Chen et al., 2022). The findings showed that the SDR mechanism is particularly beneficial for energy buyers, while the DA mechanism is more advantageous for energy vendors and agents with energy storage systems. Moreover, the MMR mechanism is considered the optimal choice for assessing energy flatness.

iii. Game-Theoretic Strategies

Game theory is recognized as a mathematical tool employed to assess the actions and interactions of diverse participants within a competitive environment, providing suitable outcomes. This model is utilized extensively to offer solutions by comprehending the behavior of all players (Nayak et al., 2020). Game theory has been suggested and utilized to discover suitable solutions across diverse cognitive domains, encompassing economics, engineering, sociology, biology, and more, over the past fifty years (Orrego et al., 2020). Within the realm of electrical engineering, game theory finds applications in various areas, such as power system planning, electric power scheduling, and the development of strategies to address regulatory aspects of power markets. The articles highlight game theory as a valuable tool for addressing challenges in local energy trading market contexts by integrating it into decision-making strategies and outlining different energy auction models applied to the P2P energy trading markets. Game theory mechanisms encompass three fundamental components: participants, strategies, and payoffs.

Participants or Decision Makers: These are the entities involved in the game, possessing the capacity to make decisions autonomously or collaboratively. In the context of energy markets, participants represent MG and distribution network operators.

Strategy: This element delineates the rules of the game, providing a framework through which participants can independently make decisions based on their interests or collectively align their decisions with the interests of all participants.

Payoff: Payoff refers to the gains achieved by participants during the gaming process, often oriented towards maximizing their overall capabilities.

In a broader classification, game theory can be categorized into cooperative and non-cooperative games.

In the cooperative game theory approach, participants collaborate to enhance their profits in the energy market. This involves considering the interests of all players and establishing an effective alliance. The collective cooperative game focuses on finding the optimal solution for all participants and distributing the additional benefits obtained from cooperation among the participants. Representative theoretical consequences of cooperative games include concepts such as Nash bargaining game theory and Shapley value (S. Malik et al., 2022). Within Cooperative Game Theory, participants persist in exploring optimal solutions through successive rounds of bargaining until reaching the Nash bargaining point. This point represents a balanced solution that satisfies all participants. The solution must adhere to the Nash referendum, encompassing criteria such as individual rationality, Pareto optimality, linear transformation independence, and more (Huang & Li, 2022). Cooperative game theory is recommended for regulating selling prices in energy contracts in situations where there is a substantial energy surplus exceeding the total energy shortage. Similarly, it is suitable for determining energy purchase prices when the total energy surplus is less than the total energy shortage.

Non-cooperative game theory approaches are regarded as self-interested strategies for establishing energy prices in local markets. In these approaches, decisions on energy contracts are made in a conflicting manner, lacking coordination among participants who act based on their interests and achieve profits. Utilizing non-cooperative game approaches empowers energy market participants to efficiently exchange energy and make crucial decisions, both in static and dynamic scenarios (Liang et al., 2021). In static scenarios within the energy market, participants operate based on a predetermined model without the need to be aware of the decisions made by other players. In dynamic scenarios, on the other hand, participants adapt their actions based on the maneuvers of other players. Most solutions rooted in non-cooperative game theory commonly rely on Nash equilibrium to identify optimal solutions and establish a stable situation that is favorable for all players (Fang et al., 2020).

iv. Auction Strategies

Energy market auctions refer to the commercial procedures conducted by participants (both buyers and sellers) in the energy market. These processes aim to establish equilibrium between the supply and demand for energy through a sequence of negotiation procedures involving available buy and sell bids, guided by specified bidding rules (Xu et al., 2021). Furthermore, energy auctions can be characterized as negotiating mechanisms with rules established by a designated intermediary. The objective is to ensure optimal energy trading among participants in the energy market. Strategies employed in energy market auctions can be classified into two primary categories: dynamic energy market auctions and single-round energy market auctions, as outlined in (Muhsen et al., 2022).

Dynamic or multi-round auctions refer to open auctions where participants in the energy market can adjust their trading price offers across successive auction rounds, providing flexibility for bidders to update their bid prices over the rounds of the energy market (Malik et al., 2023).

In single-round auctions within the energy market, each participant submits a single fixed bid for each transaction. During these auctions, participants are unable to access information about the price or quantity of energy offered by other participants (Sowrirajan & Wang, 2023). The goal is to maximize participants' profits within the defined parameters. Energy auctions can be categorized based on the organization of energy bids into three types (Zahraoui et al., 2023):

a) **Ascending bidding auctions** (English auctions) involve participants initially proposing relatively low selling prices. Prices then incrementally increase until the bids are matched, with the highest bidder ultimately securing the offered item.

b) **Descending bidding auctions** (Dutch auctions) operate in contrast to ascending auctions. In these auctions, contracts for energy sales commence at high prices and gradually decrease until a bid aligns with the specified price.

c) **Fixed-price auctions** are commonly employed in single-round auctions. In this format, buyers and sellers submit bids at fixed prices, which cannot be adjusted later. Following the submission of all bids, compatible contracts are selected, ensuring that energy-selling prices are either higher or equal to the energy-purchasing prices.

Regarding the number of participants in the energy market, energy auctions fall into two main categories: unilateral auctions and reverse auctions (Islam & Sivadas, 2022). Unilateral auctions involve one energy buyer and multiple sellers, or vice versa. On the other hand, DA encompasses scenarios with multiple sellers and buyers. CDA stands out as the predominant form of dual auctions in electric energy markets. These auctions facilitate flexible, two-sided energy markets, allowing both buyers and sellers to interchange their roles in the energy buying and selling process. While both multi-round and single-round auctions are widely used in LEM, significant research gaps remain in optimizing these mechanisms to enhance participant profitability and market efficiency under varying conditions. In multi-round auctions, the flexibility of adjusting bid prices across rounds presents challenges in ensuring price stability, preventing market manipulation, and balancing real-time demand-supply fluctuations. Conversely, single-round auctions lack the dynamic adaptability that multi-round formats offer, as participants cannot respond to competitors' bids, potentially limiting profit maximization and market responsiveness. Limited research has focused on hybrid auction models or innovative frameworks that combine the adaptability of multi-round systems with the stability and simplicity of single-round auctions, potentially enhancing efficiency and profitability across diverse energy market scenarios. Moreover, there is a need to investigate advanced predictive algorithms and machine learning techniques to assist participants in formulating optimal bid strategies in both auction types, promoting fair competition and resilience in increasingly complex energy markets. Table 2.4 outlines the advantages and disadvantages of energy auction strategies, comparing the attributes of both single-round and multi-round approaches.

Table 2.4 : Advantages and Disadvantages of Single-Round and Multi-Round Energy Auction Strategies

Auction	Advantages	Disadvantages
multi-round auctions	Participants in the energy market acquire ample information regarding the price fluctuations of other participants in the auction. Anticipation and overpricing are mitigated during the formulation of energy trading contracts due to the advanced awareness of other participants' prices. There are no significant differences in the bid prices of participants in the energy market.	The introduction of multiple rounds in energy auctions introduces significant complexity in reaching a unanimous agreement on energy bids. The approval process for auction contracts is prolonged, extending the time required for completion. Bids featuring lower prices might face challenges in accessing the auction market or securing consensus.
Single-round auctions	The energy market experiences reduced complexity when confined to a single round. This reduction in complexity diminishes speculation within the bids made by participants in the energy market. Competition of compatibility for energy offers is expedited, requiring less time.	Participants experience a decline in income and profits. The exchange processes fall short of achieving optimal energy outcomes for participants, primarily due to limited information about the remaining participants.

2.4.3 Mechanisms for Determining Auction Prices

The determination of auction prices in energy trading involves a diverse array of mechanisms tailored to the characteristics of the local market. Participants, comprising both buyers and sellers, present their pricing proposals in energy auction contracts (Kim et al., 2023). The aggregate demand for energy and the available energy is subsequently assessed. The baying bids (bn) are then arranged in descending order, from high to low, while the selling bids (sm) are organized in ascending order, from low to high. The pivotal step in this process is the identification of the equilibrium point (EP), which signifies the intersection between the aggregated buying and selling prices. Figure 2.9 shows the general outline of the energy market auction strategy. Following the determination of EP, energy trading contracts are finalized at prices reflective of this equilibrium, adhering to specific pricing strategies that may vary based on market design and regulatory considerations according to one of the following pricing strategies: Uniform-Price Rule (UPR), and Discriminatory Pricing Rule (DPR) (Qian et al., 2024). In uniform price mechanisms, every energy buyer incurs an identical equilibrium price, illustrated in Figure 2.9-a. In contrast, discriminatory pricing mechanisms dictate that the energy trading price is contingent upon the price offers presented by both buyers and sellers. This dependency is exemplified by the shaded area in Figure 2.9-b, reflecting the prices paid by buyers, or in Figure 2.9-c, depicting the prices paid by sellers.

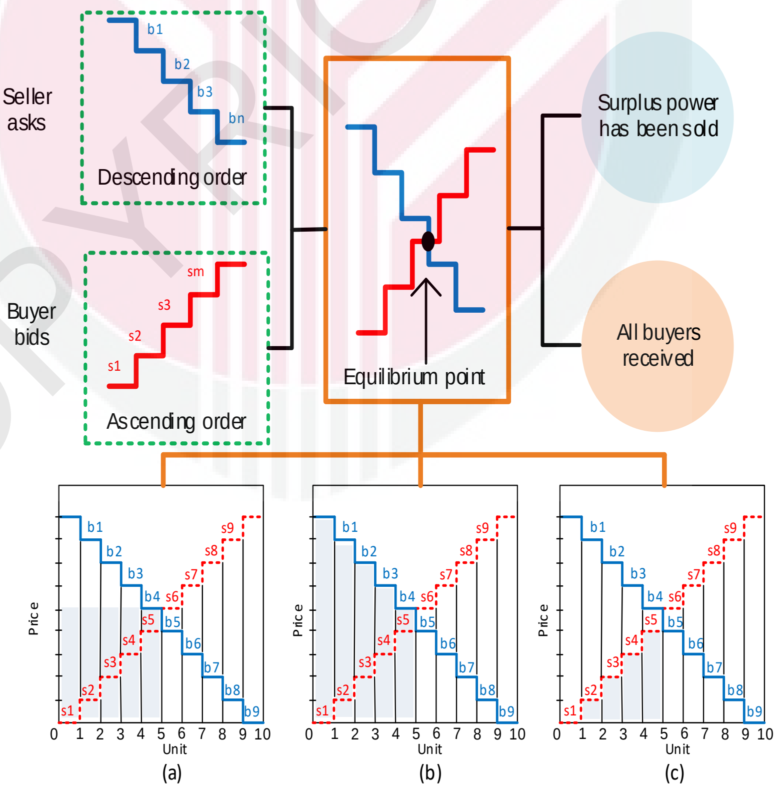

Figure 2.9 : Auctions as a Market Clearing Mechanism (a) Uniform Price, (b) Discriminatory Pricing Rule, (c) Discriminatory Pricing Rule

2.5 Summary

This study delves into the pivotal aspects of NMG systems design, management, and energy trading. It begins with a thorough literature review, defining the components, operational modes, and advantages of both MG and NMG systems. Notably, it explores key strategies and methods, particularly artificial intelligence approaches, for determining optimal MG system configurations and sizes across various objective functions.

Moving on to management systems, the study reviews various research works, outlining their structures, performance patterns, and types. Environmental management systems are categorized into centralized, decentralized, and distributed, with detailed explanations provided for each. Additionally, different modules of EMS are discussed in the literature review.

The study then shifts focus to the mechanisms and strategies employed in local energy markets. It outlines energy trading patterns such as Peer-to-Peer, Peer-to-Grid, and distributed energy trading. Subsequently, it examines four significant mechanisms identified in previous studies, analyzing their respective pros and cons. Finally, the study offers a comprehensive explanation of price approval mechanisms within the energy auction strategy.

Emphasizing the incorporation of high-quality, reliability, and contemporary studies, the research aims to avoid redundancy and duplication, focusing solely on information pertinent to enhancing the understanding and advancement of NMG systems.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The substantial technological revolution within the electrical energy sector, particularly in the realm of RES, has resulted in a broadening array of energy generation resources with enhanced capabilities and efficient storage in energy storage systems. While these advancements have positively impacted the availability of clean and cost-effective energy, they have also contributed to the heightened complexity of electrical energy distribution networks (Alnowibet et al., 2021).

MGs play a pivotal role in addressing these challenges by deploying diverse systems that aim to devise solutions for both distribution networks and end consumers through controlled management systems. MGs go beyond being mere systems for generating and storing electrical energy; they are meticulously planned and designed systems geared toward delivering stable, reliable, and sustainable energy to consumers (X. Liu et al., 2022). This involves the implementation of tailored programs, devices, and strategies designed for predefined applications. Optimizing the performance of NMGs involves addressing three fundamental aspects: attaining optimal design, effective management, and strategic marketing of energy. In this chapter, these essential aspects for achieving effective performance are delved into more detail. Initially, a thorough modeling procedure is outlined for all components of MG. Utilizing various AI techniques and basic mathematical formulas, optimal sizes for the proposed configurations are explored based on diverse single and multiple objective functions. The subsequent section investigates the application of a dual hierarchical management strategy to oversee the NMG system. Mathematical formulations are developed for both a DRMS and a DSMS, incorporating energy scheduling constraints in both grid-connected and stand-alone modes. The final segment of this chapter focuses on modeling energy trading markets and outlining mechanisms for computing fundamental factors in energy trading contracts. This includes the determination of energy trading prices and quantities of energy traded in both P2P and P2G modes. Figure 3.1 shows the general outline of the methodology followed in this study.

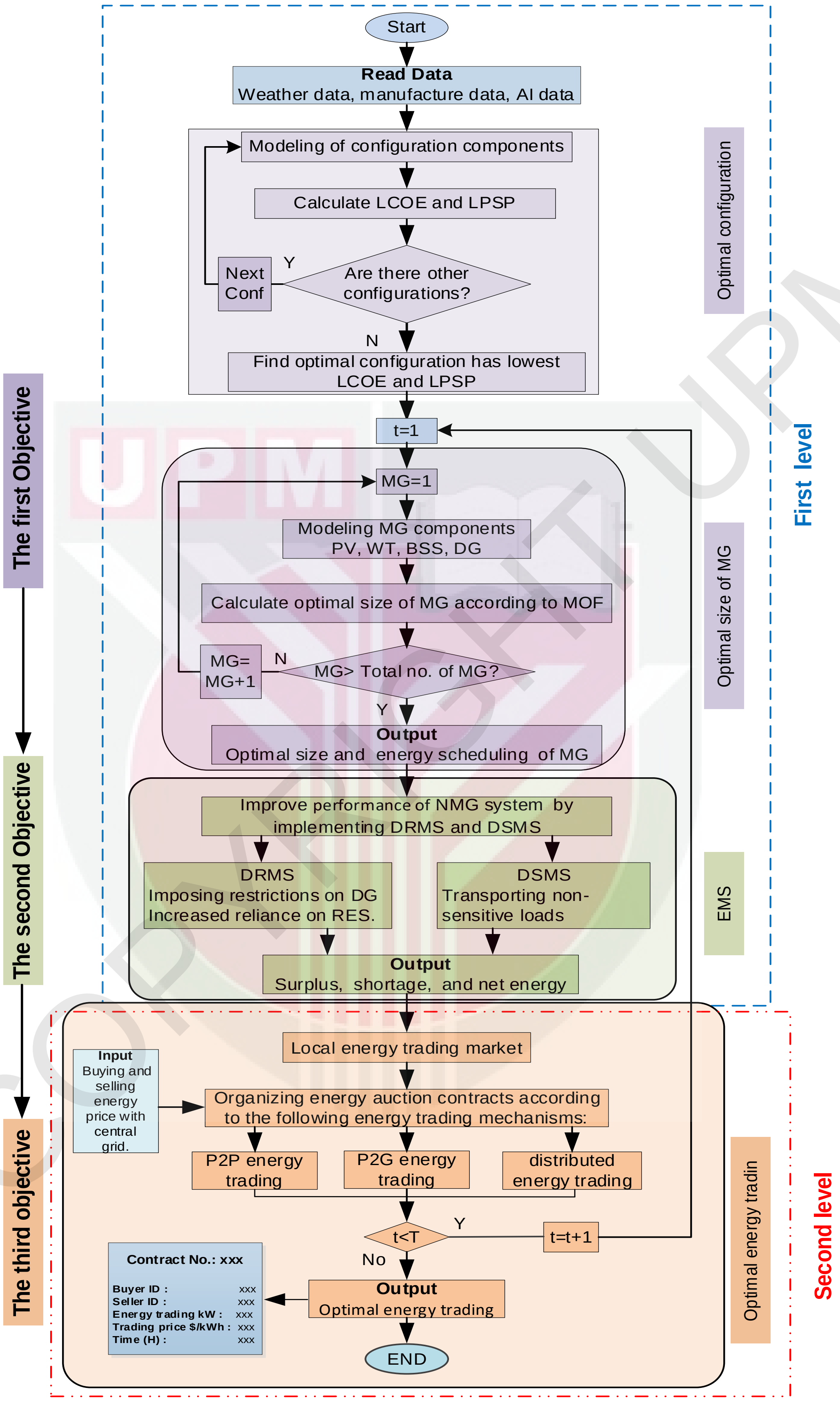

Figure 3.1 : Overall Flow Chart of Methodology

3.2 Optimal Configuration and Sizing of Microgrid

Numerous countries worldwide have expressed a keen interest in embracing RES, particularly solar energy systems and wind turbines, alongside other sustainable technologies. The integration of these resources into distribution networks has experienced significant growth, driven by factors such as cost-effectiveness, prolonged lifespan, and environmental friendliness (Eluri & Naik, 2021).

The composition of MG exhibits variability across locations, influenced by economic, technical, and environmental factors, as well as the specific goals of MG operators and distribution networks. Achieving an optimal, stable, and scalable MG configuration, along with determining the ideal size for individual components, necessitates the modeling of MG components. This involves employing AI techniques to calculate their optimal sizes based on predefined objective functions. As depicted in Figure 3.2, the overarching goal is to find the optimal configuration and size for MG. This process involves delving into mathematical formulations utilized for designing MG components, defining objective objectives, addressing critical operational constraints, and ultimately determining the optimal sizing of MG components. AI techniques play a crucial role in facilitating this intricate process.

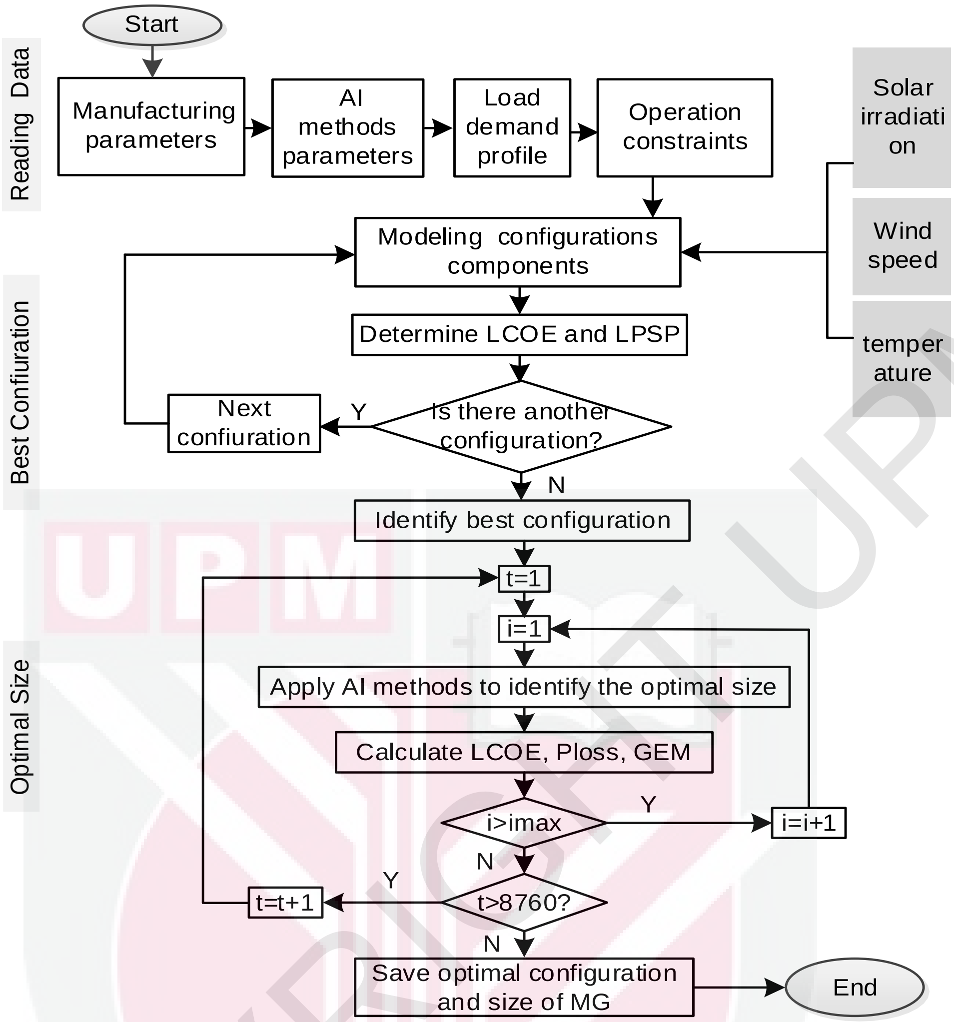

Figure 3.2 : The General Scheme for Finding the Optimal Configuration and Size of MG

3.2.1 Microgrid Design and Modelling

When undertaking the design of an MG project, it is crucial to prioritize the utilization of high-quality and highly efficient components to ensure the project's long-term viability. Emphasizing the ease of use and high reliability of these components is also paramount for the anticipated success of the project (Uddin et al., 2023). Several factors demand thorough examination before embarking on the selection of an appropriate MG configuration.

One pivotal consideration involves conducting an in-depth study of the weather topology and historical data specific to the study area. This includes scrutinizing parameters such as solar radiation, temperature, wind speed, percentage of cloudy days, and other relevant factors (Escobar-Orozco et al., 2023). This meticulous selection aims to minimize the likelihood of malfunctions and reduce maintenance expenses. The subsequent paragraphs present mathematical models employed in the design of MG components.

i. Modeling of Photovoltaic Energy System

Harnessing solar energy for electricity generation stands out as a highly promising technology within the realm of renewable energy, particularly within the context of the evolving smart grid. Over the past decades, there has been a substantial increase in the adoption of solar energy systems, showcasing its significance (Aloo et al., 2023). Solar thermal energy production typically involves large-scale power plants, making it particularly well-suited for integration into MG.

Photovoltaic generators comprise an extensive array of photovoltaic cells arranged in a back-to-back configuration, converting sunlight into direct current (DC) electricity. Subsequently, depending on the specific application, the DC produced by the photovoltaic cells undergoes conversion into alternating current (AC) using an inverter (Smaisim et al., 2023). Despite the acknowledged benefits of solar energy, photovoltaic technology faces obstacles that currently limit its optimal integration into the broader electrical grid system. The manufacturing of solar panels is influenced by various factors, including alterations in the angle of sunlight incidence, cloud patterns, shaded areas, and variations between day and night (Al-Quraan & Al-Qaisi, 2021). The output energy of PV panels (E^{PV}) in [kW] for MG_i, can be estimated using equations (3-1) and (3-2) (Humada et al., 2020).

$$E_{MGi}^{pv}(t) = N_{MGi}^{pv}\left[pv_{MGi}^{rate} f_{PV}\left(\frac{G(t)}{G_{ref}}\right)\left(1+\alpha_p\left(T_c(t)-T_{ref}\right)\right)\right]\times(1-\mu) \quad (3\text{-}1)$$

$$T_c(t) = T_{amb}(t) + \left[\frac{(NOCT)-20}{800}\times G(t)\right] \quad (3\text{-}2)$$

Where N^{PV} is the number of PV panels, pv_{MGi}^{rate} is the PV-rated capacity [kW], f_{PV} is the PV panels derating factor [%], $G(t)$ is the solar radiation [W/m2], G_{ref} is the standard episode solar radiation [1000 W/m^2], α_P is the coefficient of temperature [%/℃], $T_c(t)$ is the cell temperature [℃], T_{ref} is the standard cell temperature at test conditions [25 ◦C], T_{amb} is the ambient temperature, *NOCT* is the nominal operating temperature of a PV panel, and μ is the generative disturbance coefficient.

ii. Modeling of Wind Turbine Energy System

For millennia, the potential of wind has been harnessed in various businesses, propelling sailboats, and grinding grain. In contemporary times, wind energy evolved into a prominent RES, primarily through the utilization of wind turbines. These turbines serve the purpose of converting the kinetic energy of the wind into electrical energy (MansourLakouraj et al., 2022). Presently, thousands of sizable turbines are operational worldwide, establishing wind energy as the second major contributor to RES, following solar panels. This technology generates gigawatts of electrical energy annually (Doshi & Harish, 2021). The wind exerts a force on the blades, initiating their rotation. This rotational motion is then transmitted to the generators, resulting in the production of electricity . Notably, wind turbines boast the lowest greenhouse gas emissions, minimal water requirements, and positive social impacts compared to other RES (Mohamed et al., 2020).

However, wind turbines face challenges, such as their operational dependency on wind speed, leading to intermittent energy production. Additionally, factors like the moment of inertia impact on wind speed and high maintenance costs present notable drawbacks (Ramesh & Yadav, 2022). Wind turbines come in various sizes, featuring either horizontal or vertical axes, with the horizontal orientation being the more prevalent design. Since the speed of the wind is very intermittent, the output energy of a wind turbine (E^{WT}) in [kW] is a function of wind speeds and is defined by (3-3) (He et al., 2021).

$$E_{MGi}^{WT}(t) = N_{MGi}^{WT}\begin{cases} 0 \quad v(t) \leq v_{cutin} or\ v(t) \geq v_{cutout} \\ WT_{MGi}^{rate}\left(\frac{v^3(t)-v_{cutin}^3}{v_r^3-v_{cutin}^3}\right) \times (1-\mu) \quad v_{cutin} < v(t) < v_r \\ P_r \times (1-\mu) \quad v_r < v(t) \leq v_{cutout} \end{cases} \tag{3-3}$$

Where, N^{WT} is the number of WT, $v(t)$, v_r, v_{cutin}, v_{cutout}, and WT^{rate} is the wind speed [m/s], rated speed [m/s], cut-in speed [m/s], cut-out speed [m/s], and output power at the rated speed [kW], respectively.

The wind speed at the turbine blades (v_w) is calculated using a power law as given by equation (3-4):

$$v_w = v_i\left(\frac{h}{hr}\right)^{\alpha} \tag{3-4}$$

Where v_i is the measured wind speed, (α) is the power law exponent, and (hr), (h) are the reference height and hub height respectively.

iii. Modeling of Battery Storage System

Amid an increased focus on RES, BSS compensates for the intermittent of these sources, providing essential value for operators by enabling a stable supply of electricity thus avoiding curtailment of RES and maximizing their revenue. Electrochemical energy technologies can be utilized to store energy in BSSs in one or more electrochemical cells (Moncecchi et al., 2020). Batteries represent the basis of the work of these systems and the stages of the battery can be distinguished into three stages: charging, discharging, and rest (Silva et al., 2020). During charging operations, abundant electrical energy from an external source is stored as stable chemical energy inside the battery cells, while the reactions are reversed to transform the stored chemical energy into electrical energy that can be used in discharging operations, while there are no chemical reactions and no energy transferred at rest (Khalid et al., 2021).

Various technologies exist for battery-based energy storage systems, with lead-acid batteries standing out as a preferred choice due to their exceptional reliability, cost-effectiveness in maintenance, and extended operational lifespan (Hajebrahimi et al., 2020). The battery's performance during both the charging and discharging phases is contingent on the battery's state of charge (*SOC*) and the power demand, along with factors like battery capacity, efficiency, and ambient temperature. The calculation of the battery's *SOC* during charging intervals at a specific time (t) relies on the prior state of charge (t-1), as illustrated in equation (3-5) (Al-Ghussain et al., 2020).

$$SOC_{MGi}^{BSS}(t) = SOC_{MGi}^{BSS}(t-1)(1-\sigma) + \left[E_{MGi}^{pv}(t) + E_{MGi}^{WT}(t) - \frac{E_{MGi}^{load}(t)}{\eta_{MGi}^{inv}}\right] * \eta_{MGi}^{BSS} \tag{3-5}$$

Where σ denotes the self-discharge rate, η^{inv} is the inverter's efficiency, η^{BSS} is the battery efficiency, and E^{load} is the load required. When the output power of RES is less than the load demand, the BSS changes the state to discharge.

The new state of BSS during the discharge state can be obtained by equation(3-6).

$$SOC_{MGi}^{BSS}(t) = SOC_{MGi}^{BSS}(t-1)(1-\sigma) - \left[\frac{E_{MGi}^{load}(t)}{\eta_{MGi}^{inv}} - E_{MGi}^{pv}(t) + E_{MGi}^{WT}(t))\right] * \eta_{MGi}^{BSS} \tag{3-6}$$

The equilibrium of power within both WT and PV systems can result in either surplus or shortage of energy (Reza et al., 2023). In instances of surplus energy where the BSS hasn't reached its maximum capacity (SOC_{MGi}^{BSS}), it transitions into a charging mode ($E_{MGi}^{BSS,ch}$), characterized by equation (3-7), depicting the energy being stored.

$$E_{MGi}^{BSS,ch}(t) = SOC_{max} - SOC_{MGi}^{BSS}(t) \tag{3-7}$$

Conversely, during energy shortages, when the BSS capacity remains above its minimum threshold (SOC_{min}), it switches to discharge mode ($E_{MGi}^{BSS,dich}$), as outlined in equation (3-8), releasing stored energy.

$$E_{MGi}^{BSS,dich}(t) = SOC_{MGi}^{BSS}(t) - SOC_{min} \tag{3-8}$$

To ensure continuous operation, the BSS must either discharge or charge during each period according to BSS mode (k), as articulated in equation (3-9).

$$E_{MGi}^{BSS}(t) = N_{MGi}^{BSS}\left[\left(k \times E_{MGi}^{BSS,ch}\right) + \left(k \times E_{MGi}^{BSS,dich}\right)\right], \quad \begin{matrix} k = 1\ in\ charche \\ k = 0\ in\ discharch \end{matrix} \tag{3-9}$$

Typically, the autonomy duration is set at 2 or 3 days when calculating the total capacity of the BSS (Aghdam et al., 2020), as given by equation (3-10).

$$C_{MGi}^{BSS} = \frac{E_{MGi}^{load} S_D}{V_B (DOD)_{max} T_{cf} \eta_{BSS}} \tag{3-10}$$

Where, S_D signifies the battery autonomy or storage days; V_B denotes the battery voltage; DOD_{max} stands for the maximum battery depth of discharge; and T_{cf} indicates the temperature correction factor.

iv. Modeling of Diesel Generators

Microgrid incorporates diverse conventional power sources, including DG, gas turbines, steam turbines, and internal combustion engines. These sources offer numerous benefits, such as rapid response, capacity for handling high loads, and the ability to operate efficiently at low loads, potentially as low as 20%. Nonetheless, they come with drawbacks like elevated harmful emissions necessitating treatment and the burden of high fuel expenses (Long et al., 2020).

DGs are known for their notable efficiency and substantial capacity. The efficiency of DG is notably high when they operate at elevated load levels, optimizing fuel utilization. Therefore, the output energy of the DG (E^{DG}) during any period (t) in [kW] is restricted within the range from 0 to the rated design power of the DG (E_{rate}^{DG}) as shown in the formula (3-11) (Premadasa et al., 2023).

$$E_{MGi}^{DG}(t) = N_{MGi}^{DG} \times E_{rate}^{DG}(t) \tag{3-11}$$

The fuel consumption of the DG at intervals (t), denoted as DG^{feul} (l/h), is expressed as a function dependent on the output energy of DG as given by equation (3-12) (Ghosh & Shatil, 2021).

$$DG_{MGi}^{feul}(t) = N_{MGi}^{DG}[\left(0.246 * E_{MGi}^{DG}(t)\right) + (0.08415 * E_{max}^{DG})] \tag{3-12}$$

The fuel consumption of a DG is intricately linked to both its generated power (E^{DG}) and the maximum generated power (DG_{max}). Consequently, it is imperative to heed the manufacturer's specifications, particularly the stipulated minimum value. Operating the diesel generator below this specified minimum may have adverse effects on its performance and efficiency.

v. Modeling of DC/AC Converter

DC/AC inverters within MG play a crucial role in converting electrical energy between DC and AC, catering to specific requirements. These inverters link to the PV systems to transform direct current into alternating current. The efficiency of these inverters can be quantified using the following equation (3-13) (Kong & Nian, 2020):

$$\eta_{inv} = \frac{P}{P+P_o+kP^2} \tag{3-13}$$

The values of P, P_0, and k are ascertained by employing the subsequent equations from (3-14) to (3-16):

$$k = \frac{1}{\eta_{100}} - P_o - 1 \tag{3-14}$$

$$P_o = 1 - 99\left(\frac{1}{\eta_{10}} - \frac{1}{\eta_{100}} - 9\right)^2 \tag{3-15}$$

$$P = \frac{P_{out}}{P_{in}} \tag{3-16}$$

Where, the efficiency of the inverter at 10% and 100% of its nominal power is denoted by η_{10} and η_{100}, respectively, and P_{out}, and P_{in} are the output and input power of the inverter.

vi. Modeling of Load

The demand for electrical energy fluctuates throughout the day, influenced by factors such as the nature of the load (residential, commercial, or industrial), the number of consumers, among others. Broadly, MG loads can be categorized into two primary types: sensitive or fixed loads and non-sensitive or movable loads. Sensitive loads encompass essential requirements that must consistently receive electrical energy, as seen in hospitals and critical circuits (Penaloza et al., 2021). Conversely, non-sensitive loads comprise less critical demands that can be either eliminated or rescheduled outside peak periods of electrical energy demand. Load profile charts depict daily energy consumption patterns, enabling the anticipation of peak and off-peak hours.

3.2.2 Formulation of Objectives Function

Microgrids have emerged as a pivotal technological tool for shaping smart energy systems, especially in accommodating the escalating integration of RES. The design of MGs is typically tailored to specific objectives that aim to fulfill requirements, such as operational cost reduction, emissions reduction, enhanced MG reliability, and more (Nikmehr, 2020). A notable trend in MG technology involves the integration of economic, technical, and environmental objectives into a comprehensive multi-objective function, which has become a focal point for achieving optimal performance. While single-objective algorithms can offer a unique optimal solution, ensuring direct access to it, they often overlook other critical aspects necessary for achieving ideal performance. Recognizing the importance of aligning various goals, the adoption of multi-objective performance technology has become essential in addressing optimal design challenges for MGs (Parast et al., 2021). This study delves into the optimal design and sizing of an MG incorporating diverse generation resources. The investigation centers around minimizing a multi-objective function, encompassing the Levelized Cost of Energy (*LCOE*) as an economic objective, the power losses (P_{loss}) as a technical objective and harmful gas emissions (*GEM*) as an environmental objective. In addition to maintaining an eye on the three crucial reliability indicators, the *LPSP*, *CBI*, and *REI*. Equation (3-17) illustrates the general formulation of the research problems.

$$minimize\ (OF) = \min\ (OF_1 + OF_2 + OF_3) \tag{3-17}$$

Where OF_1, OF_2, and OF_3 represent the objective functions; *LCOE*, P_{loss}, and *GEM* are to be minimized, respectively. The problematic triple-objectives function model can be transformed into a simple single-objective function by placing weighting parameters as shown in equation (3-18):

$$OF = \min\left(w_1 LCOE \times + w_2 \times P_{loss} + w_3 \times GEM\right) \quad (3\text{-}18)$$

Where w_1, w_2, and w_3 are the weighting variables for the objective function.

