OPTIMAL ENERGY MANAGEMENT OF MICROGRID CONSIDERING DEMAND RESPONSE AND UNCERTAINTIES

SANE LEI LEI WYNN

A Thesis Submitted in Partial Fulfillment of the Requirements for the
Degree of Doctor of Philosophy in Electrical Engineering
Suranaree University of Technology
Academic Year 2023

การจัดการพลังงานที่เหมาะสมที่สุดของไมโครกริดโดยคำนึงถึงการตอบสนองความต้องการและความไม่แน่นอน

นางสาว แซน ไล ไล วินน์

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรดุษฎีบัณฑิต
สาขาวิชาวิศวกรรมไฟฟ้า
มหาวิทยาลัยเทคโนโลยีสุรนารี
ปีการศึกษา 2566

OPTIMAL ENERGY MANAGEMENT OF MICROGRID CONSIDERING DEMAND RESPONSE AND UNCERTAINTIES

Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy.

Thesis Examining Committee

(Assoc.Prof. Dr. Kaan Kerdchuen)
Chairperson

(Asst. Prof. Dr. Boonruang Marungsri)
Member (Thesis Advisor)

(Assoc.Prof. Dr. Keerati Chayakulkheeree)
Member

(Assoc.Prof. Dr. Anant Oonsivilai)
Member

(Asst. Prof. Dr.Terapong Boonraksa)
Member

(Assoc. Prof. Dr. Yupaporn Ruksakulpiwat)
Acting Vice Rector for Academic Affairs
and Quality Assurance

(Assoc. Prof. Dr. Pornsiri Jongkol)
Dean of Institute of Engineering

SANE LEI LEI WYNN: การจัดการพลังงานที่เหมาะสมที่สุดของไมโครกริดโดยคำนึงถึงการตอบสนองความต้องการและความไม่แน่นอน (OPTIMAL ENERGY MANAGEMENT OF MICROGRID CONSIDERING DEMAND RESPONSE AND UNCERTAINTIES)
อาจารย์ที่ปรึกษา : ผู้ช่วยศาสตราจารย์ ดร.บุญเรือง มะรังศรี, 215 หน้า.

คำสำคัญ:การจัดการพลังงานไมโครกริด/การจัดตารางการผลิต/การตอบสนองความต้องการ

วิทยานิพนธ์นี้นำเสนอระบบการจัดการพลังงานที่ดีที่สุด สำหรับไมโครกริดภายใต้ความไม่แน่นอน ความไม่แน่นอนเด่นชัดสุดสำหรับหน่วยงานการไฟฟ้าคือ ความต้องการพลังงานไฟฟ้าและการผลิตไฟฟ้า แหล่งผลิตพลังงานหมุนเวียนจำนวนมากถูกรวมเข้ากับโครงข่ายพลังงานหลัก เพราะว่าการใช้พลังงานจากทรัพยากรหมุนเวียน เป็นแนวทางในการลดผลกระทบต่อสิ่งแวดล้อมของโครงข่าย อย่างไรก็ตามแหล่งพลังงานหมุนเวียนมีความผันผวนในการผลิตพลังงานการผลิตและไม่สามารถผลิตได้เต็มกำลัง การใช้แหล่งพลังงานหมุนเวียนให้เกิดประโยชน์สูงสุด จำเป็นต้องมีการพยากรณ์ที่แม่นยำเนื่องจากมีความไม่แน่นอนโดยธรรมชาติ การพยากรณ์ที่แม่นยำเป็นสิ่งสำคัญในการรับประกันความเชื่อถือได้ของทำงานและการวางแผนกำลังการผลิต วิทยานิพนธ์นี้นำเสนอระบบการจัดการพลังงานไมโครกริด บนพื้นฐานการปรับให้เหมาะสมร่วมกับการตอบสนองความต้องการโหลด (Demand Response:DR) เพื่อจัดการกับปัญหาความไม่แน่นอนของการผลิตและความต้องการโหลด เพื่อแก้ไขปัญหานี้แบบจำลองความไม่แน่นอนถูกดำเนินการสร้างจากการสุ่มเชิงสถิติแบบกระบวนการสโตแคสติก(Stochastic Process) ซึ่งแต่เดิมถูกประเมินด้วยแบบจำลองที่สังเคราะห์ขึ้นมาจากตัวอย่างหรือฉากทัศน์ในแบบจำลองอินพุต สำหรับกระบวนการตัดสินใจที่เหมาะสมที่สุด (Decision-making Optimization) ต่อมาแบบจำลองได้ประยุกต์ใช้กระบวนการส-โตแคสติกอย่างง่ายในแบบจำลองการตัดสินใจที่ซับซ้อน อย่างไรก็ตาม การเชื่อโยงแบบจำลองการพยากรณ์ตามสถาณการณ์ที่ซับซ้อนกับแบบจำลองรูปแบบการตัดสินใจที่ซับซ้อน นั้นทำได้ยาก ดังนั้นวิทยานิพนธ์จึงนี้เน้นการเชื่อมโยงแบบจำลองการพยากรณ์ตามอนุกรมเวลา ด้วยการเรียนรู้เชิงลึก (Deep Learning) กับแบบจำลองการตัดสินใจ ข้อมูลการพยากรณ์ถูกฝังอยู่ในปัญหาการหาค่าเหมาะสมที่สุด อันเนื่องจากธรรมชาติของความต้องการโหลดและการผลิตจากแหล่งพลังงานหมุนเวียนที่ไม่แน่นอน ความพร้อมของการผลิตไฟฟ้าและความต้องการโหลดของไมโครกริดล่วงหน้าในแต่ละวันได้รับการพยากรณในระบบทดสอบ ความต้องการพลังงานและการผลิตพลังงาน

จากแหล่งพลังงานหมุนเวียน ถูกพยากรณ์โดยใช้เทคนิคการเรียนรู้เชิงลึกแบบหน่วยเวียนกลับแบบมีประตู (Gate Recurrent unit: GRU) และผลการพยากรณ์ที่ได้จาก GRU ถูกนำไปเปรียบเทียบกับแบบจำลองค่าเฉลี่ยเคลื่อนที่ถดถอยอัตโนมัติ (Auto Regressive Moving Average: ARMA) ในเชิงของความแม่นยำในการพยากรณ์ ในวิธีการที่นำเสนอการทำงานของระบบถูกนำมารวมกับ DR เข้ากับระบบ ซึ่ งไม่ต้องใช้พารามิเตอร์จำกัดที่กำหนดไว้ล่วงหน้าเพื่อรับมือกับค่าเบี่ยงเบนจากการพยากรณ์ วิทยานิพนธ์ยังนำเสนอโครงสร้างสิ่งจูงใจการตอบสนองความต้องการ สำหรับการจัดกำหนดการโหลดเพื่อลดอัตราส่วนเฉลี่ยสูงสุด(Peak Average Ratio: PAR) ของความต้องการพลังงานกับการรักษาความลับของผู้บริโภค เทคนิคที่นำเสนอนี้ช่วยลดต้นทุนค่าไฟฟ้า ลดความไม่พอใจของผู้ใช้ และลดค่าความต้องการกำลังงานสูงสุด สำหรับไมโครกริดที่ใช้งานแบบ TOU วิทยานิพนธ์นี้ยังวิเคราะห์ การสร้างแบบจำลองของการจัดกำหนดการโหลดที่เหมาะสมสุดของไม-โครกริด โดยใช้ปัญหาที่มีข้อจำกัดหลายข้อและหลายวัตถุประสงค์เป็นฐาน ผลการศึกษายืนยันประสิทธิผลของเทคนิคที่นำเสนอเป็นอย่างดี

สาขาวิชา วิศวกรรมไฟฟ้า ลายมือชื่อนักศึกษา.......................................

ปีการศึกษา 2566 ลายมือชื่ออาจารย์ที่ปรึกษา.......................................

SANE LEI LEI WYNN: OPTIMAL ENERGY MANAGEMENT OF MICROGRID CONSIDERING DEMAND RESPONSE AND UNCERTAINTIES
THESIS ADVISOR: ASST. PROF. BOONRUANG MARUNGSRI, Ph.D 215 PP.

Keyword: Microgrid energy management/Generation scheduling/ Demand response

This thesis proposed the optimal energy management system for microgrids under uncertainties. The most remarkable uncertainty for electricity entities lies in the energy demand and generation in the power systems. Many renewable energy generation sources are integrated into the power network because renewable resources provide guidelines for minimizing the network's environmental impact. However, renewable resources have volatile production energy and are unavailable at peak power output. Maximizing the utilization of renewable energy sources requires accurate forecasting due to its inherent uncertainty. Accurate forecasting is essential to guarantee reliable operation conditions and planning for generation capacities. This thesis presents an optimization-based microgrid energy management system incorporating demand response (DR) to tackle the issues of generation and demand uncertainties. To address this problem, uncertainty modeling is typically executed by a statistics-based stochastic process. The former is evaluated by modeling synthetic samples or scenarios in the input model for decision-making optimization. The latter model applied a simple stochastic process in the sophisticated decision-making model. However, it is hard to interface the complex scenario-based forecasting models and the sophisticated decision-making model. Therefore, this thesis highlights the interfacing of deep-learning-based time-series forecasting models with decision-making models. Forecasted information is embedded into the optimization problems due to the uncertain nature of demand and renewable generation. The day-ahead availability of power generation and microgrid demand were forecasted on the test system. The energy demand and RE generation forecasting are employed along with the Gate Recurrent unit (GRU), and the out results of the Gate Recurrent unit (GRU) are compared with the Auto Regressive Moving Average (ARMA) model in terms of forecasting accuracy. In the proposed method, the system operation is further incorporated with DR, which does not require predefined constrain parameters to tackle the deviation from the forecasting. The thesis also presents an incentive demand response structure for scheduling the load to reduce the peak average ratio of power demand with consumers' confidentiality. The proposed technique reduces electricity costs, reduces users' dissatisfaction, and minimizes peak load for microgrids in the presence of Time of Use (TOU). This thesis analyzes the modeling of microgrid optimal scheduling based on the multi-constrained, multi-objective problem. The study results confirmed the effectiveness of the proposed techniques as well.

School of Electrical Engineering
Academic Year 2023

Student's Signature ....
Advisor's Signature ....

ACKNOWLEDGEMENT

First, the author is deeply grateful to the Suranaree University of Technology for funding this research.

The author is greatly indebted to her supervisor, Asst. Prof. Dr. Boonruang Marungsri, for his encouragement, willingness to share ideas, helpful suggestions, and support. The author is very grateful to committee members for their invaluable advice, helpful suggestions, and encouragement throughout this study.

The author also wishes to sincerely thank Dr. Watcharakorn Pinthurat for his helpful suggestion and necessary assistance in preparing the publication. The author would also like to thank the International Affairs (CIA) of Suranaree University of Technology for their invaluable help and guidance.

Lastly, I would like to thank my family for their continued support, keeping me motivated.

SANE LEI LEI WYNN

TABLE OF CONTENTS

Page

TABLE OF CONTENTS (Continued)

Page

TABLE OF CONTENTS (Continued)

Page

TABLE OF CONTENTS (Continued)

Page

TABLE OF CONTENTS (Continued)

LIST OF TABLES

LIST OF FIGURES

TABLE OF FIGURES (Continued)

TABLE OF FIGURES (Continued)

Figure | Page

LIST OF ABBREVIATIONS

Y (t + 1)	the position vector of a grey wolf in the t + 1th iteration
Y (t)	the position vector of the grey wolf at the tth iteration
A	coefficient of position update
D	the distance between the grey wolf and the location of the prey (X_p)
a	parameter to balance exploration and exploitation
r1 and r2	the coefficient random parameter between [0,1]
t	the current iteration
T	the maximum number of iterations
Y1, Y2, Y3	the new position of a wolf
n_i	the number of non-dominated solutions in the i-the segment
c	constant set to 1
f_{imin}, f_{jmin}, f_{kmin}	minimum from the corresponding solution from all objective functions
d	minimum distance
ϕ_i	the ith AR coefficient
x_{t-i}	the time series values.
ω_t	the white noise with zero mean and constant variance
θ_t	the jth MA coefficient
ω_{t-j}	the white noise that is uncorrelated random parameters with zero mean and constant variance
$V^*(n, y)$	the standardized hourly average wind speed
$V'_{n,y}$	hourly average wind speed
$\mu(t), \sigma(t)$	the sample mean and the standard deviation of all transformed wind speeds in 24 hours
W_u, W_f, W_o	the weights function of update gate, forget gate, and output gate,

LIST OF ABBREVIATIONS (Continued)

b_u, b_f, b_o	biases govern the behavior of the update gate, forget gate and output gate
W_c, b_c	the weights and bias of the memory cell
W_u, W_r,	the weights function of the update gate and relevance gate
B_u, b_r	the bias governs the behavior of the update gate and relevance gate
W_c, b_c	the weights and bias of the memory cell candidate
$C^t_{opeation}$	operation cost at a time "t"
$\Pi^t_{operation}$	operational peak load at a time "t"
$\Gamma^t_{operation}$	operational dissatisfaction factor at a time "t"
$P^t_{PV,}$ $P^t_{wind,}$	power from PV and wind turbine
P^t_{DG}	power from DGs
P^t_{grid}	power from the main grid
λ^t_{PV}, $\lambda^t_{wind,}$	installation and maintenance cost of PV and wind turbine.
λ^t_{grid}	electric price from grid power
P^t_g	the total generated power at time "t"
$P^{max}_{L,}$ P^{avg}_L	maximum and average load demand in specific time "t"
T^t_{shift}, P^t_{shift}	the shiftable time and power at a specific time "t"
$T^{total}_{operation}$	the total operation time at a specific time "t"
$P^{total}_{operation}$	the total power demand at a specific time "t"
P^t_d	the total power demand needed at a time "t

CHAPTER I

INTRODUCTION

1.1 Background Introduction

The conventional power grid faces infrastructure aging and a considerable rise in power demand due to the increasing population worldwide. Most power companies desire to transform smart grid network technology to meet the fundamental requirement of the increase in electric demand. This system can permit a bulk power transmission network with flexible penetration of RE resources based on large-scale distributed generation and reliable power flow control capability. Power line engineers face the risks of power delivery capability and flexible expansion of traditional AC networks, such as controlling heavy and complex load flow analysis, voltage or frequency transient instability, and environmental impact in overhead and underground high voltage AC transmission (Pan et al., 2008).

A microgrid combines advanced electrical network infrastructure, where the fundamental component is the same as the existing network structure modified with advanced information and communication technology. Another significant revolution of network structure allows any generating resource (DGs) penetration at any voltage level into the power system network. The distributed resource (DG) size is available from kilowatts to megawatts capacity, generally connected at the distribution level network. Generally, DG is preferred to RE-based generation plants, such as wind, solar, and hydro. On the other hand, increasing RE resources at local networks may give rise to the system's energy security in the main grid and the distribution network (Costianu, Arghlra, Fagarasan, & St Iliescu, 2012).

Moreover, fast synchronization of the microgrid with the main grid back and black start capabilities must also handle a microgrid in islanded mode. The power balance and the controlling function were responsible for the utility grid in grid-connected mode. The microgrid system can regulate and optimize generation resources based on its economical operation criterion. Generally, local renewable generation is more financial resources than the main grid. In such a case, the objective is to extract the maximum power from RE resources. The microgrid is guaranteed to generate constant power output and act as a filter for the active power injection or absorption to the utility grid under the grid-connected operation (Rozinajová et al., 2018).