The summation of all weight values should be equal to one as in equation (3-19) (Chamandoust et al., 2020).

$$\sum_{i=1}^{n\,i} w_i = 1 \quad (3\text{-}19)$$

The weight values vary according to the concerns of stakeholders and the importance of electrical standards. Also, the weight values are specified to give importance to each objective depending on the required analysis of the system.

i. Economic Objective

The *LCOE* stands out as a paramount economic metric for assessing the economic viability of any project, particularly in MG systems where it enjoys widespread adoption. This index signifies the cost per unit of energy generated at a given time ($/kWh), encompassing the initial investments in all equipment and devices utilized in the MG, along with the operational and maintenance expenses (Younesi et al., 2021). The *LCOE* serves as a crucial tool in assessing the economic viability of various MG configurations, aiding in determining optimal component sizes. Balancing investments against reliability and energy costs, *LCOE* analysis ensures that MGs efficiently meet customers' demands. Striking this balance is essential: excessive investments may guarantee high reliability but result in significant energy expenses, while insufficient investments risk failing to meet load requirements, particularly during independent operation (Nazari et al., 2021). The *LCOE* can be determined as in equation (3-20).

$$LCOE_{MGi}\left(\frac{\$}{kW}\right) = \frac{TNPC_{MGi}}{\sum_{t=1}^{8760} E_{MGi}^{load}(t)} \times CRF \tag{3-20}$$

Where *TNPC* is the total net present cost and it is equal to the sum of the capital investment cost (C^c), operation and maintenance cost ($C^{o\&m}$), replacement cost (C^r), fuel cost (C^f), and salvage cost (C^s) as in equations from (3-21) to (3-28) (Habib et al., 2021).

$$TNPC_{MGi} = C_{MGi}^{C} + C_{MGi}^{o\&m} + C_{MGi}^{r} + C_{MGi}^{f} - C_{MGi}^{s} \tag{3-21}$$

$$C_{MGi}^{C} = (C_{c,PV} + C_{c,WT} + C_{c,DG} + C_{c,BSS} + C_{c,inv}) \tag{3-22}$$

$$C_{MGi}^{o\&m} = (C_{o\&M,PV} + C_{o\&M,WT} + C_{o\&M,DG} + C_{o\&M,BSS} + C_{o\&M,inv}) \tag{3-23}$$

$$C_{MGi}^{r} = \xi \times (C_{r,PV} + C_{r,WT} + C_{r,DG} + C_{r,BSS} + C_{r,inv}) \tag{3-24}$$

$$C_{MGi}^{f} = (DG_{MGi}^{feul} \times \rho_{fuel}) \tag{3-25}$$

$$C_{MGi}^{s} = PVF(C_{s,PV} + C_{s,WT} + C_{s,DG} + C_{s,BSS} + C_{s,inv}) \tag{3-26}$$

$$PVF = \frac{(1+Ir)^n}{Ir \times (1+Ir)^n} \tag{3-27}$$

$$\xi = \sum_{n=1}^{y} \frac{1}{(1+Ir)^{n\times l}} \tag{3-28}$$

Where PVF is the present value factor, ξ is the coefficient of a lump-sum payment, I_r is the interesting factor, n is the project lifetime, and l is the component lifetime.

CRF is the capital recovery factor that can be calculated by (3-29).

$$CRF = \frac{1}{PVF} \tag{3-29}$$

ii. Technical Objective

The second objective of this study is to minimize the power losses of MGs. Power losses P_{loss} in [kW] are calculated using equation (3-30) (Marqusee et al., 2021).

$$P_{loss(i,j)}(t) = \left(\frac{P_{(i,j)}(t)}{V_i(t)}\right)^2 * \left(\frac{\rho}{A}\right) * C_l \tag{3-30}$$

Where, $P_{(i,j)}$ (t) is the power transmission between bus i and j at time (t). $V_i(t)$ is the distribution voltage at the i^{th} bus, ρ is the resistivity of the conductor, A is the cross-section of the conductor, and C_l is the length of the conductor connecting two buses. Thus, the total P_{loss} of the MG at any time can be calculated as in (3-31) (Wang et al., 2020).

$$P_{loss}(t) = \sum_{i=1}^{j} \sum_{j=1\ \&i\neq j}^{i} P_{loss(i,j)}(t) \tag{3-31}$$

iii. Environmental Objective

The electric power sector stands out as a significant contributor to detrimental emissions, particularly carbon dioxide, stemming from the combustion of fossil fuels in power plants. In response to challenges such as the intermittent nature of RES and the elevated costs associated with BSS, Microgrids are adopting a strategy of integrating DG resources with their energy infrastructure to serve as backup power units during periods of heightened demand (Kamarposhti et al., 2022). Typically situated in distribution networks proximate to consumers and human habitats, MGs pose a potential hazard due to the harmful emissions produced by DG. The escalation in greenhouse gas emissions is not a mere hypothetical scenario; rather, it is an existing reality with tangible consequences for human life, air quality, water systems, and climatic conditions, especially when concentrations surpass permissible limits. Consequently, there is an imperative to assess and quantify the environmental repercussions of supplying MGs with electricity generated by DGs (Trivedi & Khadem, 2022).

The DG emitted a variety of pollutants, including CO_2, SO_2, CO_1, and NO_2. Among these gases, CO_2 was quantified as a key indicator of environmental pollution due to its significant harmful effects. Gas emissions *GEM* in [t/year] is considered as the third objective. The CO_2 weight is calculated using equation (3-32) (Nazir et al., 2021).

$$CO_{2_{MGi}}(t) = \left(\frac{C_c}{E_{MGi}^{DG}(t)}\right)/1016.04 \qquad (3\text{-}32)$$

Where, C_c is the carbon element's proportion, which equals 0.6078 (kg/kWh).

The total emissions *GEM* (t/y) can be estimated as given in equation (3-33).

$$GEM_{MGi} = \sum_{t=1}^{8760} CO_{2\,MGi}(t) \tag{3-33}$$

3.2.3 Operating Constraints and Performance Indicators

Modeling for MG systems is conducted with meticulous attention to a spectrum of vital constraints and limitations. Alongside the ongoing evaluation of reliability indicators, these considerations shape the effective operation of MGs.

i. Constraints and Limitations

Ensuring the energy balance of the system and adhering to the physical limits of power generation units are essential considerations for the operation of MG within power systems. The operational model described above must comply with the following constraints shown in equations from (3-34) to (3-40):

- Sustaining equilibrium between energy generation and consumption (Yu et al., 2024):

$$E_{MGi}^{load}(t) = E_{MGi}^{pv}(t) + E_{MGi}^{WT}(t) + E_{MGi}^{BSS}(t) + E_{MGi}^{DG}(t) \tag{3-34}$$

- Restrictions on the output of the PV system and wind turbine

$$0 \le E_{MGi}^{pv}(t) \le E_{max}^{pv} \tag{3-35}$$

$$0 \le E_{MGi}^{WT}(t) \le E_{max}^{WT} \tag{3-36}$$

Here, E_{max}^{pv} represents the maximum output energy of the PV system, and E_{max}^{WT} signifies the maximum output energy of the wind turbine.

- Limitations of the battery storage system.

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{3-37}$$

$$-E_{min}^{BSS} \leq E_{MGi}^{BSS}(t) \leq E_{max}^{BSS} \tag{3-38}$$

Here, E_{max}^{BSS} denotes the maximum power for charging and discharging the battery. SOC_{min} and SOC_{max} represent the lower and upper limits of the *SOC*, respectively. Additionally, it is required that the initial *SOC* matches the *SOC* at the end.

$$SOC_{initial} = SOC_{end} \tag{3-39}$$

- The limitation on the operation of the diesel generator.

$$k_{min}^{DG}E_{min}^{DG} \leq E_{MGi}^{DG}(t) \leq k_{max}^{DG}E_{max}^{DG} \tag{3-40}$$

Here, E_{max}^{DG} and E_{min}^{DG} represent the upper and lower limit of the DG output.

The minimum and maximum load rates of the DG are denoted by k_{min}^{DG} and k_{max}^{DG}, respectively. To ensure economic operation and provide a spinning reserve for the system, the values for k_{min}^{DG} and k_{max}^{DG} are established at 0.3 and 0.8, respectively, following manufacturers' recommendations.

ii. Reliability Indices

The MG faces many reliability challenges related to the variability in generation from RES, tied to climatic conditions and varying hours of the day. To assess the system's reliability, the *LPSP, REI*, and *BCI* indices are evaluated.

- **Losses of Power Supply Probability Index**

LPSP serves as a metric indicating the probability of customers experiencing a loss of power supply, offering insights into the resilience and dependability of the MG system (Abid et al., 2024). The definition of *LPSP* is given in equation (3-41) (Ma et al., 2022).

$$LPSP_{MGi} = \frac{\sum_{t=1}^{T}\left[E_{MGi}^{load}(t)-(E_{MGi}^{pv}(t)+E_{MGi}^{WT}(t)+E_{MGi}^{BSS}(t)-E_{min}^{BSS})\right]}{\sum_{t=1}^{T}E_{MGi}^{load}(t)} \tag{3-41}$$

- **Renewable Energy Index**

REI is an abbreviation for the ratio of energy produced from wind turbines and solar panels to the overall system energy. This indicator is confined to a numerical range between 0 and 1, as depicted by the mathematical expression in (3-42) (Younesi et al., 2023).

$$REI_{MGi} = \sum_{t=1}^{T}\frac{E_{MGi}^{pv}(t)+E_{MGi}^{WT}(t)}{E_{MGi}^{pv}(t)+E_{MGi}^{WT}(t)+E_{MGi}^{DG}(t)} \tag{3-42}$$

- **Cost-Benefit Index**

In engineering project economics, assessing both the costs and expected benefits is crucial for determining feasibility. The *CBI* is a key metric used for this purpose, particularly in evaluating microgrid systems. A high *CBI* signifies favorable economic performance. The formula to compute *CBI* is as in (3-43) (J. Zhou & Xu, 2023):

$$CBI_{MGi} = \frac{1-LPSP}{TNPC} \times 100\% \tag{3-43}$$

3.2.4 Artificial Intelligence Techniques Mechanism

AI techniques are primarily employed to maximize economic and technical benefits for users by determining the optimal sizes of energy generation units. These methods offer substantial advantages for addressing complex optimization challenges, leveraging extensive data analysis and predictive strategies to optimize unit sizing while balancing energy supply and demand in energy generation. In this study, a hybrid AI technique was developed to meet these objectives, with results compared to three robust and widely used AI techniques: the Grey Wolf Optimizer, Firefly Algorithm, and Particle Swarm Optimization. The following sections provide a detailed overview of the implementation mechanisms for each AI technique.

i. Grey Wolf Optimizer

The cooperative and hierarchical approach allows GWO to efficiently navigate complex, multi-dimensional optimization problems, making it particularly suitable for determining optimal sizes in power generation and other engineering applications. The GWO is an optimization technique inspired by the social hierarchy and hunting behavior of grey wolves in nature. To find the optimal sizes of a MGs using the GWO, the following steps are followed:

1. **Define objective function(s)**: Establish objective functions that reflect the goals of optimization, such as minimizing operational costs,

maximizing energy efficiency, or balancing energy supply and demand across the microgrid.

2. **Initialize the population of Grey Wolves**: Generate an initial population of grey wolves (candidate solutions), where each wolf represents a possible configuration for the microgrid's components (e.g., RES, BSS, DG).

3. **Evaluate fitness of each wolf**: Assess each wolf's fitness (LCOE, Ploss, GEM) according to the defined objective function(s). This value indicates the quality or performance of each candidate microgrid configuration.

4. **Rank wolves (Alpha, Beta, Delta)**: Sort the wolves based on fitness and assign the top three wolves as alpha (best solution), beta, and delta.

5. **Update positions of wolves**: Adjust the position of each wolf in the population based on the positions of alpha, beta, and delta wolves.

6. **Simulate encircling behavior**: Use mathematical equations to simulate the encircling of the optimal solution, which helps the wolves converge towards the best solution by shrinking their search radius around the top solutions.

7. **Balance exploration and exploitation**: Adjust parameters within the algorithm to balance exploration (searching the broader space for diverse solutions) and exploitation (refining known high-quality solutions) to avoid premature convergence on suboptimal configurations.

8. **Evaluation and update**: Recalculate the fitness of each wolf after position updates, identifying new alpha, beta, and delta wolves if there are improvements in their fitness.

9. **Check for convergence or stopping criteria**: Determine if the algorithm has reached convergence or the stopping criteria, such as a fixed number of iterations or a minimum change in solution quality.

10. **Select Optimal Solution**: Once convergence is achieved, select the alpha wolf's position as the optimal configuration for the microgrid sizes.

Figure 3.3 presents an overall flowchart of the GWO used in this study to calculate the objective functions.

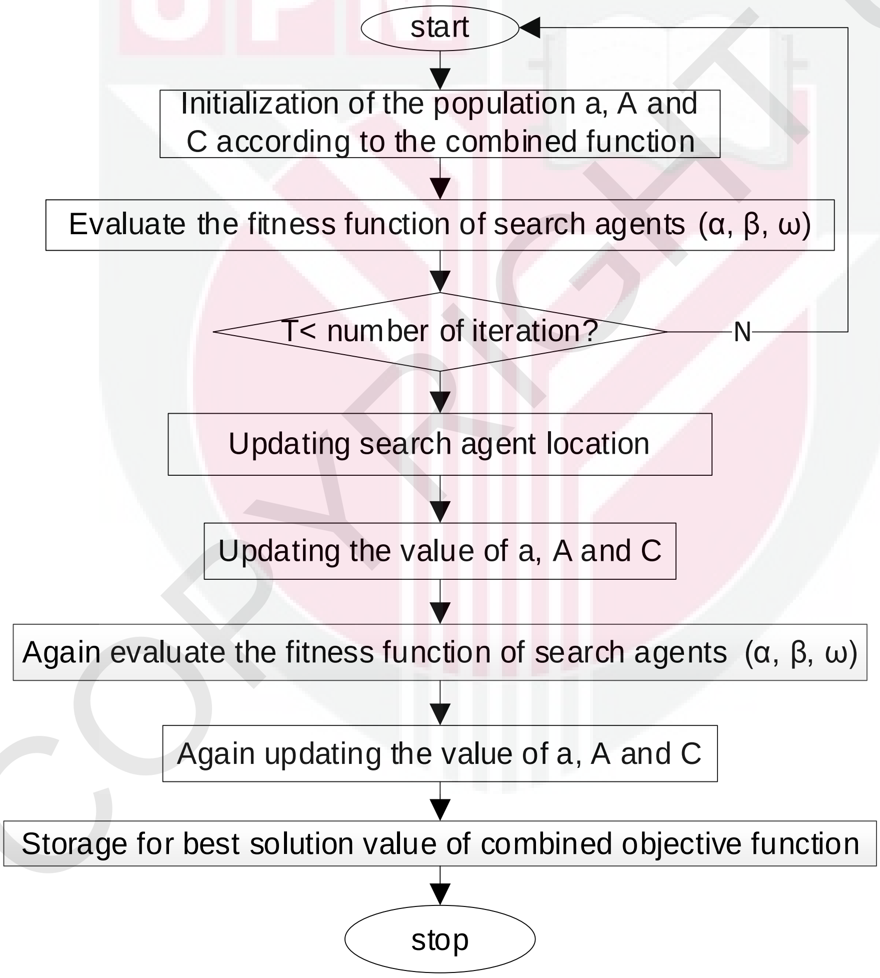

Figure 3.3 : The General Outline of the GWO Implementation Steps

ii. Firefly Algorithm

To find the optimal sizes of a microgrid using the Firefly Algorithm, the following general steps are typically followed:

1. **Define objective function(s)**: Identify the objective functions that represent the goals of optimization, such as minimizing costs, maximizing efficiency.
2. **Initialize the population of Fireflies**: Randomly generate an initial population of fireflies, where each firefly represents a candidate solution with specific sizing values for different components of the microgrid.
3. **Calculate light intensity (Objective Value)**: Evaluate each firefly's light intensity based on the defined objective function(s). The brightness or light intensity represents the quality or fitness of each candidate solution.
4. **Update Firefly positions**: For each firefly, move towards brighter (more optimal) fireflies by adjusting positions based on attractiveness and distance. This step allows the algorithm to explore and exploit the search space effectively.
5. **Attractiveness decay with distance**: Incorporate the attractiveness function, where fireflies are less attracted to one another as their distance increases. This step prevents clustering around local optima and encourages global search.
6. **Adjust random movement**: Add random movements to each firefly’s position to enhance exploration capabilities and to avoid premature convergence.
7. **Evaluate and update solutions**: Recalculate the objective function for each firefly after updating positions, adjusting brightness and rankings accordingly.

8. **Check for convergence or stopping criteria**: Determine if the algorithm has reached convergence based on criteria such as a set number of iterations or a predefined threshold for solution improvement.

9. **Extract optimal solution**: Once the stopping criteria are met, select the firefly with the highest brightness (best objective value) as the optimal sizing configuration for the microgrid components.

The general schematic of the Firefly Algorithm is depicted in Figure 3.4.

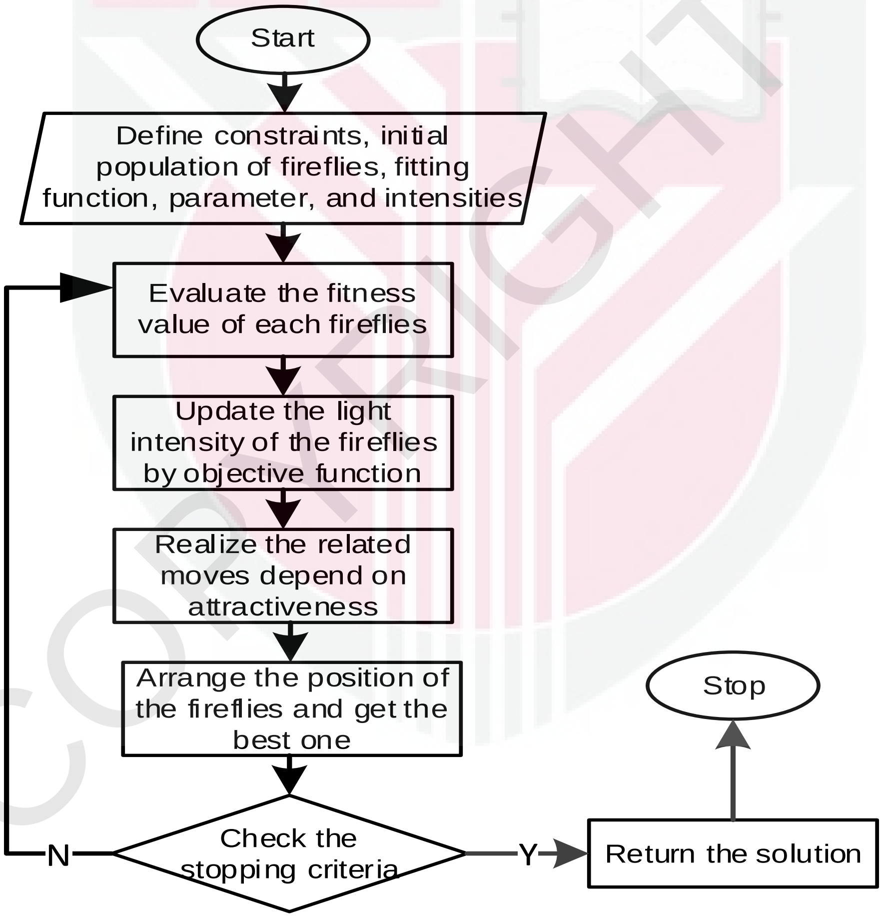

Figure 3.4 : The General Steps in FA Technique

iii. Particle Swarm Optimization

To find the optimal sizes of a microgrid using PSO, the following steps are generally followed:

1. **Define objective function(s):** Establish objective functions that represent the goals for optimizing the microgrid, such as minimizing costs, maximizing efficiency, or balancing supply and demand across components.

2. **Initialize particle swarm:** Generate an initial population (swarm) of particles, where each particle represents a candidate solution with specific sizing values for different microgrid components.

3. **Set Initial velocities and positions:** Assign initial random velocities and positions to each particle within the defined solution space.

4. **Evaluate fitness of each particle:** Calculate the fitness (objective value) of each particle based on the objective function(s).

5. **Identify personal best (*pbest*) and global best (*gbest*):** For each particle, track the best position it has achieved so far (pbest). Then, identify the particle with the best overall fitness in the entire swarm, known as the global best (gbest).

6. **Update Particle Velocities:** Update the velocity of each particle using PSO's velocity equation.

7. **Update particle positions:** Adjust the position of each particle based on its updated velocity. This step ensures that particles explore new areas of the search space, potentially finding improved solutions.

8. **Evaluate fitness and update *pbest* and *gbest*:** After moving to new positions, re-evaluate the fitness of each particle. Update *pbest* for particles with improved fitness and update *gbest* if a particle surpasses the current global best.

9. **Check for convergence or stopping criteria:** Determine if the stopping criteria are met, such as reaching a set number of iterations or achieving a minimal improvement threshold in solution quality.

10. Extract Optimal Solution: Once the algorithm converges, the *gbest* position represents the optimal sizing configuration for the microgrid components.

PSO leverages to dynamically adjust and converge on optimal microgrid sizes, offering a balance between local and global search for high-quality solutions as illustrated in Figure 3.5.

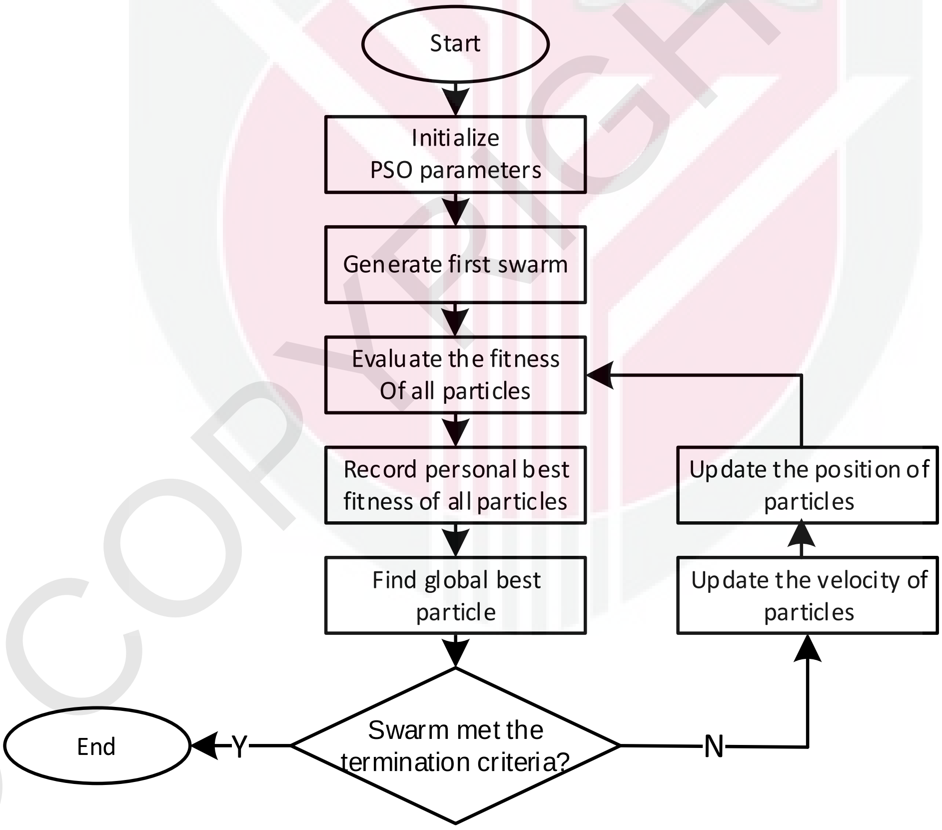

Figure 3.5 : The General Steps in the PSO Technique

iv. Hybrid Grey Wolf and Particle Swarm Optimization Method

Hybrid AI approaches leverage the strengths of multiple AI technologies to enhance performance, robustness, flexibility, and adaptability. By integrating different methods, hybrid methods can achieve better results compared to individual techniques alone (Ibrahim et al., 2021). In this research, two effective and efficient AI methods, namely GWO and PSO, were hybridized to obtain a new mechanism for calculating the optimal size of MG systems, termed HGWPSO.

PSO is characterized by its simplicity of use compared to other optimization algorithms, containing a few parameters that are easy for practitioners to utilize. Its high convergence speed towards the optimal solution and ability to explore large areas are significant advantages. However, it suffers from early convergence, falling into local solutions without fully exploring the search space, and may become stagnant (Abdolrasol et al., 2021).

On the other hand, GWO is known for its power and efficiency in solving complex optimization problems. It also offers simplicity, flexibility, and fewer parameters compared to other AI methods (Seyyedabbasi & Kiani, 2021). Its main strength lies in its ability to converge to the global optimal solution by considering multiple solutions.

The main goal of the HGWPSO method is to leverage the strengths of both GWO and PSO to improve the calculation of the optimal size of MG systems. By combining the exploration and exploitation capabilities of GWO with the convergence speed of PSO, HGWPSO aims to overcome the limitations of each method and achieve better performance in optimizing MG system sizes. The proposed HGWPSO method leverages the strengths of both GWO and PSO to achieve efficient convergence and precise tuning in solving optimization problems. The HGWPSO can be implemented by following these steps:

1. **Configuration of Basic Parameters:** Begin by defining fundamental parameters such as the number of variables representing components in the MG system (e.g., PV, WT, DG, BSS), their respective size ranges (*min and max*), the number of groups, and the total number of iterations. Each configuration represents a particle in the initial matrix.

2. **Initialization of Matrices:** Create two initial matrixes - the first matrix represents particle positions (X), and the second matrix represents particle velocities (V).

3. **Evaluation of Fitness:** Calculate the objective function (*fitness*) for each particle (component size) to determine its individual best position (*pbest*).

4. **Global Best Determination:** Determine the global best position (*gbest*) using a combination of PSO and GWO methods. In PSO, the best objective function within the initial matrix identifies the best global particle. In GWO, the three best objective functions are selected as main wolves, guiding the update for the rest of the wolves. For instance, Figures 3.6 illustrate the process of determining the *gbest* in both the PSO and GWO methods.

Figure 3.6 : Determine the Best Method in Both PSO and GWO Methods

5. **Comparison and Update:** In each iteration, the *gbest* is compared with the *gbest* of the previous iteration. If its fitness is lower than the previous one, the location of the particle is not updated as disabled in equation (3-44). Otherwise, the *gbest* obtained using GWO and PSO is compared. If *gbest* obtained using GWO is higher than or equal to *gbest* obtained using PSO, update the particle position and velocity values according to GWO (3-45) otherwise use gbest determined by PSO (3-46).

$$fx_i(t) = \begin{cases} true, \ \ if \ \ fitness\,particle, i(t) \leq gbest(t-1) \\ false, \ \ if \ \ fitness\,particle, i(t) > gbest(t-1) \end{cases} \tag{3-44}$$

$$x_i(t+1) = \frac{x_{i1}(t)+x_{i2}(t)+x_{i3}(t)}{3} \tag{3-45}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{3-46}$$

6. **Iteration and constraint check:** Repeat steps 3 to 6 until either the total number of iterations is reached, or any imposed constraints are violated. Figure 3.7 shows the general outline of the proposed GWPSO mechanism.

By iteratively refining particle positions based on both exploration (GWO) and exploitation (PSO) strategies, the proposed HGWPSO method efficiently navigates the search space to find the optimal solution for the given problem. This hybrid approach balances exploration and exploitation, enhancing the algorithm's performance in optimization tasks.

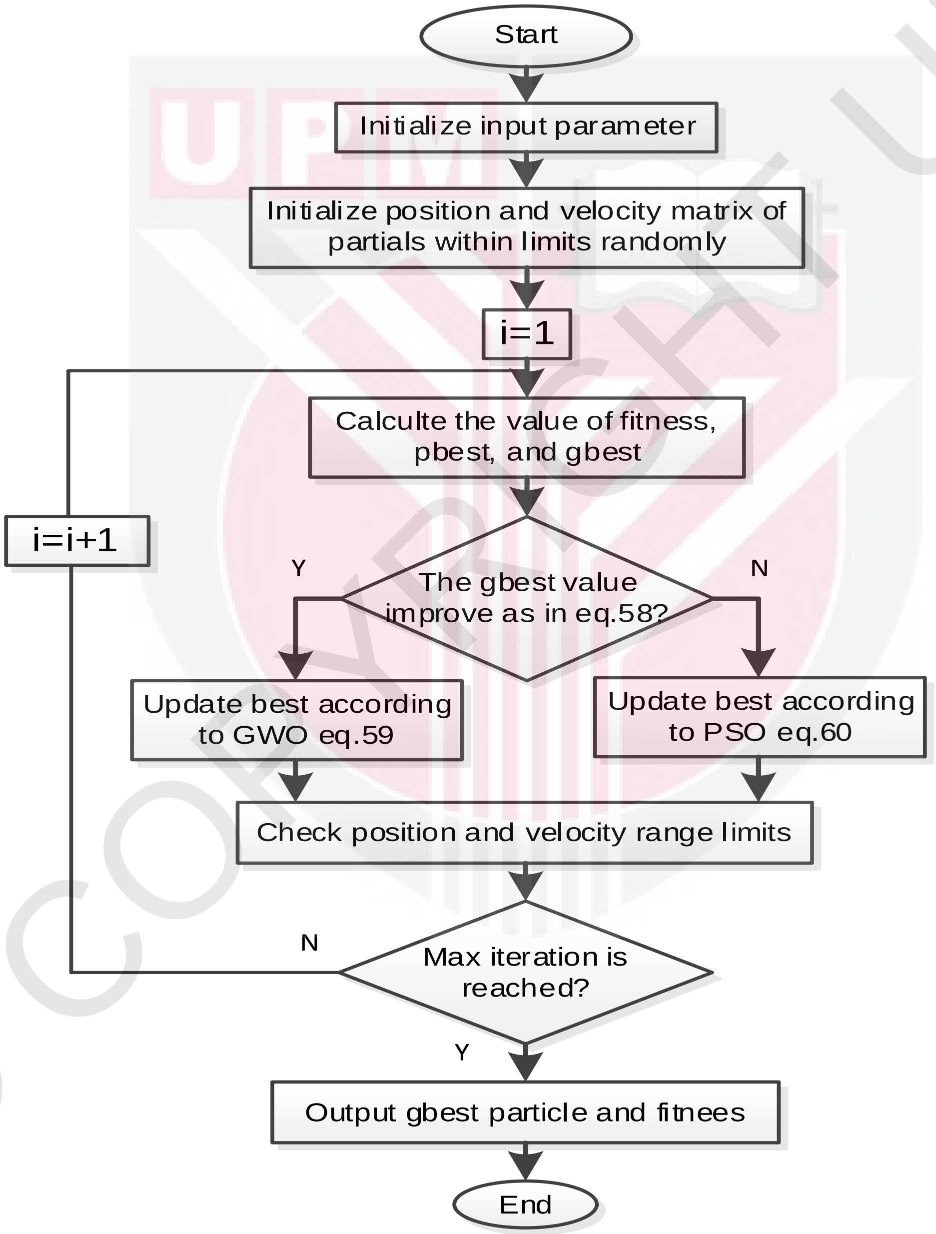

Figure 3.7 : General Flowchart of the HGWPSO Method

3.3 Energy Management Strategies

EMS plays a crucial role in overseeing and coordinating the efficient operation of NMG systems. The primary objective is to maintain an optimal energy balance by aligning supply with demand. EMS is a multifaceted control process designed to achieve alignment with various technical, economic, and environmental objectives across different time frames, all within the constraints of energy balance, market dynamics, and other operational and design limitations (Ishraque et al., 2021). Numerous studies have been conducted to enhance the performance of NMG systems, addressing key areas such as managing fluctuations in RES, optimizing BSS efficiency, and implementing DSMS.

This study focuses on developing a distributed resources management strategy DRMS and DSMS to reduce reliance on conventional units. The aim is to decrease energy costs by minimizing fuel consumption, reducing operational periods, reducing harmful emissions, and promoting greater reliance on RES. The subsequent paragraphs delve into the specifics of implementing these strategies and their impact on optimizing energy usage in NMG systems.

3.3.1 Distributable Resources Management Strategy

Distributed resources, such as DG, play a crucial role in increasing the stability of MG, enabling rapid and highly reliable compensation for energy shortfalls. However, a major drawback is that these sources use conventional fuel, which contributes significantly to pollution and increases the overall cost of energy

(Grisales-Noreña et al., 2022). To maximize dependence on RES, optimize the cost-effective operation of, and regulate harmful emissions, the DRMS is implemented. Within the framework of DRMS, stringent regulations and restrictions are enforced on the operation of distributable resources. These measures are implemented to curtail their usage and foster greater reliance on RES. In conventional operating strategies commonly employed in prior MG research, DG units are utilized to offset energy shortages arising when RES fails to meet demand and the BSS reaches its minimum SOC level (Abid et al., 2023). In this context, DG units are activated directly to address energy deficits, irrespective of the magnitude of the shortfall. This practice elevates dependence on DG units, subsequently amplifying the costs of energy production and the associated harmful emissions. During the initial design phase of an MG, it becomes imperative to consider augmenting the RES capacity by a reasonable percentage. This adjustment aims to bolster the utilization of RES without unduly impacting project investment costs.

Within the envisioned DRMS strategy, the net energy (E_{net}) in [kW] is determined for all periods. This calculation involves computing the disparity between the energy generated by RES and the prevailing energy demand, as elucidated in the equation (3-47).

$$E_{MGi}^{net}(t) = \left(E_{MGi}^{pv}(t) + E_{MGi}^{WT}(t)\right) - E_{MGi}^{load}(t) \tag{3-47}$$

After calculating the net energy, the proposed DRMS is implemented according to the following scenarios:

Scenario 1: If PV and WT resources generate ample energy to meet the load demand, the surplus energy is directed towards charging the BSS ($E_{MGi}^{BSS,ch}$), provided that the *SOC* at time (t) is less than the maximum allowable *SOC* as demonstrated in equations, (3-48) and (3-49).

$$if\ \left(E_{MGi}^{pv}(t) + E_{MGi}^{WT}(t)\right) > E_{MGi}^{load}(t)\ \&\ E_{MGi}^{BSS}(t) < E_{max}^{BSS} \quad (3\text{-}48)$$

$$E_{MGi}^{BSS,ch}(t) = E_{max}^{BSS} - SOC_{MGi}(t) \quad (3\text{-}49)$$

Scenario 2: When the energy generated by PV and WT resources surpasses the load demand, and the BSS has reached its maximum *SOC*, the excess energy is diverted to a dump (E_{dump}) for consumption as shown by equations (3-50) and (3-51).

$$if\ \left(E_{MGi}^{pv}(t) + E_{MGi}^{WT}(t)\right) > E_{MGi}^{load}(t)\ \&\ E_{MGi}^{BSS}(t) \geq E_{max}^{BSS} \quad (3\text{-}50)$$

$$E_{MGi}^{BSS}(t) = 0\ and\ E_{dump}(t) = SOC_{MGi}(t) - E_{max}^{BSS} \quad (3\text{-}51)$$

Scenario 3: In situations where the energy produced by PV and WT sources falls short of meeting the load demand, and the *SOC* at the time (t) exceeds the minimum *SOC* threshold, the deficit in energy will be compensated by drawing upon the stored energy within the BSS to fulfill the load requirements and discharging the energy of BSS ($E_{MGi}^{BSS,disch}$) can calculated as in equations (3-52) and (3-53).

$$if\ \left(E_{MGi}^{pv}(t) + E_{MGi}^{WT}(t)\right) < E_{MGi}^{load}(t)\ \&\ E_{MGi}^{BSS}(t) \geq E_{min}^{BSS} \quad (3\text{-}52)$$

$$E_{MGi}^{BSS,disch}(t) = E_{min}^{BSS} - SOC_{MGi}(t) \quad (3\text{-}53)$$

Scenario 4: When the power generated by PV and WT sources proves insufficient to satisfy the load demand, and the *SOC* at the time (t) falls below the minimum *SOC* threshold, the prescribed DRMS is activated. Before transitioning the MG to a different run mode (DG_{mode}), a pre-start limit check is conducted. If the power shortage within the MG surpasses the startup limit of the DG (DG_{strtup}), the DG shifts to the running mode (ON) to offset the energy shortage, and any surplus power is directed towards charging the BSS. Conversely, if the energy shortfall is below the startup limit, the DG remains inactive (OFF) as demonstrated in equations (3-54), (3-55), and (3-56).

$$if\ \left(E_{MGi}^{pv}(t) + E_{MGi}^{WT}(t)\right) < E_{MGi}^{load}(t)\ \&\ E_{MGi}^{BSS}(t) < E_{min}^{BSS} \quad (3\text{-}54)$$

$$if\ E_{MGi}^{load}(t) - \left(E_{MGi}^{pv}(t) + E_{MGi}^{WT}(t)\right) > DG_{strtup} \quad (3\text{-}55)$$

$$DG_{mode} = ON\ else\ DG_{mode} = OFF \quad (3\text{-}56)$$

Extensive testing of DG startup limits, ranging from 5% to 40%, revealed that optimal outcomes were attained when setting the startup limits between 25% and 30% (Cagnano et al., 2020).