Forecasting is an essential and powerful tool in the microgrid environment to maintain the power system's supply-demand balancing. Exceedingly accurate, quick, reliable balance and specific forecasting results are vital in the power and individual energy management systems in microgrids, industrial, commercial, and residential areas. Various forecasting data can be available based on different time horizons, from more than a few hours to quite a few days ahead. Forecast demand can support the required information to evaluate unit commitment scheduling of generation capacities and demand requirements for the next day. Significantly, the scheduling scheme was assessed around midday before the next day. The scheduling of generating capacities and storage facilities can be optimized by forecasting PV output power and electricity demand. As a result, the fuel consumption of generators can be minimized.

Microgrid’s energy management system (EMS) monitors and controls the operational status of optimal economic dispatch power from the various energy resources to the controllable and critical loads. In the advanced interconnected system, the controllable loads can be dispatched to ensure reliability in the system. The EMS collected the load profiles and forecasted energy resource information, consumer preference, policy, and electricity market price to evaluate optimal power flow, energy price, load dispatch, and generation scheduling (Conejo & Carrion, 2006).

The objective of EMS in the microgrid is to optimize local generation for network connection and standalone operation conditions. The microgrid's management system mainly focuses on economic generation scheduling with load shedding or shifting from the demand side. The system voltage/ frequency control and supply/demand balancing were essential tasks under the island operation mode. Controllable generation sources in microgrids, such as fuel-based generation, fuel cells, or storage systems, were responsible for energy balancing by absorbing or injecting energy from the non-controllable renewable generation. Another task is to adjust the noncritical or controllable loads from the demand side at the system's unbalanced circumstance (Rozinajová et al., 2018).

1.2 Problem Statement

The penetration of many distributed generations (DGs) into the network has significantly impacted the electricity market (Vivekananthan, 2014). Moreover, a restructuring system can potentially bring new risk concerns with the system's reliabilities in the electricity market and the network. Supply/demand balancing and voltage/frequency profiles must be maintained below the threshold level in the distribution level (Khoa, Dos Santos, Sechilariu, & Locment, 2016). The optimization from the network operator standpoint was to ensure the serving capacity of the lines, the stable margin of the voltage profiles, and balance the network power flows, security, quality, and reliability (Arias, Rivas, Santamaria, & Hernandez, 2018). The unpredictable nature of renewable generation and unstable demand characteristics caused bus voltage fluctuation. Demand growth in the main grid often led to stringent operating circumstances. In the meantime, available power generation overflowing or underflowing negatively impacted system operation and gave the stress back to the whole system. Another risk concern with microgrid EMS is the increased use of controllable loads; it increases load forecasting accuracy. PHEVs/PEVs can be integrated into the grids at any charging location and at any time, giving rise to uncertain load forecasting. Multiple charging of EV loads onto signal feeder at peak time will bring transformer overload (Conejo & Carrion, 2006). The factors concerned with the nature of various types of renewable generation and robust energy management systems have gradually become a significant problem in autonomous microgrids (Shi, Liang, Huang, & Dinavahi, 2019).

Recently, the concepts of microgrid planning addressed the economic feasibility and substantial stability issues. It is a complex process due to existing system constraints and uncertainties. The planning process goals usually conflict, and optimization problems accompany the planning process. Technical and environmental constraints and uncertainties are vital parameters to consider in planning. All decision factors considered in the planning stage can influence the system's capability in the competitive energy market. In general, the microgrid planning process is created with particular objective functions and constraints, and this is a vital source of risks necessary to avoid or control before decision-making (Gamarra & Guerrero, 2015).

With the increase of renewable energy source generation and nonlinear loads causing the voltage to fluctuate in the power system, supply-demand balancing becomes unstable. The building process may be termed energy management, the process of monitoring, controlling, and conserving energy in an organization. In a microgrid where the consumers can generate local energy from several distributive generation units, and there is plenty of space for different pricing schemes, many researchers have pointed out the need for energy management programs (Nguyen et al., 2020).

Traditional load shedding processes, under-voltage and under-frequency load shedding, and breakers' interlocking are generally carried out based on the magnitude of voltage and frequency variation. It did not consider individual loads' priority or evaluate the correct load value needed to be shed (Khoa et al., 2016). In this scenario, this traditional process created unwanted conditions, such as excessive and unnecessary load reduction in the system (Shokooh et al., 2005). In this regard, demand-side management can also reduce CO_2 emissions and power system reliabilities and minimize total energy costs for end-users. The conventional grid cannot be a demand-side management method on the utility side due to the lack of efficient communication structure, automation tools, and sensor technologies. In an advanced microgrid environment, modern information and communication technology gives opportunities for energy management programs (Costianu et al., 2012).

1.3 Significance of the Study

This research provides significant benefits and outcomes for the microgrid operator and the microgrid's consumer perspectives to minimize operation cost and peak-to-average ratio to support the network's cost-effective energy demand balance conditions. This work is unique from the previous methods due to considering the cost benefits to the microgrid grid operator and customer perspectives with minimum dissatisfaction—the optimal generation scheduling algorithm with the forecasting technique developed in the first phase of this research. The monthly uncertainties of power consumption and RE generation variation are considered in this work. This fact is realized in the microgrid's EMS implementation process. The proposed algorithm developed to set up the DR option is the final phase of this work. The DR program can be implemented efficiently with the incentive-based DR option. This EMS framework considers the perspectives of the end-user and the grid operator during decision-making for load shifting/shedding. This system also provides an electricity cost-benefit to actively participate end-users by changing or reducing the appliance usage pattern allowable time frame.

1.4 Research objectives

This research aims to produce an optimal microgrid energy management model considering the demand response and monthly uncertainties of RE generation and demand in Thailand. Specific research objectives are set as follows:

(1) To estimate solar power, wind power, and demand forecasting in the microgrid distribution network using the autoregressive moving average (ARMA) method, deep-learning method, and employ advanced forecasting techniques in energy management system;

(2) To implement the optimal energy management system considering operation cost minimization, peak load minimization, end-user satisfaction, and demand response program;

(3) To test the performance of the proposed system on an IEEE 34 node system and Nakhon Ratchasima distribution system.

1.5 Scope and limitation of the study

The decentralized microgrid energy management system with demand response is implemented with generation and demand forecasting to minimize operating costs and peak-to-average ratio. This work emphasizes the optimal energy management system to benefit the grid operator and consumers who participate actively in the electricity mart by responding to hourly demand information provided by microgrid operators. Exceedingly accurate, quick, reliable balance and specific forecasting results are vital in the power and individual energy management systems in microgrids, industrial, commercial, and residential buildings. The day-ahead forecast technique, short-term forecasting, is an essential and powerful tool in the advanced microgrid environment to maintain the power system's supply-demand balancing. An hour ahead and a few hours ahead of forecasting the demand are also essential for the network economic load dispatching control. The scheduling of generating capacities and storage facilities can be optimized by forecasting PV output power and electricity demand. This study implemented the application of a statically base ARMA forecasting method to predict medium-term RE generation and demand forecasting and an artificial neural network-based deep-learning model (Gate-recurrent unit (GRU), long-short term model (LSTM)) to predict day-ahead forecasting. The day-ahead forecasted hourly data is applied to this study's energy management system

CHAPTER II

LITERATURE REVIEWS

2.1 Smart Management and Control System

Smart management and control systems improve electricity use, balance supply and demand, control greenhouse gas emissions, reduce electric bills, and maximize utility profit. The smart management and control system provides advanced load management techniques and control facilities. The fundamental functions are to provide an efficient and reliable control structure, secure data collection, and two-way data transmission with supportive sensing. Huge data collection is carried out by an extensive collection of smart meters (SMs) or sensors to sense the actual grid status at every location through the network in real time. Two-way transmission links deliver sensor information signals to the control centers and vice versa. The control function typically provides data from smart meters, sensors, and control devices located at all places of the network to grid components and vice versa. Therefore, to reliably perform the critical function of smart grid communication infrastructure. The basic architecture must have integration of enabling networking technologies, home area networks (HANs), business area networks (BANs), neighborhood area networks (NANs), data centers, and substation automation (SA) integration systems (Costianu et al., 2012).

The Day-ahead forecast technique is an essential and powerful tool in the smart grid environment to maintain the power system's supply-demand balancing and smart protection system. Exceedingly accurate, quick, reliable balance and specific forecasting results are vital in the power and individual energy management systems in the microgrid, industrial, commercial, and residential buildings. Various forecasting data can be available based on different time horizons, from more than a few hours to quite a few days ahead. Day-ahead forecast demand can support the required information to evaluate unit commitment scheduling of generation capacities and demand requirements for the next day. Significantly, the scheduling scheme is assessed around midday before the next day. The unit commitment and scheduling process of electricity markets must be employed approximately 36 hours ahead of forecasted information. A few hours ahead of demand forecasting, ultra-short-term is also essential for the network economic load dispatching. The operation time scheduling of generating capacities and storage facilities can be optimized by forecasting PV output power and electricity demand forecasting. As a result, the fuel consumption of generators can be minimized.

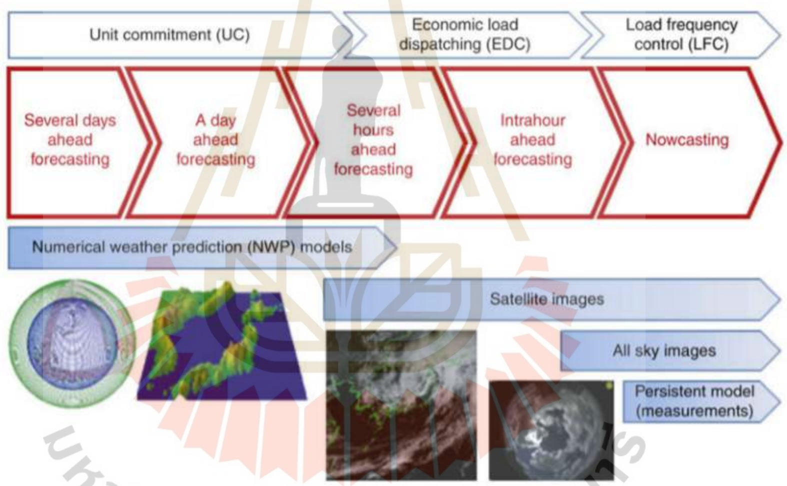


Figure 2.1 Various Forecasting methods for smart grid environment (Borghetti & Nucci, 2016)

For instance, the motion of clouds along a PV project ground can suddenly cause an increase or decrease in solar irradiance, namely ramp events. A few hours ahead, forecasting the ramp rate and width is essential for the solar project to diminish the consequences of ramp events. Different forecasting methods are employed in the smart environment for unit commitment, economic load dispatch, and load frequency control purposes. According to essential forecasting techniques in the whole network or individual system operations, several days ahead forecasting, day ahead forecasting, several hours ahead forecasting, intra-hour ahead forecasting, and nowcasting have been investigated in recent years. Available resources technology is numerical weather prediction (NWP) models, satellite images, all-sky images, and PV power output measurement (Borghetti & Nucci, 2016).

With the increase of renewable energy source generation and nonlinear loads causing voltage fluctuation in the power system, supply-demand balancing becomes unstable. Energy management monitors and controls the organization's building system to transform efficient energy-conserving forms. In a smart grid environment, the prosumers can generate energy locally from several available distributive generation resources, and there is plenty of space for different pricing schemes. In this regard, many researchers have pointed out the essential of energy management programs in the advanced power system.

Demand-side management can also support reducing CO_2 emissions, power system reliabilities, and minimizing total energy costs for end-users. The conventional grid cannot be a demand-side management method on the utility side due to the lack of efficient communication structure, automation tools, and sensor technologies. In a smart grid environment, smart meters and modern information and communication technology can give opportunities for home energy management programs. HEM application can control domestic energy usage by scheduling the domestic load from peak to off-peak intervals. Once the end-user switches on their appliance, a data signal is instantaneously sent to the energy management unit (EMU) system. The EMU system is then delivered to the smart meter and local generation units to get the hourly price information from the utility and the available local energy resources. EMU can schedule the end-user appliance's starting and shifting time based on this hourly price information. The appliance waiting time is evaluated by the difference between the allowable time resigned by EMU and the consumer request start time. Consumer-side

HEM generally uses home area networks (HAN) for load forecasting, energy management systems, and smart meter communication. Generally, HAN technology is based on a command-based system and link-based system communication (Costianu et al., 2012).

2.2 Microgrid System Architecture

The microgrid is an intelligent system with self-control, protection, and management in the local network. The operation mode of such a system can connect or disconnect with the bulk power system. The system's main task is the flexible and efficient integration of distributed energy resources, especially for connecting many RE resources. The conventional power network is inflexible to integrated DGs, lacks self-healing, system recovery ultimately depends on entities, and cannot get advanced communication. Therefore, such a system imperfection cannot bring to perform automation system in the conventional network. According to Fig 2.2, a microgrid energy management system mainly works for grid-connected or disconnected distribution networks, and local distributed generation and responsive load are featured in advanced microgrids. Generally, demand response resources mainly depend on the different types of loads on the demand side. Demand response resources in the smart microgrid system include managing the demand side loads and DG power generation. The end-user's load can be mainly categorized into adjustable load, shiftable load, controllable or uncontrollable load, and electric vehicle. The distributed generation includes photovoltaic solar power, wind turbine, and distributed energy storage (Y. Wang et al., 2018).

2.3 Advantages of Microgrids

Microgrids have potential advantages over existing power networks: Reduced losses, reliability, environmental benefits, and energy independence.

In the traditional main grid, power generation is often far away from the demand side, and power is transferred for long transmission lines that may cause power losses in the lines. The total power losses from the transmission and distribution systems were approximately 4%–5%. In a microgrid, the power generation is generally located near the load center. Therefore, reducing the line distance required to transport power can significantly reduce power losses in the entire network.