DRMS play a pivotal role in diminishing reliance on DG resources and optimizing the utilization of RES. This effectiveness is contingent upon RES adequately offsetting the energy deficit incurred by non-operation of the DG. This compensation is achieved by augmenting the capacity of RES during the initial design phase. Figure 3.8 illustrates the overarching framework for a proposal management strategy.

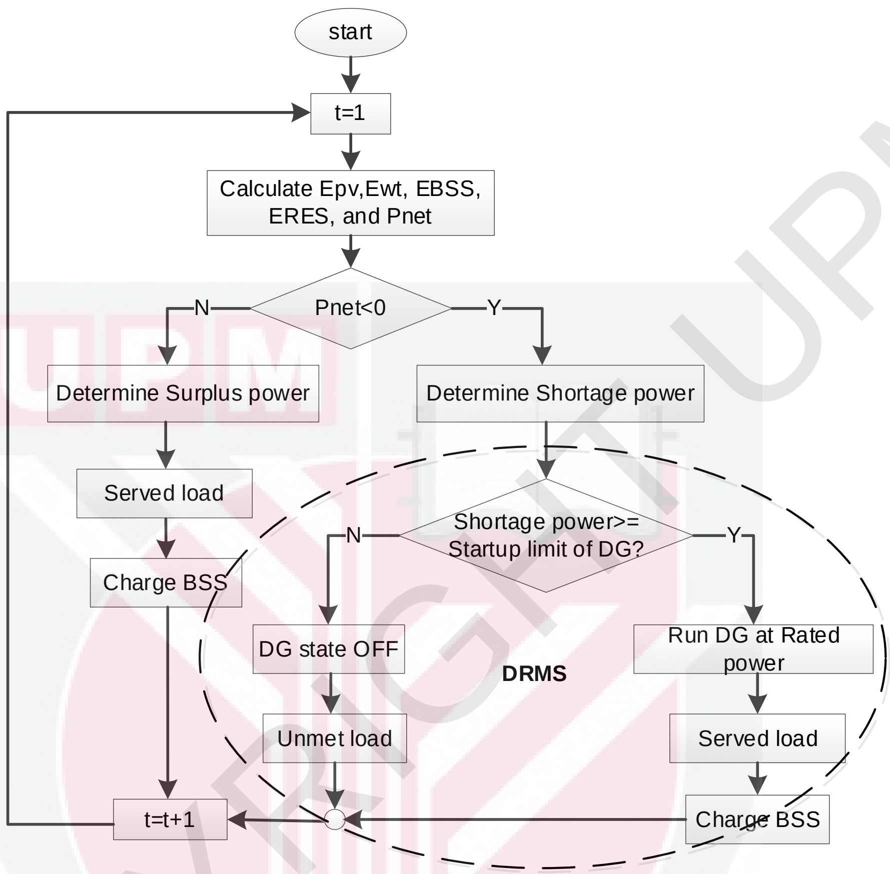

Figure 3.8 : Flowchart Illustrating the Proposed DRMS Strategy

3.3.2 Demand Side Management Strategy

Effectively managing microgrids is a challenging endeavor that demands the implementation of various administrative measures to mitigate the disparity between energy supply and demand. This challenge is exacerbated by irregularities in generation stemming from fluctuations in RES. A proven and efficient solution to address this issue involves the implementation of demand-side management strategies (Erenoğlu et al., 2022). DSMS incentivizes end customers to actively engage in regulating their energy consumption throughout the day. This active participation aims to decrease peak energy demand, and, in return, participants receive special incentives related to electricity prices. Within NMG systems, DSMS functions by reconfiguring high-capacity loads, minimizing energy consumption during peak hours, and shifting non-sensitive loads to off-peak periods (Erenoğlu et al., 2022). This flexibility empowers MG operators to effectively address energy demand through reliable and cost-effective operations.

As previously discussed in the load modeling section, electrical loads are categorized into two types: fixed loads and shiftable loads. DSMS specifically governs the adjustment of non-sensitive loads (Gao & Ai, 2021). The quantity of shiftable loads ($E_{sh,load}$) in [kW] transferred from interval *t* to another time is expressed by equations (3-57) and (3-58).

$$E_{MGi}^{sh,load}(t) = f_{sh,load} \times E_{MGi}^{load}(t) \quad (3\text{-}57)$$

$$0 \leq f_{sh,load} \leq f_{max}^{sh,load} \quad (3\text{-}58)$$

where, $f_{sh,load}$ and $f_{max}^{sh,load}$ represent the percentage factor for load shifting from hour t and its maximum value, respectively.

In the proposed DSMS, load adjustments involve redistributing loads from peak to off-peak periods within the load profile. The approach begins by determining a reference load (l_{ref}). Subsequently, the load profile is segmented into distinct levels, differentiating between periods exceeding and falling below the reference load ($f_{sh,load}$). For instance, the load profile is divided into two categories: one for periods surpassing 10% above the l_{ref} and another for periods falling 10% below l_{ref}. The calculation of load adjustments involves summing the load reductions (l_{red}) and load increases (l_{inc}), as illustrated by the equations (3-59) and (3-60).

$$l_{red}(t) = E_{MGi}^{load}(t) - E_{MGi}^{sh,load}(t) \tag{3-59}$$

$$l_{inc}(t) = E_{MGi}^{load}(t) + E_{MGi}^{sh,load}(t) \tag{3-60}$$

The total daily consumed energy of MG remains constant before and after implementing DRMS as supported by equation (3-61).

$$\sum_{t=1}^{T} l_{red}(t) = \sum_{t=1}^{T} l_{inc}(t) \tag{3-61}$$

Figure 3.9 illustrates the mechanisms for load profile redistribution over a horizontal period using the proposed DSMS. Figure 3.10 lists the logarithm for implementing the DSMS strategy.

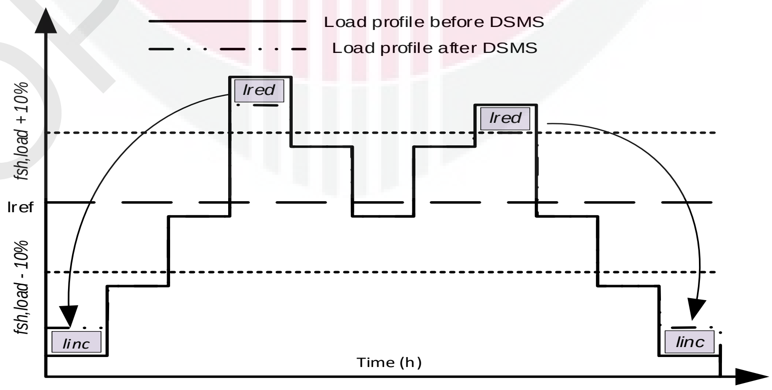

Figure 3.9 : The Proposed Demand Side Management Strategy

Identify I_{ref}, $f_{sh,load}(+10\%)$, $f_{sh,load}(-10\%)$
for t=1 to T
    If $E_{load}(t) > f_{sh,load}(+10\%)$
        $E^{sh,load}(t)=E_{load}(t)-(E_{load}(t) * f_{sh,load}(+10\%))$
    end
end
        $I_{red}=sum\ E^{sh.load}(t)$
for t=1 :T
    If $E_{load}(t) < f_{sh,load}(-10\%)$
        $E_{adj,load}(t)=E_{load}(t)+(E_{load}(t) * f_{sh,load}(-10\%))$
        $I_{inc}=sum\ E_{adj,load}(t)$
    else
        $E_{adj,load}(t)= E_{load}(t)$
    end
end

Figure 3.10 : Illustrates the Algorithm Employed for Calculating the Quantity of Load Shifted from Peak Periods to Off-Peak Periods

3.4 Local Energy Trading Market

Efficient management and regulation of LEM, in line with the strategies outlined in the preceding chapter, are paramount for ensuring energy equilibrium and fostering mutual benefits for all stakeholders involved. Central to achieving optimal energy market dynamics is the meticulous regulation of energy trading contracts. Energy trading contracts encapsulate three primary parameters: the classification of participants within the energy market, distinguishing between sellers and buyers; the pricing of energy trades; and the volume of energy transacted (Zhao et al., 2023). Additionally, these contracts may include ancillary information such as designated periods and confidential data linked to hash numbers. Figure 3.11 illustrates a representative sample comprising three consecutive energy trading contracts, showcasing pivotal data essential for effective market operation.

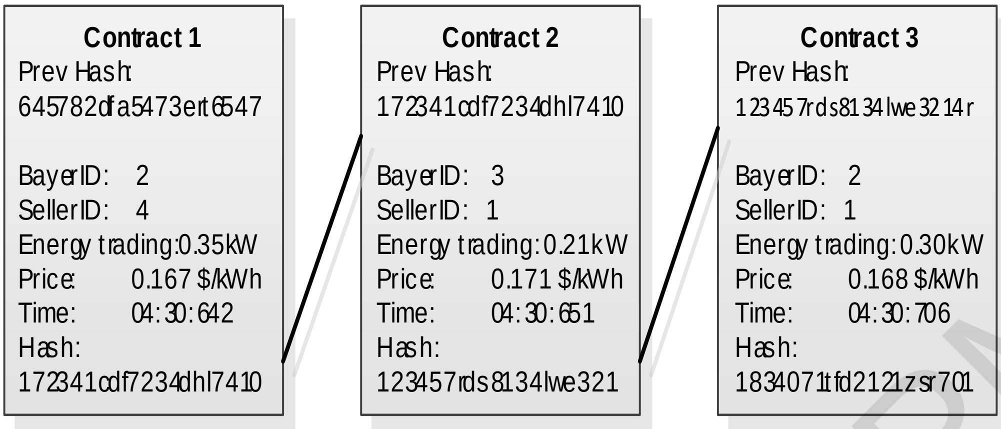

Figure 3.11 : A Model of Serial Energy Trading Contracts Containing Basic Data

3.4.1 Categorizing Participants Mechanism

MGs are categorized into energy sellers and energy buyers during each round in the LEM. MGs with negative P^{net} are identified as buyers, while MGs with positive P^{net} are identified as sellers, as illustrated in equations (3-62) and (3-63) (Bandeiras et al., 2020).

$$P_{MGi}^{net}(t) > 0 \rightarrow MGi = Seller \tag{3-62}$$

$$P_{MGi}^{net}(t) < 0 \rightarrow MGi = Buyer \tag{3-63}$$

When P^{net} equals 0, it implies that the MG has achieved a balance between generation and demand.

3.4.2 Price setting mechanismsThe mechanisms for establishing prices in energy trading contracts hinge on the selected contract execution strategy and the operational framework of the NMG system. This system may operate in different modes: standalone, facilitating energy exchange solely among participants (P2P); connected to the grid, enabling energy trading exclusively with it (P2G); or in a common mode, where energy transactions occur between participants as well as with the central grid. Further elucidation of these modes will be provided in the subsequent paragraphs.

i. Prices Setting in the Standalone Mode

The standalone NMG system is configured to function autonomously, where it is capable of exclusively engaging in P2P energy trading to fulfill the necessary energy balance. To promote engagement in P2P energy trading, sellers, during the initial round, endeavor to establish energy selling prices that surpass the selling price of the main grid, denoted as ρ_G^{sell} (D. Zhu et al., 2020). To ensure equitable selling prices while preventing commercial speculation among sellers, all MG operators collectively establish a maximum selling price denoted as ρ_{fixed}^{sell}. The energy selling price in the initial round $\rho_{MGi}^{sell}(t, r-1)$ is equal to ρ_{fixed}^{sell}. In successive rounds, if the proposed sales contracts do not reach a consensus or energy surplus persists, sellers adjust selling prices to avoid the costs associated with consuming BSS, and curtailment energy, as depicted in equation (3-64).

$$\rho_{MGi}^{sell}(t, r1) = \rho_{MGi}^{sell}(t, r-1) - \tau\left(C_{BSS}P_{MGi}^{BSS} + \alpha C_{cur}\left(P_{MGi}^{sell} - P_{MGi}^{BSS}\right)\right) \quad (3\text{-}64)$$

This equation is structured to encompass, in its initial segment, the expenses associated with the consumption of BSS because of charging and discharging operations, followed by the cost of curtailment of excess energy after exceeding the maximum BSS charging limit. The variable τ is binary, assuming a value of 0 in the inaugural round and 1 in subsequent rounds. This formula incentivizes sellers to adapt their energy selling prices to prevent incurring additional costs in case they are unable to sell their surplus energy.

Conversely, buyers in the initial round endeavor to negotiate energy buy contracts at lower buy prices ρ_{MGi}^{buy}, which may occasionally be below the price of energy sold by the main grid (Zhou & Xu, 2023). To avoid manipulation in adjusting purchasing prices, all MG owners agree to set a minimum for buying energy cost ρ_{fixed}^{buy} and, the energy buying price in the initial round $\rho_{MGi}^{buy}(t, r - 1)$ is equal to ρ_{fixed}^{buy}. The buyers enhance their prices by buying contracts, increasing them in successive rounds according to the formula outlined in formula (3-65).

$$\rho_{MGi}^{buy}(t,r) = \rho_{MGi}^{buy}(t,r-1) + \tau(C_{gen}P_{MGi}^{gen} + \beta C_{sh}(P_{MGi}^{buy} - P_{MGi}^{gen})) \quad (3\text{-}65)$$

Where C_{sh} represents the cost of load shedding in [$/kWh].

The total MGs benefit (β) is computed following equation (3-66), whereas the energy balance constraint is expressed in equation (3-67).

$$\beta_{MGi} = \sum_t^T \left(C_{gen}P_{MGi}^{gen}(t) + C_{BBS}P_{MGi}^{BSS}(t) + C_{cur}P_{MGi}^{net}(t) + \sum_{i=1}^{NMG} C_{P2P}P_{MGi}^{P2P}(t)\right) \quad (3\text{-}66)$$

$$P_{MGi}^{load}(t) - P_{MGi}^{net} + P_{MGi}^{BBS}(t) - P_{MGi}^{gen} + \sum_{i=1}^{NMG} P_{MGi}^{P2P}(t) = 0 \quad (3\text{-}67)$$

Figure 3.12 outlines the steps involved in the price adjustment algorithm for standalone NMG system.

For i =1 to 24
If *Pnet*<0
MGi=seller
If Pnet>0
MGi=buyer
end
r=1
While contract=FALSE
If r=1
$\rho_{MGi}^{sell}(t,r1) = \rho_{fixed}^{sell}$
$\rho_{MGi}^{buy}(t,r1) = \rho_{fixed}^{buy}$
else
$\rho_{MGi}^{sell}(t,r1) = \rho_{MGi}^{sell}(t,r-1) - \tau\left(C_{BES}P_{MGi}^{BES} + \alpha C_{cur}\left(P_{MGi}^{sell} - P_{MGi}^{BES}\right)\right)$
$\rho_{MGi}^{buy}(t,r) = \rho_{MGi}^{buy}(t,r-1) + \tau(C_g P_{MGi}^{gen} + \beta C_{sh}\left(P_{MGi}^{buy} - P_{MGi}^{gen}\right))$
If $\rho_{MGi}^{buy} \geq \rho_{MGi}^{sell}$
Contract=TRUE
else
r=r+1
end

Figure 3.12 : Price Adjustment Algorithm for NMG in the Standalone Mode

ii. Prices Setting in Grid-Connected Mode

In the grid-connected mode, commonly referred to as P2G, Microgrids possess the capability to exclusively trade energy with the distribution system. Participants in P2G aim to craft competitive proposals for energy buy and sale contracts aligned with net energy considerations. During the initial rounds, the sellers establish the initial selling price using the specified formula presented in formula (3-68) (Hossain et al., 2021). Simultaneously, buyers compute the initial buy price utilizing the formula outlined (3-69).

$$\rho_{MGi}^{sell}(t,1) = \left(1 + \frac{\sqrt{P_{MGi}^{sell}}}{3}\right)\rho_{G}^{sell} \tag{3-68}$$

$$\rho_{MGi}^{buy}(t,1) = \left(1 - \frac{\sqrt{P_{MGi}^{buy}}}{3}\right)\rho_{G}^{buy} \tag{3-69}$$

Buyers and sellers commence by releasing initial sales and buy contracts, detailing the quantities of energy available for sale or needed for buy, along with corresponding prices. During the initial round, the prices specified in participants' energy buy and sale contracts are juxtaposed with the prices set by the main grid. For all contracts, if the buying price surpasses the selling price of the main grid, or if the energy sale price falls below the energy buy price from the main grid, an immediate match is established, and the transaction is executed based on the buy or sell price in the contracts. In cases where the prices do not align, buyers and sellers modify their prices as outlined in equations (3-70) and (3-71) before progressing to the next round (Bui et al., 2022).

$$\rho_{MGi}^{buy}(t,r1) = \rho_{MGi}^{buy}(t,r-1)\left(1 + \alpha\left(kP_{MGi}^{buy}\right)\right) + \tau\left(C_{pk}P_{MGi}^{pk} + \vartheta C_{sh}\left(P_{MGi}^{net} - P_{MGi}^{pk}\right)\right) \tag{3-70}$$

$$\rho_{MGi}^{sell}(t,r1) = \rho_{MGi}^{sell}(t,r-1) - \tau\left(C_{BES}P_{MGi}^{BSS} + C_{cur}\left(P_{MGi}^{sell} - P_{MGi}^{BSS}\right)\right) \tag{3-71}$$

According to equation (3-70), buyers progressively increase their buying prices in successive rounds to align with the energy bid prices. The second part of the formula accounts for transmission loss cost. The cost of peak generation is incorporated in the third term, while the fourth term encompasses the load-shedding cost. The binary variable τ is assigned a value of 0 for the initial round and 1 for subsequent rounds. In contrast, the binary variable α takes a value of 1 in the first round and 0 otherwise. Finally, the constraint ϑ dictates that the reduction in load should not exceed 1 percent of the remaining load. Regarding sellers, they decrease prices in energy sales contracts, as indicated in formula (3-71), which encompasses the cost of energy reduction, and the expenses related to BSS. The peak generation (P_{MGi}^{pk}) is computed using equation (3-72).

$$P_{MGi}^{pk} = 0.1 \times P_{MGi}^{buy} \tag{3-72}$$

Likewise, the total benefit and the energy balance constraint are determined according to formulas (3-73) and (3-74).

$$\beta_{MGi} = \sum_t^T \left(C_{gen} P_{MGi}^{gen}(t) + C_{BES} P_{MGi}^{BES}(t) + C_{cur} P_{MGi}^{net}(t) + \sum_{i=1}^{NMG} C_{P2G} P_{MGi}^{P2G}(t) \right) \tag{3-73}$$

$$P_{MGi}^{load}(t) - P_{MGi}^{net} + P_{MGi}^{BES}(t) + P_{MGi}^{P2G}(t) - P_{MGi}^{gen} = 0 \tag{3-74}$$

Figure 3.13 illustrates the energy contract matching algorithm in the P2G mode.

```
For i =1 to 24
If    Pnet<0
      MGi=seller
If Pnet>0
     MGi=buyer
end
    r=1
while contract=FALSE
If r=1
```

$$\lambda_{MGi}^{sell}(t,1)=\left(1+\frac{\sqrt{P_{MGi}^{sell}}}{3}\right)\lambda_{gred}^{sell}$$

$$\lambda_{MGi}^{buy}(t,1)=\left(1-\frac{\sqrt{P_{MGi}^{buy}}}{3}\right)\lambda_{gred}^{buy}$$

else

$$\lambda_{MGi}^{buy}(t,r1)=\lambda_{MGi}^{buy}(t,r-1)\left(1+\alpha\left(kP_{MGi}^{buy}\right)\right)+\tau\left(C_{pk}P_{MGi}^{pk}+\beta C_{sh}\left(P_{MGi}^{net}-P_{MGi}^{pk}\right)\right)$$

$$\lambda_{MGi}^{sell}(t,r1)=\lambda_{MGi}^{sell}(t,r-1)-\tau\left(C_{BES}P_{MGi}^{BES}+C_{cur}\left(P_{MGi}^{sell}-P_{MGi}^{BES}\right)\right)$$

If $\lambda_{MGi}^{buy}\geq\lambda_{MGi}^{sell}$

```
    Contract=TRUE
else
     r=r+1
end
```

Figure 3.13 : Price Adjustment Algorithm for NMG in Grid-Connected Mode

iii. Prices Setting in the Distributed Mode

In the common mode, the NMG system facilitates energy trading either between independent MGs or with the central grid. The pricing mechanism for energy trading in this mode is contingent upon the operational state of the NMG system during contract execution, whether it operates autonomously or is interconnected with the grid (Yan et al., 2022).

When energy exchange occurs between MGs, pricing follows an iterative process. Initially, energy is priced based on predetermined factors and then adjusted in subsequent rounds using equations (3-64) to (3-67). Conversely, when energy is traded with the central grid, pricing is determined within the energy market rounds, governed by equations (3-68) to (3-71), correspondingly.

However, the overarching benefit of the system encompasses the total energy traded in both P2P and P2G scenarios, as demonstrated by equation (3-75). Moreover, the energy balance constraint undergoes modification to align with equation (3-76).

$$\beta_{MGi} = \sum_{t}^{T}\Big(C_{gen}P_{MGi}^{gen}(t) + C_{BES}P_{MGi}^{BES}(t) + C_{cur}P_{MGi}^{net}(t) + \sum_{i=1}^{NMG} C_{P2P}P_{MGi}^{P2P}(t) + \sum_{i=1}^{NMG} C_{P2G}P_{MGi}^{P2G}(t)\Big) \quad (3\text{-}75)$$

$$P_{MGi}^{load}(t) - P_{MGi}^{net} + P_{MGi}^{BES}(t) + P_{MGi}^{P2P}(t) + P_{MGi}^{P2G}(t) - P_{MGi}^{gen} = 0 \quad (3\text{-}76)$$

The comprehensive flowchart of the proposed trading model is illustrated in Figure 3.14.

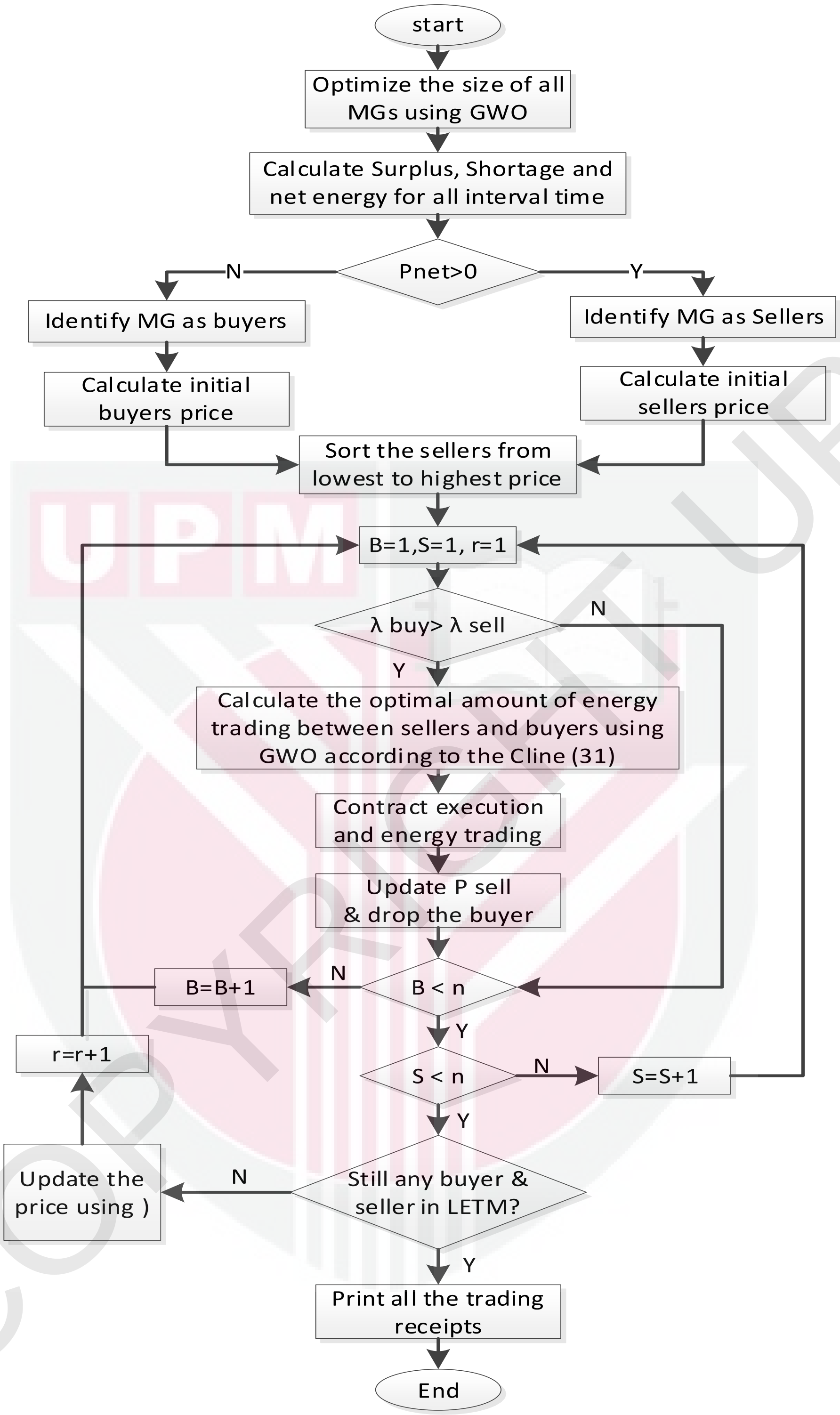

Figure 3.14 : The Comprehensive Flowchart of the Proposed Trading Model

3.4.3 Energy Allocation Mechanisms

In NMG systems, energy is exchanged via transmission lines within distribution networks. However, a thorough review of existing mechanisms for determining energy quantities in previous studies uncovered a shortfall: these approaches often neglect technical considerations of transmission lines, the associated costs, and historical participant data within the energy market. The subsequent paragraphs will delve into an analysis of the methodologies employed in previous studies for quantifying energy transfer amounts, highlighting their limitations. Furthermore, a proposed method will be presented, addressing these deficiencies by integrating technical aspects of transmission lines, cost factors, and historical participant data, thus offering a more comprehensive approach to energy quantity determination.

i. Conventional Energy Allocation Mechanism

Most prior inquiries into the regulation of energy contracts in LEM have conformed to the normal operating mechanisms for executing energy trading contracts. Buyers of energy are organized in descending order based on high to low purchase prices, while energy sellers are arranged in ascending order from low selling prices to high. Subsequently, contracts are matched and adjusted using diverse strategies, and the amount of energy traded is calculated through the following steps (Zhou et al., 2021):

1- If the selling price of the energy is lower than the buying price, the contract is executed automatically according to the following options:

i- If the amount of energy available for sale exceeds the amount required for purchase, the entire required energy is traded in the current round, leading the buyer to exit the energy market for that specific period. Any surplus energy available for sale is carried over to subsequent rounds (Liu, Li, et al., 2020).

ii- Conversely, if the energy offered for sale is insufficient compared to the energy required for buying, all the available energy is traded within the current round, prompting the seller to exit the energy market. The outstanding energy needed is then carried forward to subsequent rounds for further consideration and trading.

2- If the price of energy offered for sale exceeds the price of energy needed to buy, buyers have the option of exploring other available contracts until they find a suitable price match to complete the deal.

ii. Energy Allocation in the Proposed Mechanism

Energy trading contracts encompass not only buying and selling prices but also specify the quantities of energy available for trade between sellers and buyers in each round of the LEM. The apportionment of energy trading is choreographed with a "greedy" approach, with the overarching goal of optimizing advantages for participating entities (Liu, Li, et al., 2020). This strategy entails prioritizing buyers with higher buying prices. To eliminate the greedy approach to energy trading, energy buying contracts are organized in descending order based on historical data and the loads required during each round, following the approach outlined in equation (3-77).

$$\omega_{MGi} = P_{MGi}^{sh} / \gamma_i^{\mu} \tag{3-77}$$

Where γ_i represents the priority factor for each buyer, computed as outlined in equation (3-78), and *μ* is the weight factor that accentuates the importance of the priority factor (assumed to be 1.5 for all buyers).

$$\gamma_i = \frac{C_i}{C_{Total}} + \frac{D_i}{D_{Total}} \tag{3-78}$$

The initial segment of equation (3-92) provides insights into the historical contributions made by buyer MG_i. Here, C_i represents the frequency of occurrences in which MG_i recorded an energy shortage up to the present period. C_{Total}, on the other hand, denotes the overall occurrences of energy deficits recorded by MG_i for all buyers up to the current period (Xia et al., 2022). Turning to the second component, D_i delineates the load demand for MG buyers and D_{Total} is the total load demand of the MMG system. The permissible level of energy trade between MGs is intricately linked to the dynamics of energy flow through the transmission lines of distribution systems (H. Zhu et al., 2022). Elevated energy transactions result in escalated fees from the DNO, underscoring the imperative to uphold the stability of the distribution system and avert overloads on transmission lines. The optimal quantity of energy flowing between any two subscribers is determined by considering the costs associated with the utilization of transmission lines in distribution networks. These costs escalate with the increased trading of energy through the lines, denoted as (C_{line}), as illustrated in (3-79).

$$C_{line(i,j)} = \sum_{l=1}^{Nl} \frac{PTDF_{i,j}^{l} \times \eta_l}{F_l} \tag{3-79}$$

Where Nl represents the total number of transmission lines in the distribution network, and ηl and Fl denote the usage charges and the total energy flow in the respective transmission line.

The Power Transfer Distribution Factors ($PTDF$) indicate the incremental change in real power that occurs on transmission lines due to real power transfers between two regions. These regions can be defined by areas, zones, super areas, single buses, injection groups or the system slack (Jiang et al., 2023). The trading energy P_{MGi}^{trad} must not exceed the maximum energy of the tie line$P^{tie,max}$ as in (3-80).

$$\left|P_{MGi}^{trad}\right| \leq P^{tie,max} \tag{3-80}$$

Figure 3.15 illustrates the mechanism for determining the optimal amount of energy trading between NMG systems using AI methods, considering the costs associated with using transmission lines.

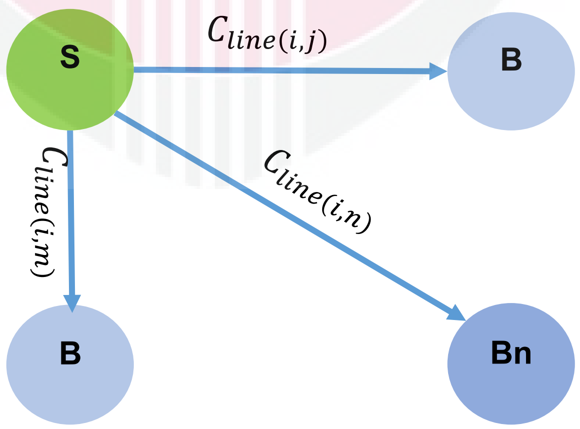

Figure 3.15 : Mechanism for Determining the Optimal Amount of Energy Exchange between the NMG Systems Considering the Costs Associated with the Use of Transmission Lines

3.5 Summary

The methodology chapter of the research project focuses on a systematic approach to enhance the performance of networked microgrid systems. The first step involves determining the optimal size of the MG, a critical factor in ensuring its efficiency. This process likely incorporates various considerations such as energy demand, available resources, and environmental factors. A multi-objective function that includes economic, technical, and environmental goals to find the optimal output for the mother using various artificial intelligence methods. Following the determination of the optimal size, the chapter outlines the implementation of a management strategy aimed at improving the overall performance of the NMG system. This strategy may encompass aspects such as load balancing, demand response, and the integration of RES to optimize energy generation and consumption within the MG. Moreover, the methodology chapter delves into the application of mathematical formulas within the context of energy trading markets, specifically in peer-to-peer transactions. This suggests an exploration of quantitative models or algorithms utilized in energy trading scenarios, emphasizing the significance of mathematical frameworks for effective decision-making and resource allocation. Overall, the methodology chapter provides a comprehensive guide to systematically address the optimization of MG size, implementing a management strategy, and applying mathematical formulas in the context of peer-to-peer energy trading markets. This structured approach aims to contribute valuable insights into enhancing the overall performance and efficiency of Microgrid systems.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents a comprehensive mathematical analysis of the performance of an NMG system comprising four MGs. These MGs can operate in a connected mode or independently in a standalone mode. Each MG incorporates a distinct DER along with a BSS to reliably supply load requirements. Furthermore, the NMG system can engage in energy sharing among themselves and with the central grid to achieve energy balance.

The research problem was formulated and addressed using the MATLAB software installed on a computer equipped with an Intel(R) Core(TM) i7-6600HQ CPU 2.90 GHz and 4 GB RAM (hp). The NMG performance analysis results are categorized into three sections. In the first section, the optimal configuration and size of the NMG are explored using AI methods and a multi-objective function. This evaluation aims to assess the economic, technical, and environmental aspects of performance, with a specific focus on the overall benefits of leveraging NMG systems. The second section focuses on the outcomes related to the investigation of proposed DRMS and DSMS. The study analyzes the impact of these strategies on the primary objectives, providing a detailed examination of the sensitivity of each parameter affecting the system's performance. This analysis offers valuable insights for NMG system operators, addressing uncertainties and enhancing the resilience of the entire MG system. Finally, the third section highlights the results of local energy markets, encompassing P2P, P2G, and distributed trading modes. This investigation contributes to understanding the dynamics of the energy trading market within the NMG system.

4.2 Test Systems and Data Collection

The objective of this study is to enhance the efficiency of NMG systems through the implementation of proposed methodologies and strategies. The performance of the system was evaluated under standardized test systems using approved mathematical formulations. The subsequent paragraphs contain comprehensive information on the testing systems, including essential technical, economic, and climatic data crucial for designing the NMG systems.

4.2.1 Test Systems Description

The NMG system's performance underwent design, testing, and analysis following two IEEE standard test systems. These systems include a Benchmark Test System tailored for modeling Networked Microgrids and the IEEE 13 test system, utilized for assessing the energy market's performance.

i. Benchmark for Networked Microgrid System

The NMG system is structured by the IEEE benchmark for networked microgrid systems, adapted from and incorporating certain modifications to align with the IEEE 1547-2008 standard (Alam et al., 2020). Comprising four interconnected MGs, this system allows for energy exchange among the individual MGs as well as with the central grid, as illustrated in Figure 4.1. The numerical values depicted in the diagram correspond to the resistance, impedance, and lengths of the transmission lines. Additional information about the system is provided in Appendix A.