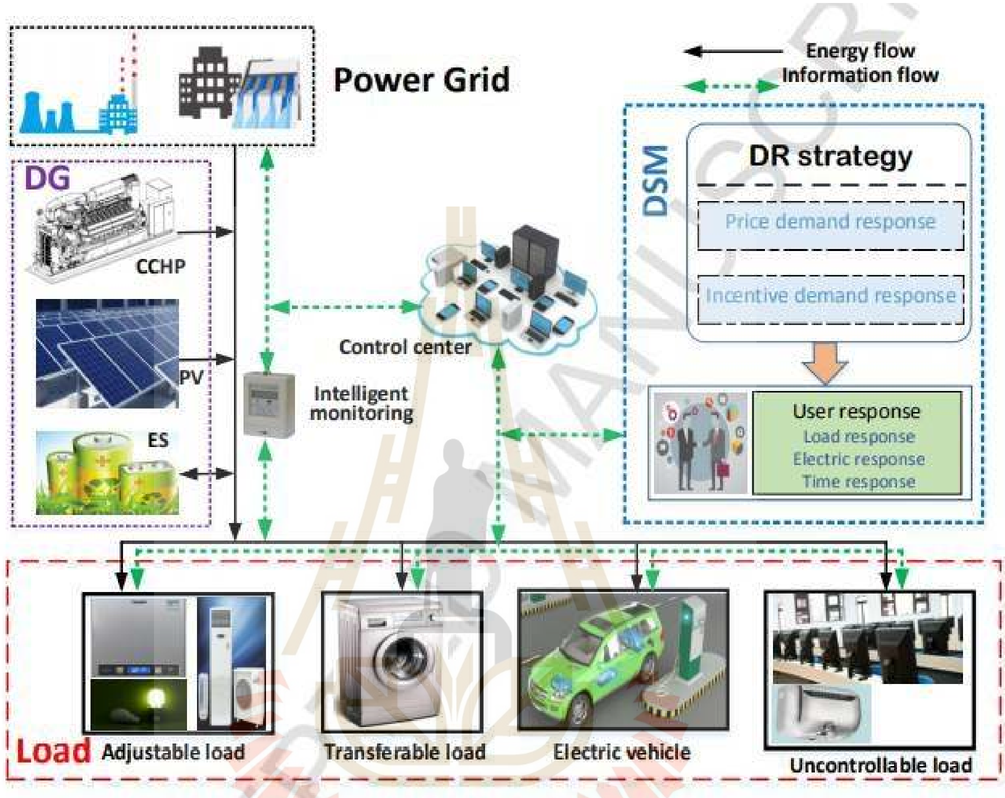


Figure 2.2 Structural diagram of a typical Demand Response smart micro-grid (Wang et al., 2018)

This is because the microgrids have their generation resources and are independent of the main network. It can ensure continuous operation during a blackout or shortage in the main grid. Therefore, microgrid has been interested in recent years to improve system reliability. Usually, most microgrid generation resources are renewable energy-based generation sources. The microgrids can change either grid-connected or islanded mode operation, which creates the event to use more locally generated and reduce the critical power from the grid when it is unavailable. This system can provide a higher integration of renewable DG than in the existing network. Therefore, it can minimize carbon emissions and environmental benefits.

High penetration of DG and energy storage becomes more reliable and independent from the main grid in energy requirement. In the future, well-designed DG penetration could be effectively operated on the entire energy industry. This system will reduce the influence of large electricity companies in the electricity market and create a significant electricity market share as the business models established years ago (Y. Wang et al., 2018).

2.4 Demand Side Management

Energy demand varies by time series and depends on the year's season. The power flow in the smart grid environment has been changed into bi-directional power transfer. Therefore, the customer can generate electricity to reduce power demand and transfer excess power to the grid to increase the grid capacity. DSM technologies also allow them to use local storage capacity during peak times. In such a case, the DSM concept can support the load ability that does not need to reduce total demand. Generally, demand-side management effectively manages load utilization to match the available hourly supply rather than filling the hourly consumer demand. Demand response and energy efficiency are the two main concepts of DSM. While energy efficiency reduces a certain amount of demand for all time, demand response manages the total demand level during the on-site interval. This concept changes consumers' power usage behavior or cuts a specific demand in a particular time interval to balance production suppliers and consumers. Currently, the industrial sector mainly applies DR to minimize overall power consumption. Therefore, DR is a simple model that reduces overall power consumption in a short time interval. DSM can persuade consumers to limit their usage through an energy consumption scheduler (ECS) unit inside a smart meter to make the demand curve flatten a particular house (Hayes, 2017).

2.5 Advantages of demand-side management

Demand-side management (DSM) plays a significant role in developing the power industry, energy planning, and environmental protection. It can bring benefits to the power market: the efficient electricity market environment and restrain the market power, the realized information exchange the status of supply and demand, and accelerated the formation mechanism for electricity price information sharing, the effective mitigation of demand growth at peak hours and elevating the system reliability, significantly reduce the capital investment on generation sides, and also mitigate transmission, and distribution upgrading, facilitate the new aspects of energy conservation and reduction of CO_2 emissions (Li, Chiu, & Sun, 2017).

2.6 Demand Response

Demand Response (DR) is the economic benefits concept to interact with end-user. It also provides the potential benefits for reliability improvement and electricity market development. It can reduce the capital investment required for generation plant upgrading. The positive impact of load shedding, which can restore the acceptable system reliability level, is significantly initiated by the insufficient available power from generation resources by load reduction from the end-user side (Li et al., 2017). Real-time market or day-ahead prices and market mechanisms are the basic requirements for demand response implementation in the power market. Using demand response in the system provides economic benefits and ensures energy efficiency and storage. The demand response program can typically offer six services in the system, as shown in Fig 2.3. The peak clipping, valley filling, and load shifting approaches were used for load management in the system, and the last three were used to change the load shape in the system. Therefore, the changing shape depended on customers' willingness to participate and the nature of the demand side (Li et al., 2017).

2.6.1 Peak Clipping

Peak clipping reduces or clips the total demand below the threshold level based on the transmission system supply capacity. Although this can be implemented in the industrial, commercial, and accommodation sectors, it can be more effectively implemented in the accommodation environment by directly controlling the load. This service can significantly help the system by avoiding stress during peak hours. On the other hand, this can create customer dissatisfaction due to load curtailment.

2.6.2 Valley Filling

Valley filling increases demand during off-peak hours, potentially causing system instability. The more applicable method for this service in the system is the application of storage devices, such as energy storage and plug-in electric vehicles. This is forced to increase the total power consumption of customers at off-peak hours. This may not significantly increase electric billing.

2.6.3 Load Shifting

Load shifting is forced to change particular loads from peak to valley time when total consumption exceeds the specific level. Since this strategy offered to change the time of use rather than force to reduce the total consumption, it does not violate customer satisfaction.

2.6.4 Strategic Conservation

This conservation encourages reducing demand to improve energy efficiency when the total load exceeds the supply capacity. This work can be implemented by replacing traditional devices with energy-efficient apparatuses. The consumption and cost of information support can persuade customers to reduce power demand.

2.6.5 Strategic Load Building

The load-building strategy is encouraged to pull up overall demand when the total demand is lower than the usual supply level. This work can be done using energy storage services (Li et al., 2017).

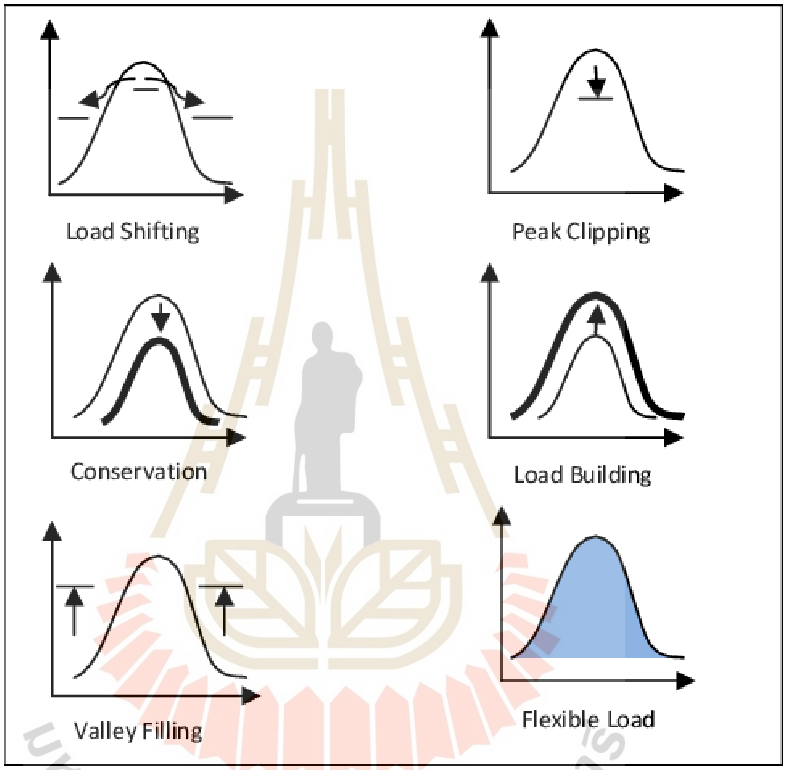


Figure 2.3 Six types of demand-side management (Li et al., 2017)

The load shifting and peak shaving are generally actions from the demand side, and they can significantly impact the whole system context under stringent operating conditions. The function of load shifting is to remove the load from the peak interval to off-peak time intervals to mitigate system stress and reduce end-user power costs. The high energy price usually occurs during peak load hours due to the expensive generation startup to meet system demand. Therefore, peak shifting can reduce energy consumption at peak hours. The viewpoint of energy management is to minimize system operation costs by replacing more expensive energy production with cheaper production (Mortaji, Ow, Moghavvemi, & Almurib, 2017).

An adaptive under-frequency load shedding UFLS method can reduce the possible outage. This analysis considers daily load profiles of different loads to evaluate the amount of load to be shed. Moreover, the dynamic characteristics of the load aggregator and daily load profiles of various load types were considered (Dietrich, Latorre, Olmos, & Ramos, 2011). Demand-side management is a balancing tool for supply and demand using game theory to reduce the peak-to-average ratio and save consumer costs. The storage system with rooftop PV power was used as an energy source at the load-shedding interval (Horri & Roudsari, 2020).

2.7 Classification of Demand Response

The consumer DR participation manner can be categorized into three types. Firstly, the end-user's power demands to reduce during high price or peak demand but do not need to minimize action at regular periods. However, this strategy can be possible to give the temporary loss of a comfortable lifestyle. In the second type, end-users respond to shifting their power usage pattern from the spike demand period to the valley time. This approach would not violate domestic customer satisfaction.

Still, it is difficult for the industrial consumer to reschedule the production line again, negatively impacting manufacturing services. Third, some customers would respond to load reduction using small-scale own-generation resources, especially renewable energy resources. In this case, consumers do not need to change their electricity usage pattern very much, and total power demand will also be significantly minimized at a particular time (Noor et al., 2018). There are two types of DR frameworks for consumer persuasion: price-based DR and incentive-based DR offered to end-users. The price-based DR program aims to reduce energy demand or change usage patterns by offering time-varying dynamic electricity prices under high wholesale prices. The incentive-based DR is to pay a particular amount of financial to customers, who curtail or shift some of the electric loads at times of high demand (Albadi & El-Saadany, 2008).

Price-based DR has been offered fluctuating electricity prices to end-users under the dynamic time-varying scheme: time-of-use pricing (TOU), critical and extreme day CPP (CPP & ED-CPP), excessive day pricing, and real-time pricing (RTP). Demand response with CPP, ED-CPP, or EDP was to minimize the peak load at a specific or emergency period. TOU pricing is adjusting electricity usage patterns based on different time price signals. The RTP program is also an effective time-shifting method to export unimportant loads to the hour of valley demand (Ahmadi, Charwand, & Aghaei, 2013). However, it is not easy to persuade customers in the long term to shift or curtail hourly or daily (Zhong, Xie, & Xia, 2012).

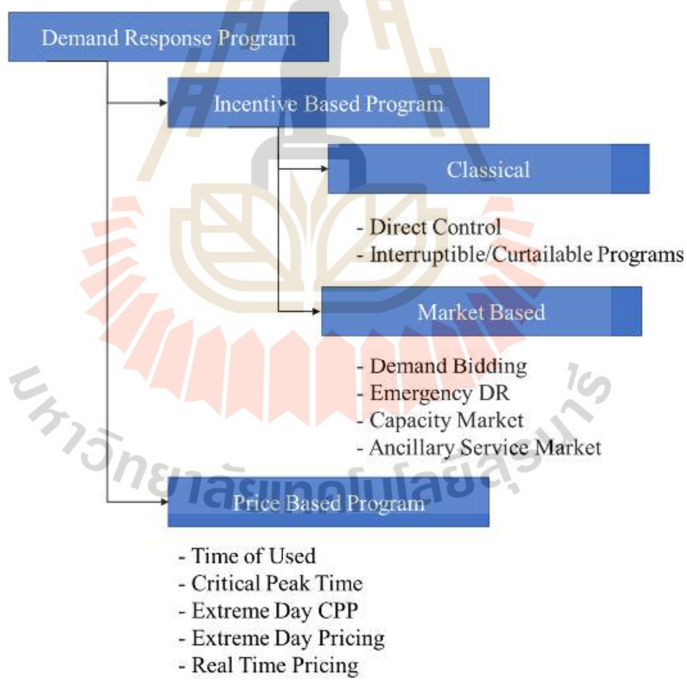


Figure 2.4 Classification of Demand Response (Albadi & El-Saadany, 2008)

The incentive-based program can be classified into classical and market-based programs, as shown in Fig. 2.4. Both offer rewards, financial payments, or discount credit payments to the customers depending on the amount of DR participation during a particular time. According to the utility side notification, direct Load Control and Interruptible/Curtailable programs cut the load at a specific amount and time interval. Such programs were more suitable for domestic or small business customers. In such a program, however, participators must be paid a penalty payment for contract omission. In demand bidding programs, the consumer must curtail their loads until a specified amount for bidding. In emergency DR and capacity market programs, participants must be responsible for load reduction with a specific amount. The consumers will also receive financial rewards according to the participation amount in emergencies or contingencies. The ancillary services market is concerned with end-user-level demand bidding in the market. These incentive programs are day-ahead notifications (Albadi & El-Saadany, 2008).

The price-based time-varying program was non-dispatchable and reduced flexibility for the operator side. This will sometimes impose a spike in power selling prices on the customers, adversely impacting such programs. In this fact, incentive-based DR programs offer a dispatchable and more flexible contribution to the operator. However, some investigations highlight that consumers are less willing to participate in DR programs because of the inconvenience of load interruption during a particular period and dissatisfaction with the mandatory daily power cutting (Yu, Hong, & Kim, 2016). Therefore, the time for load reduction in the entire horizon should be set as a feasible option for several network consumers. According to the theoretical investigation, the price-based time-varying option still has some challenges to become widely deployed. Incentive-based DR programs have also been proposed to reduce peak load by offering a financial reward (Yu et al., 2016).

2.8 Energy Management System

The Energy management system monitors the operational status of various energy resources under optimal economic dispatch power and controls the controllable and critical loads. In the advanced interconnected system, the controllable loads can be dispatched to improve system reliability. EMS collects the load profiles and forecasts energy resources, consumer preference, energy policy, and electricity market price. Afterward, optimal power flow, energy price, load dispatch, and generation scheduling were implemented (Conejo & Carrion, 2006).

2.8.1 Centralized Microgrid EMS

The centralized EMS has three control levels: distribution network operator (DNO) and market operator (MO); microgrid central controller (MGCC); and local controllers (LCs) associated with energy resources and load units. At the operator level, the market operator exchanged information between the microgrid and the electricity market. The distribution network operator managed the real-time and operating commands from the multiple microgrids and main grids. In the second level, the microgrid central controller is responsible for an information and control center gateway between the operator and local controllers to get information from utility requirements and the energy market. The MGCC can update the system operational status, handle system disturbance, switch, and resynchronize the microgrid with the primary grid. Another essential task concern with MGCC is scheduling energy output from all resources based on information from load aggregators, particular objective functions, and system constraints. The centralized MGCC operation is a powerful computational mechanism to handle real-time signals from all resources and loads. Although MGCC design is easy implementation, standardized procedure, high expansion cost, high communication capacity, and fast computational ability become drawbacks due to the increment of control devices in the system (Su & Wang, 2012).

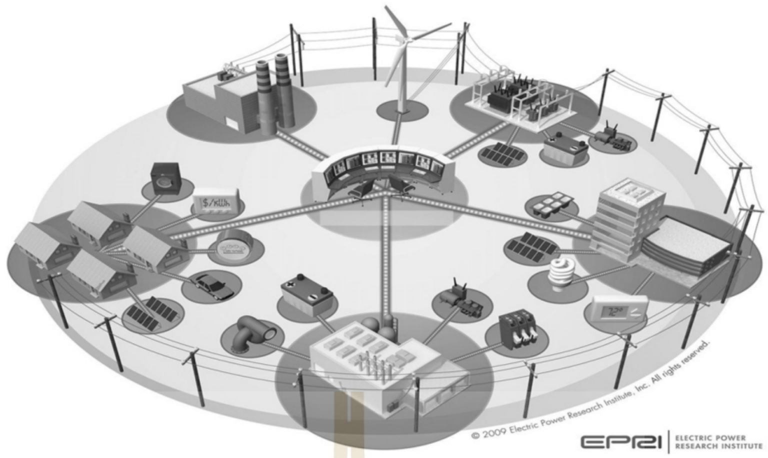


Figure 2.5 Centralized microgrid EMS (Su & Wang, 2012)

2.8.2 Decentralized Microgrid EMS

In decentralized control, autonomous intelligence and several local controllers monitor every component in the interconnected system. Fig. 1.6 shows the architecture of a decentralized control scheme. Because the local controllers only need decision-making and communication locally, the communication congestion and computational burden are significantly less than centralized EMS. In this scheme, local controllers must not determine the optimal power output in such a distributed system. Therefore, this design significantly reduces the computational power requirement in the entire microgrid. Due to the local controllers having local authority, it is challenging to detect and troubleshoot security issues. A highly dependent and smooth communication infrastructure is the drawback of this system (Su & Wang, 2012).

A new control aspect of decentralized EMS for the distributed microgrid operation is shown in Fig 2.6. The primary control is for reliable function of frequency and voltage below the set points when communication fails. The secondary control controls the voltage and frequency deviations for the entire system. The third is to perform optimization to get cost-effective energy scheduling. The control process is performed locally (De Brabandere et al., 2007).

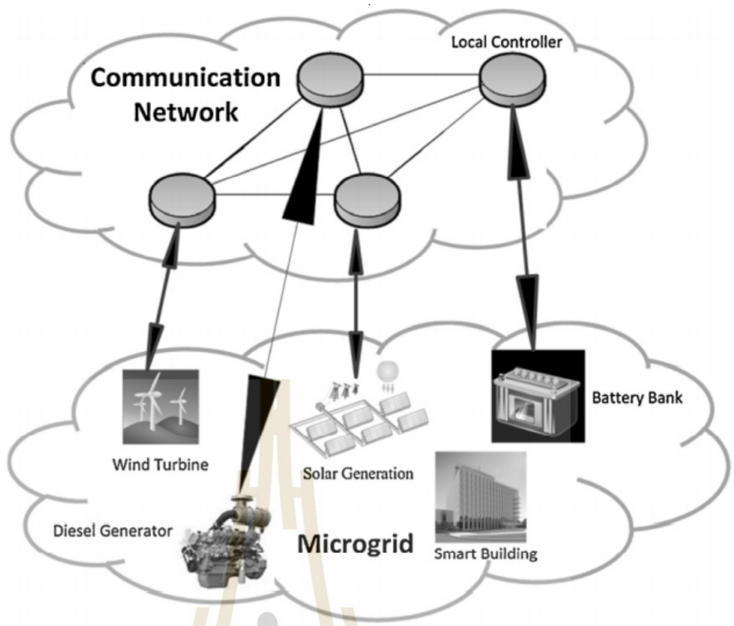


Figure 2.6 Decentralized Microgrid EMS (Su & Wang, 2012)

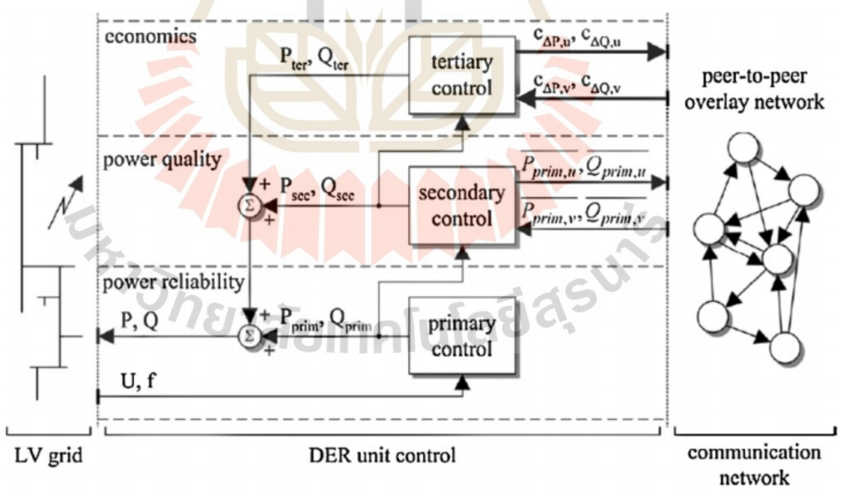


Figure 2.7 Overview of overall decentralized EMS (De Brabandere et al., 2007)

The objective of EMS in the microgrid is to ensure local generation optimization for both modes of operation. The microgrid management system was mainly focused on economic generation scheduling with demand-side management. The system voltage and frequency control and supply and demand balancing were essential tasks under the island operation mode. Controllable generation sources in microgrids such as fuel-based generation, fuel cells, or storage systems were responsible for energy balancing by power absorption or injection from the non-controllable renewable generation and local loads. The energy management system is also responsible for adjusting the noncritical loads under imbalance in the microgrid.

Moreover, fast synchronization of the microgrid with the main grid back and black start capabilities must also handle a microgrid in islanded mode. The power balance and the controlling function were responsible for the utility grid in grid-connected mode. The microgrid system can regulate and optimize generation resources based on its economical operation criterion. Generally, local renewable generation has more financial resources than the utility grid. In such a case, the objective is to extract the maximum power from RE-based resources. On the basic, the microgrid was guaranteed to generate to evaluate power output and act as a filter for the active power injection or absorption to the utility grid under the grid-connected operation (Rozinajová et al., 2018).

2.9 Unit Commitment (UC) and Economic Dispatch (ED)

Unit commitment is the evaluation of minimum generation cost from different generations to support the energy needed quickly and to satisfy system constraints. The results from UC control provide the decision of generation plants' startup/shutdown and support the total production capacity of all generation units economically in the power network in individual operation hours. This optimization problem minimizes operational costs for every generation unit over every hourly horizontal. The constraints related to generation scheduling consider the power balance constraint, spinning reserve, and generation capacity limitation (Logenthiran & Srinivasan, 2009). Coordinate interconnected loads with Distributed Energy Resources (DERs) in the system and act as a centralized or decentralized controlling entity concerning the utility grid. The Energy Management System (EMS) in the microgrid takes action to ensure microgrids' reliable and economical operation. The generation scheduling and dispatching operation system maintains reliable power reserve levels, mitigates the uncertain nature of renewable resources, and introduces demand response (DR) action at the demand side management. The two concepts of centralized EMS were based on Unit Commitment (UC) and Optimal power flow (OPF) models. Unit Commitment (UC) based energy management system (EMS) takes into account the network constraints and operational constraints concerned with distributed energy resources; optimal power flow (OPF) based EMS considers the optimal network flows (Solanki, Raghurajan, Bhattacharya, & Canizares, 2015).

Unit Commitment (UC) and Economic Dispatch (ED) are the microgrid's two main functions of generation scheduling. Unit commitment is the optimization problem of scheduling the operation and compensation of the generation from available generation resources in the microgrid daily to weekly based on the generator and system constraints. Many different generation technologies in the system can exponentially increase the UC problem. Optimization of generation scheduling becomes the central management function performed to meet forecast demand and spinning reserve under minimum operating cost in a short time (Logenthiran & Srinivasan, 2009). The UC optimization is to solve the unit-scheduled problem and economic dispatch (ED) problem. The constraints for the unit-scheduling optimization problem usually consider the system capacity requirements, generation limits, and the constraints on the startup and shutdown of the scheduled units. System demand and spinning reserves must be considered for optimal generation dispatch problems for every interval (Yong, Zhi-Jian, & Chuan-Wen, 2005).

With improved communication infrastructure in the microgrid community, smart demand response, load shedding, load shifting, and restoration have also become the options to ensure supply/demand balancing based on customers' willingness to participate. Load shedding restores the total loads needed to shed and recovers the power supply according to appliance operating characteristics. The traditional load-shedding processes are under-voltage, under-frequency load shedding, and breakers interlocking based on the voltage and frequency variation magnitude. The conventional system did not require considering individual load priority and did not need to evaluate the correct load-shedding value (Khoa et al., 2016). In this scenario, the conventional method has the drawback of excessive or unnecessary load reduction problems in the system.

Moreover, the volatile nature of renewable generation and demand growth are drawbacks to bus voltage fluctuation. Demand growth in the system often led to stringent operating circumstances. In the meantime, the issues of available power generation can affect appliances' operation and cause stress to the whole system (Shokooh et al., 2005).

2.10 Microgrid Energy Management System

EMS controls a cluster of different resources and responsive loads as a single entity from the upstream generation system, allowing full use of RE's generation capacity while minimizing operation costs and pollution (Moradi, Esfahanian, Abtahi, & Zilouchian, 2018). The microgrid usually consists of different types of distributed generation, such as dispatchable and non-dispatchable generation. Dispatchable units include diesel engines (DEs), microturbines (MTs), and fuel cells (FCs), while non-dispatchable sources consist of wind turbines (WTs) and photovoltaic cells (PVs) (Li, et al., 2019). It is challenging to schedule a microgrid effectively under the volatility of non-dispatchable sources.

The integration of distributed generation (DG) enhanced the performance of distribution systems, such as reducing power losses, improving system reliability, economical operation, and reducing pollution. On the other hand, the high penetration of intermittent DGs raises the challenge of modern power systems, such as voltage exceeding, network congestion, and the randomness of DG power supply (C. Wang et al., 2016). The energy management system (EMS) performs optimal dispatch resource management upstream, dealing with REs uncertainty and demand response and increasing REs penetration with high profit. The effectiveness of an advanced microgrid system is that the structure provides a local distribution system in which the uncertainty from RE resources can adequately be captured by load pattern change, namely demand response (DR) (Lu, Cheng, & Carli, 2021). Demand response (DR) has been considered in the scheduling problem, operating the existence of RE uncertainty to respond to the variation of RE. The idea of flexibilities DR participants tracked the uncertainty problem of RE resources and energy reserve. Generation scheduling with flexible DR is an effective structure for hosting a high penetration of RE resources in the distribution system (Du et al., 2021).

2.11 Microgrid active distribution network

Emerging in the electricity market with advanced communication technologies, consumers have become active in optimizing energy usage. Furthermore, local generation scheduling and EMS systems become the solution for smart microgrid operations to reduce financial losses. It will also be flexible to extend RE-based distributed generation integration locally (Essayeh, El-Fenni, & Dahmouni, 2016). The microgrid system can regulate and optimize generation resources based on its economical operation criterion. Generally, local renewable generation is a more economical resource than the utility grid. In such a case, the objective is to extract the maximum power from RE-based resources. The active distribution network was created to guarantee the generation of constant power output and filter the active power export and import with the utility grid under the grid-connected operation.

This microgrid system combines fuel-based conventional generators and renewable-based generation from the supply side with demand response on the demand side. The energy trading scheme back to the grid is an option in the advanced system, whereas local generation can be sold to the local demand side and the main grid. When the local generation capacity is insufficient, the utility grid imports the energy to this distribution system in grid-connected mode. Microgrid aims to maximize

RE-based generation utilization to minimize both operation modes' fuel cost consumption (Mokryani, 2015).

2.12 Techniques for uncertainty issues

Accurately predicting upcoming demand and RE generation is the prerequisite information to construct a model of an efficient energy management structure. Many research articles highlight that the uncertainty of parameters accompanies the predicting error (Yang et al., 2021). The nature of uncertainty in forecasting wind and PV generation considerably impacts the scheduling decision. In recent years, many research works have focused on improving forecast methodology with less error (Tan et al., 2020).

According to research articles, physical methods, mathematical methods, machine learning, and hybrid methods are the available tools for forecasting. The above work mainly highlights the impact of wind or PV generation forecast errors on system stability issues. There is little consideration of analyzing the comprehensive forecasting errors of all available renewable resources on the microgrid dispatching system (Hajiamoosha, Rastgou, Bahramara, & Bagher Sadati, 2021). On the other hand, the favored methods applied in the model to analyze the uncertainties are Monte-Carlo simulation (MCS), point estimation method (PEM), scenario analysis, and risk-averse analysis (Hajiamoosha et al., 2021). Currently, four methods are mainly used for power systems and microgrid dispatch systems based on uncertain renewable power characteristics: fuzzy method, stochastic method, robust optimization methods, and interval optimization methods (Mokryani, 2015).

2.12.1 The stochastic method

The existing research article discussed the need to use a method to capture the nature of uncertainty, mainly with stochastic, probabilistic, and robust planning. The stochastic approach is the most utilized technique in distribution network planning (Mokryani, 2015). The scenario generation represented a discrete distribution model from the continuous probability density distribution function. The probability density distribution function with fewer scenarios cannot guarantee the secure complex optimization problem in the scenario generation method (Tabar, Jirdehi, & Hemmati, 2017). This is the multiple scenarios generation method to obtain the optimal solution, and this method takes high computational time to identify the probability distribution function (PDF) of uncertainty problems (Z. Yang et al., 2021). The wind/PV sources and demand are considered uncertainty parameters and probabilistic methods for handling microgrid uncertainty problems (Nikmehr & Najafi Ravadanegh, 2016). The predicted wind, solar irradiance, and load profile uncertainty are generally solved by the predictive control (MPC) approach (Saez et al., 2015). This work presented stochastic EMS formulations to address uncertainty issues. These formulations determined the necessary reserves of the microgrid to avoid arbitrarily fixing these reserves a-priory (Saez et al., 2015).

The advantage of stochastic programming is that this method does not require accurate forecasting parameters and is based on probability distribution. Therefore, this method suits conditions with unknown parameters and hardly predictable circumstances (Tostado-Véliz, Rezaee Jordehi, Icaza, Mansouri, & Jurado, 2023). In the stochastic method, uncertainties are presented as probabilistic distributed stochastic variables. Their probabilistic distributions are usually assumed as certain standard probabilistic density functions. For instance, Weibull and Beta distribution are well-known probability density functions that attempt to describe wind and PV uncertainties. of wind speed and solar irradiance.

2.12.2 The fuzzy method

The fuzzy variable and fuzzy memberships are represented for uncertainty parameters to establish a fuzzy dispatch model. The fuzzy method provided an optimal solid solution from the system dispatcher's specified memberships function (Mokryani, 2015).

2.12.3 The robust optimization method

Some articles propose the achievement of a mathematics-based and evolutionary algorithms robust optimization method with less computation time for uncertainties problems. This work observes that although the executability of robust modeling has an advantage on linear problems, achieving the guaranteed result on non-linear problems is challenging (Mokryani, 2015). Robust optimization has become a popular method to solve scheduling problems with uncertainty in the power system. Robust optimization evaluates the optimal solution under the worst-case scenario with less computation time. However, the application of robust optimization has limitations due to the low probability of a worst-case scenario. The robust optimization is a non-probabilistic model that models uncertainty based on the expected value and predicted intervals. Although the robust optimization method is efficient for solving the minimization problem, it has difficulty for the min-max dual optimization problem due to interval numbers. The main drawback is that this method never optimizes the problem in the worst scenario (Tostado-Véliz et al., 2023). To overcome the problem of complexity methods in the operation of MGs, robust optimization is investigated to achieve a simple way to solve the characteristic of uncertainty problems (Wang et al., 2017). This work highlights the advantage of robust multi-objective optimization for microgrid scheduling. The results show that the proposed method does not necessarily generate the scenario probabilistic function and experiential information.