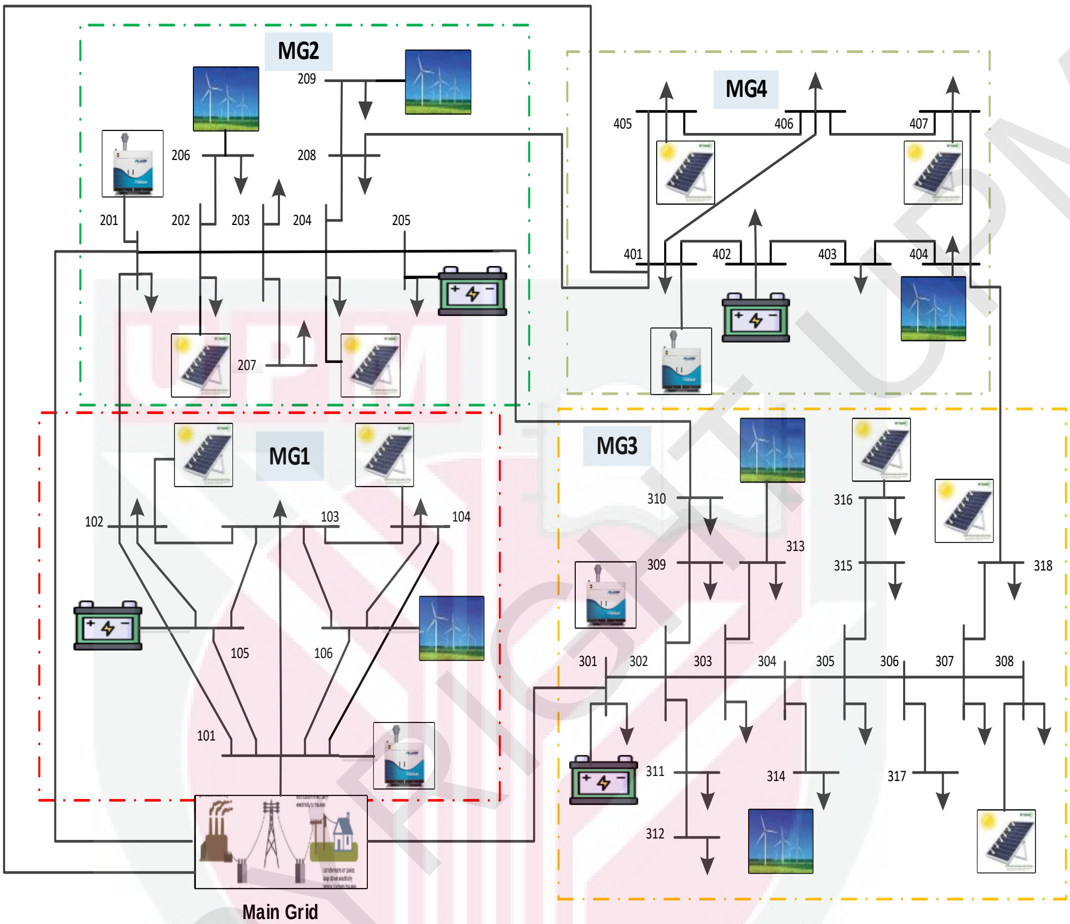

Figure 4.1 : Benchmark Test System Tailored for Modeling Networked Microgrids

ii. IEEE 13-Bus Test System

The application of proposed energy trading contracts in local markets is assessed using the IEEE 13-bus distribution testing system (Imtiaz et al., 2021). The testing system simulates interactions between buyers and sellers, utilizing data regarding transmission line capacities and the costs of using these lines. Figure 4.2 offers an illustration of the testing system, depicting the geographical distribution of MGs. Further details about the system can be found in Appendix B.

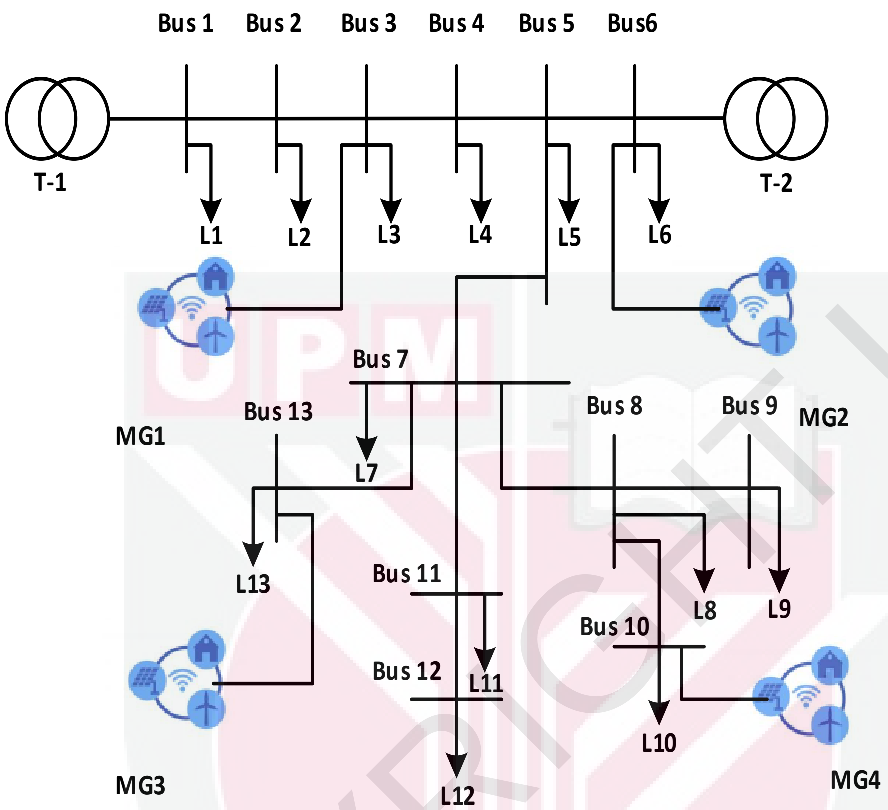

Figure 4.2 : IEEE 13-Bus Distribution Testing System

4.2.2 Load Profile Estimation and Data Collection

Before determining the optimal configuration and size of NMG systems and effectively modeling their components, it is imperative to estimate the daily load profile and collect industrial and economic data alongside pertinent meteorological information.

i. Estimating Load Profile

The MG components are engineered to fulfill electrical load demands to the best extent possible. For this study, four random models of annual load profiles were generated using the Homer program. Figure 4.3 illustrates the daily load profiles of different MGs, which served as the basis for their design. The total daily load for MG1, MG2, MG3, and MG4 amounts to 1270.28 kW, 1503.74 kW, 6017.27 kW, and 1619.77 kW, respectively. The annual profiles for all MGs are detailed in Appendix C.

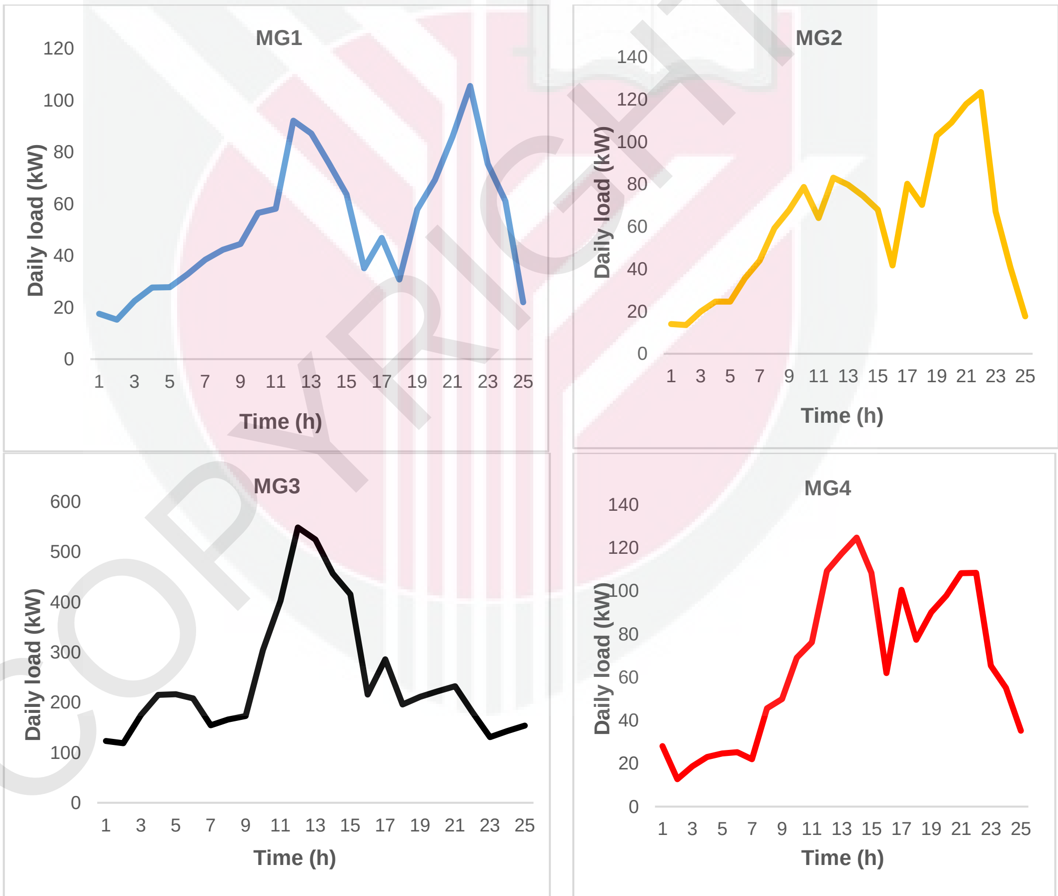

Figure 4.3 : Estimated Daily Load Profile in kW for the Proposed NMG System

ii. Meteorological Data

The meteorological data of the location (Latitude 2.9977 and Longitude 101.714) located in Kuala Lumpur, Malaysia, are obtained from the National Aeronautics and Space Administration (NASA) (Liu et al., 2020). The solar irradiation, ambient temperature, and wind speed for one day are shown in Figure 4.4. From an economic point of view, the ratio of solar irradiation and ambient temperature is acceptable to produce sufficient electrical energy, as the percentage of solar irradiation exceeds 500 W/m2 most days of the year (Elhassan, 2023). The range of temperature is between 28 and 32 C, while the average wind speed is unsuitable for installing large-capacity wind turbines (Guo et al., 2022). The difference in solar radiation, ambient temperatures, and wind speed will increase the volatility of RES, which is limited by using an appropriate energy storage system. The annual load and weather data are presented in Appendix C.

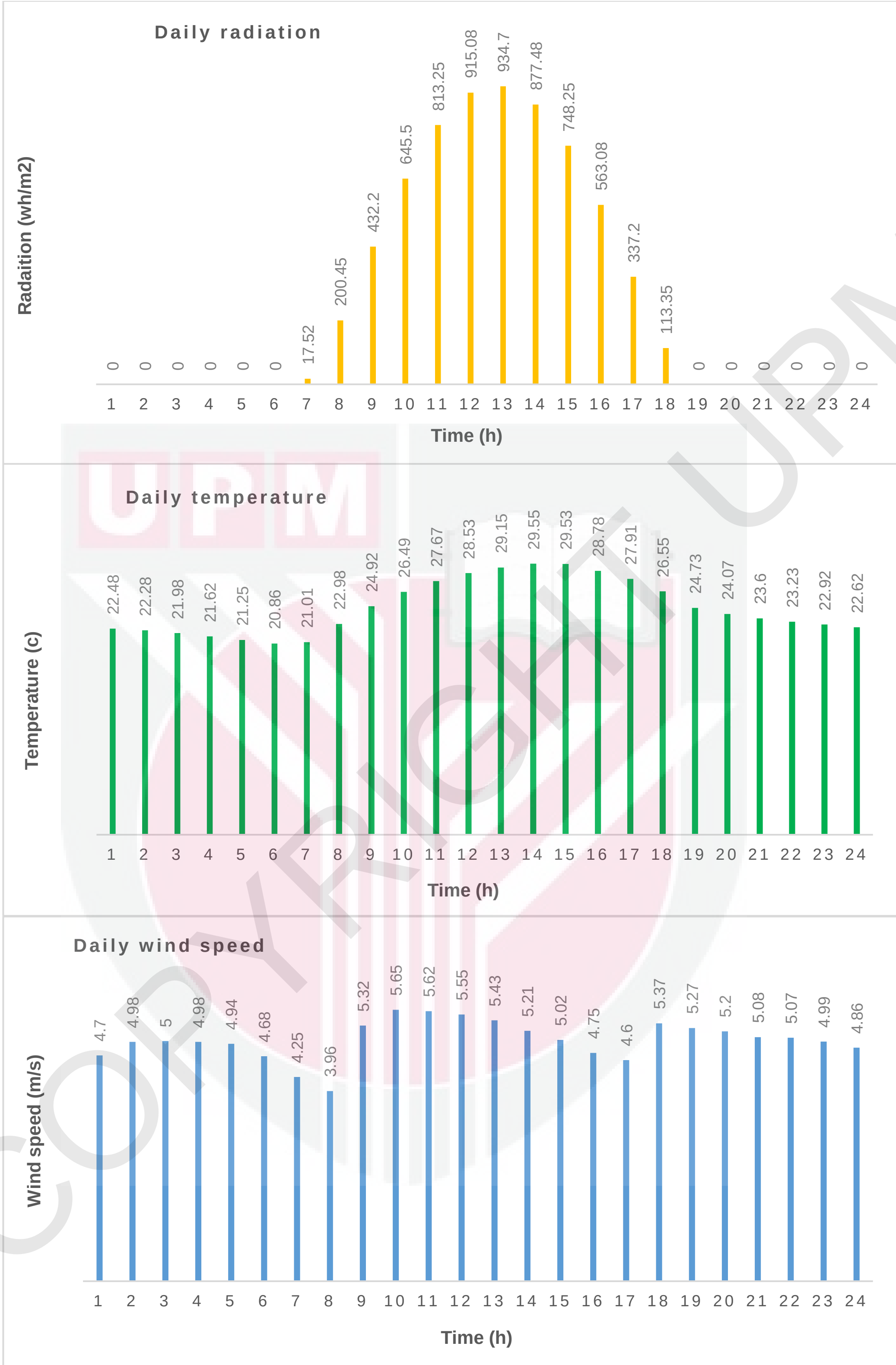

Figure 4.4 : Meteorological Data for the Study Area

iii. Manufacturing and Technical Data

Manufacturing and technical data are fundamental for accurately modeling the components of MG, relying on standardized mathematical formulas outlined in Chapter Three. This data specifics may vary between factories based on the manufacturing controls indicated in the datasheet. Tables 4.1 and 4.2 offer extensive insight into the essential technical and economic parameters essential for modeling all MG components. In optimizing the performance of the proposed NMG system, AI techniques such as FA, PSO, GWO, and HGWPSO were employed. These techniques operated under identical optimization parameters: a population size of 200, an iterative procedure threshold of 100, a data processing time of 1 hour, and a data length of 8760 hours. Assuming a lifespan of 20 years for the MG project and an interest rate of 6%, the objective function was computed for each population in every generation. Populations failing to meet pre-defined constraints were excluded from subsequent generations, ensuring continual refinement until the maximum generation was attained. These methodologies ensure a systematic approach to optimizing MG performance while considering various constraints and parameters.

Table 4.1 : The MG Technical Parameters

Equipment	Parameter	Value
PV	Rated capacity	0.625 kW
	Nominal temperature	46 °C
	Efficiency at STC	85%
	Derating factor	13%
WT	Rated capacity	25 kW
	Cut-in wind speed	2.4 m/s
	Cut-out wind speed	20 m/s
	Rate wind speed	11 m/s
ESS	Rated capacity	1kWh
	Charge efficiency	95%
	Discharge efficiency	90%
	Depth of discharge	0.8
	Self-discharge rate	2%
DG	Rated capacity	0-25 kW
	Efficiency	85 %
Inverter	Conversion efficiency	95%

(Yang & Li, 2020)

Table 4.2 : Economic Parameters of MG

Equipment	C_c ($/unit)	$C_{o\&m}$ ($/unit/y)	C_r ($/unit)	C_f ($/l)	Lifetime (y)
PV	2000	20	1800	0	20
WT	3200	32	3000	0	20
ESS	750	8	700	0	10
DG	12000	300	10000	0.2	10
Inverter	800	7	750	0	15

(Abdalla et al., 2021)

4.3 Determine the Objective Function Weights

Determining the weights in multi-objective function equations is a crucial aspect that hinges on the underlying project objectives, requiring the involvement of specialists and individuals possessing relevant experience. In this research, the economic dimension takes precedence for NMG system operators due to its direct impact on end consumers. While other indicators hold significance, their importance is comparatively lesser. To enhance flexibility in weight assignments, each specific weight is constrained within a predefined range, ensuring that the cumulative sum of all weights remains equal to one.

Emphasizing the economic aspect, the first weight (*w_1*) is accorded the highest priority and is tested within the range of 0.4 to 0.6. Simultaneously, the second weight (*w_2*) concerning technical aspects, and the third weight (*w_3*) related to environmental considerations share equal importance and are explored within the range of 0.2 to 0.4. The sizes of the MG components remained consistent across all potential scenarios. Utilizing GWO, the objective function was derived, with the terms denoting the upper and lower bounds of the weights. This methodology strives to attain equilibrium aligning with project objectives while permitting flexibility in weight allocation. Table 4.3 presents the top ten candidate solutions for multi-objective function values based on the proposed weight ranges.

Table 4.3 : Set of Weights with Corresponding Fitness Values

Set No.	W_1	W_2	W_3	sum	Best Fitness
1	0.40	0.20	0.40	100	0.7581
2	0.40	0.40	0.20	100	0.8050
3	0.45	0.20	0.35	100	0.8520
4	0.45	0.35	0.20	100	0.7611
5	0.50	0.20	0.30	100	0.8050
6	0.50	0.30	0.20	100	0.8989
7	**0.50**	**0.25**	**0.25**	**100**	**0.7211**
8	0.55	0.20	0.25	100	0.8520
9	0.55	0.25	0.20	100	0.7581
10	0.60	0.20	0.20	100	0.8520

In this study, multiple objective functions aim to minimize *LCOE, P_{loss}, and GEM*. To determine the optimal combination of these objectives, 6. Specifically, in set no 7, the values were set as follows: w_1 = 0.5, w_2 = 0.25, and w_3 = 0.25. Consequently, the final multi-objective function (MOF) is expressed by equation (4-1), incorporating these weights.

$$MOF = (0.50 * LCOE) + (0.25 * P_{loss}) + (0.25 * GEM) \quad (4.1)$$

4.4 Optimal Configuration and Size of Microgrids

The initial phase of this study centers on the planning and design aspects of MG systems. This entails identifying the optimal configuration and size that align with the specific conditions of the study area, as elaborated in the subsequent paragraphs.

4.4.1 Optimal Configuration of Microgrids

The energy sources integrated into MG systems vary based on the objectives of MG operators and their suitability to the specific study area. Generally, this research concentrated on the most prevalent and widely used energy sources, including PV, WT, DG, and BSS. Four potential configurations were examined: (PV-WT-DG-BSS), (PV-DG-BSS), (WT-DG-BSS), and (PV-WT-BSS). Each configuration represents a combination of different energy sources, with BSS components being essential in all configurations to ensure a dependable energy supply. The optimal configuration was determined based on two fundamental criteria: *LCOE* and *LPSP*, calculated using AI methods outlined in the previous chapter. Considering that all MGs share the same climatic conditions, the optimal configuration was adopted for all MGs. Table 4.4 presents the numerical results regarding the optimal configuration of the MGs.

Table 4.4 : The Numerical Outcomes of LCOE and LPSP Indicators for the Suggested MG Configurations Employing Different IA Methods

Configuration	FA		PSO		GWO		HGWPSO	
	LCOE $/kWh	LPSP %	LCOE $/kWh	LPSP %	LCOE $/kWh	LPSP %	LCOE $/kWh	LPSP %
PV-WT-DG-BSS	0.129	0.030	0.129	0.029	0.128	0.028	0.127	0.027
PV- DG-BSS	0.133	0.052	0.133	0.052	0.131	0.051	0.130	0.050
WT-DG-BSS	0.142	0.066	0.141	0.064	0.140	0.064	0.140	0.063
PV-WT -BSS	0.132	0.057	0.131	0.057	0.131	0.0.55	0.129	0.055

The findings presented in Table 4.4 indicate that the most economically advantageous configuration is the first one, namely (PV-WT-DG-BSS), boasting an *LCOE* of 0.127 $/kWh. Moreover, this configuration exhibit's superior reliability, with the lowest *LPSP* of 0.027. This robust performance is attributed to the diverse energy resources it incorporates and its capacity to retain a significant portion of energy generated from RES. Conversely, the third configuration (WT-DG-BSS) fares poorly both in economic and reliability terms, with an energy production cost of 0.140 $/kWh and a LPSP of 0.063. This underperformance stems from the configuration's sole reliance on wind turbines as an RES, coupled with the low wind speeds prevalent in the study area. Consequently, this configuration proves unreliable from both economic and technical perspectives. Furthermore, it's evident from the results that the HGWPSO method outperforms other methodologies. This superiority can be attributed to leveraging the speed and efficiency of PSO in exploration, coupled with the robustness and effectiveness of GWO in target attainment.

4.4.2 Optimal Size of Microgrids

Determining the optimal size of MG components is of paramount importance in maximizing the economic, technical, and environmental feasibility of NMG systems. Increasing the size of MG's energy resources may generate sufficient energy to meet load requirements, but at the same time, it imposes major economic, technical, and environmental challenges that affect consumers. In this section, the results are presented for finding the optimal sizes of the components of the optimal configuration (PV-WT-DG-BSS) using the proposed AI methods. The optimal sizes of the various MG components were searched by exploring a multi-objective function that includes *LCOE*, P_{loss}, and *GEM*, considering the design and technical constraints. At the same time, other performance indicators are monitored on an ongoing basis. Table 4.5 shows the optimal sizes of the different MG components.

The results in Table 4.5 reveal the optimal sizes of MG components, providing valuable insights into the comparative performance of different strategies. It is worth noting that the HGWPSO strategy appears to be a more cost-effective option, demonstrating lower energy costs across MG 1, 2, 3, and 4 (up to 0.127, 0.128, 0.130, and 0.129) \$/kWh, respectively, compared to alternative technologies. For MG 1, the sizes of PV-WT-DG-BSS are indicated by (697.33, 363.52, 113.23, 157.98) kW, for MG 2 by (710.89, 339.72, 108.46, 225.15) kW, for MG 3 by (2467.88, 1720.61, 329.81, 687.00) kW, and for MG 4 as (710.95, 415.24, 243.83, 134.74) kW respectively, showing the specific configurations optimized by this strategy. These results confirm the efficiency and effectiveness of the HGWPSO approach in reducing energy costs across NMG settings.

Table 4.5 : The Optimal Sizes of Diverse System Components, Evaluated with Various System Indicators Employing Different AI Methodologies

MG	AI technique	Optimal size (kW)				LCOE	Ploss	GEM
		PV	WT	DG	BSS	$/kWh	kW/d	t/y
MG1	FA	682.31	341.15	118.61	146.64	0.129	39.97	8.576
	PSO	688.78	355.37	120.18	147.93	0.129	39.92	8.689
	GWO	696.53	357.95	118.55	149.22	0.128	39.31	8.571
	HGWPSO	697.33	363.52	113.23	157.98	0.127	38.19	8.187
MG2	FA	706.51	322.41	124.72	221.65	0.130	46.26	9.018
	PSO	705.64	321.19	122.78	220.69	0.129	46.04	8.877
	GWO	708.20	322.23	119.08	222.78	0.129	45.18	8.610
	HGWPSO	710.89	339.72	108.46	225.15	0.128	45.09	7.842
MG3	FA	2453.15	1714.3	332.61	638.95	0.132	187.14	24.049
	PSO	2426.33	1716.6	331.84	639.47	0.131	185.77	23.994
	GWO	2444.82	1718.9	332.12	654.15	0.131	183.69	24.014
	HGWPSO	2467.88	1720.6	329.81	687.00	0.130	180.51	23.847
MG4	FA	658.94	413.92	270.32	128.81	0.130	52.61	19.545
	PSO	670.53	417.19	263.77	123.39	0.129	51.24	19.072
	GWO	675.49	419.81	249.67	125.36	0.129	49.73	18.052
	HGWPSO	710.95	415.24	243.83	134.74	0.129	48.57	17.630

Figures 4.5, 4.6, and 4.7 depict the LPSP, CBI, and REI reliability indicators across all MG systems, as influenced by various AI methodologies.

Figure 4.5 : The LPSP Reliability Index for All MGs Using Various AI Methods

Based on the data in Figure 4.5, it's evident that the probability of power losses for the MG1, MG2, MG3, and MG4 utilizing HGWPSO stands at 2.7 %, 2.5 %, 3.1%, and 2.9% respectively. These percentages are considered acceptable in comparison to the daily demands, particularly given their significant reliance on RES. Furthermore, Figure 4.6 indicates that the cost-benefit index attains values of 79.43 %, 80.73 %, 76.64 %, and 78.43% for MGs 1, 2, 3, and 4 respectively.

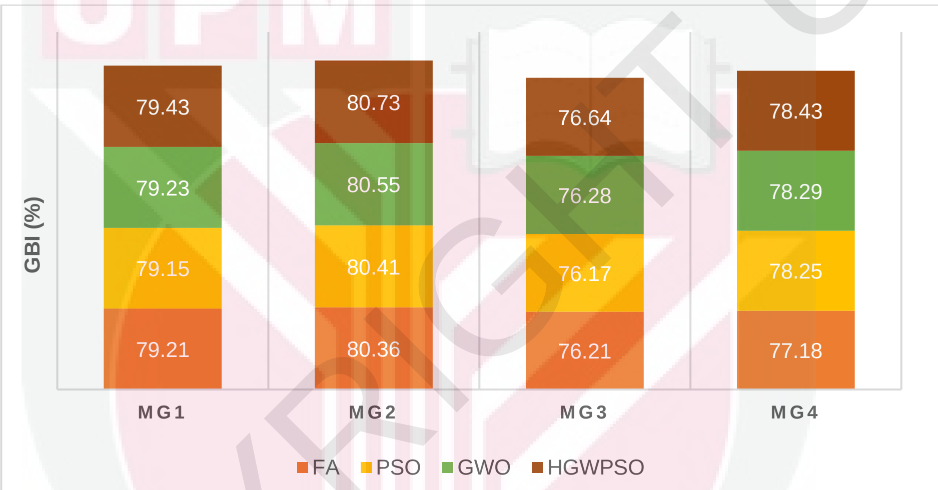

Figure 4.6 : Cost-Benefit Index for All MGs Using Various AI Methods

Additionally, Figure 4.7 illustrates the contribution of RES (PV and WT) in the total power generating with MGs 1, 2, 3, and 4 achieving contributions of 79.63%, 75.89%, 80.46%, and 74.84% respectively.

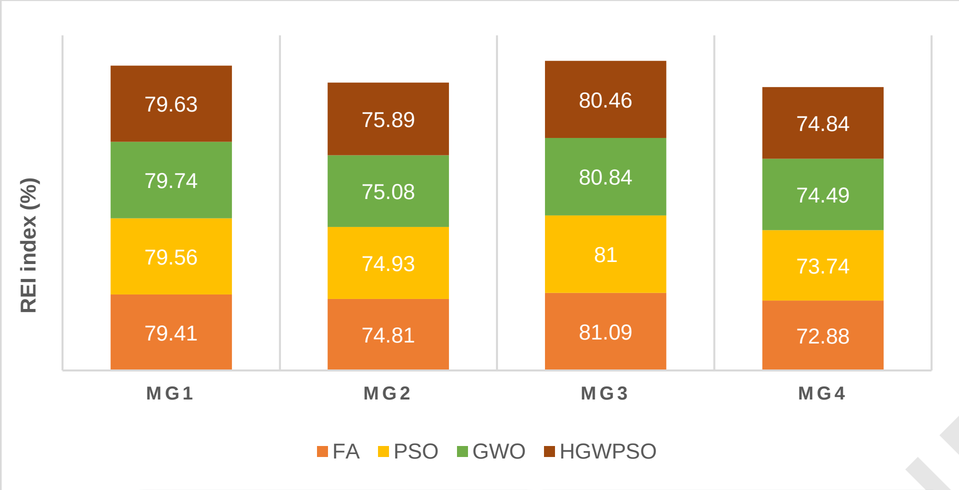

Figure 4.7 : The Contribution of RES to Energy Generation across All MGs Using Various AI Methods

In Figure 4.8, the convergence speed of various AI techniques employed to determine the optimal size is compared. Notably, HGWPSO demonstrates a notably faster convergence rate compared to FA, PSO, and GWO. This advantage can be attributed to HGWPSO's ability to maintain high convergence accuracy and its capacity to tolerate optimization problems characterized by high non-linearity and zero tolerance for torsion. Moreover, the proposed HGWPSO technique achieves convergence after approximately 28 iterations, whereas the convergence curves of other methods plateau around 40 iterations.

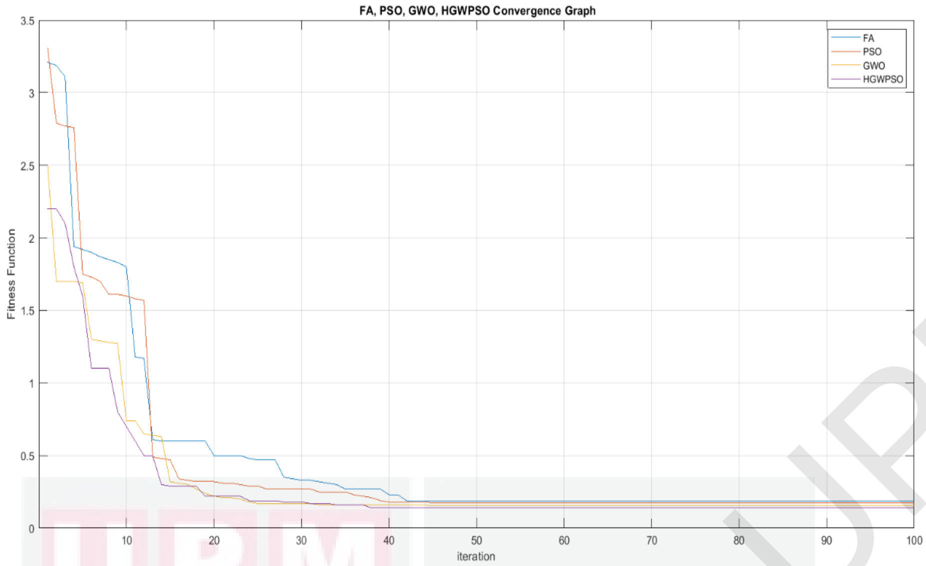

Figure 4.8 : Comparison of Convergence towards Optimal Solutions across Various AI Methods

Table 4.6 displays conclusive data concerning the standard operation of the NMG system, fulfilling the primary objective of this study. This dataset forms the foundation for enhancing the system's effectiveness and efficiency through the implementation of diverse management strategies outlined in the second objective.

Table 4.6 : Summary of Data Using HGWPSO of the Standard Operation of the NMG System

Function	Parameters	MG1	MG2	MG3	MG4
Optimal size	PV kW	697.33	710.89	2467.88	710.95
	WT kW	363.52	339.72	1720.61	415.24
	DG kW	113.23	108.46	329.81	243.83
	BSS kW	157.98	225.15	687.00	134.74
Objective function	LCOE $/kWh	0.127	0.128	0.130	0.129
	Ploss kW/d	38.19	45.09	180.51	48.57
	GEM t/y	8.187	7.842	23.847	17.630
Reliability indices	LPSP %	2.7	2.5	3.1	2.9
	CBI %	79.43	80.73	76.64	78.43
	REI %	79.63	75.89	80.46	74.84

4.4.3 Optimal Schedule of Networked Microgrid Systems

After determining the optimal configuration and size of all MGs within the NMG system, the challenge shifts to devising an ideal schedule for their operation. Optimal MG scheduling entails precisely calibrating the energy generation from various energy resources and determining storage capacities. This schedule is predicted on numerous factors including load demand, generation and storage capacities, fuel costs, renewable energy availability, and grid connectivity status. Utilizing the data from Tables 4.7 through 4.10, the optimal schedule for each microgrid (MG1, MG2, MG3, and MG4) is delineated, reflecting the precise allocation of energy generation and storage capacity. This schedule allows for the determination of surplus and deficit energy, as well as the net energy balance, enabling efficient resource allocation and management within each MG system.

Figures 4.9 to 4.12 depict the weekly energy schedules for MG1, 2,3, and 4 in comparison to the daily load profiles. These figures offer a comprehensive visualization of energy generation and distribution from the MG components align with the fluctuating demands over the course of a week. The energy generation schedules depicted in these figures reveals distinct patterns. PV units actively generate electrical energy from 7 am until 6 pm, leveraging the available solar radiation during daylight hours. Concurrently, WT units contribute a modest proportion of energy output due to the relatively low wind speeds prevalent in the study area. To offset energy shortfalls during periods when PV units are inactive, BSS comes into play. They operate to compensate for the absence of PV-generated electricity, specifically allocated during the timeframes from 2 am to 6 am and from 8 pm to 12 midnight. Additionally, DG units are engaged during these periods to further mitigate any energy deficiencies.