2.12.4 The interval optimization method

Interval optimization has recently been introduced to overcome the limitation of a robust method. This method finds an optimal minimization solution to address uncertainties concerning specific objective functions' upper and lower bounds (Li et al., 2019). The work in (Khalili, Nojavan, & Zare, 2019) analyzed quality prediction of electricity prices under uncertainty. It presented the outcome of the expected interval to construct a preassigned probability of future electricity prices. Predicting the volatile interval is more suitable than the specified exact stochastic distribution for optimal unit commitment in practical operation. Interval prediction is helpful in power systems, such as load flow with uncertain demand, electric energy markets, and boundary analysis for reliability and economic assessment in distribution systems. The limitations of accurate interval forecasting are the difficulty of estimating the forecasted interval and the distribution variance. Due to the volatility of the predicted parameter, it is challenging to represent the parameter with traditional linear time series models. The estimation of distribution is commonly based on the assumed analysis because of unknown parameters. Although the variance is essential in interval prediction, it is challenging to predict due to time-varying. From the above mentions, interval optimization is usually applied for a single optimization problem due to its complexity. However, the microgrid optimization problem usually comes with simultaneous operation multiple criteria problems, such as reduced operation cost, satisfactory levels, power quality, and system security (Jun Hua, Zhao Yang, Zhao, & Kit Po, 2008).

2.13 The Advanced Forecasting Techniques

With the emergence of advanced artificial neural networks, solar irradiance, and wind speed can be forecasted from several minutes to several days ahead, depending on the requirement of the application over the time horizon. Forecasting several minutes to days ahead is essential for system operation optimization and electricity market participation. Therefore, RES forecasting has become a target for an advanced system operation, and appropriate forecasting methods must also be selected according to advanced applicability (Rajagukguk, Ramadhan, & Lee, 2020). (Y. Wang, Xia, & Kang, 2011). Although various articles presented the precise methods to mitigate the uncertainty, RE capacity forecasting results still showed a 10% average MAE error in the practical field for the day-ahead scheduling process. In this regard, the total REs capacity error with demand variation brings the risk of forecasting error amplification (Y. Wang et al., 2011).

Forecasting the ramp rate and width an hour ahead of time is essential for the solar project to diminish the consequences of ramp events. Different forecasting methods are employed in the smart environment for unit commitment, economic load dispatch, and load frequency control purposes. According to essential forecasting techniques in the whole network or individual system operations, several-days ahead forecasting, day ahead forecasting, several hours ahead forecasting, intra-hour ahead forecasting, and nowcasting have been investigated in recent years (Borghetti & Nucci, 2016). The advanced forecasting methods can be classified as the physical method, conventional statistical method, and artificial neural network (ANN) based method (Ko et al., 2021). After a high penetration of RE access in the active distribution network, there is also an increase in the complexity of scheduling. The accuracy improvement of power forecasting for RE generation has become the primary technology for securing the status of operational scheduling, reducing additional capacity reserves, and decreasing generation costs. According to the feature, the prediction process can be divided into direct and indirect prediction, and the spatial scale of prediction can be divided into a single field and regional prediction. The time scale can be divided into ultra-short-term, short-term, medium-term, and long-term forecasts. According to the classification of the prediction method, the method can be divided into point prediction, interval prediction, and probability prediction; the class can be divided into the physical model, conventional statistical model, and machine learning model. The prediction research is usually carried out by prediction methods such as the physical method, statistical method, and machine learning method (K. Wang, Qi, & Liu, 2019).

2.13.1 The physical method

The physical method builds on the mesoscale weather information, namely the numerical weather prediction system (NWP). This mathematically expressive model is based on geographical and meteorological information (Ko et al., 2021). This method can effectively perform for medium-term forecasting periods but has limitations on short-term forecasting due to geographical or meteorological gathering difficulty. For instance, the motion of clouds along a PV project ground can suddenly cause an increase or decrease in solar irradiance, namely ramp events. Available resources technology is numerical weather prediction (NWP) models, satellite images, all-sky images, and measured PV power output data (Borghetti & Nucci, 2016). The representative of the physical model is modeling with mathematical or numerical to interact with the solar radiation in the atmosphere according to the laws of physics. This model usually involved numerical weather prediction, sky imagery, and satellite image models. The statistical model is the way to find the solution from the relationship of the input and output variables. The well-known conventional statistical models are the fuzzy theory, Markov chain, autoregressive, and regression models (Rajagukguk et al., 2020).

2.13.2 The Conventional Statistical Method

The conventional statistical method is built on historical data and is characteristic of the linear statistical method. ARMA and ARIMA models are the most popular methods, but the nonlinear characteristic of the statistical data cannot guarantee the accuracy of this method (Ko et al., 2021). The statistical model maps correlation to the data model by curve fitting, parameter estimation, and correlation analysis. The correlation mapping processed the historical input data, such as solar radiation and PV power generation output, to realize the prediction of output data. The advantage of the statistical model over the physical model is that it does not need to thoroughly understand the complex theoretical relationship of advanced systems, such as photoelectric conversion and wind speed correlation. The statistical model only needs the knowledge of partial realization through different data analysis techniques; therefore, this is a simple technique with strong universality for different regions. However, a vast amount of correct historical past data, data acquisition, and complex calculation processes are the drawbacks of statistical methods for implementation. The complex numerical calculation process usually takes time to predict, and ultra-short-term prediction speed is another drawback to implementing with ordinary computers. Due to the prediction process being related to the reserve of historical data, data screening and elimination of false data are the primary concerns for the accuracy of the conventional statistical method. Therefore, the prediction accuracy depends on many numerical calculation processes of higher dimensions, considerably increasing the calculation time and the prediction speed (K. Wang et al., 2019).

2.13.3 The artificial neural network

The artificial neural network is a powerful tool representing historical data's nonlinear and complex features with many parameters. ANN methods have been widely applied in forecasting to improve memories and arithmetic units. ANN models for forecasting (WSF) provide results with higher accuracy than physical and conventional statistical methods. The introduction of deep learning neural networks improved the accuracy of ANN models. Recurrent neural networks (RNN), long short-term memory (LSTM) networks, and gated recurrent units (GRU) are the advanced structures of the deep learning ANN method (Ko et al., 2021).

2.13.4 Machine learning techniques

Machine learning is a highly efficient model based on artificial intelligence; this model can effectively extract high-dimensional complex nonlinear input functions (Rajagukguk et al., 2020). Machine learning is a powerful tool that can extract high-dimensional complex nonlinear features and directly map the output. The support vector machine (SVM), k-nearest neighbors, artificial neural network (ANN), naive Bayes, and random forest are the former well-known machine learning models. The input variable of the machine learning statistical models usually relies on historical past data to predict near-future time series models (Wang et al., 2019).

Recently, machine learning has become a popular time series prediction technique. In the recent research article, analysis prediction of REs resources with machine learning in which the meteorological data is used as the input data, such as irradiance, temperature, humidity, wind speed, air pressure, etc. (K. Wang et al., 2019). This work presented an ANN-based fitting tool and the rapid miner technique to predict solar irradiance with numerous input variables. The prediction model is compared with different ANN models, such as RBFNN and GRNN.

2.13.5 Deep learning techniques

The deep learning model has recently become a popular forecasting technique. The deep learning model is the development of the machine learning model; this model can solve a complex nonlinear problem with vast data in a short time. The structure of the multiple can automatically learn the abstract features from the raw data to find valuable representations. The outperforming result of deep learning models over other conventional is improving the accuracy as the training data increases, whereas conventional models' performance has been limited improvement at a certain amount of data (Rajagukguk et al., 2020).

2.14 Concepts of energy management system with Forecasting techniques

The reliable forecasting of demand and distributed generation has become vital in the active distribution system. The data is helpful information for system operators to manage the power flows, maintain dispatching, and ensure continuous servicing in the network. Distribution system operators (DSOs) manage the network power flow, balance supply and demand, and dispatch the power system. Thus, continuity and reliability are important issues for ensuring service provision. This concept has become important significantly due to the improved integration of distributed generation and overall demand response, making the distribution system an active network (Massrur, Niknam, & Fotuhi-Firuzabad, 2018). The RE uncertainties with multi-objective optimization energy management for the networked microgrids cooperation are highlighted (Karimi & Jadid, 2020). Multi-objective stochastic optimization is solved by the Compromised Program (CP). This technique converts the multi-objective into a single-objective function. This analysis aims to reduce power transfer from the main grid, reduce system losses, reliable operation of cooperative MMG, and minimize greenhouse emissions.

Incentive-based integrated demand response is a powerful tool to reduce the supply-demand imbalance of integrated energy systems with high penetration of renewable energy resources. Moreover, to reduce total electricity costs, demand response programs are applied in this work as an option for economic aspects. The output uncertainties of RE generation, load uncertainties from the demand side, double coupling including the energy conversion effect on the energy aggregators side, and appliance coupling effect on the end-user side created a challenge to model incentive-based demand response programs. In this model, the applicability of curtailment integrated and absorbing integrated demand response is planned to be added to the bi-level stochastic programming method. The final results show that this model can decrease multi-energy aggregators' total operating and risk costs and increase consumers' profits (Zheng et al., 2020). Due to the increasing dependence on electrical, heat, and gas systems to supply various purpose load types, multi-energy carrier systems face challenges concerning any uncertainty given rise from one carrier. These issues would influence the whole system's energy flow and secure operation. These cases become a critical issue due to the integration of industrial energy carrier demand response (ECDR) consumers, who participated randomly, and renewable resources (RESs) and their inherent characteristics (Massrur et al., 2018). The work in this paper shows the 2m + 1 point estimate method as a powerful probabilistic tool to analyze energy flow, which considers ECDR, RES, and various types of demand uncertainties. According to the results, the incentives for DR integration on electricity suppliers increased the additional operating cost. Therefore, incentives for DR should be employed when the system faces a security risk. The work of Du et al. (2020) proposed an uncertainty RE generation model with demand response in the unit commitment problem. The mixed-integer linear is used to solve the problem of UC scheduling. In this scenario, demand response is cooperative work to optimize load and RE generation curtailment risk when the RE output runs out of the adjustable uncertainty set. The adjustable uncertainty set of RE is divided into subintervals and evaluated bounds of the set. In these subintervals, consider DR to reduce operation which has not deviated from the forecasted value.

The distribution system operator (DSO) is responsible for maintaining the reliable operation of distribution systems and aggregating the DRs and controllable loads into the network. Therefore, the advanced microgrid network must be considered the optimal framework for a demand response (DR) program with the uncertainty of wind power generation. The load reduction offers include load curtailment, load shifting, and generation from DERs. Then, the DSO handles the market-clearing price using mixed-integer linear programming (MILP) for the day-ahead market. For uncertainty problems, Weibull probability distribution is fitted scenario generation of the wind power. Many scenarios are the various realizations of uncertain parameters that must be considered for modeling this stochasticity. The results show that the proposed model minimized the peak demand and system cost. Stochastic risk-constrained with DR framework are employed for short-term scheduling considering generation and demand uncertainty in advanced microgrids. The proposed method is to demonstrate demand response influence on the system's reliability and financial issues. The risk-constrained stochastic method is employed to maximize the profit of the grid operator by considering the uncertainty of RE output, day-ahead prices, and load. The optimal power flow determines the amount of power reserve from dispatchable distributed generation and evaluates responsive load operation for the next day. Moreover, the indices of the system's reliability and economic impacts are investigated by the appropriate level of DR participants, the number of losses, and the risk-aversion parameter (Vahedipour-Dahraie, Rashidizadeh-Kermani, Anvari-Moghaddam, & Guerrero, 2019).

Based on the concept of bidding in the electricity market, the work of Gao et al. (2017) demonstrates the competitive electricity market model with various types of resources that integrate into the VPP. The centralized dispatchable virtual power plant (VPP) is a step to improve the integration of distributed energy resources into the competitive electricity market. The bidding model has been considered the DR model and the uncertainty of RE for VPP to mitigate the negative impacts of RE penetration. The scenario analysis deals with the impact of elastic demand due to the demand side's inherent nature and the risk of VPP bidding. The numerical results show that the proposed VPP is superior in handling the management of the system with RE and DR resources. Shi et al. (2019) proposed the multistage robust energy management model with generation and demand uncertainties for the network-connected microgrid. Dual dynamic programming is applied to handle the complexity of multistage management problems. Haddadian and Noroozian (2017) highlight a model of the optimal active distribution network in the multi-microgrid system. Firstly, the proposed system carried out a probabilistic dual load flow model of all distributed generation, including the

Monte Carlo algorithm. In this stage, the objective function considered in the test system is to minimize the cost and power transfer from the main network. The stochastic nature of demand and RE generation is estimated by Rayleigh PDF, Beta PDF, and Normal PDF, respectively, from historical information. This study also takes into consideration a time-dependent storage system. This scenario is timely due to the energy storage system's hourly state of charge. This approach is solved by MCS, limiting the number of stochastic states for all intermittent intervals having their PDF. Then, probabilities of power flow are evaluated for the generated states.

2.15 Time Series prediction for day-ahead economic dispatch

Recently, a more accurate timescale prediction model has been introduced to address the challenge of REs uncertainty (Xu, Chang, Zhao, & Wang, 2023). The timescale scheduling schemes regarding the basis of shorter timescales eliminate uncertainty factors. Day-ahead scheduling, intraday rolling, and real-time scheduling are the basic models of timescale scheduling schemes in which uncertainty is eliminated to ensure system stability and economic dispatch. With the emergence of the active distribution network, demand response (DR) is a method for eliminating uncertainty; it is the interaction between the consumer and operator to change the load curves and eliminate peak load at a particular time. According to the timescale characteristic, the accuracy of the PV/wind power prediction has been improved with the refinement of the prediction method. In addition, the demand response performance also provided peak load shaving and valley filling. The uncertainty referred to the prediction error of the randomness of the volatility resources. This strategy aims to meet the worst case of the system. Uncertainty reflected the randomness of volatility and the unpredictability of RE resources. This paper adopted the time series deep learning model to address the uncertainty of RE resources for the day-ahead scheduling process. In the optimal day-ahead scheduling, the dispatch outputs of the upstream generation units are arranged optimally for the next day over 24 hours at a one-hour time step (Xu et al., 2023). The optimal day-ahead operational management and power bidding DR strategy are incorporated to provide dispatch operation with no supply/demand deviation. The highly accurate deep-learning neural network forecasts the day-ahead wind/PV power generation and the aggregate load profile. Then, the optimization algorithm implemented dispatch generation for the next day according to day-ahead forecast information to satisfy the multi-criteria objective and system constraints. The optimal day-ahead scheduling phase results are considered a decision-making strategy for the demand response program to compensate for the imbalances caused by RE uncertainty and prediction error. Therefore, the day-ahead operation strategy prevents the main disturbance caused by RE uncertainty in realities (Khosravi, Afsharnia, & Farhangi, 2022). The above algorithms present the efficient usage of mathematical formulation to capture uncertainty. The previous model ignored the effectiveness of the time-series model and real-world applicability in the calculation process. The equivalent continuous demand profile combines the random outage of the generating units effectively predicted with the artificial neural network model. The model assumes that responsive load users fully respond to the demand side management according to the response amount requirement before the violent circumstance. In practice, there is also significant uncertainty in the user's response after the load change order is issued. Therefore, demand response has three situations: over-demand response, full-demand response, and under-demand response. This work presents the possibility of over-demand response caused by REs uncertainty and its impact on the upstream side generation cost (Y. Yang, Wang, Gao, & Gao, 2022).

The work of (Nourollahi, Salyani, Zare, & Razzaghi, 2022) presented the application of a hybrid scenario and robust optimization techniques to model the uncertainty of the ITMG under normal and resiliency operations. The results show that the robust optimization modeled the uncertainty of the electricity price due to its unpredictable market environment. The Scenario probability technique will capture the other uncertainties, such as the renewable generation, load, and resiliency period.

A microgrid is an active distribution network that makes activities feasible economically with available resources. Due to forecasting features of REs and load in the active system, the available time horizon for the energy management system is the day ahead, intra-day ahead, and real-time operation. Moreover, day-ahead, intra-day-ahead, and real-time operations require an active distribution network to control current and future operation situations. Furthermore, the day-ahead management system requires current input information to update important information daily. The forecasting input module is responsible for forecasting the daily REs generation and daily load curves according to historical data and weather conditions. The day-ahead EMS contains the forecasted information of wind/PV, load profile, local generation units' settings data, the mathematical model of desired operating conditions, and decision-making optimizer. The decision-maker evaluated the optimal condition of dispatch unit costs according to the data setup from the input module to satisfy system constraints and objective function. The output of the decision-maker is the optimal dispatch operation of each generation unit, which is formed as dispatch powers. The optimal dispatch powers are to set up the operating status of the real-time microgrid EMS for the next day. The decision-maker also compensates for RE generation and demand deviation due to real-time forecast errors (Silva, Aoki, & Lambert-Torres, 2020).

The REs generation and load forecasts vary considerably over the year; addressing the day-ahead scheduling problem for every day under uncertainty is a limitation of previous work. Moreover, the simulation results of the day-by-day analysis to cover the uncertainty of four seasons and variations in load and solar generation forecasts could not be suitable for the real-world set of simulations. Therefore, accurate forecasting of REs is compulsory to mitigate system stability issues (Akhter, Mekhilef, Mokhlis, & Mohamed Shah, 2019).

2.16 Literature reviews of renewable energy forecasting with the statistical method

Generation forecasting is the basis of managing tools for existing and restructuring systems (Ghofrani & Alolayan, 2018; Martín et al., 2010; Voyant, Muselli, Paoli, & Nivet, 2012). Suppose the generation output is not accurately forecasted. In that case, inappropriate system operation in practices and inadequate power transactions are implicated (Ghofrani & Alolayan, 2018; Vahedipour-Dahraie et al., 2019). Many renewable energy sources penetrations, such as wind and solar, can significantly raise uncertainties in the systems and have complicated power system operation and planning. The use of energy storage (ES) or the forecasting of the power sources becomes the option to handle these risks. Therefore, forecasting of RE generation became vital information to solve the complicated system into more efficient and reliable systems operation. Generally, wind and solar forecasting have three categories: classical statistical techniques, intelligent computational methods, and hybrid algorithms. Time-series statistical techniques are the most commonly applied for various forecasting. The mathematical formulation developed the time-series method that can be applied to observe near-future predictions based on available historical data (Voyant et al., 2012).

Moreover, the critical aspect of generation forecasting is its increasing penetration rate into the network, guaranteeing the supply-demand balance and optimal managing process in the active grid structure. In the case of the PV system, the generated power mainly depended on solar irradiance. Therefore, solar power forecasting can be executed by predicting solar irradiance (David, Ramahatana, Trombe, & Lauret, 2016). This work highlights the performances of the combined use of linear models (ARMA and GARCH) to provide probabilistic solar irradiance. This model used historical solar irradiance data and provided reliabilities probabilistic statistical distribution. The result testing procedure has been implemented to assess for point forecasts and probabilistic forecasts. The work of (Paoli, Voyant, Muselli, & Nivet, 2010) highlights the error comparison with an ANN prediction approach and statical prediction methods such as AR and ARMA k-NN, and Markov Chains. These proposed methods evaluate daily solar irradiation and grid-connected PV output at Corsica Island, France. AR (8) and ANN models with clearness index and precise sky index reduce the normalized root mean square error (nRMSE) errors by approximately 5–6% compared to those without the preprocessing model. This model got better results than 20%-25% in nRMSE than the Markov chain, Bayes, and k-NN methods. In conclusion, the combined use of ANN and ARMA simulation confirms that it improved daily irradiation profiles' accuracy.

The comparison of output perdition for half-daily values and three-day temporal horizon solar irradiance data is presented (Martín et al., 2010). The statistical time series model, such as autoregressive and neural networks with fuzzy logic models, is tested with the clearness index and lost component time series model. For autoregressive analysis, half daily irradiance data are changed into stationary time series variables used as input parameters. The relative root mean squared deviation (rRMSD) measures the performance index. Neural Networks and Adaptative-network-based fuzzy inference system (ANFIS) models provided the best results for lost component input variables. However, Clearness index time series model provided better results in the models with lost component. Therefore, this evaluation process shows that the accuracy of forecasting model strongly depended on the metrological meteorologist conditions and temporal data set sequence.

The prediction of hourly solar irradiation was analyzed by (Ji & Chee, 2011) by the combined use of Autoregressive and Moving Average (ARMA) and the controversial Time Delay Neural Network (TDNN). Before implementing the ARMA model, a non-stationary set of solar irradiations is removed in the detrending process. The goodness of the stational model is tested by the Augmented Dickey-Fuller and Augmented Dickey-Fuller methods and normalized root means square error (NRMSE). According to overall testing, the TDNN model provided a better result, but this model sometimes has enormous prediction errors and unstable phenomena. Moreover, the hourly solar irradiation data set will involve linear and nonlinear parts. The ARMA model is applied for linear stationary series in the prediction process, and the TDNN model is employed to predict the nonlinear function in the input data set. Although the hybrid model does not always provide the best performance, the combined use maintained stable and accurate performance in the prediction process. The two-stage method's hourly rooftop PV power prediction is presented (Bacher, Madsen, & Nielsen, 2009). The first step of the proposed method is a statistical normalization using a clear sky model. Then, the prediction process is evaluated by linear time series autoregressive (AR) and AR with exogenous input (ARX) models. The information from numerical weather predictions (NWPs) is used as an exogenous input variable for ARX model. In this scenario, ARX model minimize 35% root mean square error than AR model. A root means square error improvement of around 35% is achieved by the ARX model. This method is suitable for online forecasting to access the solar system's conditions and the surrounding environment's state. The overall results show that 2 hours ahead of prediction can be forecasted by the available solar power data set. Nevertheless, online adaptive NWPs are the essential variable for longer prediction horizons.

The numerical weather prediction model (NWP) with hybrid ARMA/ANN is also proposed (Voyant et al., 2012). This paper presented an hourly radiation time series model using meteorological forecasting data from a numerical weather prediction (NWP) model. The static input variable for auto-regressive and moving averages (ARMA) uses multilayer perceptron (MLP) and endogenous data. This hybrid model has compared the persistence predictor and standalone ANN for performance checking. This work proposes the confidence interval of every prediction process to validate reliability. The work (Voyant, Randimbivololona, Nivet, Paoli, & Muselli, 2014) highlights the day ahead forecasting solar irradiation. This work compares the artificial neural network (ANN) with the statistical-based autoregressive-moving average model (ARMA) and references the persistent method. A method based on artificial intelligence using an artificial neural network (ANN) is reported. The ANN multi-layer perceptron (MLP) with endogenous and exogenous input variables is employed to pretreat time series data sets.

The autoregressive time series model for wind power forecasting in three different site areas is analyzed (Poggi, Muselli, Notton, Cristofari, & Louche, 2003). The statistical time series model simulates the wind speed data in this scenario. Then, the result data are compared with experimental data to check the production of studied periods. This work aims to create a monthly data set in a particular reference year for wind power simulation in Corsica. Erdem & Shi (2011) work focuses on short-term wind speed and direction forecasting with four-time series autoregressive moving average (ARMA) model types. This model was applied to observe wind speed in two different sites. The overall final performance is compared by the mean absolute error (MAE). The ARMA model first forecasted lateral and longitudinal wind direction and speed components. The traditional ARMA model predicts the Wind speed. Linked ARMA predictor evaluates the Wind direction. In the final methods, vector autoregression (VAR) models and restricted versions of the VAR are applied to forecast wind speed and direction sequence. According to the results, the component model provided better direction forecasting than the traditional-linked ARMA. The VAR model improved wind direction results more than traditional-linked ARMA and significantly improved speed performance. Restricted VAR models would be a suitable approach for forecasting models compared to other counterparts.

The work of Santamaría-Bonfil, Reyes-Ballesteros & Gershenson, (2016) presents the combination of hybrid Support Vector Regression and the Phase Space Reconstruction method to predict wind speed using historical wind data from Mexico. According to the historical data set, the wind speed of the selected location has a non-Gaussian distribution nature and has positive Lyapunov exponents. Therefore, the Time Delay Coordinates model and Phase Space Reconstruction procedure were selected as the proposed model. The hybrid method is checked with the persistence and autoregressive models (AR, ARMA, and ARIMA) by AIC and Ordinary Least Squares for comparison purposes. The performance of this method is more accurate in medium and short forecasting than persistence and autoregressive models, and it is best to use it for mitigating fluctuating wind speed. The autoregressive moving average with generalized autoregressive conditional hetero-scedasticity technique (ARMA–GARCH) is used to evaluate the means and the volatility from the historical wind speed in time series at different heights (Liu, Erdem, & Shi, 2011). In volatility forecasting, the interval estimation provided possible results. For wind speed forecasting, mean estimation shows accurate and robust results. The difficulty in wind power generation is due to its unstable nature, and the interval estimation mitigated this drawback and provided accurate information on mean and volatility to the operator who can effectively manage system operation. The analysis of (Hill, McMillan, Bell, & Infield, 2012) provided detailed wind speed modeling, such as diurnal, seasonal, and geographical area effects, to evaluate real wind power on the grid. Univariate, multivariate, and vector autoregressive models are employed for detrended wind data. The main feature of this work is to determine the annual and seasonally diurnal variations, which are the critical impacts on wind power generation.

Moreover, it is also pointed out that the detrending is also considered for regional site variations. All models are compared with root-mean-square error (RMSE) for accuracy assessment. According to the outcomes, the VAR model demonstrated a better synthesis reference for the GB wind plant planning and operation.

2.17 Literature reviews of Demand forecasting with the statistical method

Many works of literature have studied demand forecasting based on duration and methodology of forecasting. Demand forecasting can be classified into three according to their analysis tools: traditional, modified traditional, and soft computing methods (A. K. Singh, Ibraheem, Khatoon, Muazzam, & Chaturvedi, 2012). Accurate demand forecasting provided the utility information for decisions such as purchasing electricity, generating power, switching load, and improving system infrastructure. Moreover, demand variation was a significant issue in the electricity markets. This variation created the technical network's vulnerability and undesired economic effect on the spot electricity price, whose decisions are based on the existing plants' expanded investment. Thus, demand forecasting has also become an important topic with the emergence of the competitive electricity markets. According to many research methodologies, the demand forecasting field can be concluded as linear regression and econometric models, neuro-fuzzy models and data mining procedures, artificial intelligent techniques, Auto-Regressive Integrated Moving Average (ARIMA), and Auto-Regressive Moving Average (ARMA) models (Pappas et al., 2008). The work of (A. K. Singh et al., 2012) addresses modeling demand and electricity price forecasting with the deseasonalized and Auto Regressive Moving Average (ARMA) method in Greece. For the validation process, the results are validated with three types of order selection criteria, namely AICC, Akaike's Information Criterion (AIC), and Schwarz's Bayesian Information Criterion (BIC).

Another aspect of demand forecasting is system operators' performance of system safety and management. The demand variation due to active demand response has become subject to active distribution network management problems. The work of (Garulli, Paoletti, & Vicino, 2015) demonstrated the effects of load variation in the active distribution network and the validity of the proposed load forecasting methods. Active demand behavior and seasonal components are considered exogenous inputs of load forecasting. The load identification approach has been analyzed and tested based on different demand classes, such as commercial and accommodation areas. It is pointed out that neglecting the load variation with demand response in the model leads to unsatisfactory results. Therefore, ongoing investigation regards that it needs to analyze more accurately to model for the system with active demand component of the load and the sensitivity of forecasting algorithm that can improve performance of dynamic demand modeling errors. The work of (Shyh-Jier & Kuang-Rong, 2003) employed the load forecast using the Autoregressive moving average (ARMA). They proposed a model that considered the non-Gaussian nature of historical load data. The cumulant and bi-spectrum concepts are used with ARMA to tackle the Gaussian and non-Gaussian parts. It is concluded that the performance of the proposed model is ensured for accuracy improvement in the load forecast. Effective short-term load forecasting and information utilization become the requirements in active system development. However, the system's monthly and yearly demand forecasting is complicated because of its seasonal volatility effect. The work of (Pappas et al., 2008) presented the multi-model partitioning theory for short-term load forecasting for all seasonal periods and compared its performances with the Corrected Akaike Information Criterion (AICC), Akaike's Information Criterion (AIC), and Schwarz 's Bayesian Information Criterion (BIC) time series techniques. The applicability of the proposed method is proved by comparing it with the actual demand for the Hellenic power system. It proves that the proposed method's reliability and accuracy make usefulness in the studies of concern electricity consumption and electricity prices forecasting. This effectiveness of proposed work concern with energy consumption and electricity prices forecasting that provided the information to the electricity authorities to guarantee supply uninterruptable power supply with a low cost.

2.18 Literature reviews of multi-objective optimization economic dispatch

The work in (Guoping Zhang, Wang, Du, & Liu, 2020) presented an economic multi-objective optimization model using a hybrid particle swarm optimization algorithm and the simulated annealing (SAPSO) algorithm for a standalone microgrid system involving photovoltaic panels, wind turbines, diesel generators, and energy storage battery system. Since the power of the storage system and the diesel generator is the optimal decision variable, the multi-objective variable is defined to minimize the costs of generation, battery depreciation, and environmental protection. The results demonstrated that the increased battery depreciation cost caused a dramatic decrease in economic and environmental costs. Moreover, the energy storage system charging and discharging capacity of the storage power during peak and night can shave the peak load, fill the valley, and smooth the output power of traditional diesel generators. The work in (Alilou, Nazarpour, & Shayeghi, 2018) highlights the multi-objective demand-side management strategy in the distribution system with the multi-distributed generation and demand response program. The non-dominated sorting firefly algorithm and fuzzy decision-making method were applied to optimize distribution systems' technical, economic, and environmental indices. The results presented that indices of the distribution system have been significantly improved by utilizing optimal schedule DSM. The dispatchable DG units fulfill part of the demand requirement due to their stable productivity and low start-up/shutdown costs. The generated power of non-dispatchable DGs is almost one-third of the demand, and the effect of environmental indices is considerably clean and eco-friendly.