Table 4.7 : Optimal Output Scheduling of MG1 for One Day

Time (h)	Load (kW)	PV (kW)	WT (kW)	BSS (kW)	DG (kW)
1	17.5362	0	14.1894	3.7055	0
2	15.2461	0	17.2109	0	0
3	22.4481	0	17.4403	5.4681	0
4	27.6409	0	17.2109	10.9969	0
5	27.7559	0	16.7577	11.5681	0
6	32.7095	0	13.9868	19.3945	0
7	38.5019	2.40878	10.0358	20.4037	23.2451
8	42.2778	22.6095	7.7843	12.7516	0
9	44.5513	48.4047	21.3654	0	0
10	56.5791	70.9498	25.9390	0	0
11	58.1012	88.4294	25.5003	0	0
12	92.2275	98.3450	24.4947	0	0
13	87.2621	99.7952	22.8290	0	0
14	75.6588	93.0663	19.9611	0	0
15	63.7033	75.6104	17.6715	0	0
16	35.1303	54.9349	14.7035	0	0
17	46.8323	31.8276	13.1935	2.7771	0
18	30.7407	10.9511	11.0624	9.3654	0
19	57.8861	0	10.2029	16.8008	22.1518
20	69.3262	0	9.6247	0	22.3122
21	85.9966	0	8.6774	0	22.4355
22	105.5887	0	8.6010	0	22.5345
23	75.4386	0	8.0026	0	22.6175
24	61.1462	0	7.0802	0	22.6923

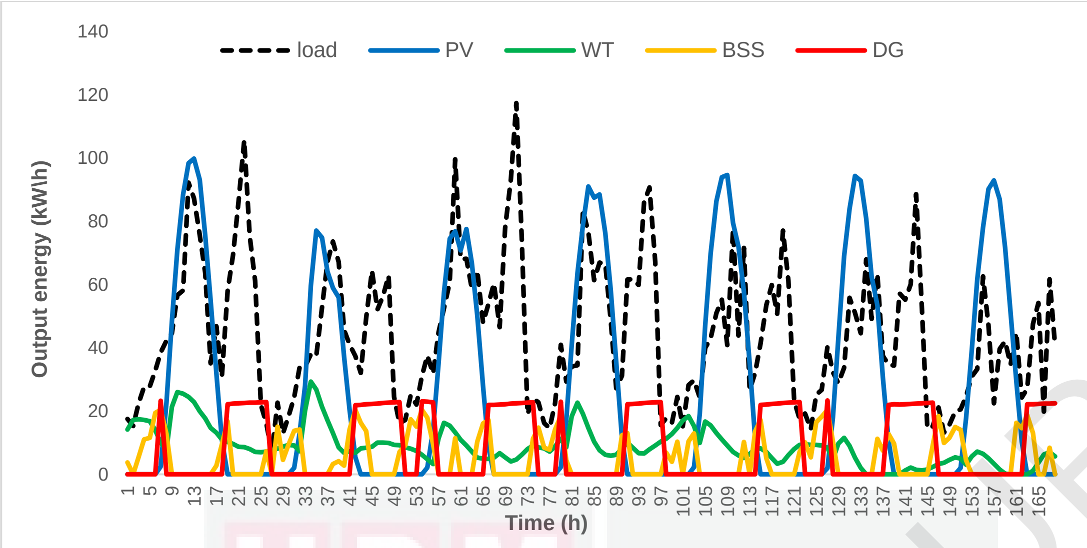

Figure 4.9 : Optimal Weekly Energy Distribution of MG1 Aligned with Load Requirements

Table 4.8 : Optimal Output Scheduling of MG2 for One Day

Time (h)	Load (kW)	PV (kW)	WT (kW)	BSS (kW)	DG (kW)
1	14.0145	0	13.2902	1.01131	0
2	13.5380	0	16.0202	0	0
3	19.9332	0	16.2274	4.1155	0
4	24.5442	0	16.0202	9.0289	0
5	24.6463	0	15.6107	9.5435	0
6	35.6461	0	13.1072	23.2724	0
7	43.9565	2.4556	9.5375	29.1645	23.2451
8	59.1275	23.0491	7.50334	19.5420	23.0346
9	67.8172	49.3458	19.7737	0	0
10	78.6370	72.3292	23.9059	0	0
11	64.0452	90.1486	23.5096	0	0
12	83.0484	100.2571	22.6010	0	0
13	79.6997	101.7353	21.0961	0	0
14	74.4175	94.8756	18.5049	0	0
15	67.8796	77.0803	16.4363	0	0
16	41.5927	56.0029	13.7547	0	0
17	80.2006	32.4463	12.3905	12.7890	22.1324
18	70.1916	11.1640	10.4651	0	21.9993
19	102.8019	0	9.6885	0	22.1518
20	108.9903	0	9.1661	0	22.3122
21	117.8158	0	8.3103	0	22.4355
22	123.4878	0	8.2412	0	22.5345
23	66.9869	0	7.7005	0	22.6175
24	40.7218	0	6.8671	0	22.6923

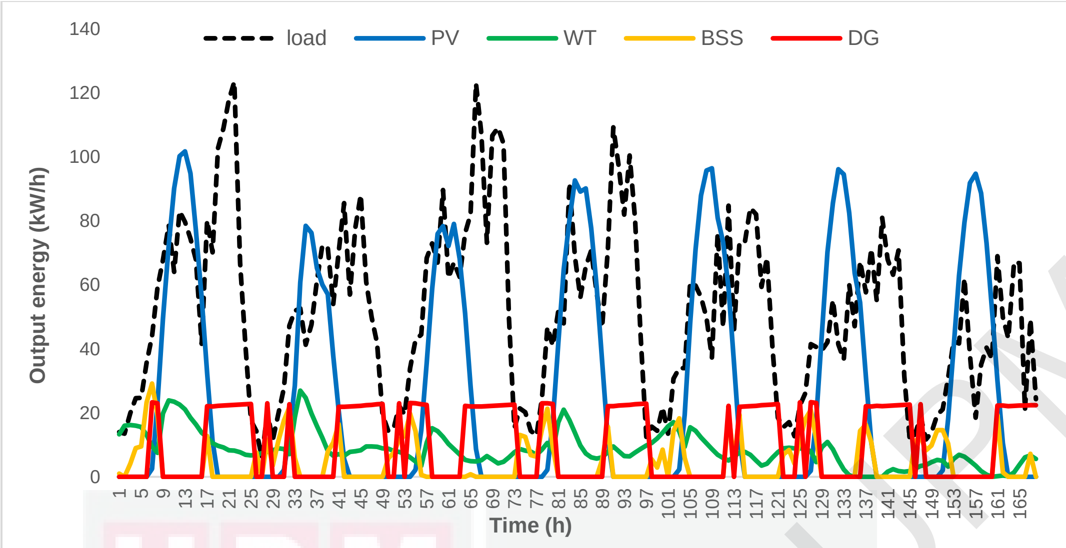

Figure 4.10 : Optimal Weekly Energy Distribution of MG2 with Load Requirements

Table 4.9 : Optimal Output Scheduling of MG3 for One Day

Time (h)	Load (kW)	PV (kW)	WT (kW)	BSS (kW)	DG (kW)
1	122.8482	0	47.04201	48.3152	0
2	118.6709	0	86.9754	48.2457	0
3	174.7295	0	88.48841	34.6451	0
4	215.1483	0	78.9754	17.79372	63.07098
5	216.0431	0	93.98563	0	69.16854
6	208.3099	0	75.70545	18.61235	69.24828
7	154.1248	8.524763	49.64042	0	0
8	165.9609	80.01598	34.78736	0	0
9	172.9267	171.3061	124.3825	0	0
10	304.5284	251.094	104.5548	0	0
11	402.4062	312.9548	104.6607	0	0
12	548.4559	348.0465	105.0269	0	42.69585
13	524.4694	353.1786	104.038	0	42.66039
14	456.6276	329.3649	100.1181	31.25436	0
15	415.5549	267.5877	90.01358	0	52.57076
16	215.5908	194.4167	70.43349	0	0
17	285.5592	112.6391	60.47248	37.13249	0
18	195.9234	38.75656	56.41333	24.568	0
19	211.2303	0	50.74313	32.54231	0
20	222.2398	0	46.92874	0	69.31226
21	232.2444	0	40.67955	18.245	69.4355
22	180.4103	0	40.17504	18.4562	69.53451
23	130.4868	0	36.22751	0	69.61754
24	142.7829	0	30.14233	0	69.69231

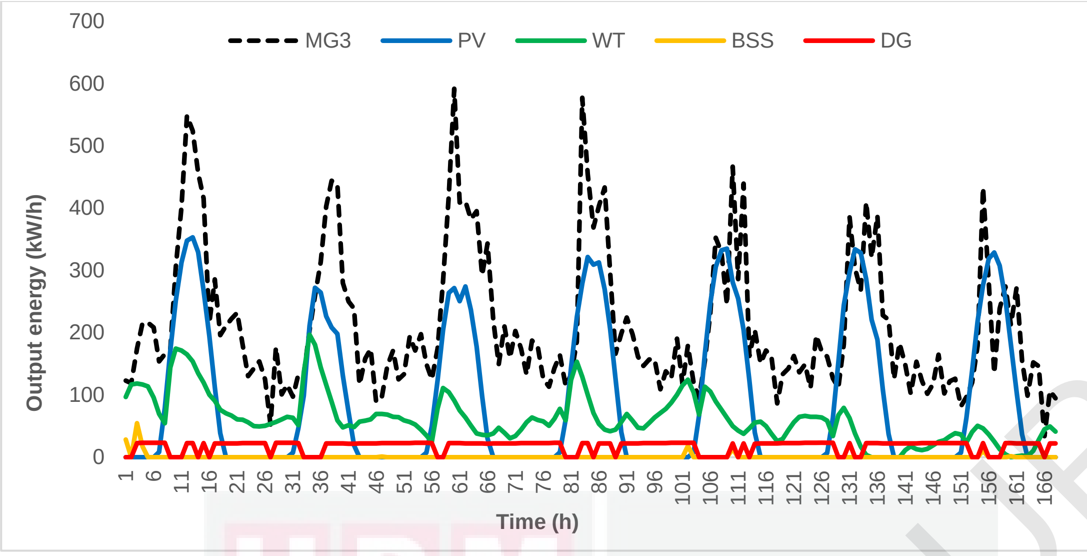

Figure 4.11 : Optimal Weekly Energy Distribution of MG3 Aligned with Load Requirements

Table 4.10 : Optimal Energy Scheduling of MG4 for One Day

Time (h)	Load (kW)	PV (kW)	WT (kW)	BSS (kW)	DG (kW)
1	28.0954	0	16.2446	12.4260	0
2	12.7219	0	19.5814	0	0
3	18.7315	0	19.8347	0	0
4	23.0646	0	19.5814	3.9615	0
5	24.7045	0	19.0809	6.1374	0
6	25.3090	0	16.0209	9.8162	0
7	22.0302	2.4558	11.6576	8.3798	0
8	45.5088	23.0510	9.17129	14.2307	0
9	49.9210	49.3499	24.1693	0	0
10	68.9701	72.3353	29.2201	0	0
11	76.2334	90.1562	28.7356	0	0
12	109.2586	100.2651	27.6251	0	0
13	117.3356	101.7432	25.7856	0	0
14	124.7113	94.8836	22.6184	9.7809	0
15	108.4392	77.0868	20.0900	13.5041	0
16	61.8852	56.0076	16.8123	0	0
17	100.4871	32.4491	15.1449	54.9773	0
18	77.3933	11.1650	12.7914	55.0510	0
19	90.1642	0	11.8422	55.5659	22.1518
20	97.8679	0	11.2037	0	22.3122
21	108.2531	0	10.1576	0	22.4355
22	108.3072	0	10.0731	0	22.5345
23	65.2801	0	9.4123	0	22.6175
24	55.1044	0	8.3937	0	22.6923

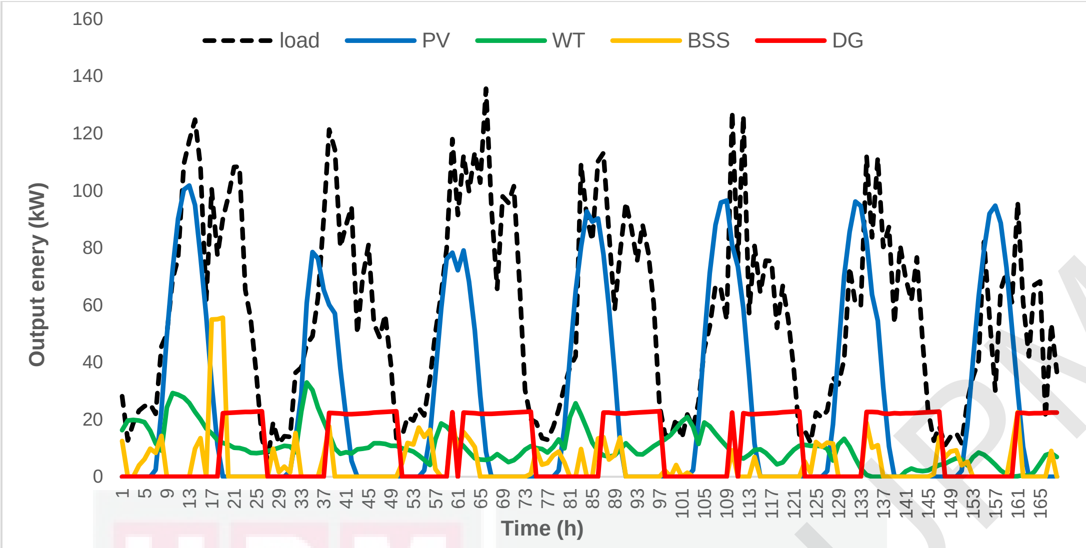

Figure 4.12 : Optimal Weekly Energy Distribution of MG4 Aligned with Load Requirements

Figure 4.13 illustrates the contributions of various power resources towards fulfilling the load demand across all MG systems. In MG 1, PV, WT, BSS, and DG accounted for 52%, 27%, 9%, and 12% of total power generated, respectively. In MG 2, these resources contributed 51%, 25%, 8%, and 16%, respectively. MG 3 saw participation rates of 45%, 40%,6%, and 9%, respectively. Finally, in MG 4, the participation percentages were 47%, 28%,16%, and 9% for all resources.

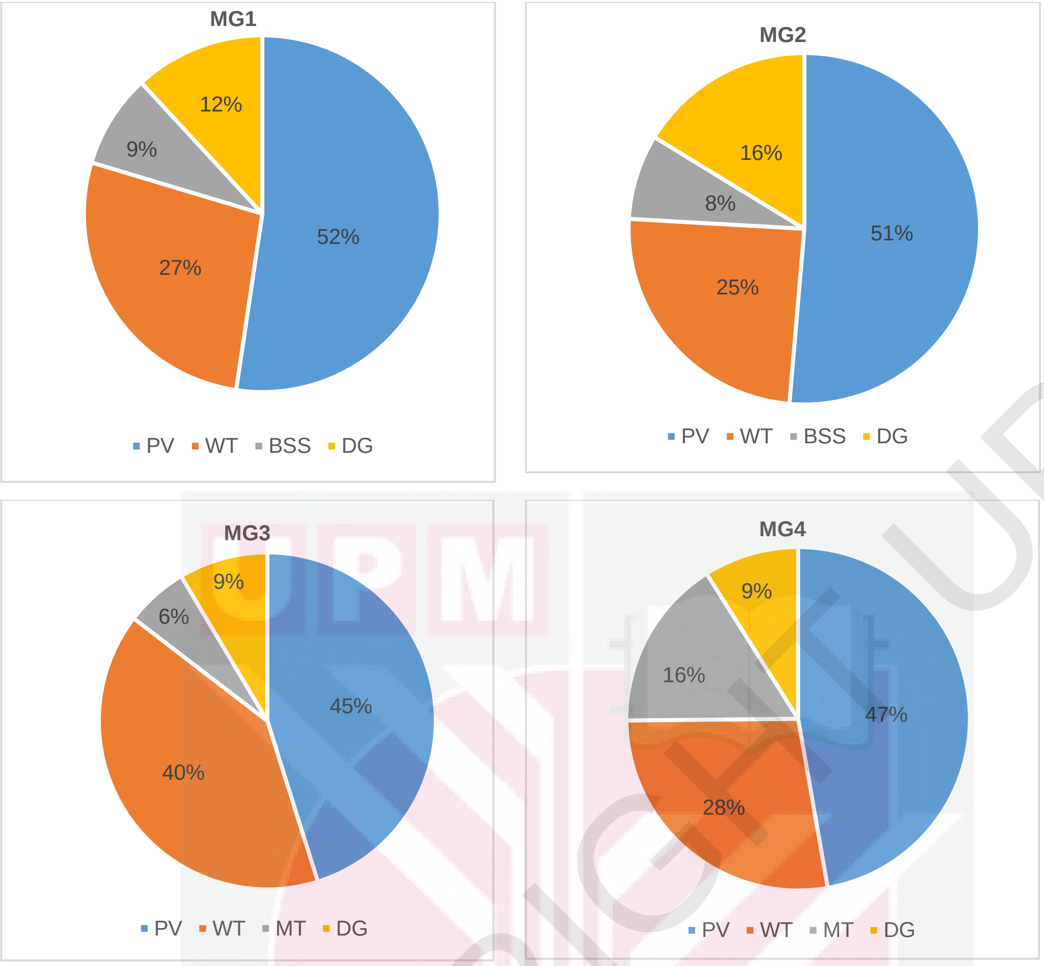

Figure 4.13 : Contribution of Various Energy Resources to Meeting Load Demand across All Microgrids

4.5 Improving Performance Using DRMS and DSMS

Managing NMG systems is inherently complex, demanding the application of tailored strategies to meet specific objectives. While previous research has predominantly focused on enhancing NMG performance through RES technology and various BSS, this study introduces a novel approach to further improve system efficiency, bolster reliance on RES, and mitigate energy costs and emissions through the adoption of DRMS and DSMS.

4.5.1 The Impact of Implementing Distributed Resources Management Strategy

DG units play a crucial role in mitigating severe energy shortages within MG systems. Renowned for their high reliability and rapid response to demand, DG units often serve as a fitting solution in various scenarios. However, the amplified dependence on DG units correlates with heightened emissions from fuel combustion and elevated energy production costs, constituting the primary drawbacks associated with these resources.

In the context of DRMS, strict regulations govern the activation of DG units, requiring them to transition from an OFF to an ON mode. This process adheres to predefined start-up thresholds, ensuring that DG units initiate operation only when reaching a minimum activation level. When the energy deficit surpasses this threshold, DG units are activated to offset the shortfall. Conversely, if the shortage falls below this minimum threshold, DG units remain inactive, and the energy deficit is addressed either by neighboring MGs or the central grid.

Indeed, there are instances where the energy shortage is minimal, often amounting to just a few kilowatts, rendering the operation of DG units unnecessary to compensate for the shortfall. Incorporating considerations regarding the threshold at which DG units commence operation during the planning and design phases facilitates a greater reliance on RES by allowing for the scaling up of their capacities.

Table 4.11 presents a comparative analysis of the fundamental operating parameters of MG1, as derived from different optimization methods, across both scenarios: without and with DRMS implemented. When assessing MG1's performance with DRMS during the planning phase, a notable enhancement is observed in bolstering reliance on RES by enlarging their capacities. Particularly noteworthy is the distinctiveness of the HGWPSO method, evident in the achieved outcomes relative to other approaches.

Table 4.11 : Comparative Evaluation of Basic MG1 Parameters with and without DRMS Utilizing Various AI Methods

			Operating without DRMS				
AI methods	Optimal size (kW) PV	WT	DG	BSS	LCOE $/kWh	Ploss kW/day	GEM t/y
FA	682.31	341.15	118.61	146.64	0.129	39.97	8.576
PSO	688.78	355.37	120.18	147.93	0.129	39.92	8.689
GWO	696.53	357.95	118.55	149.22	0.128	39.31	8.571
HGWPSO	697.33	363.52	113.23	157.98	0.127	38.19	8.187
			Operating with DRMS				
FA	695.21	347.35	93.51	153.37	0.128	38.84	6.567
PSO	699.43	358.51	94.37	160.32	0.128	38.16	6.628
GWO	709.94	363.36	92.41	157.61	0.127	37.57	6.490
HGWPSO	712.24	371.81	82.17	168.08	0.125	35.16	5.771

Through the utilization of the HGWPSO method, the energy resource sizes were determined as follows: 712.24 kW of PV, 371.81 kW of WT, 82.17 kW of DG, and 168.08 kW of BSS. Additionally, there was a reduction in the energy cost to 0.125 $/kWh with DRMS, compared to 0.127 $/kWh without it. The reduction in power losses to 35.16 kW with the implementation of DRMS, down from 38.19 kW without it, is noteworthy. This improvement can be attributed to the decrease in power generated from DG, which typically consists of both active and reactive power components. In contrast, RES primarily contributes effective power, without the reactive component.

This observation underscores the significance of managing and optimizing energy generation sources to mitigate losses effectively. The harmful emissions decreased from 8.187 t/y to 5.771 t/y, where t/y refers to tons per year.

Figure 4.14 shows the *LPSP* and *CBI* for the two operating modes. The introduced DRMS facilitated marginal improvements in power loss rates, showcasing its effectiveness, particularly in scenarios where energy is exchanged between MGs, as outlined in the study's third objective. Moreover, this strategy played a pivotal role in elevating the cost-benefit index rate by diminishing reliance on DG units.

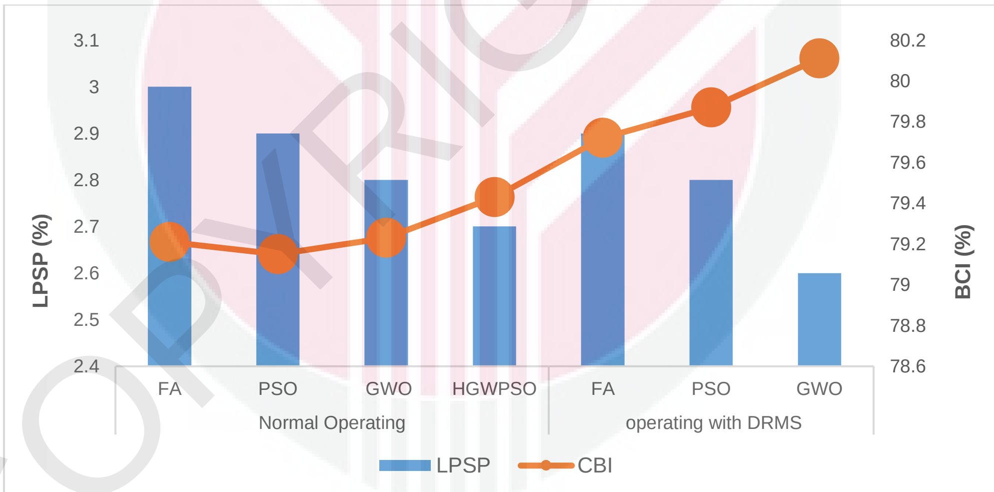

Figure 4.14 : LPSP and CBI indices of the MG1 under Two Operating Modes

In the context of MG2, the implementation of the proposed DRMS further augmented dependence on RES while concurrently diminishing reliance on DG. The comparative analysis depicted in Table 4.12 underscores the impact of the management strategy on the performance indicators of MG2. The integration of DRMS has notably bolstered dependence on RES to offset deficiencies stemming from restrictions placed on DG unit operations. With the implementation of HGWPSO within the DRMS framework, the optimal sizing of MG components is determined as follows: 719.06 kW for PV, 342.73 kW for WT, 78.73 kW for DG units, and 230.14 kW for BSS. Energy costs, system losses, and emissions witnessed a reduction from (0.128, 45.09, 7.842) without DRMS to (0.127, 43.94, 5.529) with DRMS, respectively.

Table 4.12 : Comparative Evaluation of Basic MG2 Parameters with and without DRMS Utilizing Various AI Methods

AI methods	Optimal size (kW) PV	WT	DG	BSS	LCOE $/kWh	Ploss kW/d	GEM t/y
Operating without DRMS							
FA	706.51	322.41	124.72	221.65	0.130	46.26	9.018
PSO	705.64	321.19	122.78	220.69	0.129	46.04	8.877
GWO	708.20	322.23	119.08	222.78	0.129	45.18	8.610
HGWPSO	710.89	339.72	108.46	225.15	0.128	45.09	7.842
Operating with DRMS							
FA	710.23	326.37	97.34	225.74	0.129	44.54	6.836
PSO	711.31	325.78	95.32	226.93	0.128	43.51	6.694
GWO	714.61	329.45	91.51	228.41	0.128	44.69	6.427
HGWPSO	719.06	342.73	78.73	230.14	0.127	43.94	5.529

The metrics assessing potential power loss and cost benefits for MG2 demonstrate enhanced system performance when operating under the proposed strategy compared to normal operation without it, as illustrated in Figure 4.15.

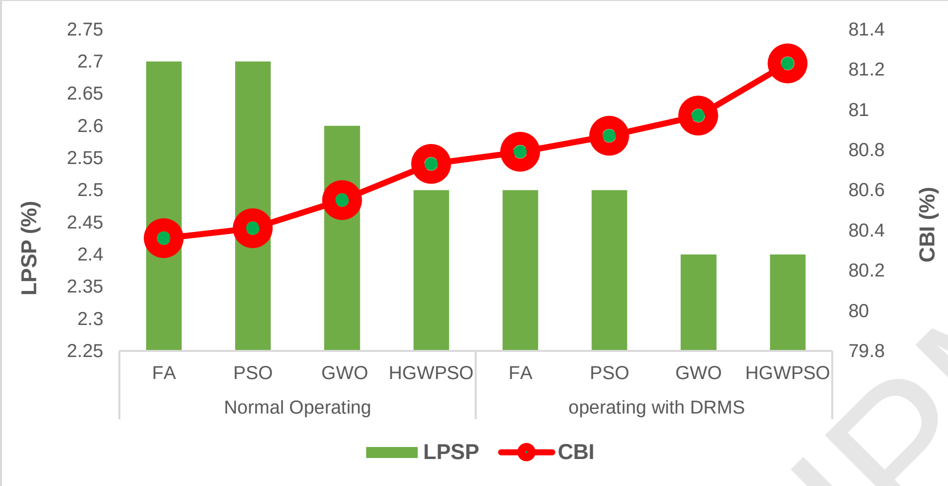

Figure 4.15 : LPSP and CBI indices of the MG2 under Two Operating Modes

The performance of MG3 experienced significant enhancement through the proposed strategy, characterized by a decrease in the utilization of DG units. Additionally, the power shortfall was effectively addressed by augmenting the size of RES units within acceptable thresholds, as illustrated in Table 4.13.

Table 4.13 : Comparative Evaluation of Basic MG3 Parameters with and without DRMS Utilizing Various AI Methods

Operating without DRMS							
AI methods	**Optimal size (kW)**				**LCOE $/kWh**	**Ploss kW/d**	**GEM t/y**
	PV	**WT**	**DG**	**BSS**			
FA	2453.15	1714.3	332.61	638.95	0.132	187.14	24.049
PSO	2426.33	1716.6	331.84	639.47	0.131	185.77	23.994
GWO	2444.82	1718.9	332.12	654.15	0.131	183.69	24.014
HGWPSO	2467.88	1720.6	329.81	687.00	0.130	180.51	23.847
Operating with DRMS							
FA	2469.73	1728.03	289.27	653.39	0.131	184.62	20.317
PSO	2453.29	1722.67	290.74	649.34	0.130	181.35	20.420
GWO	2465.24	1728.63	288.54	668.21	0.130	179.41	20.265
HGWPSO	2476.52	1734.21	284.51	712.29	0.129	178.24	19.982

Figure 4.16 illustrates a comparison of the performance indicators for *LPSP* and CBI with and without the proposed strategy. The substantial upsurge in dependence on RES emerged as a key driver behind the notable

enhancement in the *CBI*. Conversely, although the system's power generation with the proposed strategy slightly surpassed that without it, this led to a relatively acceptable decrease in the *LPSP* index.

Figure 4.16 : LPSP and CBI indices of the MG3 under Two Operating Modes

The numerical findings presented in Figure 4.17 and Table 4-14 demonstrate a significant improvement in the performance parameters of MG4. This improvement is attributed to the reduction in power output from DG units and the heightened dependence on RES. Furthermore, reliability indicators, exemplified by the cost-benefit index and energy loss tolerance index, exhibited notable enhancements.

Figure 4.17 : LPSP and CBI indices of the MG4 under Two Operating Modes

Table 4.14 : Comparative Evaluation of Basic MG4 Parameters with and without DRMS Utilizing Various AI Methods

Operating without DRMS							
AI methods	**Optimal size (kW)** PV	WT	DG	BSS	**LCOE $/kWh**	**Ploss kW/d**	**GEM t/y**
FA	658.94	413.92	270.32	128.81	0.130	52.61	19.545
PSO	670.53	417.19	263.77	123.39	0.129	51.24	19.072
GWO	675.49	419.81	249.67	125.36	0.129	49.73	18.052
HGWPSO	710.95	415.24	243.83	134.74	0.129	48.57	17.630
Operating with DRMS							
FA	675.38	423.35	236.97	138.25	0.129	51.41	16.643
PSO	684.41	425.37	227.93	138.63	0.128	49.63	16.008
GWO	687.32	427.21	217.31	141.95	0.128	48.02	15.262
HGWPSO	716.64	429.46	210.67	149.28	0.128	45.74	14.796

4.5.2 The Impact of Implementing Demand-Side Management Strategy

The prevailing dependence on RES presents a critical challenge characterized by the discrepancy between energy supply and demand, resulting in an energy imbalance. This imbalance can be alleviated through the integration of demand-side management strategies. DSMS operates on the consumer side, encouraging end-users to decrease consumption during periods of acute energy shortages and to shift peak demand to times of surplus energy availability, with customers receiving incentives such as favorable electricity pricing. In this study, DSMS was implemented to redirect a portion of demand away from periods characterized by shortages, typically occurring during evening hours (7 p.m. to 11 p.m.), when energy production from photovoltaic units is absent. Figure 4.18 depicts the daily load profile for the NMG system both without and with the DSMS strategy implementation. This strategy involves reallocating a portion of non-sensitive loads from the peak evening hours, characterized by severe energy shortages, to other periods of the day. It's important to note that despite the implementation of this strategy, the total daily load requirement remains constant across all MGs.

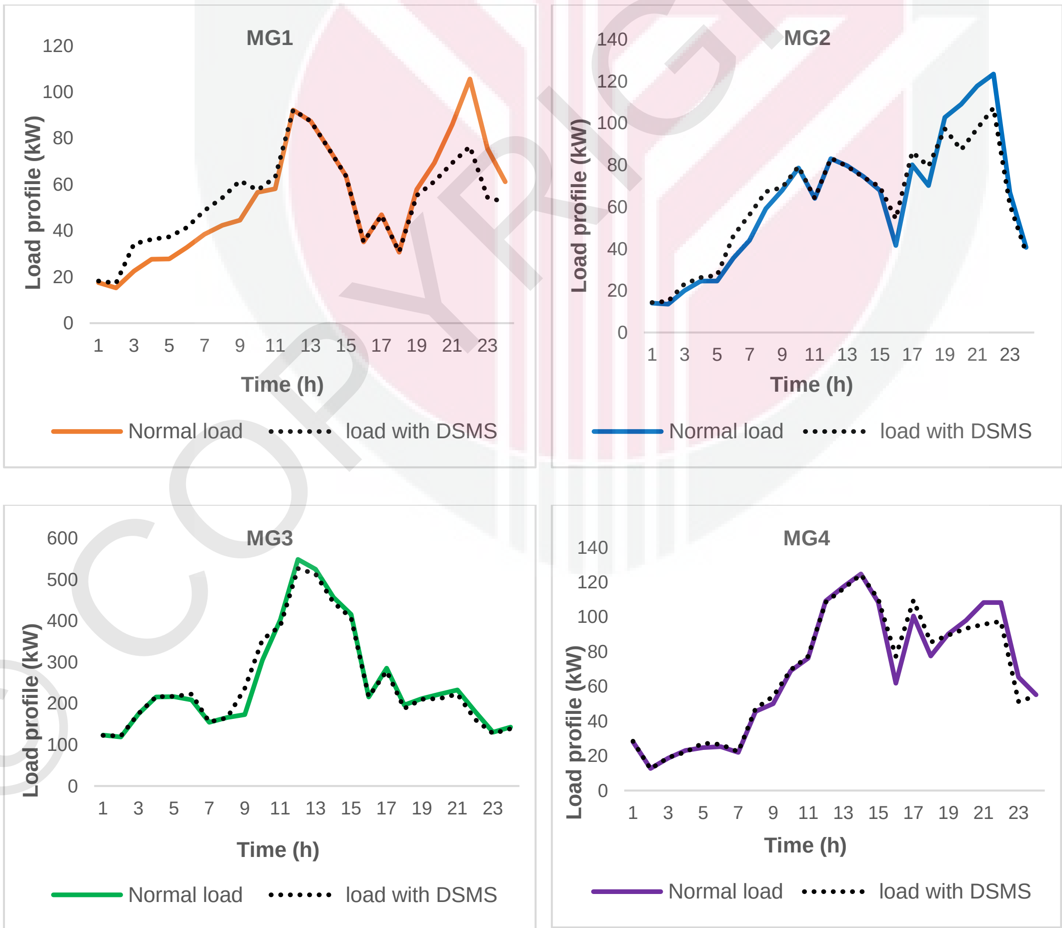

Figure 4.18 : Daily Load Profile of the MGs with and without DSMS Implementation

The integration of the suggested management strategies, DRMS and DSMS, has resulted in notable enhancements in the overall system performance, as demonstrated by the assessment of the cost-benefit and potential energy loss indicators. Figure 4.19 illustrates the values of these indicators under three conditions: normal operation without the proposed strategies, implementation of DRMS alone, and implementation of both DRMS and DSMS strategies.

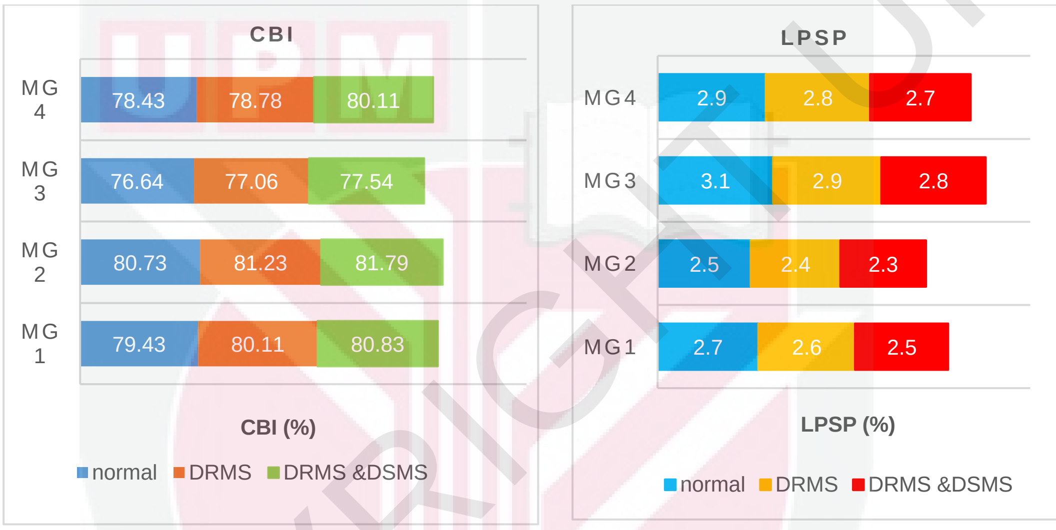

Figure 4.19 : Values of CBI and LPSP Indicators across Various Operating Modes

The implementation of DSMS has significantly enhanced the performance of MGs by effectively utilizing surplus energy to fulfill non-sensitive load requirements. This approach has led to a reduction in energy shortages and the establishment of a more balanced energy distribution. Figure 4.20 presents a comparison of the net energy (the disparity between generated and demand) per MG in the NMG system under both scenarios: operating without and with DSMS. In the visualization, positive values indicate surplus energy, while negative values denote energy shortages. The graphical representation unmistakably illustrates that the proposed DSMS strategy has notably mitigated power shortages across all MGs. Particularly, MG3, which previously experienced energy shortages throughout much of the day, has seen significant improvement.

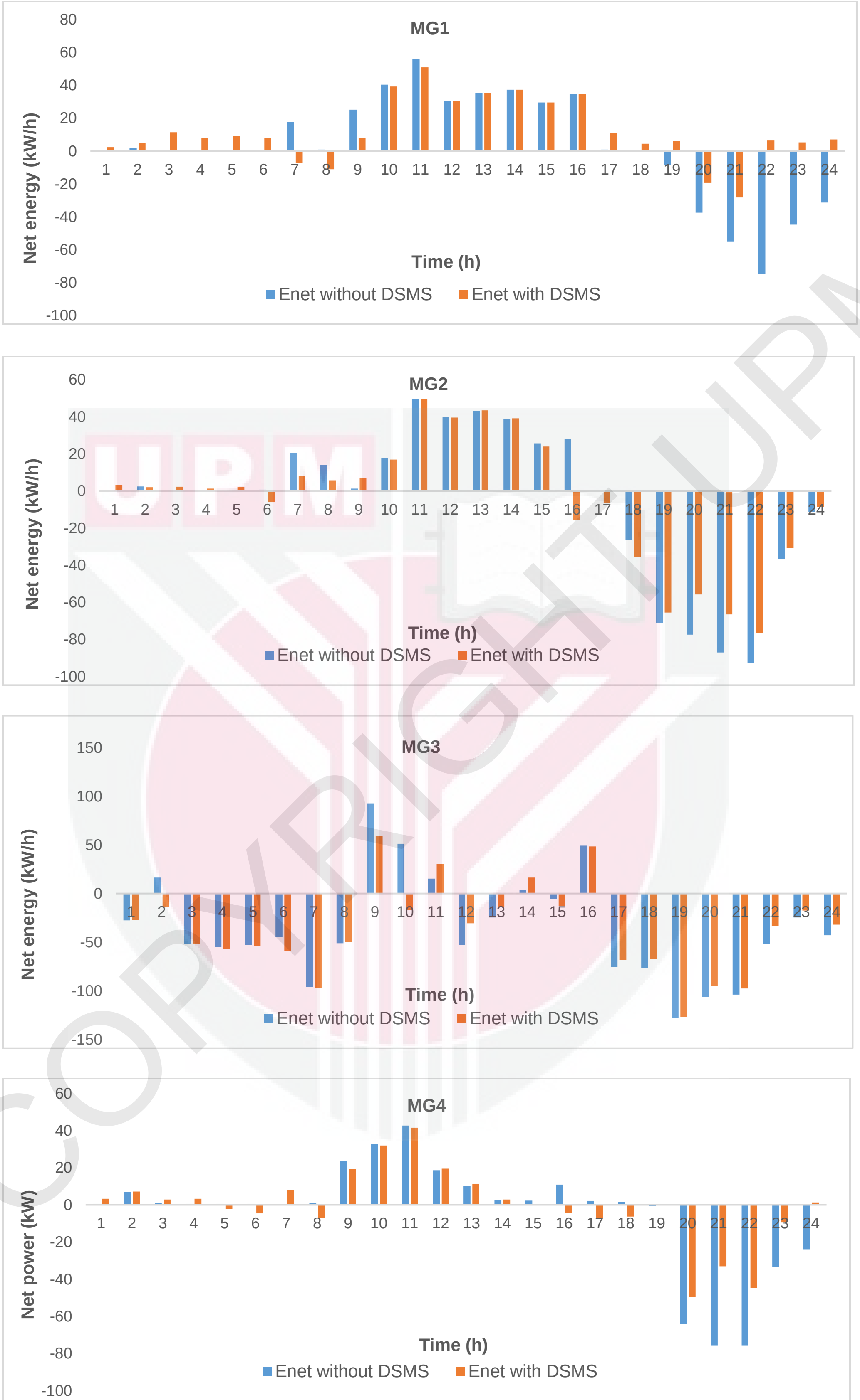

Figure 4.20 : Total Net Energy Comparison for the MGs with and without DSMS Implementation

The numerical data presented in Table 4.15 depicts the surplus and shortage of energy quantities across all MGs, which are slated for transfer to the local energy market for trading. These transfers are executed by the strategies delineated in the third objective of this study.