The work (F. Wang et al., 2018) presented multi-objective optimization for the community- building level intelligent energy management system (BEMS) based on the forecasting of building integrated PV power, noncontrollable load, and outdoor temperature. In the BEMS system, the occupants' indoor environment comfort was considered to be the main aspects: visual comfort, thermal comfort, and indoor air quality comfort. Considering controllable load DR programs, the system's different energy usage, electricity, thermal, and cooling loads are balanced to guarantee optimized operation. The results showed that the multi-objective optimization model simultaneously improved the system economy of the BES and less affected occupants' comfort level by the synergetic optimized dispatch. The work of (Paterakis, Gibescu, Bakirtzis, & Catalao, 2018) presented a multi-objective optimization model of risk-aware joint energy and reserve market structure incorporating demand-side resources. The risk-averse multi-objective optimization of stochastic programming is considered to mitigate significant wind power uncertainty and minimize expected operational costs. The results observed that stochastic optimization controls the risk of wind uncertainty and the risk embedded in the decisions making reserved by procuring the necessary. The participation of DRPs can mitigate risk related to sensitivity for the load recovery and the costs of demand side reserves. The elastic demand side management allowed for higher exploitation of wind energy at all risk aversion levels.

The work by (Soares, Fotouhi Ghazvini, Silva, & Vale, 2016) presented the optimization of the centralized Energy Resource Management (ERM) system for a Virtual Power Plant (VPP) with multi-dimensional signaling to maximize profits. Since VPP includes several different generation resources, such as Demand Response (DR), Electric Vehicles (EV), and Energy Storage Systems (ESS), it requires advanced tools to manage competitive resources at a reasonable cost. The results observed that deterministic optimization is more resource-intensive and needs more system memory than metaheuristics in large-scale problems. The decision-making of large-scale VPP operations required more computing efficiency platforms to solve large-scale problems and provide better decision support in adequate time. This work proposed stochastic algorithms to ensure reliable microgrid daily optimal scheduling operation considering intermittent generation and load behavior. The metaheuristic algorithm is applied to solve uncertainties of RESs and loads. Moreover, the strength of demand response programs is considered on optimal day-ahead scheduling of microgrids to reduce cost fluctuations and flatten the demand curve. The numerical results show the effectiveness of the metaheuristic algorithm through comparison with stochastic optimization. The results suggested that deterministic methods are no longer suited for precise analysis of advanced microgrid system operation and planning. The work in (Shewale, Mokhade, Funde, & Bokde, 2020) analyzed multi-objective optimization problems for residential appliance scheduling problems regarding operation cost minimization, PAR minimization, and user satisfaction maximization. This work carried out a state-of-the-art comparison of RASP using classical, heuristic, and meta-heuristic algorithms. The finding discussed the performance of three algorithms in terms of computing time and optimal solution. Although the classical method provided the exact global optimal solution, this method takes a long computational time. The heuristic method provides an approximate optimal solution faster and can be helpful for specific schedules of appliances. The nature-inspired meta-heuristic algorithm is a faster convergence way to find the optimal schedule in appliance scheduling at an acceptable time. The work of (Phani Raghav, Seshu Kumar, Koteswara Raju, & Singh, 2022) proposed the multi-objective day-ahead three-layer stochastic energy management framework to optimize operational costs, energy losses, and voltage deviation under uncertainty. This work addressed the uncertainties of wind power, solar irradiance, load demand, and market price with the scenario generation/reduction method. This work developed a flexible price elasticity-based incentive-driven model, and the performance of the proposed model is evaluated based on a techno-economic multi-criterion. The results observed that the emergency demand response program outperforms nonlinear and linear-based incentive and penalty models regarding load factor improvement.

Tavakoli Ghazi Jahani, Nazarian, Safari, & Haghifam (2019) developed a multi-objective model with demand response that solves the distribution networks' reliable/economic performance with the epsilon-constrained (EPC) method. The uncertainty-based multi-objective optimization model is developed with stochastic programming. The results show that optimal reconfiguration of the distribution system reduced power loss and energy not supplied (ENS) index, demand response reduced total power loss, amount of curtailed load, and enhanced voltage profile. Dan et al. (2018) developed the multi-objective hierarchical three-layer model of a day-ahead management system with an artificial immune algorithm to solve operation cost, network benefit, and social welfare simultaneously. The results observed that the feasible optimization model could provide the utility level of operation cost minimization and the peak-to-average ratio, demand side management offered profit maximization to DR aggregators, and electricity bill minimization to customers.

Aghajani, Shayanfar, and Shayeghi (2015) proposed a multi-objective short-term energy management system to optimize microgrid operating costs and pollutant emission in the presence of renewable energy sources (RESs) with a randomized natural behavior. The results presented that the demand side management (DSM) scheduling model can effectively reduce the uncertainty problem obtained from the actual generated and predicted power of wind turbines and photovoltaic in microgrids. The results observed that incentive-based payment demand response is a possible way to apply in a competitive electricity market. Reddy (2016) presented a multi-objective day-ahead market clearing (DAMC) mechanism with demand response for social welfare maximization, load reduction minimization (PredM), and load-served error (LSE) minimization. The proposed system considers reduced stress system conditions where only demand response cannot provide a feasible solution. The multi-objective strength Pareto evolutionary algorithm 2+ (SPEA 2+) is used to solve the DAMC problem. This work highlights the requirement for judiciously selecting a combination and suitable choice of conflict objectives function for the multi-objective problem. The results show that voltage-dependent load modeling is required to optimize SWM and LSE multi-objective functions simultaneously. The Pareto optimal front provided to make a better choice of decision variable regarding compromise between the conflicting objective functions.

The work of Hajebrahimi, Abdollahi, and Rashidinejad (2017) presented probabilistic multi-objective transmission expansion planning (TEP) to provide a structure elasticity of demand and customer benefit function. This work investigates the impact of responsive load on power system planning and considers the uncertainties associated with wind power and demand. The congestion costs, RC, and TIC are multifarious objectives in probabilistic multi-objective TEP incorporating demand response programs (DRPs). The result observed that the inflicted costs and additional investment were significantly deferred by implementing a demand response program through transmission expansion planning (TEP). The work of Falsafi, Zakariazadeh, and Jadid (2014) presented a multi-objective two-stage stochastic generation scheduling model using the augmented epsilon constraint method and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method. This work highlights the effectiveness of a demand response reserve to recover the uncertainty of wind power forecasting in the smart grid. The results show that demand response and reserve market compensated for the effect of forecasting uncertainty and reduced the operational cost and air pollutant emissions. Hong and Lin (2013) presented short-term active power scheduling of a stand-alone system with wind and PV power uncertainties to simultaneously reduce fuel cost and CO2 emission. The interactive multi-objective problem is solved by adaptive chaos clonal evolutionary programming (ACCEP), and the uncertainty of wind and PV powers is modeled by the fuzzy interval prediction method. The work of Azizipanah-Abarghooee, Niknam, Roosta, Malekpour, and Zare, (2012) implemented the wind-thermal economic emission optimal dispatch problem with a teaching-learning algorithm, and the probabilistic of wind power uncertainty was solved by the stochastic 2m point estimated method. The proposed work is to analyze energy costs and emissions costs simultaneously. The probabilistic economic emission dispatch problem considers overestimating and underestimating available wind power. The results observed that the precise modeling of uncertainty is essential for generating unit scheduling and generation costs, wind power can reduce the emissions cost, and the stochastic approach is an efficient way to cope with uncertain resources for the system operator's likelihood estimate.

2.19 Literature reviews of advanced forecasting method

Renewable energy forecasting is a more practical application than the various methods to capture upstream side variation. The prediction accuracy facilitated high penetration of REs through secure and economical operation. Compared to solar power, it has been understood that wind and solar power are less predictable resources due to their highly uncertain characteristics (Ko et al., 2021). Many research articles have investigated the accuracy improvement method and its impact on the power system. ANN-based forecasting models have become widely applicable practically due to higher accuracy than physical and conventional statistical methods. Forecasting is essential for the decision-maker to provide information dealing with the operating system's stability (Nikoobakht, Aghaei, Shafie-Khah, & Catalao, 2019). Wind and solar power generations are considered a negative load due to uncertainty in steady-state conditions. Therefore, predicting wind and PV generation curves is a practical deployment concept, especially for estimating standby capacity and optimal unit scheduling processes. The increased penetration of RE levels also elevated the importance of accurate forecasting methods. Adequate renewable energy and load forecasting are essential to mitigate related uncertainties; this concept provides conductive planning and operation of energy systems. The accuracy of forecasting is a challenging task due to the intermittent and randomness of renewable energy data. Numerous forecasting algorithms have been used in the previous literature to provide accurate predictions for the several minutes ahead to the few days ahead. The uncertainty of forecasting harmed the daily power system operation and control. Therefore, the research articles have recently been paying significant attention to forecasting uncertainty (Wang, Lei, Zhang, Zhou, & Peng, 2019).

Renewable energy, especially solar PV, will become a significant energy source. Regressive methods have benefited short-term time series prediction models in the last decade. Recent articles highlight that deep learning based on artificial neural networks has the adaptability to solve complex nonlinear problems and a powerful acceleration capability for difficult computation problems. Recently, artificial neural networks (ANNs) based prediction method has continuously grown to carry out time-series application due to their superior working characteristics offered on the nonlinear models. The deep learning-based ANN has become popular in the time-series prediction application due to its accelerating function to overcome the difficulty of complex statical methods. The multi-layer perceptron (MLP)-type ANNs is a helpful model for complex relationships, but this method cannot assimilate the long- and short-term dependencies present in the historical data. The dependencies are the ability of ANN to identify and remember the behavior patterns from the distant past and the near past. ANN is a particular type to make functional near-future predictions of historical sequential behavior patterns. To address this, Recurrent Neural Networks (RNN) emerged where the networks have internal feedback loops. The prediction of REs is fundamental to increasing system reliability. The generated power from sources is the medium-level integration to the distribution networks. In the energy market, electric production and actual consumption patterns are the factors with the programmed offer. The high integration of renewable energy intensifies the complexity of managing power distribution and the distinctions of the ongoing energy balance due to its unpredictable and intermittent nature. Several methodologies have been available for the prediction process at different horizons. This work predicted the PV, wind, and demand power for the day ahead in 1-hour intervals from historical records during one year using Long Short-Term Memory (LSTM) and Gate Recurrent Units (GRU). The artificial neural network-based prediction method predicted the near future data from the data in the past as current input data. A multi-layer perceptron (MLP) neural network learns the relation between input and output data and does not consider time series characteristics (Elsaraiti & Merabet, 2022).

Time series prediction of future values is a frequently studied problem in the electrical power system. Over the last decade, the infrastructure of power systems has progressively changed from centralized to decentralized systems, allowing the integration of small-scale distributed generation (DG) scenarios through the distribution system. The dispersal of DG in the energy market, especially from Renewable Energy Sources (RESs), has been facilitated by economic and environmental reasons. However, the high penetration of DG into conventional electricity systems has brought challenges for system operators to monitor and control the operation and maintenance of grids. The smaller generation units are directly connected to distribution networks near the consumer to characterize decentralized systems.

Therefore, future energy systems' proactive and transactive nature offers many opportunities. However, the challenge of future energy systems is related to integrating the highly intermittent and stochastic nature of RES production into deterministic energy systems. In this regard, the conventional energy system demands to change into the modern grid with improved flexibility. This is the reason the prediction topic has become a necessary tool for all energy sectors: prediction is required to prepare respective offer strategies for producers, to maximize profit for consumers, to optimize short and medium-term decisions for energy regulation and dispatching for Transmission (TSO) and Distribution (DSO) System Operators. According to these facts, the accuracy of the prediction system has become the point for the automatic modeling tools for data analytics and intelligent operation control, enabling prosumer-oriented home energy management systems and reducing energy and operation costs. Many of the power system's practical operations greatly rely on scenario-predicted data, which is especially important for producers', network operators', and market players' applications. In the last decade, this scenario-predicted is mainly essential for the production comes from expected and intermittent RES resources. This intermittent brings considerable uncertainty about the difference between predicted and actual production. This uncertainty challenges stability issues, dispatch ability, and electricity market problems concerning the day-ahead market. The advantage of RES energy in the electric system is the environmental and economic benefits since the production cost and levelized cost of energy from RESs are usually lower than the market-clearing price. The drawback of this source is its difficulty predictability, which will increase potential costs to compensate for the imbalance problem between demand and actual production (Succetti, Rosato, Araneo, & Panella, 2020).

The approaches mentioned above usually carry out univariate and multivariate energy time series. The univariate model involving energy time series considers a single time series to obtain the prediction result of the future time series. Multivariate is the way to observe different situations relating to considering two or more time series simultaneously, and it is a complex system that generates a broader generalization capability. The multivariate data is suitable for developing a model to describe the results of the relationship between the original time series and the related physical variables. This method is required to analyze data and collect time series data from different physical variables related to physical phenomena such as wind, solar radiation, humidity, air pressure, etc. In this work, the forecasting results were tested on real-world data to show and compare the performance of univariate deep learning with the basic ARMA model. According to numerical results from the literature, the multivariate analysis offers better results than the univariate way in most cases. The accuracy of the work is proved in terms of MAE. Improvements in prediction accuracy are required in the field of the energy management of distributed energy resources. The active prosumers in the smart grid need efficient data-driven modeling tools to enable active participation and diffused coordination tasks (Succetti et al., 2020).

The work of Rosato, Panella, Araneo, and Andreotti (2019)presented that energy storage is a solution for RESs generation dispatchable, and the dispatchable work is often combined with the accurate forecasting method to predict generation and demand profiles. This work is in the microgrid context with renewable embedded generation and involves responsive load. The structure of power systems is progressively changing to be flexible to meet the requirements of high RES penetration in current infrastructures. RES infrastructures generally come from intermitted natural resources, which favor use to achieve and enhance carbon diversity and climate change. The future energy infrastructure envisions a scenario of decentralized systems that will replace the importance of existing bulk power systems. Moreover, in this framework, many small generating units will be connected to distribution networks, and all the consumers will become flexible prosumers capable of interacting with responsive load control programs. However, the uncertainty issues remain a challenge related to the predicted deviation of forecast and actual generation of RESs. This is the problem for stability issues and dispatch ability reasons to the day-ahead market.