Table 4.15 : Net Surplus and Shortage of Energy across all MG Following EMS Implementation over a Single Day

Time (h)	Surplus energy (kW/h)				Shortage energy (kW/h)			
	MG1	MG2	MG3	MG4	MG1	MG2	MG3	MG4
1	2.340	3.237	0	3.301	0	0	-26.968	0
2	5.114	2.054	0	7.126	0	0	-14.006	0
3	11.421	2.314	0	2.869	0	0	-52.191	0
4	8.043	1.276	0	3.317	0	0	-56.458	0
5	8.999	2.171	0	0	0	0	-54.170	-2.106
6	7.944	0	0	0	0	-5.985	-58.754	-4.684
7	0	8.077	0	8.136	-7.409	0	-97.049	0
8	0	5.803	0	0	-11.105	0	-50.094	-6.872
9	8.208	7.205	59.14	19.287	0	0	0	0
10	39.307	16.913	0	31.928	0	0	-17.323	0
11	50.828	49.632	30.401	41.566	0	0	0	0
12	30.611	39.592	0	19.524	0	0	-30.557	0
13	35.349	43.504	0	11.287	0	0	-13.335	0
14	37.367	39.165	16.505	2.891	0	0	0	0
15	29.570	23.904	0	0.309	0	0	-12.932	0
16	34.508	0	48.524	0	0	-15.423	0	-4.445
17	11.165	0	0	0	0	-6.473	-68.151	-6.987
18	4.534	0	0	0	0	-35.698	-67.623	-6.318
19	6.091	0	0	0.094	0	-65.483	-126.84	0
20	0	0	0	0	-19.347	-55.847	-95.084	-49.809
21	0	0	0	0	-28.212	-66.604	-93.874	-33.105
22	6.321	0	0	0	0	-76.549	-33.229	-44.747
23	5.245	0	0	0	0	-30.667	-21.480	-9.295
24	7.108	0	0	1.279	0	-8.675	-38.930	0

4.6 Sensitivity Assessment Analysis

The performance of the MGs was investigated in this section along with several significant technical and economic factors. The sensitivity analysis approach depends on evaluating the effects of changing fundamental variables and uncertainties on the economic viability of an engineering project and determining whether the project's expenses can be comfortably borne when certain variables reach critical boundaries. Consequently, the MGs' overall performance in many technical and economic circumstances is evaluated to provide reliable investment requirements for the implementation of more practical MGs. The operating startup limit of the DG, the interest rate, and the failure rate of renewables are the major variables evaluated in this study for system sensitivity analysis. A HGWPSO was utilized to determine the repercussions of each difference to explain and assess the practical results of the investigation.

4.6.1 Diesel Generators Startup Limit Variations

DG are used as backup energy sources in MGs to compensate for extreme energy shortages. DG significantly contributes to rising emissions and rising operating costs for the system. As part of a planned management strategy, this study established an individual limit on the utilization of DG.

The performance of MGs was assessed under different start-of-operation thresholds for DG units: 10%, 15%, 20%, 25%, 30% (baseline), and 35% of DG-rated capacity. Analysis of the results presented in Table 4.16 reveals a direct correlation between the decrease in the start-of-operation threshold for DG units and the escalation of the *LCOE*. This phenomenon occurs because lower operating start-up limit rates permit greater dependence on DG units, thereby resulting in heightened fuel consumption. Multiple objective functions were computed for each of the proposed starting limits. Subsequently, it was determined that a starting limit of 0.30 yielded the lowest objective function, based on the design data. Consequently, this starting limit was selected for implementation.

Table 4.16 : Assessing the Impact of Sensitivity of the DG Startup Threshold on the Performance of the NMG System

Start-up limit %	MOF	LCOE ($/kWh)			
		MG1	MG2	MG3	MG4
10	0.689	0.137	0.137	0.140	0.136
15	0.675	0.133	0.135	0.138	0.133
20	0.667	0.130	0.133	0.134	0.131
25	0.658	0.127	0.130	0.131	0.129
30	**0.642**	**0.125**	**0.127**	**0.129**	**0.128**
35	0.649	0.125	0.127	0.128	0.128

On the contrary, Figure 4.21 illustrates that increasing the operating start-up limit from 10% to 35% has indeed increased the *LPSP* index. This is due to the prolonged periods during which DG units remain inactive. However, conversely, there is a discernible decrease in the *GEM* rates. This reduction stems from the same underlying reason as mentioned earlier. The investigation into economic and environmental factors showed that the operating startup limits of the DG have broad implications for the overall benefit of the system, so they must be taken into consideration when designing MGs.

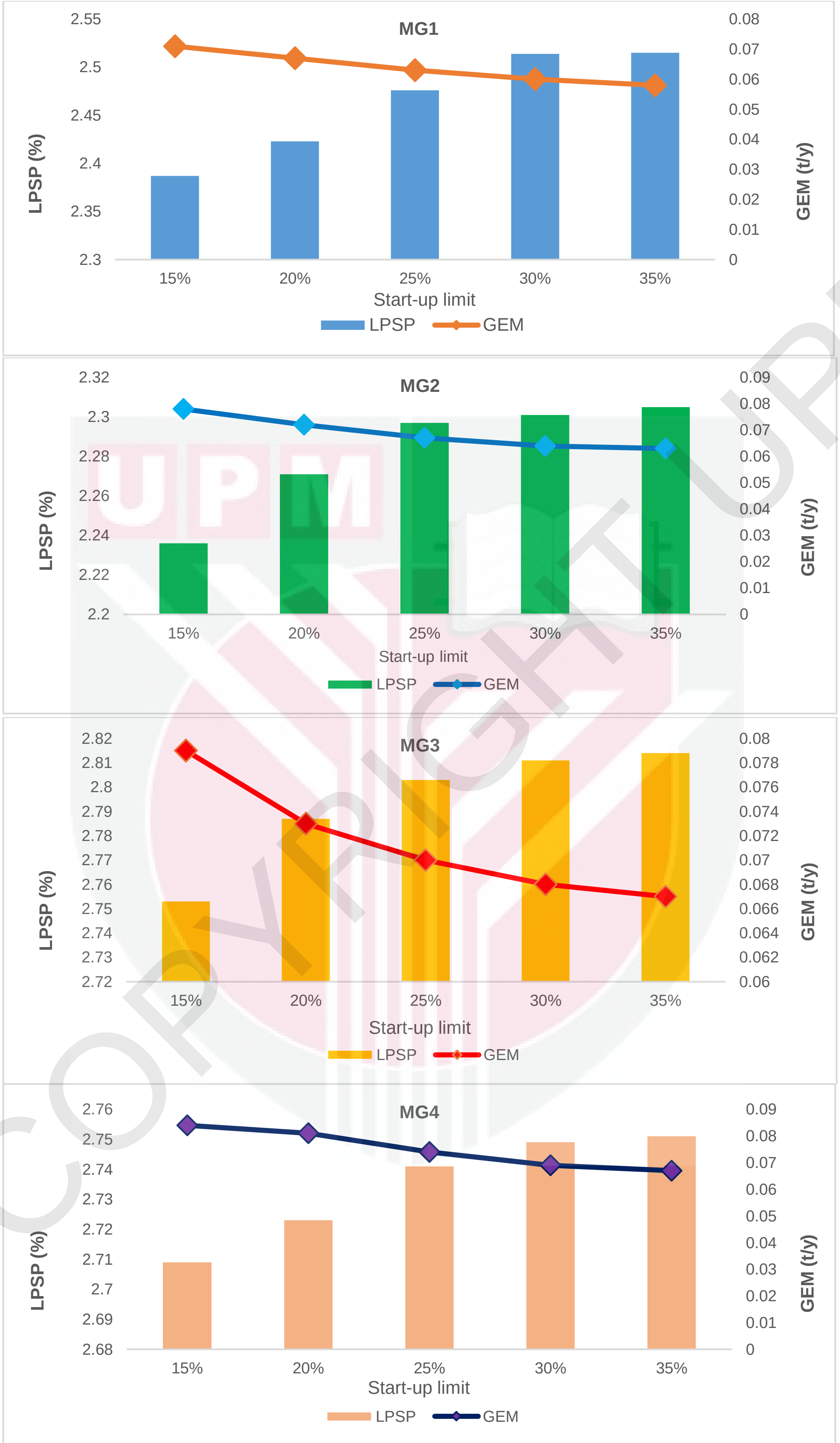

Figure 4.21 : Evaluating the Effect of the DG Startup Threshold Parameter on the LPSP and GEM Performance Indicators

4.6.2 Interest Rate Variations

The impact of interest rate variations is very important to determine the cost-effectiveness of NMG systems. Selecting an appropriate interest rate increases the economic returns on investments made in the clean energy industry, decreases unneeded investments, and promotes the expansion of clean MGs. The impact of altering the interest rate by 3%, 6% (baseline), 9%, and 12% while holding the other variables constant is covered in this research. According to equation (3-20) used to calculate the *LCOE*, an escalation in interest rates, from 3% to 12%, inevitably increases the *LCOE*. Such an outcome is typical when the annual interest rates required for any project rise, consequently augmenting the production costs and the *TNPC* index, which signifies the net cost of energy production. This escalation in these two metrics inevitably leads to a reduction in the *CBI*. Table 4.17 presents the production cost of energy for all MGs. Figure 4.22 illustrates the correlation between the *TNPC* and *CBI* indices across interest rates ranging from 3% to 12%. Among the various interest rates considered, the interest rate of 6% resulted in the lowest objective function, specifically at 0.682, as per the system's data. Hence, this interest rate was chosen for adoption in the study.

Table 4.17 : Impact of Interest Rates on the Cost of Energy across All Microgrid Systems

interest rates I_r	MOF	LCOE ($/kWh)			
		MG1	MG2	MG3	MG4
3	0.691	0.125	1.127	0.128	0.128
6	**0.682**	**0.125**	**0.127**	**0.129**	**0.128**
9	0.687	0.127	0.128	0.131	0.129
12	0.690	0.129	0.130	0.133	0.131

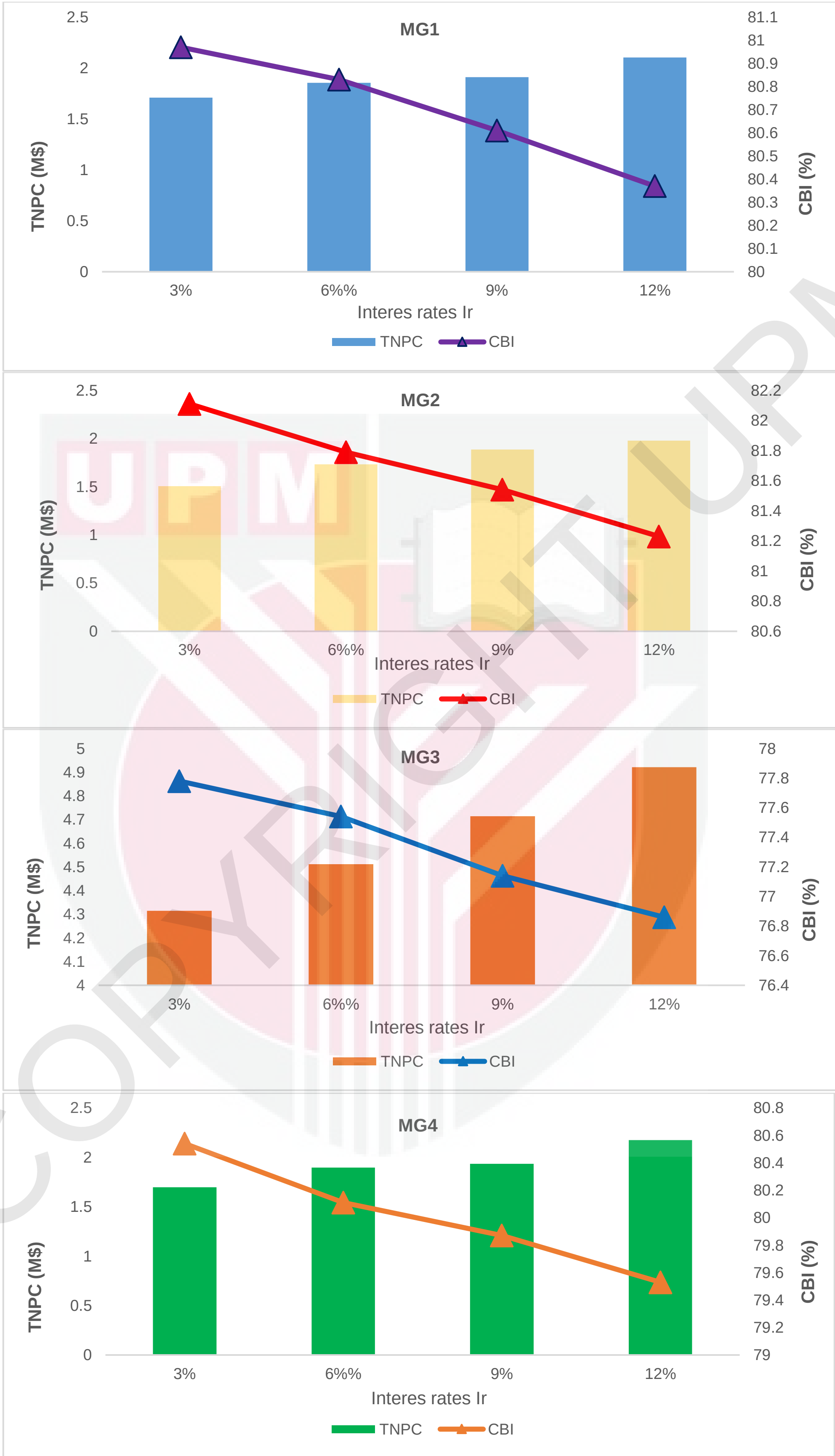

Figure 4.22 : Evaluating the Effect of the Interest Rates Parameter on the LPSP and GEM Performance Indicators

4.6.3 Generative Disturbance Coefficient Variations

The rate of generation of RES is affected by many different technical and atmospheric factors, which affect the reliability and estimation of the optimal size of the MG components. The generative disturbance coefficient *ɥ (%)* changes the rate at which energy is generated from RES. The disturbance factor must be maintained to a minimum to maximize the power generated from RES. The optimization results are obtained using the generative disturbance coefficient in the ratios of 0% (baseline), 5%, 10%,15% and 20%. Table 4.18 displays the evaluation outcome. It's evident that when there's no generation disturbance rate, the system attains the lowest objective function.

Table 4.18 : Evaluating the Effect of the RES Disturbance Coefficient on the Cost of Energy for All MG Systems

disturbance coefficient *ɥ*	MOF	LCOE ($/kWh)			
		MG1	MG2	MG3	MG4
0	**0.641**	**0.125**	**0.127**	**0.129**	**0.130**
5%	0.657	0.127	0.129	0.130	0.131
10%	0.664	0.129	0.131	0.132	0.133
15%	0.669	0.131	0.135	0.134	0.135
20%	0.672	0.134	0.139	0.135	0.137

As the rates of disturbances in RES generation escalate, there's a noticeable decline in the energy output from RES. This situation necessitates compensating for the energy shortage by intensifying reliance on DG units, consequently amplifying the cost of energy. Simultaneously, as disturbance rates rise, the LPSP increases due to the loss of energy, resulting in a decline in the *CBI*. Figure 4.23 depicts the correlation between the LPSP and *CBI* indices across varying rates of disturbances.

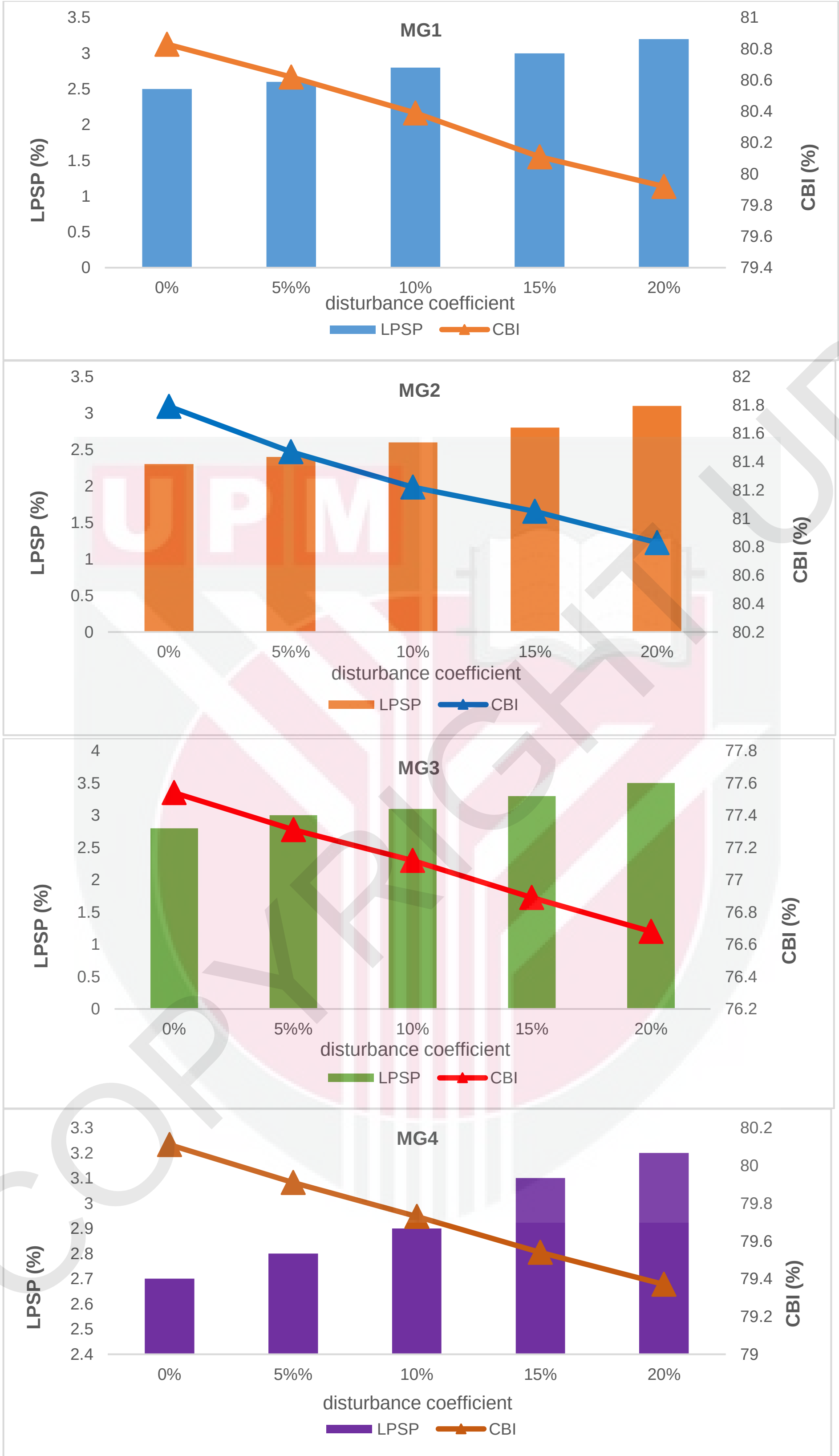

Figure 4.23 : Evaluating the Effect of the RES Disturbance Coefficient on the LPSP and GEM Performance Indicators

The sensitivity analysis results highlight the substantial impact of various critical factors on the performance indicators of MG systems. These factors include the start-up threshold of DG units, the economic interest rate, and the generation disturbance factor for renewable energy sources. Establishing the values of these factors is essential before initiating the modeling of MG components, aligning with the system data and its primary objectives.

4.7 Optimal Energy Trading

The NMG system represents the future of clean electric energy and stands as the most promising avenue for economic development. It achieves this through the attainment of self-sufficiency, reduction in productive capacity costs, and improvement of environmental impact. The third objective of this study focuses on efficiently managing energy trading within local energy markets. The energy trading management strategy underwent testing using the IEEE 13 buses test system with specific modifications. These modifications involved the addition of MG1 to bus 3, MG2 to bus 6, MG3 to bus 7, and MG4 to bus 10. According to (N. H. Ahmad et al., 2023), from 2019 to 2021 in Malaysia, the electricity purchase price of energy from the central grid was 40 cents per kilowatt-hour, while the selling price of energy to the central grid was 20 cents per kilowatt-hour. The cost of charging BSS C_{BSS} was 0.03 \$/kW, the cost of load shedding C_{sh} was 1.0 \$/kW, the cost of curtailment C_{cur} was 1 \$/kW, and transmission cost C_{tr} was 2.8×10^{-6} \$/ (kW. km). Energy trading prices and quantities across different operational modes were detailed in the following sections.

4.7.1 Classification of Energy Market Participants

Throughout various day hours, MGs experience significant fluctuations in energy surplus or shortage, influenced by changes in generation levels and load demands. Net energy is calculated for each period, determining whether the MG functions as a seller (**S**) if it has a surplus energy or buyer (**B**) if it has a shortage energy. Figure 4.24 offers a visual representation of the net energy quantities of the NMG system, while Table 4.19 presents the classification of MGs based on their energy surplus or shortage status.

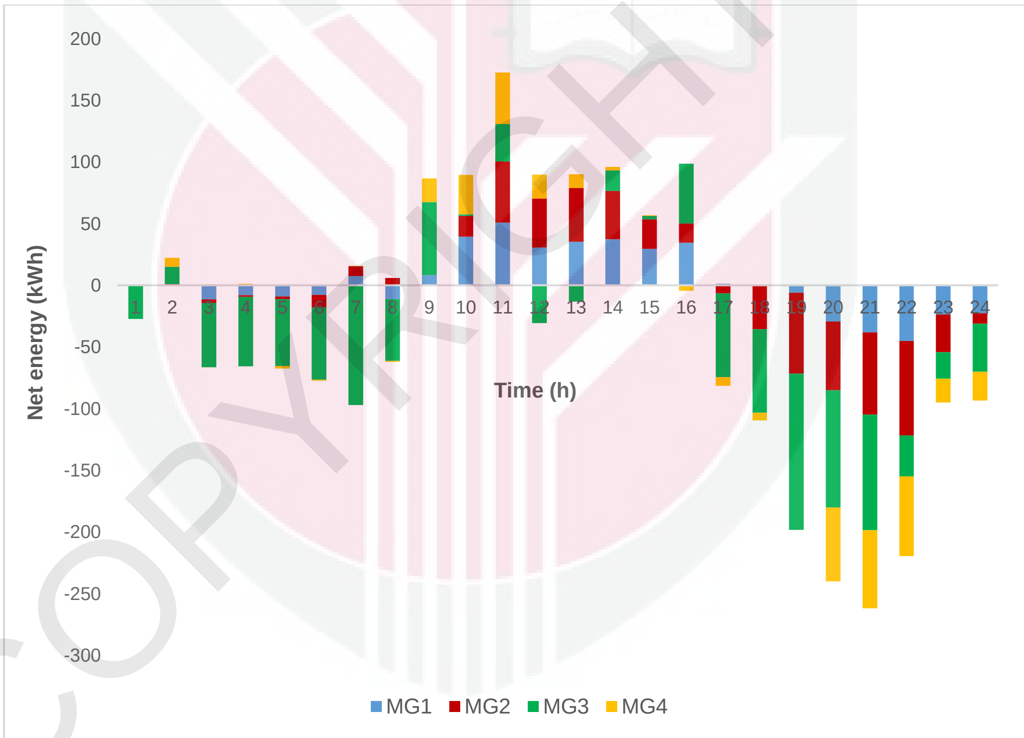

Figure 4.24 : Net Energy of the NMG System, with Positive Values Indicating Surplus Energy and Negative Values Indicating Shortage Energy

4.7.2 Energy Trading in Peer-to-Peer Mode

P2P energy trading mechanisms are employed to facilitate energy recycling within the LEM when the NMG system operates in standalone mode. The primary focus lies in efficiently managing energy trading without dependency on centralized grids during this operational mode. At the onset of each period, surplus energy within the NMG system is exchanged among its peers to achieve optimal balance. Following the conclusion of energy auction rounds for the period, any remaining surplus energy is either disposed of or recorded as an energy shortage. LEM operators analyze individual MG data, encompassing surplus and shortage energy amounts. Based on this data, energy trading contracts are formulated, covering buying and selling prices along with the amount of energy traded in each round. By the proposed strategy, buyers are prioritized based on historical data and total demand. The initial round of the energy auction commences, wherein purchase and sale contracts are matched, and energy transfer quantities are determined, accounting for transmission line capacities and usage costs within the distribution networks. If excess capacity persists or if discrepancies arise between buy and sell contracts in the first round, price adjustments are made, proceeding to subsequent auction rounds. Table 4.20 illustrates the prices and quantities of energy transferred during successive rounds of energy auction among MGs. The table results underscore a two-round energy auction process. During the initial round, a total of 209.25 kW of power was traded, which then decreased to 19,986 kW in the subsequent round. Notably, the energy trading price remained constant at 0.226 $/kWh in the first round, while adjustments were made in the second round to align with market dynamics. Roles for both buyers and sellers within MGs are delineated in this context.

Furthermore, the analysis indicates a recurring pattern of energy abundance and insufficiency in most periods following the closure of the energy market.

Table 4.19 : Details of Energy Contracts for the NMG System Operating in Standalone Mode

H.	Total energy (kWh)		Round No.	Energy trading		Seller	Buyer	Total power trading	
	Surplus	Shortage		Price ($/kWh)	Amount (kW)	MG	MG	Round no.	Amount (kW)
1	8.878	-26.968	1	0.226	2.340	1	3	1	8.878
			1		3.237	2	3	2	0
			1		3.301	4	3		
2	14.294	-14.006	1	0.226	5.114	1	3	1	14.294
			1		2.054	2	3	2	0
			1		6.838	4	3		
3	16.604	-52.191	1	0.226	11.421	1	3	1	16.604
			1		2.314	2	3	2	0
			1		2.869	4	3		
4	12.636	-56.458	1	0.226	8.043	1	3	1	12.636
			1		1.276	2	3	2	0
			1		3.317	4	3		
5	11.17	-56.276	1	0.226	8.999	1	3	1	9.064
			2	0.229	2.106	2	4	2	2.106
			1	0.226	0.065	2	3		
6	7.944	-69.423	1	0.226	4.684	1	4	1	4.684
			2	0.227	3.260	1	2	2	3.260
7	16.213	-104.45	1	0.226	7.409	2	1	1	15.545
			2	0.233	0.668	2	3	2	0.668
			1	0.226	8.136	4	3		
8	5.803	-68.071	1	0.226	5.803	2	4	1	5.803
								2	0
9	93.84	0	0	0	0	1,2,3,4	No	1,2	0
10	88.148	-17.323	1	0.226	17.323	4	3	1	17.323
								2	0
11	172.42	0	0	0	0	1,2,3,4	No	1,2	0
12	89.727	-30.557	1	0.226	30.557	1	3	1	30.557
								2	0
13	90.14	-13.335	1	0.226	11.287	4	3	1	11.287
			2	0.235	2.048	1	3	2	2.048
14	95.928	0	0	0	0	1,2,3,4	No	1,2	0
15	53.783	-12.932	1	0.226	12.932	2	3	1	12.932
								2	0

Table 4.19 : Continued

16	83.032	-19.868	1	0.226	4.445	3	4	1	19.868
			1		15.423	1	2	2	0
17	11.165	-81.611	1	0.226	6.473	1	2	1	6.473
			2	0.128	4.629	1	4	2	4.534
18	4.534	-109.63	1	0.226	4.534	1	4	1	4.534
								2	0
19	6.185	-192.32	1	0.226	0.094	4	2	1	0.094
			2	0.227	6.091	1	2	2	6.091
20	0	-220.08	0	0	0	No	1,2,3,4	1,2	0
21	0	-221.79	0	0	0	No	1,2,3,4	1,2	0
22	6.321	-154.52	1	0.226	6.321	1	3	1	6.321
								2	0
23	5.245	-61.442	1	0.226	5.245	1	4	1	5.245
								2	0
24	8.387	-47.605	1	0.226	7.108	1	2	1	7.108
			2	0.231	1.279	4	2	2	1.279

There are no energy trading activities that occurred during the 9th, 11th, and 14th hours due to surplus energy across all MG in the system, rendering them ineligible for trading with the central grid. Similarly, there were no energy trading transactions during the 20th and 21st hours, as all MG experienced energy shortages. Figure 4.25 illustrates a substantial improvement in the energy balance within the NMG system following the adoption of the P2P model, in contrast to its absence. This improvement is directly linked to the facilitation of energy trading, encompassing the sale of excess energy and the mitigation of energy deficits. Such findings underscore the efficacy of the P2P model in fortifying the overall energy equilibrium within the NMG system.

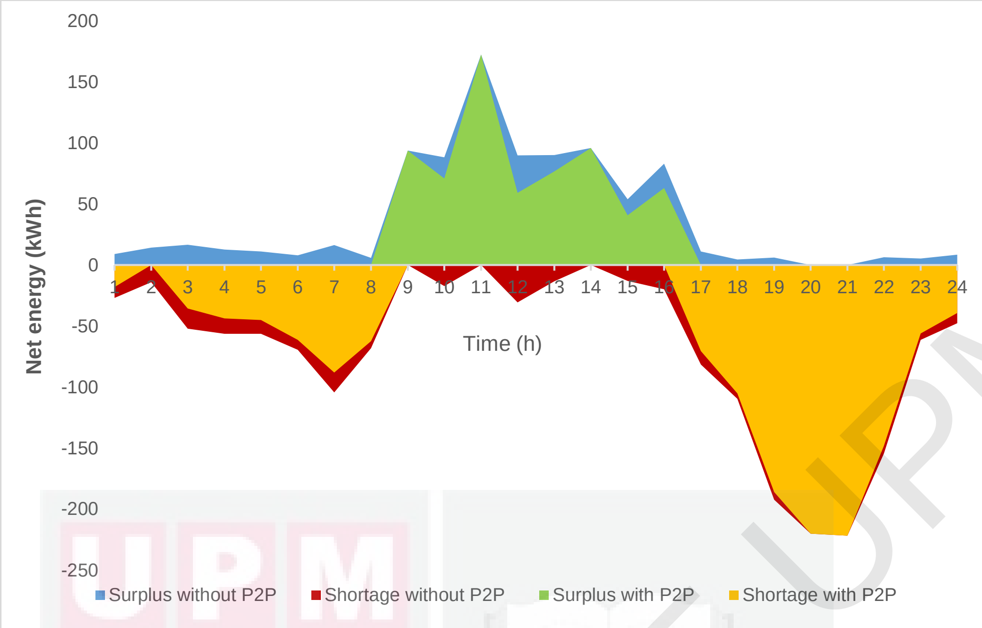

Figure 4.25 : Energy Balance of the NMG System When it Operates in Standalone Mode without and with the Implementation of P2P Energy Trading Mechanisms

4.7.3 Energy Trading in Peer-to-Grid Mode

In this scenario, the performance evaluation of NMG systems occurs under grid-connected mode, where MGs can solely energy in energy exchange with the central grid through P2G mechanisms. Like the P2P energy trading model, fundamental data is relayed to energy market operators in the P2G mode to initiate the regulation of energy trading activities. The process commences by establishing initial prices for energy purchase and sale, guided by P2G formulas. Subsequently, energy auctions commence with an initial search for price matches between buyers and sellers in the first round, followed by successive rounds were buying and selling prices are adjusted to optimize energy balance. Table 4.21 outlines the foundational data for the energy auction process. The energy auction in this scenario unfolded across three rounds, facilitating smooth energy exchange between MG and the central grid in adherence to the energy market regulations. Initially, unified buying and selling prices were enforced, with subsequent rounds adjusting prices according to predetermined formulas of the grid-connected mode.

Table 4.20 : Details of Energy Contracts for the NMG System Operating in Grid-Connected Mode

H.	Total energy (kWh)		Round No.	Energy trading		Seller MG	Buyer MG	Total power trading	
	Surplus	Shortage		Price ($/kWh)	Amount (kW)			R. no.	Amount (kW)
1	8.878	-26.968	1	0.20	2.340	1	Grid	1	35.846
				0.20	3.237	1	Grid	2	0
				0.20	3.301	4	Grid	3	0
				0.40	26.968	Grid	3		
2	14.294	-14.006	1	0.20	5.114	1	Grid	1	2.300
				0.20	2.054	1	Grid	2	0
				0.20	7.126	4	Grid	3	0
				0.40	14.006	Grid	3		
3	16.604	-52.191	1	0.20	11.421	1	Grid		
			1	0.20	2.314	2	Grid	1	37.858
			1	0.20	2.869	4	Grid	2	30.937
			1	0.40	21.254	Grid	3	3	0
			2	0.42	30.937	Grid	3		
4	12.636	-56.458	1	0.20	8.043	1	Grid		
			1	0.20	1.276	2	Grid	1	35.048
			1	0.20	3.317	4	Grid	2	34.046
			1	0.40	22.412	Grid	3	3	0
			2	0.42	34.046	Grid	3		
5	11.17	-56.276	1	0.20	8.999	1	Grid		
			1	0.20	2.171	2	Grid		
			1	0.40	2.106	Grid	4	1	32.600
			1	0.40	19.324	Grid	3	2	21.351
			2	0.42	21.351	Grid	3	3	13.495
			3	0.44	13.495	Grid	3		
6	7.944	-69.423	1	0.20	7.944	1	Grid		
			1	0.40	5.985	Grid	2		
			1	0.40	4.684	Grid	4	1	42.875
			1	0.40	24.341	Grid	3	2	19.343
			2	0.42	19.343	Grid	3	3	15.070
			3	0.44	15.070	Grid	3		
7	16.213	-104.45	1	0.20	8.077	2	Grid		
			1	0.20	8.136	4	Grid	1	47.973
			1	0.40	7.409	Grid	1	2	21.607
			1	0.40	24.351	Grid	3	3	27.836
			2	0.42	21.607	Grid	3		
			3	0.44	27.836	Grid	3		

Table 4.20 : Continued

			1	0.20	5.803	2	Grid		
			1	0.40	11.105	Grid	1	1	41.327
8	5.803	-68.071	1	0.40	6.872	Grid	4	2	19.241
			1	0.40	17.547	Grid	3	3	13.306
			2	0.42	19.241	Grid	3		
			3	0.44	13.306	Grid	3		
			1	0.20	8.208	1	Grid		
			1	0.20	7.205	2	Grid	1	50.754
9	93.84	0	1	0.20	19.287	4	Grid	2	14.365
			1	0.20	16.054	3	Grid	3	12.729
			2	0.23	14.365	3	Grid		
			3	0.25	12.729	3	Grid		
			1	0.20	17.142	1	Grid		
			2	0.22	14.876	1	Grid	1	67.806
10	88.148	-17.323	1	0.20	16.913	2	Grid	2	30.376
			1	0.20	16.428	4	Grid	3	0
			2	0.23	15.500	4	Grid		
			1	0.40	17.323	Grid	3		
			1	0.20	14.736	1	Grid		
			2	0.223	12.354	1	Grid		
			3	0.256	11.687	1	Grid		
			1	0.200	13.541	2	Grid		
			2	0.234	14.062	2	Grid	1	51.108
11	172.42	0	3	0.256	15.731	2	Grid	2	49.238
			1	0.200	10.325	3	Grid	3	49.759
			2	0.234	11.458	3	Grid		
			3	0.256	8.618	3	Grid		
			1	0.200	12.506	4	Grid		
			2	0.234	11.364	4	Grid		
			3	0.267	13.723	4	Grid		
			1	0.200	9.421	1	Grid		
			2	0.223	8.984	1	Grid		
			3	0.256	12.206	1	Grid		
			1	0.200	9.114	2	Grid	1	37.194
			2	0.234	11.539	2	Grid	2	42.604
12	89.727	-30.557	3	0.256	12.371	2	Grid	3	33.918
			1	0.200	8.794	4	Grid		
			2	0.234	10.730	4	Grid		
			1	0.400	9.865	Grid	3		
			2	0.423	11.351	Grid	3		
			3	0.445	9.341	Grid	3		
			1	0.200	8.985	1	Grid		
			2	0.223	10.143	1	Grid		
			3	0.256	16.221	1	Grid		
			1	0.200	11.259	2	Grid	1	38.615
13	90.14	-13.335	2	0.234	13.434	2	Grid	2	29.828
			3	0.256	13.542	2	Grid	3	29.765
			1	0.200	11.287	4	Grid		
			1	0.400	7.084	Grid	3		
			2	0.423	6.251	Grid	3		

Table 4.20 : Continued

			1	0.200	10.423	1	Grid		
			2	0.223	11.527	1	Grid		
			3	0.256	12.471	1	Grid	1	32.693
			1	0.200	11.547	2	Grid	2	31.150
14	95.928	0	2	0.234	10.953	2	Grid	3	24.825
			3	0.256	12.354	2	Grid		
			1	0.200	7.835	3	Grid		
			2	0.234	8.670	3	Grid		
			1	0.200	2.891	4	Grid		
			1	0.200	7.254	1	Grid		
			2	0.223	13.654	1	Grid		
			3	0.256	8.662	1	Grid	1	31.579
15	53.783	-12.932	1	0.200	11.084	2	Grid	2	26.474
			2	0.234	12.820	2	Grid	3	8.662
			1	0.200	0.309	4	Grid		
			1	0.400	12.932	Grid	3		
			1	0.200	9.218	1	Grid		
			2	0.2230	13.547	1	Grid		
			3	0.256	11.743	1	Grid	1	21.869
			1	0.200	12.651	3	Grid	2	13.527
16	83.032	-19.868	2	0.234	15.376	3	Grid	3	34.579
			3	0.256	16.495	3	Grid		
			2	0.412	9.082	Grid	2		
			3	0.434	6.341	Grid	2		
			2	0.434	4.445	Grid	4		
			1	0.200	11.165	1	Grid		
			1	0.400	6.473	Grid	2	1	34.511
17	11.165	-81.611	2	0.456	6.987	Grid	4	2	28.728
			1	0.400	16.873	Grid	3	3	22.657
			2	0.423	21.741	Grid	3		
			3	0.445	22.657	Grid	3		
			1	0.200	4.534	1	Grid		
			2	0.434	6.318	Grid	4		
			1	0.400	7.325	Grid	2	1	29.351
18	4.534	-109.63	2	0.412	17.592	Grid	2	2	46.275
			3	0.434	10.781	Grid	2	3	31.866
			1	0.400	17.492	Grid	3		
			2	0.423	22.369	Grid	3		
			3	0.445	21.085	Grid	3		
			1	0.200	6.091	1	Grid		
			1	0.200	0.094	4	Grid		
			1	0.400	14.344	Grid	2	1	35.229
19	6.185	-192.32	2	0.412	19.576	Grid	2	2	43.219
			3	0.434	20.007	Grid	2	3	42.835
			1	0.400	14.697	Grid	3		
			2	0.421	23.643	Grid	3		
			3	0.445	22.828	Grid	3		
			2	0.421	8.925	Grid	1	1	41.363
20	0	-220.08	3	0.456	10.422	Grid	1	2	64.052
			1	0.400	8.366	Grid	2	3	76.717

Table 4.20 : Continued

			2	0.412	19.332	Grid	2		
			3	0.434	22.653	Grid	2		
			1	0.400	17.885	Grid	3		
			2	0.423	21.341	Grid	3		
			3	0.445	25.947	Grid	3		
			1	0.400	15.112	Grid	4		
			2	0.434	14.454	Grid	4		
			3	0.456	17.695	Grid	4		
			1	0.400	9.392	Grid	1		
			2	0.423	19.820	Grid	1		
			1	0.401	16.025	Grid	2		
			2	0.412	21.549	Grid	2	1	27.594
			3	0.434	27.695	Grid	2	2	82.650
21	0	-221.79	1	0.400	14.588	Grid	3	3	54.861
			2	0.423	24.323	Grid	3		
			3	0.445	24.025	Grid	3		
			1	0.400	13.006	Grid	4		
			2	0.434	16.958	Grid	4		
			3	0.456	3.141	Grid	4		
			1	0.200	6.321	1	Grid		
			1	0.40	19.881	Grid	2		
			2	0.412	20.228	Grid	2		
			3	0.434	23.541	Grid	2	1	52.314
22	6.321	-154.52	1	0.400	11.419	Grid	3	2	54.114
			2	0.423	17.127	Grid	3	3	52.488
			3	0.445	15.652	Grid	3		
			1	0.400	14.693	Grid	4		
			2	0.434	16.759	Grid	4		
			3	0.456	13.295	Grid	4		
			1	0.200	5.245	1	Grid		
			2	0.434	9.295	Grid	4		
			1	0.400	9.024	Grid	2	1	23.795
23	5.245	-61.442	2	0.412	14.755	Grid	2	2	35.968
			3	0.434	6.888	Grid	2	3	6.888
			1	0.400	9.526	Grid	3		
			2	0.423	11.918	Grid	3		
			1	0.200	7.108	1	Grid		
			1	0.200	1.279	4	Grid	1	16.174
24	8.387	-47.605	2	0.412	8.675	Grid	2	2	27.658
			1	0.400	7.787	Grid	3	3	12.160
			2	0.423	18.983	Grid	3		
			3	0.445	12.160	Grid	3		

Energy transactions with the central grid occurred throughout all periods, leveraging the benefits associated with grid connectivity. However, these transactions took place at an exceptional rate compared to P2P exchanges, as specific prices were imposed by central grid operators. Purchase rates ranged between 20 cents/kw for acquiring energy from MGs and 40 cents/kW for selling energy to MGs. Figure 4.26 illustrates the surplus and shortage of energy in the NMG system, both before and after the implementation of P2G energy trading. The NMG system experienced greater benefits from trading energy with the main grid, leveraging its substantial capacity to fulfill energy requirements. Nonetheless, fluctuations occur intermittently, reflecting periods of surplus or shortage of energy. These fluctuations are influenced by factors such as the design capacities of transmission lines and associated costs.

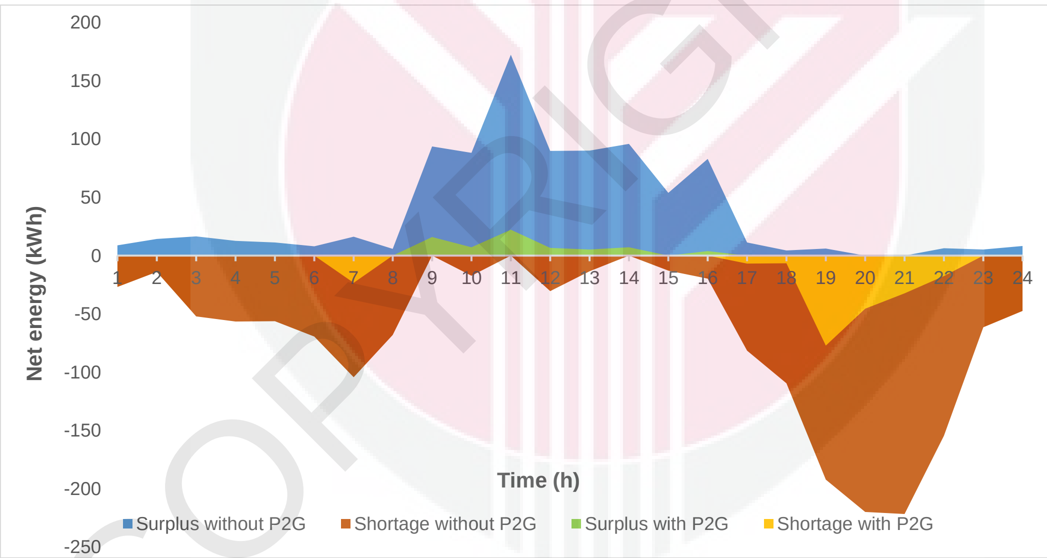

Figure 4.26 : Energy Balance of the NMG System When it Operates in Grid-Connected Mode without and with the Implementation of P2G Energy Trading Mechanisms

Throughout the power auction rounds, 867.776 kW, 766.751 kW, and 564.416 kW were traded in the first, second, and third rounds respectively. Figure 4.27 illustrates the quantity of power traded during each period.

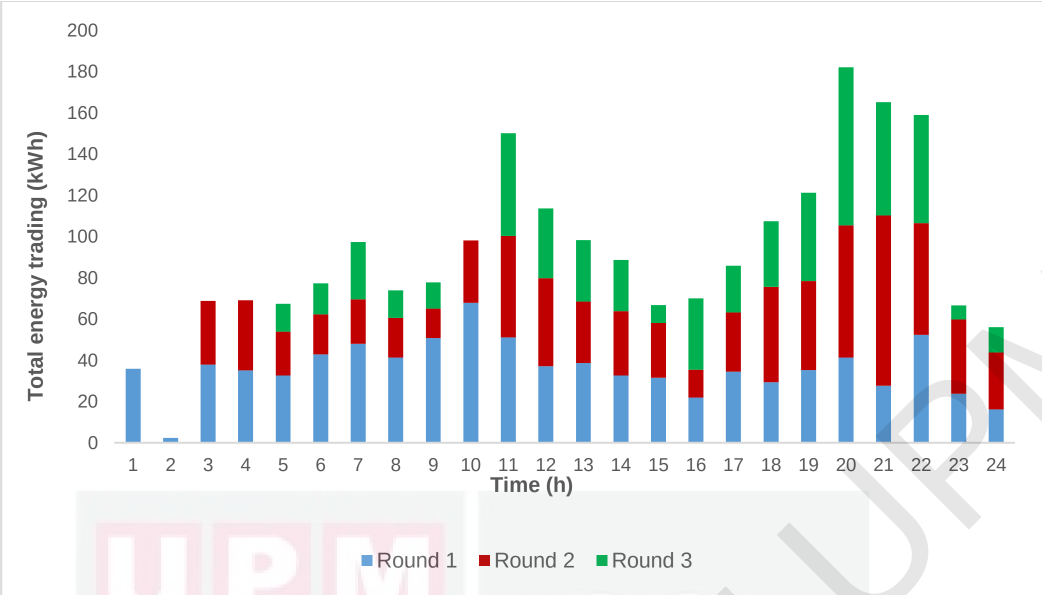

Figure 4.27 : The Amount of Energy Traded during Each Round in the Local Energy Market under the B2G Energy Trading Mechanism

4.7.4 Energy Trading in the Distributed Mode

The distributed energy trading model offers a more balanced and dependable system by leveraging the benefits of sharing energy with both P2P and P2G energy trading. However, implementing the distributed energy trading model necessitates more intricate price adjustment mechanisms to effectively accommodate all available energy within the market. This complexity is highlighted in the findings presented in Table 4.22, where energy trading occurred across five rounds, ensuring extensive energy exchange. The total power trading during the first, second, third, fourth, and fifth rounds was 367.522 kW, 432.153 kW, 482.529 kW, 477.853 kW, and 348.843 kW respectively. Examining the table reveals that in the initial rounds, selling and buying energy prices with the central grid stood at 0.40 and 0.20 $/kWh, respectively. Meanwhile, energy trading prices between peers remained consistent across all initial rounds at 0.226 \$/kWh. Subsequent rounds saw price adjustments based on the strategies employed in the study.

Table 4.21 : Details of Energy Contracts for the NMG System Operating in Distributed Mode

H.	Total energy (kWh)		R. No.	Energy trading		Seller MG	Buyer MG	Total power trading	
	Surplus	Shortage		Price ($/kWh)	Amount (kW)			R. no.	Power (kW)
1	8.878	-26.968	1	0.226	2.340	1	3	1	2.340
			2	0.233	3.237	2	3	2	3.237
			3	0.243	3.301	4	3	3	3.301
			4	0.456	18.090	Grid	3	4	18.090
2	14.294	-14.006	1	0.226	5.114	1	3	1	5.114
			2	0.233	2.054	2	3	2	2.054
			3	0.236	6.841	4	3	3	6.841
			4	0.227	0.288	4	Grid	4	0.288
3	16.604	-52.191	1	0.226	11.421	1	3	1	11.421
			2	0.233	2.314	2	3	2	2.314
			3	0.236	2.869	4	3	3	2.869
			4	0.456	17.284	Grid	3	4	17.284
			5	0.491	18.303	Grid	3	5	18.303
4	12.636	-56.458	1	0.226	8.043	1	3	1	8.043
			2	0.233	1.276	2	3	2	1.276
			3	0.236	3.317	4	3	3	3.317
			4	0.456	21.447	Grid	3	4	21.447
			5	0.491	22.375	Grid	3	5	22.375
5	11.17	-56.276	1	0.226	8.999	1	3	1	8.999
			2	0.233	2.171	2	3	2	2.171
			3	0.445	21.547	Grid	3	3	21.547
			4	0.456	20.154	Grid	3	4	20.154
			5	0.491	14.575	Grid	3	5	14.575
6	7.944	-69.423	1	0.226	5.985	1	2		
			2	0.228	1.959	1	4	1	26.349
			1	0.409	20.364	Grid	3	2	24.706
			2	0.423	22.747	Grid	3	3	15.643
			3	0.445	15.643	Grid	3	4	2.725
			4	0.456	2.725	Grid	4		
7	16.213	-104.45	1	0.226	7.409	2	1	1	30.660
			2	0.233	0.668	2	3	2	0.668
			3	0.236	8.136	4	3	3	8.136
			1	0.409	23.251	Grid	3	4	24.676
			4	0.456	24.676	Grid	3	5	27.697
			5	0.491	27.697	Grid	3		
8	5.803	-68.071	1	0.226	5.803	2	1	1	12.675
			2	0.423	6.075	Grid	1	2	6.075
			1	0.409	6.872	Grid	4	3	17.965
			3	0.445	17.965	Grid	3	4	20.021

Table 4.21 : Continued

			4	0.456	20.021	Grid	3	5	12.108
			5	0.491	12.108	Grid	3		
9	93.84	0	1	0.200	8.208	1	Grid	1	8.208
			2	0.234	7.205	2	Grid	2	7.205
			3	0.267	19.287	4	Grid	3	40.533
			3	0.256	21.246	3	Grid	4	19.735
			4	0.278	19.735	3	Grid	5	18.159
			5	0.291	18.159	3	Grid		
10	88.148	-17.323	1	0.226	17.323	1	3	1	17.323
			2	0.223	21.94	1	Grid	2	21.94
			3	0.256	16.913	2	Grid	3	16.913
			4	0.289	16.281	4	Grid	4	16.281
			5	0.301	15.647	4	Grid	5	15.647
11	172.42	0	1	0.200	15.687	1	Grid	1	24.941
			2	0.223	21.414	1	Grid	2	38.479
			3	0.256	13.719	1	Grid	3	37.742
			1	0.200	9.254	2	Grid	4	47.114
			2	0.234	17.065	2	Grid	5	6.778
			3	0.256	8.996	2	Grid		
			4	0.278	14.317	2	Grid		
			4	0.278	13.036	3	Grid		
			5	0.290	17.365	3	Grid		
			3	0.267	15.027	4	Grid		
			4	0.289	19.761	4	Grid		
			5	0.301	6.778	4	Grid		
12	89.727	-30.557	1	0.226	12.125	1	3	1	21.669
			2	0.235	18.432	1	3	2	36.103
			3	0.256	0.054	1	Grid	3	12.431
			1	0.200	9.544	2	Grid	4	6.229
			2	0.234	17.671	2	Grid	5	13.295
			3	0.256	12.377	2	Grid		
			4	0.289	6.229	4	Grid		
			5	0.301	13.295	4	Grid		
13	90.14	-13.335	1	0.226	13.335	1	3	1	26.712
			2	0.223	22.014	1	Grid	2	40.587
			1	0.200	13.377	2	Grid	3	11.554
			2	0.234	18.573	2	Grid	4	11.287
			3	0.256	11.554	2	Grid	5	0
			4	0.289	11.287	4	Grid		
14	95.928	0	1	0.200	9.546	1	Grid	1	17.293
			2	0.223	14.682	1	Grid	2	26.365
			3	0.256	13.139	1	Grid	3	25.286
			1	0.200	7.747	2	Grid	4	21.903
			2	0.234	11.683	2	Grid	5	5.081
			3	0.256	12.147	2	Grid		
			4	0.278	5.398	2	Grid		
			5	0.290	2.190	2	Grid		
			4	0.278	16.505	3	Grid		
			5	0.290	2.891	4	Grid		

Table 4.21 : Continued

			1	0.226	12.932	1	3	1	12.932
			2	0.223	16.638	1	Grid	2	16.638
15	53.783	-12.932	3	0.256	11.687	2	Grid	3	11.687
			4	0.290	12.217	2	Grid	4	12.217
			5	0.301	0.309	4	Grid	5	0.309
			1	0.226	15.423	1	2		
			2	0.223	5.474	1	Grid	1	19.868
			3	0.256	13.611	1	Grid	2	5.474
16	83.032	-19.868	1	0.226	4.445	3	4	3	20.306
			3	0.256	6.695	3	Grid	4	17.953
			4	0.278	17.953	3	Grid	5	19.431
			5	0.290	19.431	3	Grid		
			1	0.226	6.473	1	2	1	6.473
			2	0.228	4.692	1	4	2	4.692
17	11.165	-81.611	3	0.456	2.295	Grid	4	3	16.419
			3	0.445	14.124	Grid	3	4	19.544
			4	0.456	19.544	Grid	3	5	20.241
			5	0.490	20.241	Grid	3		
			1	0.226	4.534	1	4		
			2	0.434	1.784	Grid	4	1	11.859
			1	0.400	7.325	Grid	2	2	16.423
18	4.534	-109.63	2	0.412	14.639	Grid	2	3	24.759
			3	0.434	13.734	Grid	2	4	18.764
			3	0.445	11.025	Grid	3	5	19.746
			4	0.456	18.764	Grid	3		
			5	0.490	19.746	Grid	3		
			1	0.226	6.091	1	2		
			2	0.231	0.094	4	2		
			3	0.434	12.419	Grid	2	1	19.685
			4	0.456	18.934	Grid	2	2	16.732
19	6.185	-192.32	5	0.478	19.341	Grid	2	3	31.831
			1	0.400	13.594	Grid	3	4	39.076
			2	0.423	16.638	Grid	3	5	41.080
			3	0.445	19.412	Grid	3		
			4	0.456	20.142	Grid	3		
			5	0.490	21.739	Grid	3		
			1	0.400	8.021	Grid	1		
			2	0.423	12.415	Grid	1		
			3	0.456	7.740	Grid	1		
			1	0.400	9.857	Grid	4		
			2	0.434	13.579	Grid	4	1	17.878
			3	0.450	9.669	Grid	4	2	50.183
20	0	-220.08	2	0.412	11.642	Grid	2	3	46.212
			3	0.434	13.412	Grid	2	4	35.772
			4	0.456	16.359	Grid	2	5	38.461
			5	0.490	18.414	Grid	2		
			2	0.423	12.547	Grid	3		
			3	0.445	15.391	Grid	3		
			4	0.456	19.413	Grid	3		
			5	0.490	20.047	Grid	3		

Table 4.21 : Continued

			1	0.400	11.874	Grid	1		
			2	0.412	16.338	Grid	2		
			1	0.400	9.745	Grid	4		
			2	0.434	12.874	Grid	4		
			3	0.456	10.486	Grid	4	1	32.86
			1	0.400	11.241	Grid	2	2	56.105
21	0	-221.79	2	0.412	14.635	Grid	2	3	44.106
			3	0.434	17.923	Grid	2	4	38.209
			4	0.456	19.736	Grid	2	5	32.708
			5	0.478	11.024	Grid	2		
			2	0.423	12.258	Grid	3		
			3	0.445	15.697	Grid	3		
			4	0.456	18.473	Grid	3		
			5	0.490	21.684	Grid	3		
			1	0.226	6.321	1	4		
			2	0.434	11.413	Grid	4		
			3	0.456	16.984	Grid	4		
			4	0.478	10.029	Grid	4	1	18.975
			1	0.400	12.654	Grid	3	2	39.562
22	6.321	-154.52	2	0.423	13.492	Grid	3	3	41.89
			3	0.445	7.083	Grid	3	4	29.531
			2	0.412	14.657	Grid	2	5	20.61
			3	0.434	17.823	Grid	2		
			4	0.456	19.502	Grid	2		
			5	0.478	20.610	Grid	2		
			1	0.226	5.245	1	4		
			2	0.434	4.050	Grid	4	1	5.245
			2	0.412	9.114	Grid	2	2	13.164
23	5.245	-61.442	3	0.434	13.547	Grid	2	3	21.241
			4	0.456	8.006	Grid	2	4	19.553
			3	0.445	7.694	Grid	3	5	2.239
			4	0.456	11.547	Grid	3		
			5	0.490	2.239	Grid	3		
			1	0.226	7.108	1	2		
			2	0.234	1.279	4	2	1	7.108
			3	0.434	0.288	Grid	2	2	13.85
24	8.387	-47.605	2	0.423	12.571	Grid	3	3	13.972
			3	0.445	13.684	Grid	3	4	7.547
			4	0.456	7.547	Grid	3	5	5.128
			5	0.490	5.128	Grid	3		

In Figure 4.28, the energy balance is depicted by comparing surplus and shortage energy of the NMG system, both before and after the implementation of distributed energy trading mechanisms. Notably, the entire surplus energy of the system was effectively traded, with a preference towards P2P energy trading over P2G energy trading. This preference is attributed to the lower prices associated with P2P energy trading compared to trading with the central grid. However, despite this efficient trading, small amounts of energy shortage persisted, primarily due to limitations in the capacity of the transmission lines.

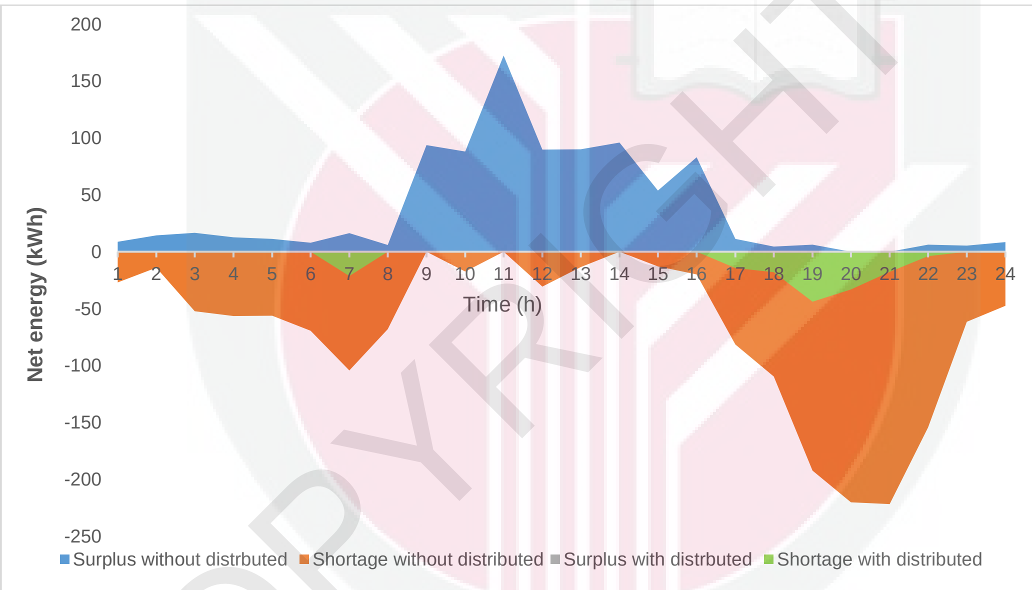

Figure 4.28 : Energy Balance of the NMG System When it Operates in Distributed Mode with the Implementation of Both P2G and P2P Energy Trading Mechanisms

Figure 4.29 illustrates the amount of energy trading observed across all rounds during a single-day energy trading market.

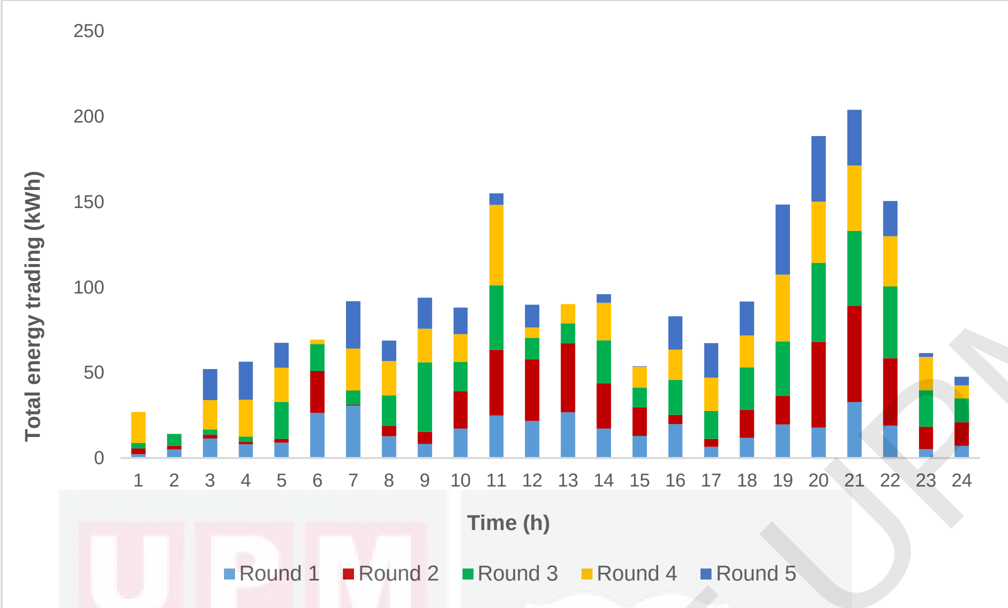

Figure 4.29 : Energy Trading during Successive Rounds of the Local Energy Market When the NMG System Operates within Distributed Energy Trading Mechanisms

Table 4.23 provides insight into the annual profits attained by various MGs employing different energy trading modes. Notably, MGs 1, 4, and 2 emerge with the highest profits, primarily attributed to their significant roles as energy sellers. Conversely, MG3 records the lowest annual profits, largely due to its recurrent energy shortages during most periods.

Table 4.22 : Annual Benefit of NMG System in Different Operating Modes

MG	Annual benefit ($/y)			
	Under Normal operating	Under P2G Energy trading	Under P2P energy trading	Under distributed energy trading
1	12675463	12975461	13517343	13287215
2	10212513	10838134	11676237	11287436
3	7253215	7610540	8305429	8103872
4	11306324	11712532	12510574	12192477

In terms of the NMG system, Figure 4.30 illustrates the annual profit rates achieved under different energy trading models. The P2P energy trading model stands out with the highest profit rate of 21.24%, followed by the distributed trading model at 19.71%, and finally the P2G energy trading model at 16.93%. This outcome is attributed to the comparatively lower energy trading prices within the P2P mode compared to the distributed and P2G energy trading modes.

Conversely, the distributed energy trading model exhibits the highest energy balance rate and the lowest incidence of energy loss, followed by the P2G mode and then the P2P mode. This disparity is due to the NMG system's capability to internally trade energy between MGs and the central grid, significantly mitigating energy discrepancies.

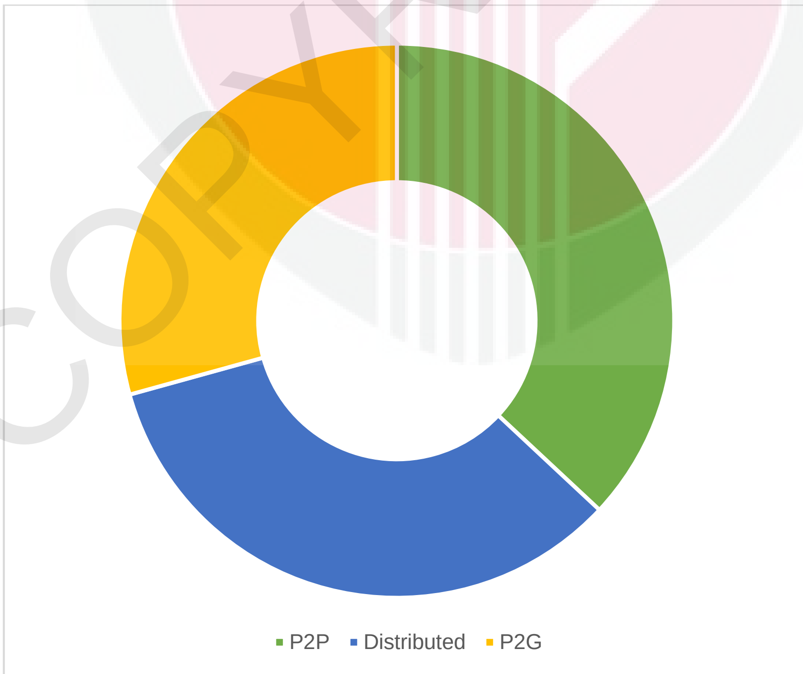

Figure 4.30 : The Annual Profit Rate for the Entire NMG System Motivates the Various Proposed Energy Trading Mechanisms

Figure 4.31 illustrates the negotiation process between MG3 (seller) and MG4 (buyer), providing a practical example to elucidate the price adjustment strategy. From table 4.22, at 4 a.m. in the initial round, the seller proposes a selling price of 0.242 $/kWh, reflecting the surplus energy available in response to market conditions. However, the buyer sets the purchase price at 0.226 $/kWh, resulting in a significant disparity between the two offers. This fundamental difference prevents an agreement, prompting both parties to adjust the contract prices to avoid operational penalties. In the second round, the seller reduces the selling price to 0.238 $/kWh, while the buyer increases the buying price to 0.231 $/kWh. Despite these adjustments, reaching an agreement remains elusive due to continued price disparities. Subsequently, a third round of negotiations occurred, leading to a reduction in the sale price to 0.236 $/kWh, with the purchase price also set at 0.236 $/kWh.

This time, it becomes easier to reach an agreement, resulting in the exchange of energy (3.314 kW) based on the revised selling price. This iterative negotiation process underscores the dynamic nature of negotiations as both parties strive to find a mutually beneficial pricing arrangement, ultimately enhancing the terms of the power swap contract between MG3 and MG4. The energy trading model introduced in this study has significantly bolstered the energy equilibrium within the NMG system, notably by mitigating both energy surpluses and shortages. This, in turn, has led to a reduction in costs associated with load distribution and energy management.

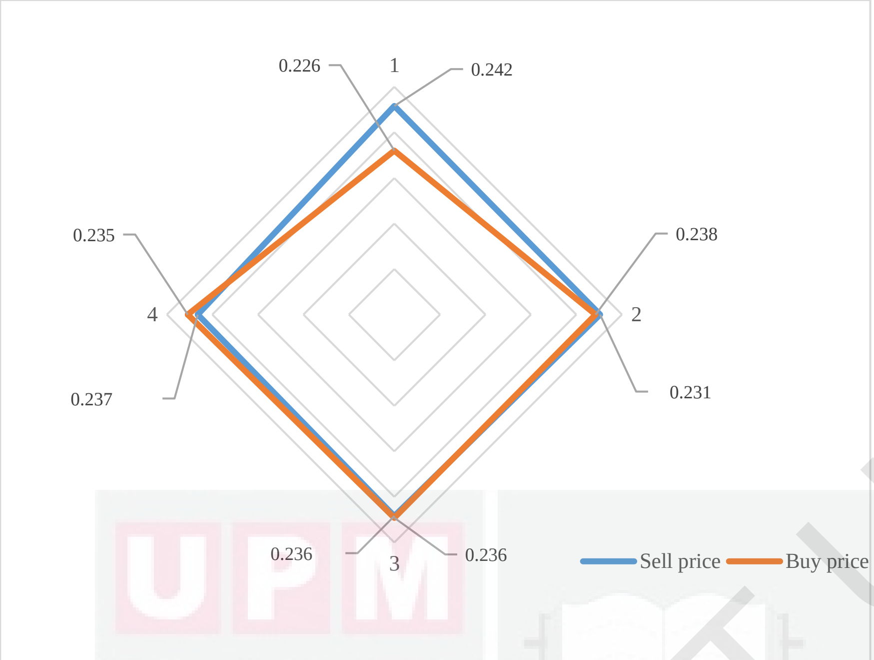

Figure 4.31 : Agreement on Prices for the Energy Contract Executed during the Third Round of the LEM at 4:00 am

4.8 Discussion

Renewable energy resources play a crucial role in advancing traditional energy systems, providing enhanced flexibility and reliability to manage load fluctuations and respond to unexpected failures. In this study, the performance of centralized energy systems integrated with NMG systems was evaluated across three primary axes.

In the first axis, the optimal configuration and sizing of energy resources were evaluated. In the initial stage, the focus is on identifying an optimal configuration of energy resources tailored for the study area. four main components: PV, WT, DG, and BSS has been evaluated. A hybrid AI technique, HGWPSO, was developed by combining the targeted search capabilities of the GWO with the exploratory strength of PSO. The performance of HGWPSO method was benchmarked against three established AI algorithms: GWO, PSO, and FA. As shown in Table 4.4, the optimal configuration—comprising PV, WT, BSS, and DG—yielded the best performance in terms of energy cost (0.127 $/kWh) and LPSP of 0.027. This configuration minimizes reliance on conventional energy resources due to its resource diversity, providing increased reliability, aligning with findings in similar studies (Liu, Wang, et al., 2020) and (Nallolla et al., 2023) . In the second stage, the focus was changed on determining the optimal sizes for each component in the optimal configuration across all microgrids within the NMG system. The optimization process was driven by a multi-objective function that balanced LCOE, Ploss, and GEM. Table 4.5 indicates that the HGWPSO method was superior in finding optimal component sizes, attributed to PSO's robust search coverage and GWO's precision in identifying optimal solutions. This outcome is consistent with similar studies focusing on component sizing optimization (Bravo et al., 2021), (Kerboua et al., 2022) and (Rathore et al., 2023).

The second axis was focused on enhancing the performance of NMG systems. Further system enhancements were pursued through two specific strategies, DRMS and DSMS. These strategies collectively aim to reduce energy costs, lower dependency on conventional resources, and decrease emissions. As seen in Tables 4.11 to 4.14, setting an optimal operational threshold for DG units led to substantial performance improvements, in line with previous studies (Kumar et al., 2021), (Adefarati et al., 2021), and (Hamad et al., 2022). Additionally, DSMS helped in shifting non-essential loads outside peak hours, redistributing load profiles, and enhancing system efficiency, as illustrated in Figures 4.18 and 4.19.

Third Axis was related to improving energy trading in LEM. The third aspect of this study examined the impact of energy trading in local markets on the reliability and economic balance of energy systems. Transmission line costs, capacity limits, and other factors, such as load-shedding costs, energy storage consumption, and the non-traded energy penalty, were considered when setting trading volumes. The NMG system's performance was evaluated under three energy trading models: Peer-to-Peer, Peer-to-Grid, and multi-round distributed energy auctions. Buyers were categorized based on their historical consumption data. Results in Tables 4.20, 4.21, and 4.22 show that distributed trading achieved a balanced and economically advantageous outcome compared to other models, aligning with findings in recent studies (Feili & Aameli, 2024), (Lokesh & Badar, 2023) and (Ali et al., 2022).

Overall, this study demonstrates that integrating renewable resources into centralized systems and leveraging advanced AI-based optimization and trading strategies can significantly enhance system flexibility, reliability, and economic performance while reducing environmental impact.

4.9 Summary

The integration of multiple microgrids within an NMG system facilitates seamless resource sharing and interaction among them. This interconnectedness not only enhances energy efficiency but also fortifies the system's robustness and dependability and enables dynamic energy management, promoting optimized resource utilization and improved overall performance. This study proposed a two level-hierarchical EMS for optimizing the NMG system. In the first level, through a triple objective function incorporating *LCOE*, P_{loss}, and *GEM*, the optimal size of all MG was determined. System reliability indicators such as *LPSP*, *CBI,* and *REI* were evaluated to assess performance. At the second level of the proposed management strategy, DRMS and DSMS were implemented. DRMS imposed restrictions on DG unit to enhance reliance on RES and reduce emissions. DSMS facilitated load shifting from peak to off-peak periods, further optimizing RES utilization and minimizing costs and emissions. The study assessed the system's performance under three energy trading mechanisms (P2P, P2G, and distributed modes) to cover standalone and grid-connected operations. Unlike previous studies, transmission line capacity and associated costs were considered in determining energy trading volumes. Additionally, financial penalties were imposed for non-participation in energy market updates. Results demonstrated the effectiveness of the implemented mechanisms and strategies in enhancing overall system performance, ensuring balanced energy markets, maximizing economic benefits for participants, and enhancing system flexibility and reliability.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS FOR FUTURE WORK

5.1 Research Conclusion and Contribution

This research offers innovative solutions to the economic and technical challenges associated with NMG systems, emphasizing the investigation, analysis, and validation of power systems. The ensuing paragraphs delve into the research conclusion and contribution that is addressed in this thesis.

5.1.1 Research Conclusion

This research study aims to enhance the performance of NMG systems integrated with distribution systems by identifying optimal operational patterns that consider economic, technical, and environmental factors. NMG systems play a crucial role in this context by facilitating the integration of RES into the grid. The primary motivations behind this study include:

1. Addressing the pressing need to upgrade energy systems to cope with the significant rise in RES penetration, necessitating reliable and efficient NMG systems.
2. Promoting the development of sustainable energy systems that minimize harmful emissions and promote the use of RES.
3. Fostering the evolution of centralized energy markets into more flexible distributed energy markets capable of facilitating energy trading.

In summary, this study successfully achieved its objectives, demonstrating significant advancements in the design optimization of MG, enhancement of

NMG system performance, and efficient management of energy trading in the LEM. The ensuing points delineate the outcomes attained across the three facets of the study:

1) Optimal Configuration and Sizing of the NMG System

To ascertain the optimal configuration tailored to the climatic conditions of the study area, four potential configurations were examined, incorporating prevalent energy resources in MG systems: PV, WT, DG, and BSS, capable of fulfilling the load demands of end users. The initial arrangement comprised PV/WT/DG/BSS, followed by PV/DG/BSS for the second, WT/DG/BSS for the third, and PV/WT/BSS for the fourth configuration. After verification, it was determined that the first configuration is the most suitable for the study area's climatic conditions, with *LCOE* and *LPSP* values of 0.127$/kW and 0.027, respectively. In comparison, the second configuration yielded 0.130 $/kW and 0.050, the third 0.140 $/kW and 0.063, and the fourth 0.129 $/kW and 0.055, indicating lower effectiveness. These findings suggest that ample solar radiation favors PV panel utilization, followed by WT due to relatively lower average wind speeds, with BSS and DGs trailing. The AI-based method, HGWPSO, stood out among other approaches for determining the optimal configuration, boasting superior accuracy and faster convergence rates. The HGWPSO method also excelled in determining the optimal sizes of PV, WT, DG, and BSS for each MG. For MG1, it yielded sizes of 697.33 kW for PV, 363.52 kW for WT, 113.23 kW for DG, and 157.98 kW for BSS. Similarly, for MG2, the sizes were 710.89 kW for PV, 339.72 kW for WT, 108.46 kW for DG, and 225.15 kW for BSS. MG3 saw sizes of 2467.88 kW for PV, 1720.6 kW for

WT, 329.81 kW for DG, and 687.00 kW for BSS. Finally, MG4 had sizes of 710.95 kW for PV, 415.24 kW for WT, 243.83 kW for DG, and 134.74 kW for BSS. In the discussion, the analysis of the objective function, incorporating LCOE, P_{loss}, and GEM, revealed insightful outcomes for each microgrid: MG1 demonstrated an LCOE of $0.127/kWh, with a P_{loss} of 38.19 kW and GEM of 8.187 t/y. MG2 displayed similar trends with an LCOE of $0.128/kWh, P_{loss} of 45.09 kW, and GEM of 7.842 t/y. Notably, MG3 exhibited a higher LCOE of $0.130/kWh, driven by a substantial P_{loss} of 180.51 kW, yet it achieved a noteworthy GEM of 23.847 t/y. MG4 presented a slightly lower LCOE of $0.129/kWh, alongside a P_{loss} of 48.57 kW and GEM of 17.630 t/y.

The application of HGWPSO in assessing the LPSP of MG1, MG2, MG3, and MG4 yielded values of 2.7%, 2.5%, 3.1%, and 2.9%, respectively. These results indicate varying levels of reliability across the MGs, with MG3 exhibiting the highest LPSP. Moreover, the evaluation of the CBI demonstrated favorable outcomes, with values of 79.43%, 80.73%, 76.64%, and 78.43% achieved for MG 1, 2, 3, and 4, respectively. This suggests that MG 1 and 2 are particularly efficient in terms of cost-effectiveness. Furthermore, the integration of RES within MG 1, 2, 3, and 4 resulted in notable contributions to the overall system performance, with percentages of 79.63%, 75.89%, 80.46%, and 74.84%, respectively. These findings underscore the significance of RES in enhancing the operational efficacy of NMG systems. In summary, the utilization of HGWPSO, coupled with assessments of LPSP, CBI, and REI provides valuable insights into the reliability, efficiency, and collaborative potential of NMG systems in power distribution systems.

2) Improving NMG Performance Using DRMS and DSMS

DG resources have been utilized as backup energy sources to directly tackle energy shortages, regardless of their scale. However, it has been observed that in many instances, the energy shortfall is minor and doesn't warrant immediate activation of DG units. Thus, this study proposes the implementation of a DRMS, leveraging AI methods to determine the minimum activation threshold for DG units. Through experimentation, the study identified that setting the threshold at 30% of the DG output rate yielded the most favorable objective functional score of 0.642. Consequently, this threshold was selected as the initial operational point for DG units, with performance recalculations conducted for all MGs. The outcomes depicted in Table 5.1 highlight a notable surge in the contribution of RES, accompanied by a reduction in reliance on DG units.

Table 5.1 : Comparison of MG Component Sizes: Impact of DRMS Implementation on RES Reliance

MG	Optimal size (kW) without DRMS				Optimal size (kW) with DRMS			
	PV	WT	DG	BSS	PV	WT	DG	BSS
MG1	697.33	363.52	113.23	157.98	712.24	371.81	82.17	712.24
MG2	710.89	339.72	108.46	225.15	719.06	342.73	78.73	230.14
MG3	2467.8	1720.6	329.81	687.00	2476.5	1734.2	284.51	712.29
MG4	710.95	415.24	243.83	134.74	716.64	429.46	210.67	149.28

The findings illustrated in Table 5.2 reveal a comparative analysis between *LCOE*, P_{loss}, and *GEM* across all MGs, both with and without the integration of DRMS. There's a discernible enhancement across all metrics for the systems, evidenced by the decrease in *LCOE* for MG 1, 2, 3, and 4 from 0.127 $/kWh, 0.128 $/kWh, 0.130 $/kWh, and 0.129 $/kWh without DRMS to 0.125 $/kWh, 0.127 $/kWh, 0.129 $/kWh, and 0.128 $/kWh respectively with its implementation. This improvement can be attributed to a reduced reliance on DG units, consequently mitigating fuel consumption and maintenance expenses.

The most remarkable outcome is evident in the emissions index GEM, where the implementation of the strategy substantially reduces emission levels to 5.771 t/y, 5.529 t/y, 19.982 t/y, and 14.796 t/y for MG 1, 2, 3, and 4 respectively. This marks a significant improvement compared to emission levels of 8.187 t/y, 7.842 t/y, 23.847 t/y, and 17.630 t/y observed without the strategy. In conclusion, the integration of DRMS yields a noticeable decrease in P_{loss} across all MGs, with figures dropping to 35.16 kW, 43.94 kW, 178.24 kW, and 45.74 kW after implementation compared to 38.19 kW, 45.09 kW, 180.51kW, and 48.57 kW without it for MG 1, 2, 3, and 4, respectively.

Table 5.2 : Comparison Demonstrating Enhanced Achievement of System Objective Function Following Implementation of Management Strategies

MG	Objective function without DRMS			Objective function with DRMS		
	LCOE $/kWh	Ploss kW	GEM t/y	LCOE $/kWh	Ploss kW	GEM t/y
MG1	0.127	38.19	8.187	0.125	35.16	5.771
MG2	0.128	45.09	7.842	0.127	43.94	5.529
MG3	0.130	180.51	23.847	0.129	178.24	19.982
MG4	0.129	48.57	17.630	0.128	45.74	14.796

3) Optimal Energy Trading

Energy trading within the LEM is assessed through three fundamental structures: P2G, P2P, and distributed. Within the P2P, energy trading occurred across two rounds, with 209.25 kW exchanged in the first round and 19,986 kW in the second, priced at 0.226 $/kWh in the initial round with varied pricing thereafter. Notably, improvements were observed in the energy balance, with reductions in surplus and energy shortage. Furthermore, the annual profits for MG 1, 2, 3, and 4 demonstrated significant increases, totaling (13,517,343; 11,676,237; 8,305,429; 12,510,574) \$/year respectively. These outcomes underscore the effectiveness of the strategies implemented, highlighting the potential for enhanced efficiency and profitability within the local energy market framework.

In conclusion, within the P2G framework, the NMG system outperformed the P2P model by achieving a superior energy balance. This was primarily attributed to the central grids' high capacity to absorb surplus energy and address energy shortages efficiently. Energy trading occurred through three rounds of auctions, with varying amounts traded: 867.776 kW in the first round, 766.751 kW in the second, and 564.416 kW in the third. Initially, energy prices stabilized at \$0.40 and \$0.20 per kWh for buying and selling, respectively, based on central grid standards. However, prices subsequently adjusted higher in later rounds. Consequently, despite the enhanced energy balancing capabilities, the annual profit rates for MG experienced a decline, with figures reaching (12,975,461; 10,838,134; 7,610,540; 11,712,532) \$/y for MG1, MG2, MG3, and MG4, respectively.

The third operational mode of the NMG system was thoroughly assessed within its distribution mechanism. This mode demonstrated the highest energy balance rates, capitalizing on the synergies of P2P and P2G. Energy exchange, facilitated through five rounds of auctions, was seamlessly integrated into the distributed mode, ensuring comprehensive trading across most periods. The total energy trading during the first, second, third, fourth, and fifth rounds was 367.522 kW, 432.153 kW, 482.529 kW, 477.853 kW, and 348.843 kW respectively. Remarkably, this mode yielded the second-highest average annual profits, with MG 1, 2, 3, and 4 achieving profits of 13,287,215 \$/y, 11,287,436 \$/y, 8,103,872 \$/y, and 12,1924,77 \$/y respectively.

Regarding system sensitivity analysis, the impact of numerous technical and economic parameters, such as DG startup limit, interest rates, and generating disturbances, on the optimal design of the MG was investigated. In terms of selecting the interest rate, the sensitivity analysis revealed that as the interest rate rises, the energy cost falls while the *LPSP* index rises, lowering the system's reliability. In other words, the costs and reliability of systems decrease in direct proportion to the rate of interest. In terms of reduction of energy cost and emissions, the decision on a start-up limit for MG is crucial due to the continuing high cost of fuel and emission restrictions. A sensitivity study of the results of this parameter showed that as the threshold limit is raised, the *TNPC* increases while the *LPSP* decreases. This means that as the operating startup limit increases, the overall cost of MGs increases. In addition, the emission rate rises as the startup decreases and vice versa. Here the investor can determine the appropriate operating startup limit in the most economical way based on the sensitivity analysis.

5.1.2 Research Contribution

The primary contributions of this research in these domains are outlined below:

1. Employing a hybrid AI algorithm leveraging GWO and PSO methods called HGWPSO to efficiently determine optimal configurations and sizes of MG components. This algorithm utilized various technical data to optimize the sizes of MG components based on a multi-objective function, considering factors like LCOE, Ploss, GEM, and reliability indicators.
2. Deploying DRMS and DSMS to boost NMG system performance. DRMS focuses on curtailing DG resource operation until energy shortages exceed a predefined threshold, thereby decreasing GEM, and LCOE, and promoting reliance on RES. DSMS involves shifting non-sensitive loads to off-peak periods, thereby reducing energy imbalances.
3. Establishing LEM and facilitating energy trading within them requires the implementation of multi-round auction strategies across three distinct energy trading mechanisms: P2P, P2G, and distributed trading. Across multiple rounds, energy trading prices undergo dynamic adjustments, accounting for economic penalties resulting from surplus or shortfall energy. Integration of AI technologies optimize energy flow across transmission lines, considering operational costs and design capacities.

5.2 Future Work

Drawing from the findings of this thesis, a promising trajectory emerges for the progression of NMG systems and the utilization of RES to bolster their efficacy and dependability. This thesis paves the way for a revolutionary voyage towards enhancing efficiency and reliability in NMG systems powered by RES. It proposes numerous avenues for future research, fostering innovation, sustainability, and the evolution of energy solutions toward a more promising tomorrow.

1. Exploring the potential benefits of expanding RES, such as geothermal heat, biomass, and hydrogen, to fulfill load demands, to optimize their configuration and scale within NMG systems.

2. Advancing the development of sophisticated management strategies leveraging AI, machine learning, and Internet of Things technologies to effectively oversee diverse energy resources within intricate NMG infrastructures.

3. Investigating the intricate relationship between MG systems and LEM, delving deeper into energy market dynamics, regulatory frameworks, pricing mechanisms, and emerging trends to enhance energy transactions within NMG networks.

4. Tackling persistent challenges facing NMG systems, including cybersecurity risks and socioeconomic implications, through interdisciplinary cooperation and targeted research endeavors.

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APPENDICES

Appendix A

Appendix A comprises pertinent data concerning the Benchmark Test System for Networked Microgrids. Figure A1 delineates the general block diagram of the test system, while Table A1 provides the connection data for the Test System. Additionally, Table A2 delineates the sizes and locations of the transmission lines for the test system, Table A3 presents the transmission line data of resistance and impedance utilized in the Load Flow program to calculate energy losses in transmission lines, and Table A4 offers data on the load imposed on each bus.

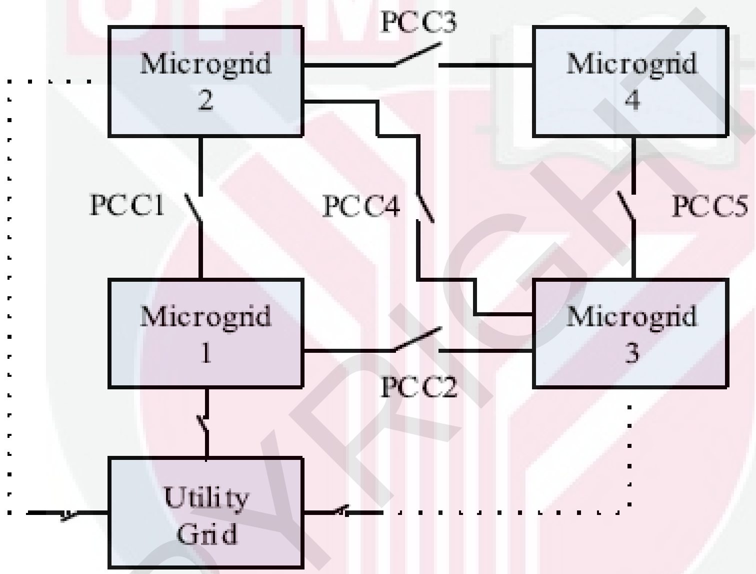

Figure A1 : Block diagram of the benchmark test system

Table A1 : Details of MGs of the benchmark test system

Components	MG1	MG2	MG3	MG4
Buses	6	9	18	7
Lines	11	8	17	8
SGs	3	3	3	2
PV systems	3	3	6	3
WT systems	0	2	2	0
Slack bus	101	201	301	401
MG type	Meshed	Radial	Radial	Meshed
Ownership	Utility	Community	Community	Private

Table A2 : Cable size and placement details in the test system

S. No.	Cross sectional area (sq. mm)	Cable Placement	Serial numbers of cables and tie-cables of Tables III and IV
1	400	Double	1, 3, T1, T2
2	300	Double	2, 4-13, 15, 17, 18, 20-22, 24, 26, 28, 33, 34, T3-T5
3	185	Double	37-44
4	150	Single	14, 16, 19, 23, 25, 27, 29, 31, 32, 35, 36

Table A3 : PCC/TIE cables data of the networked microgrid system

S. No.	From bus	To bus	Length (km)	Resistance (Ω)	Reactance (Ω)	Normal rating (A)	SCCR (kA)
T1	102	201	1	0.0309	0.0477	1000	114.4
T2	104	301	1.5	0.04635	0.07155	1000	114.4
T3	208	401	2	0.0778	0.0999	890	83.8
T4	205	310	2.5	0.09725	0.12488	890	83.8
T5	318	404	1	0.0389	0.04995	890	83.8

Table A4 : Load data of the networked microgrid system

Bus ID	Bus type	Total bus load kW	Total bus load kVAR	Critical load kW	Critical load kVAR	Bus load % of system load
101	1	0	0	0	0	0
102	2	2125	336	450	68	6.9
103	2	3329	1023	650	124	10.81
104	2	2050	555	200	50	6.66
105	3	1257	310	200	35	4.08
106	3	1056	240	200	35	3.43
201	2	600	100	0	0	1.95
202	2	1250	487	500	80	4.06
203	2	1203	410	500	80	3.91
204	2	1366	443	650	138	4.43
205	3	764	36	0	0	2.48
206	2	503	21	0	0	1.63
207	3	345	11	0	0	1.12
208	3	629	8	0	0	2.04
209	2	642	12	100	25	2.08
301	2	580	150	0	0	1.88
302	3	650	85	250	50	2.11
303	2	673	96	0	0	2.18
304	2	439	135	0	0	1.43
305	2	600	128	250	50	1.95
306	2	560	112	0	0	1.82
307	2	851	145	385	50	2.76
308	3	420	25	0	0	1.36
309	3	500	45	0	0	1.62
310	3	637	33	0	0	2.07
311	3	788	95	350	83	2.56
312	3	125	50	0	0	0.41
313	3	169	20	0	0	0.55
314	2	200	43	0	0	0.65
315	2	250	32	125	25	0.81
316	3	213	12	0	0	0.69
317	2	133	25	0	0	0.43
318	3	200	38	0	0	0.65
401	2	426	80	0	0	1.38
402	3	318	78	125	20	1.03
403	3	356	81	125	20	1.16
404	3	459	88	0	0	1.49
405	2	820	91	0	0	2.66
406	2	2500	635	850	150	8.12
407	2	816	60	250	44	2.65
Total Load		30802	6374	6160	1127	100.0

Base voltage: 11 kV; Specified voltage at all buses: 1.0 p.u.

Appendix B

Appendix B contains two tables presenting data for the IEEE 13 bus test system. Table B1 provides details regarding the transport lines, while Table B2 outlines the data about the buses.

Table B1 : Data of transmission line of IEEE 13 bus test system

Sen. bus	Res. bus	R (ohm)	X (ohm)
1	2	0.176	0.138
2	3	0.176	0.138
3	4	0.045	0.035
4	5	0.089	0.069
5	6	0.045	0.035
5	7	0.116	0.091
7	8	0.073	0.073
8	9	0.074	0.058
8	10	0.093	0.093
7	11	0.063	0.050
11	12	0.068	0.053
7	13	0.062	0.053

Table B2 : Data on the buses of the IEEE 13 bus test system

No. bus	P (Kw)	Q (Kvar)
1	0	0
2	890	468
3	628	470
4	1112	764
5	636	378
6	474	344
7	1342	1078
8	920	292
9	766	498
10	662	480
11	690	186
12	1292	554
13	1124	480

Appendix C

Appendix C includes the annual meteorological data for the study area along with the average annual loads. Figure C1 illustrates the annual solar radiation, while Figure C2 displays the average annual temperature. Additionally, Figure C3 showcases the average annual wind speed, while Figures C4 to C7 depict the average annual load demand for MG1, MG2, MG3, and MG4 respectively.

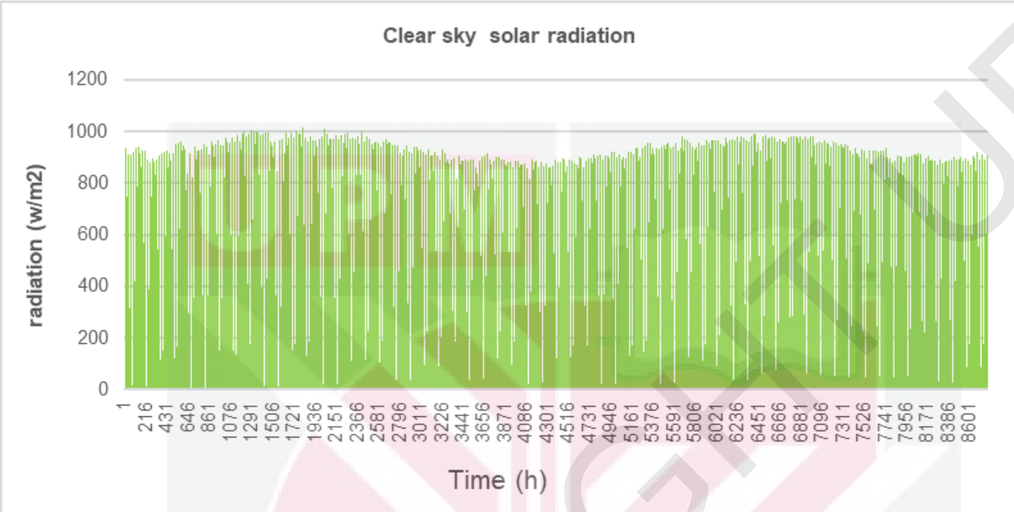

Figure C1 : Annual solar radiation

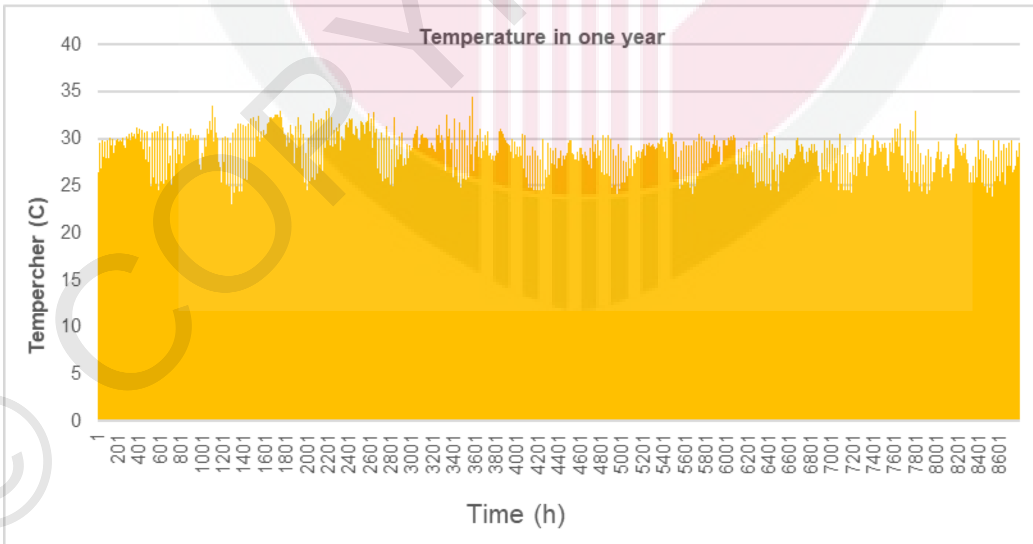

Figure C2 : Annual temperature

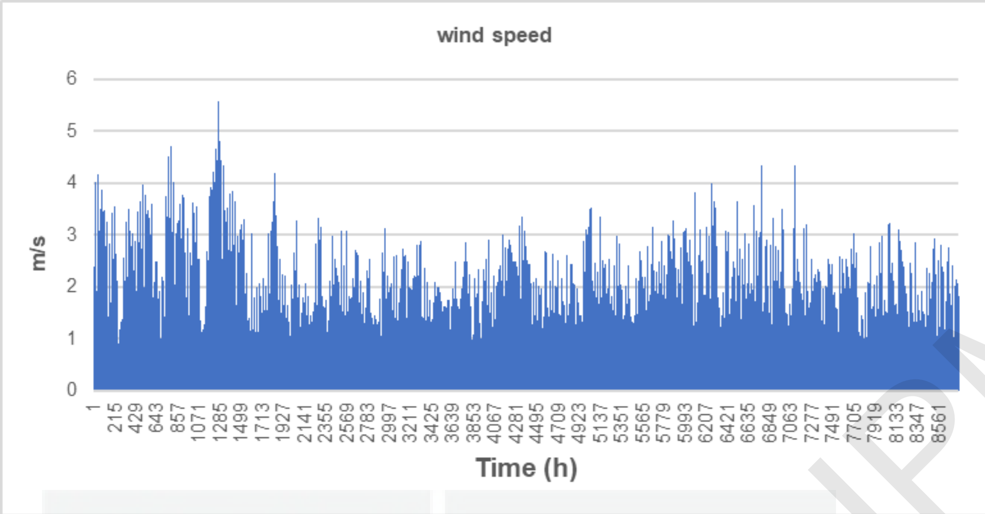

Figure C3 : wind speed

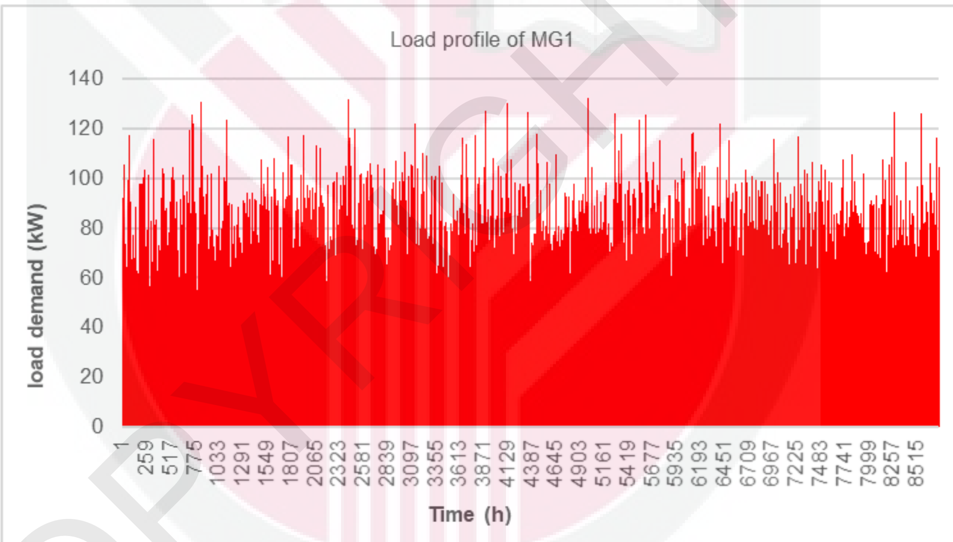

Figure C4 : Annual load profile of MG1

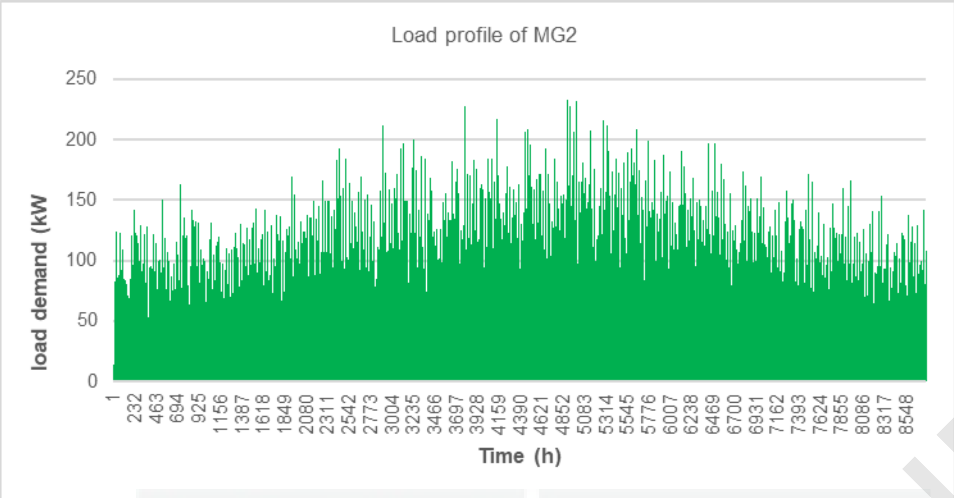

Figure C5 : Annual load profile of MG2

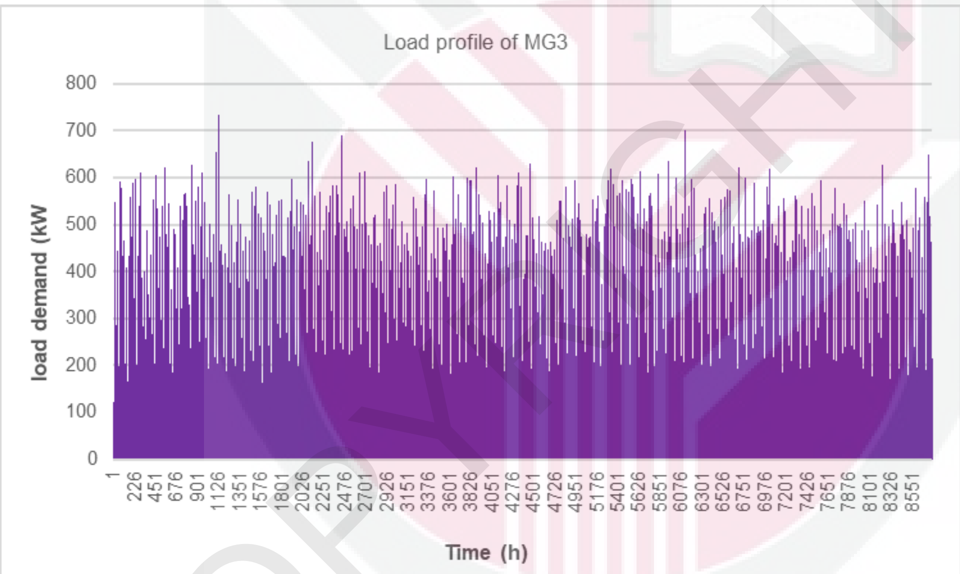

Figure C6 : Annual load profile of MG3

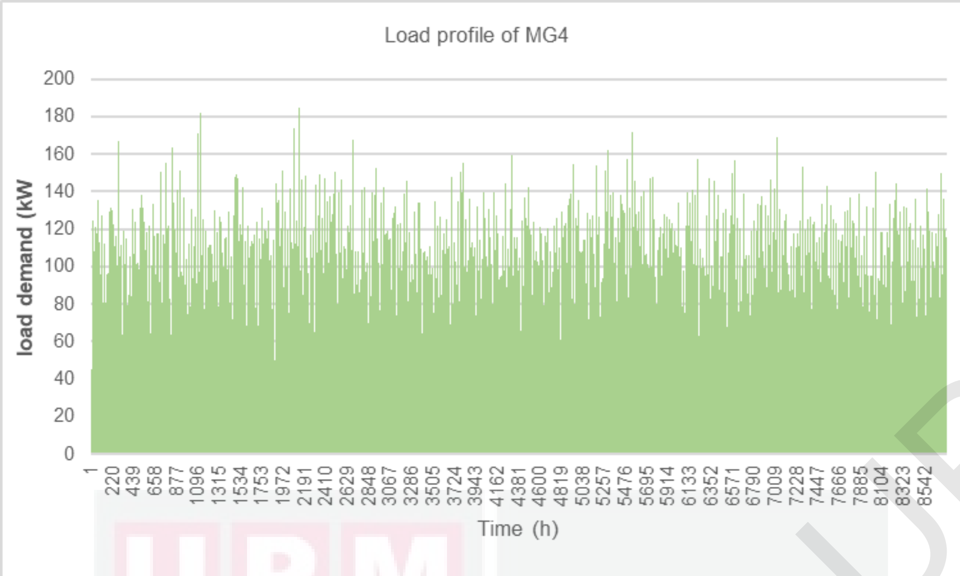

Figure C7 : Annual load profile of MG4

LIST OF PUBLICATIONS

Journal Articles

Ahmed Sahib Tukkee, Noor Izzri bin Abdul Wahab, Nashiren Farzilah binti Mailah, Mohd Khair Bin Hassan, “Optimal performance of stand-alone hybrid microgrid systems based on integrated techno-economic-environmental energy management strategy using the grey wolf optimizer”, PLOS ONE, 2024 (Q2, **Published**).

Ahmed Sahib Tukkee, Noor Izzri bin Abdul Wahab, Nashiren Farzilah binti Mailah, Mohd Khair Bin Hassan, “Optimal sizing of autonomous hybrid microgrids with economic analysis using grey wolf optimizer technique”, e-Prime - Advances in Electrical Engineering, Electronics and Energy, 2023, (Scopus, **Published**).

Ahmed Sahib Tukkee, Noor Izzri bin Abdul Wahab, Nashiren Farzilah binti Mailah, Mohd Khair Bin Hassan, “Hierarchical Energy Management Strategy to Coordinate Networked Microgrid System Based on Hybrid Grey wolf and Partial Swarm Optimization.” (**submitted to journal)**

Ahmed Sahib Tukkee, Noor Izzri bin Abdul Wahab, Nashiren Farzilah binti Mailah, Mohd Khair Bin Hassan, “Decentralized Peer-to-Peer Energy Trading Market for Multi Microgrid Systems: A Grey Wolf Optimizer Approach’. (**submitted to journal)**

Proceedings /Conference

Ahmed Sahib Tukkee, Noor Izzri bin Abdul Wahab, Nashiren Farzilah binti Mailah, Mohd Khair Bin Hassan, “Peer-to-Peer Energy Trading for Optimal Power Management of Networked Microgrid based on Particle Swarm Optimization”, 2024, IEEE ICPEA Penang.

Ahmed Sahib Tukkee, Noor Izzri bin Abdul Wahab, Nashiren Farzilah binti Mailah, “Hybrid energy management for Networked Microgrids Based on Hierarchical Optimization considering Economic Operating and Demand Response.”, 2022 10th international symposium on applied engineering and sciences, SAES 2022.