Therefore, the effective prediction tool is a feasible solution for these problems for the virtual power plant (VPP) concept. The active distribution network involved an option to implement an effective way to handle the intermittent RES generation along with the load change pattern cooperatively to optimize system management and cost reduction. To deal with this, an accurate prediction system must be involved to ensure the aggregation of the above process. Neural networks have been widely used for prediction purposes, offering better results for time series prediction at different time horizons using feedforward, recurrent, and deep architectures. The prediction processes are performed with the local data, such as irradiation, wind speed, and load data (Rosato et al., 2019). This work presented a distributed learning algorithm for long short-term memory (LSTM) networks to learn long-term dependencies for decentralized VPP, and the distributed average consensus (DAC) protocol is used to interact with local agents. This work proposed an approach of cooperative learning of LSTM networks in microgrid management, mainly working as the active distribution network. The prediction process is that wind and PV power plants operate with their LSTM network to forecast power generation. Therefore, the complex patterns of RES energy are necessary to consider through a forecasting model related to the sustainable energy system. Forecasting can reflect the intermittence and uncertainty of power supply and demand. The short-term or long-term forecasting model with intra-hour-ahead or seven days ahead is utilized in the feasibility energy system design, and it can also reduce undesired regulatory costs when integrating RES sources into the energy system (Nam, Hwangbo, & Yoo, 2020). This work developed the forecasting model with the day-ahead prediction for power demand and renewable energy generation based on LSTM and GRU deep learning methods. The simulation results of prediction are used to promote feasible and sustainable renewable energy systems in the active distribution network. This work also compares and evaluates deep learning performance with conventional statistical models. The deep learning models studied in this work included long short-term memory (LSTM) and gated recurrent unit (GRU) to overcome the drawback of the conventional statistical method, including the Auto-regressive-Moving-Average (ARMA) model. The performance evaluation of the forecasting models has a significantly different effect according to the properties of the available data. The performances of deep learning models have different solutions depending on the models' forecasting time, training duration, target data, and simple or ensemble structure. Therefore, selecting an appropriate model needs several issues to consider. Comparing and evaluating processes using accurate metric numerical evaluators and selecting appropriate forecasting models for future load demand and renewable energy generation (Nam et al., 2020). Although the expansion of RES resources can effectively positively impact economic and environmental issues, the challenges still need to be solved for using these sources. For this reason, the combination of fuel-based distributed generation and renewable energy utilization is still a complementary relationship. Moreover, it is necessary to ensure the optimal operation of different technologies from the upstream side to generate power. When the distribution system is considered to operate with both renewable and conventional fuel energy, planning and scheduling mixed power generation with different technologies becomes an issue for the upstream side operation. In this regard, the work on multiple power generation technologies involving investment issues has become a significantly increased topic. In the last years, real options and Monte Carlo simulation have been widely applied to analyze the investment issues of different generation technologies. Most of the research focuses on the optimization problem of the investment portfolios and the whole power system structure, which involves different power generation technologies. Optimizing the whole structure and each generation cycle still has challenges to response RESs uncertainty, participation of responsive load in the active distribution network, changing electricity markets, energy policies, and environments. With the development of renewable energy technologies, distribution networks have been completed to construct multiple-generation infrastructures. However, due to the uncertainty, each power generation technology's actual profit and cost are still a problem. Moreover, the problem of practical usage of the existing power generation technologies and the task of fulfilling power demand within the production cycle horizon still needs attention related to uncertainty issues (Peng, Liu, Zhang, Zeng, & Graham, 2023). Solar irradiance forecasting is required to plan and schedule solar and grid-combined generating systems. Artificial intelligence (AI) based artificial neural networks are widely used to train historical solar irradiance values and meteorological variables such as temperature, humidity, wind speed, pressure, and precipitation (Gao et al., 2019). The work by Huang et al. (2016) presented the power of the gated recurrent unit (GRU) with weather forecasts to predict solar irradiance for 24 hours. The results show that the proposed method reduces the root mean squared error by 28.4% to the CSpers algorithm, 23.3% more accurate than the BPNN algorithm, and 11.9% more accurate than the recurrent neural network (RNN). The prediction error is reduced by 36.6% compared to long short-term memory. Compared to the ARMA method, the forecast skill of the GRU is improved by 42.0%. For the five different training processes, the performance of GRU and LSTM is distinguishable in that both the LSTM and the GRU exceed the accuracy of the traditional network model. The work by Lee et al. (2018) presented utilizing convolutional neural networks and long–short-term memory for day-ahead solar power generation. This work also analyzes time series data in deep learning communities with data from photovoltaic inverters and national weather centers. This research considers that weather information is not always available, which depends on the site location of PV modules and sensors installed. The proposed model predicts solar power with roughly estimated weather data from national weather centers. The robustness of the proposed work is sophisticatedly preprocessed with input data without weather information to reduce unexpected environmental issues. The extensive simulation is processed with real-life data sets. The study by Chandran et al., (2021) presented the effectiveness of deep learning algorithms in predicting short-term wind power generation from wind speed data. This study adopted Long Short-

Term Memory (LSTM), Gated Recurrent Unit (GRU), and Recurrent Neural Network (RNN) in the projection of wind farms. The results show that deep learning models are more applicable techniques in real-life locations than other models. This study discussed that machine/deep learning algorithms were efficient modeling tools before the installation of wind farms in geographically unknown areas. The GRU model is suited for highly non-linear and complex input data sets in real-time. This work compared conventional statistical method implementation with deep learning model without NWP inputs to present accurate predictive models. The work by Malakar et al., (2021) highlights appropriate design choices of Long short- term memory (LSTM) models to show the impact significantly on short-term forecasting performance. The design choices involved pre-processing techniques such as deseasonalization, ordering of the input data, network size, batch size, and forecasting horizon. The study works on three recent benchmark methods based on random forest, recurrent neural network, and LSTM regarding forecasting accuracy. The findings discussed that the importance of the temporal order of the data and the lack of discernible data pre-processing affect the making of the LSTM stateful model. The result also found that the input data variation influences the number of nodes and batch size in an LSTM network. The work by Ibrahim et al., (2021) proposed the combination of the adaptive dynamic particle swarm algorithm (AD-PSO) and guided whale optimization algorithm (Guided WOA) to create an algorithm. This algorithm helped to select the optimal hyperparameters of the Long Short-Term Memory (LSTM) network for wind power forecasting. This work is to carry out 48-hour-ahead wind power prediction for wind farms. The results showed that the AD-PSO-Guided WOA algorithm outperforms the accuracy of comparative optimization and deep learning algorithms. The work by Hua et al., (2008) presented interval prediction of electricity price to solve uncertainty risk in the decision-making problem. This work highlights that interval prediction is a more interesting topic for market participants to make bidding strategies and investment decisions rather than forecasting the value. The interval prediction method is a valuable risk management tool for market participants in a deregulated electricity market. After conducting comprehensive experiments with real-world price data, the results show that the proposed NCHF is more effective than well-established time series models, such as ARIMA and GARCH. The work by Huang et al., (2016) presented an interval prediction model describing power and load prediction uncertainties for virtual power plant economic dispatch. This work converts the probability function into an interval prediction deterministic model. The interval-based ED model is a more flexible way of uncertainty modeling than the complicated probability distribution function (PDF) or fuzzy membership function (FMF) due to its simple known intervals and uncertain variables. The results verify that the proposed system is flexible and can be adopted for the economic dispatch of virtual power plants. The work by Wu, Shahidehpour, and Li, (2012) presented the comparative application of the Monte Carlo (MC) scenario generation method and lower and upper bounds interval optimization approaches for stochastic security-constrained unit commitment problems considering wind power uncertainty. The results presented that although the scenario method provided more stable and insensitive results to the number of scenarios, this method takes additional time due to computation burdens. The interval optimization method provides lower and upper bounds solutions for the operation cost and generation dispatch with less computation, but the optimal result is not a guaranteed solution due to the uncertainty interval sensitively. From this point, interval optimization is not a suitable method for the simulation problem having discrete type uncertainty variables such as random outages of generation units and transmission lines in power systems. The work in (Saez et al., 2015) studied the robust microgrid energy management system (EMS) for determining the optimal dispatching of generation units using day-ahead renewable resources and loads data. The fuzzy prediction interval model is applied to represent the uncertainty of future predictions. The proposed method is demonstrated with local data such as solar irradiation, wind speed, and load data from the Huatacondo, Chile, distribution system. The results suggested that the width of the prediction interval reflected higher levels of expected CP that significantly impacted the uncertainty. Shi, Liang, and Dinavahi (2018) work proposed the RNN-based LUBE method to construct an optimal PI evaluation index for real-world wind power forecasting. The RNN model is suitable for time series forecasting, and the new PI evaluation index is designed to enhance the model training process. RNN prediction model is optimized with the dragonfly algorithm to tune the parameters of the prediction model. The delay embedding theorem reconstructed the chaotic wind power data for better prediction. The results show that interval prediction is more efficient in quantifying forecasting uncertainties than the point forecast approach. The work by Wen, Zhou, Yang, and Lu (2019) presented the accurate residential power load model and the PV power short-term forecasting with the deep recurrent neural network with long short-term memory units (DRNN-LSTM). This work highlights the potential accurate short-term forecasting for grid-connected residential microgrids' economic load dispatch model to reduce daily costs and increase reliability. The results show that this model promotes system operator and consumer interaction. The PV power and residential load uncertainties were optimized in the load dispatch model based on the forecasting results of the DRNN-LSTM model. The results also presented that energy storage and EVs shifted community peak load, and utilization of PV power was promoted. The work by Cai, Pipattanasomporn, Rahman, (2019) proposed hierarchically-structured deep neural network models for day- ahead load forecasting in commercial buildings. The performances of the deep learning model are compared with the Seasonal ARIMAX model in terms of accuracy, computational efficiency, generalizability, and robustness. This work investigated that the deep learning gated 24- h CNN model outperformed in a direct multi-step manner and improved the accuracy by 22.6% compared to seasonal ARIMAX. Compared to the conventional approaches, the results reveal that hierarchically structured deep learning networks outperformed the conventional approaches for capturing the data- dependent uncertainty and increasing the computational efficiency for large-scale applications. The work in (Shen, Ma, Deng, Huang, & Kuo, 2021) analysis of three types of deep learning model, convolutional neural network, long short-term memory neural network, and hybrid model, for photovoltaic power forecasting. Many tests and verifications were carried out with different time series data lengths, and three statistical indicators were concluded with the statistical results under different data lengths. The statistical results reveal that the three models' performance provided a good solution and acceptable accuracy. This work analysis SELNet deep learning and data processing ensemble model to reduce the impact of seasonal factors. The effectiveness of the proposed model compared with the gated recurrent unit (GRU), TCN, VMD-TCN, and VMD-CNN models in terms of mean absolute percentage error (MAPE). The result shows this work can provide a universally applicable prediction of electricity demand in four seasons. It was also revealed that deep-learning models have excellent performance to reduce computational time requirements and less computing equipment and parameters.

2.20 Power generation planning

In the microgrid planning stage, choosing the available power sources is vital for satisfying the demand needed in a specific area. The suitable and available source selection requires deep analysis of microgrids in a particular area. Power source and energy storage systems must be sized based on many criteria, such as peak demand and cost-effective criteria. Types of suitable fuel base generation must also be selected for the network, which concerns cost-effectiveness and system reliability. In contrast, this issue must be considered in the system planning stage as three mains: cost-effective objective, reducing environmental impact, and improving reliability (Gamarra & Guerrero, 2015).

2.21 Operation Scheduling

Scheduling is a common problem in the feasibility planning stage; it plans the available resources in a particular area, such as generators and storage devices. This problem minimizes operational costs, environmental impact, and power quality while covering demand requirements. Multiple optimization methods with signal or multi-objective functions solve the optimal operation of various microgrids. Heuristics and metaheuristics are widely used in sizing and scheduling generation mix problems (Gamarra & Guerrero, 2015). This work highlights sources of uncertainty in every step of the decision-making process, such as uncertainties in modeling, uncertainty during model exploration, and uncertainties in interpreting results. Generally, uncertainties can be identified under two main types. External uncertainties concern the lack of knowledge and the nature of the environment. Internal uncertainties are related to the structuring process and analysis of the decision-maker. The uncertainty effect, objective function, and system constraints are the standard parameters that must be addressed in every commercial microgrid planning process to achieve cost-benefit and customer satisfaction. Consumer satisfaction means keeping reliable and quality insurance with a low environmental impact. In these facts, microgrid planning usually accompanies the optimal searching process. The optimal planning techniques are applied not only in renewable energy allocation but also in energy management systems. Energy management systems are the optimization problem to apply in different fields based on technical, environmental, and economic constraints and uncertainties (Gamarra & Guerrero, 2015).

This technique has gained attention in energy management systems (EMS) in smart homes, buildings, and grids in the last decade. Modeling energy decision-making is considered a sustainable design that plans and controls particular optimization issues. It has a complex and computational challenge in handling the traditional optimization method. The emergence of artificial intelligence, inspired by biological evolution algorithms, has recently been widespread due to its potential capability to solve this problem. Many research studies have investigated bio-inspired methods for energy management systems in smart homes, buildings, and grids (Nguyen et al., 2020).

The comprehensive design and operation of an active distribution network with REs generation and responsive load to capture the intermittence are described as follows: Firstly, deep-learning models provide the required information for the decision-makers in generating wind turbines and PV systems. Then, decision-makers create an optimal plan scheduling for modifying the optimized distribution system. Secondly, the management system's role is to implement system balancing, which is essential to creating sustainable and economically efficient activities. The system overload condition has a contrary effect on the efficient energy distribution system. On the other hand, a lack of demand fulfillment leads to safety and stability, which creates long-term generation cost problems due to energy-saving issues. The deep-learning-based Gate Recurrent Unit (GRU) model, designed to extract complex nonlinear data from real-time series data, improves the wind and PV power generation predictions. Accurate wind power forecasting improved the system stability and solved the challenge of efficient operation for the modern distribution network. Deep learning techniques have recently become popular in RE forecasting due to their effective prediction methods (Chandran et al., 2021).

2.22 Bio-Inspired Optimization Algorithms

Bio-inspired algorithms are evolutionary algorithms based on nature's biological behaviors that make novel and robust searching algorithms. Evolutionary-based and swarm-based optimization methods are two basic energy management systems (Nguyen et al., 2020).

2.22.1 Evolutionary Computing (EC)

This approach inspired the evolution of concepts to handle optimization problems automatically. Genetic Algorithm (GA) is a widespread evolutionary computing meta-heuristic optimization method. Evolutionary fittest selection and genetic operator between generations explored the searching space of the optimization problem (Nguyen et al., 2020).

2.22.2 Swarm Intelligence (SI)

This approach mimics the collective behaviors of living species, such as ants, bees, and birds, forming a group of operators and making interactions between them. These principles created decentralized searching algorithms that balance exploring and exploiting capabilities. Different techniques have different ways of exploring and exploiting manners in the searching space. Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) are popular heuristic algorithms. Furthermore, along with other modern heuristics, Artificial Bee Colony (ABC), Bat Algorithm (BA), Cuckoo Search (CS), Grey Wolf Optimization (GWO), Firefly Algorithm (FA), Social Spider Algorithm (SSA), and Kestrel-based Search Algorithm (KSA) are the modern swarm intelligence (SI) techniques (Nguyen et al., 2020).

2.23 Meta-heuristic Optimization Techniques

Metaheuristics has become popular due to its problem-solving techniques. This technique can find reasonable solutions with a wide range of algorithms where deterministic are not efficient enough to find reasonable solutions. The metaheuristics method is a stochastic operator due to creating random solutions and finding reasonable solutions in a reasonable time. The first class of metaheuristics is iteratively generated and improved the specific solution until a specific condition is met. The benefit of the first method is low computational time and high convergence speed. The drawback is less exploration and easy to trap in the local optimal solution. The second class of metaheuristics is a group of improved solutions for a given optimization problem. The group search is a highly exploratory algorithm. However, this method requires high computational time and space complexity (Khan et al., 2019). The Grey Wolf Optimizer (GWO) is the recent swarm intelligence optimization method that inspired gray wolves' hunting behavior (Mirjalili & Dong, 2020a).

Meta-heuristic techniques are the less computational complexity solvers that can handle problems with self-learning, self-optimization, self-processing, and self-healing. The fast exploration and exploitation capability is the feature of such a technique to escape from the local optimal and to search for the optimal answer from the searching area with adequate diversity. Another advantage of the meta- heuristic over the deterministic techniques is that it does not need the assumption of certainty or proportionality (Khan et al., 2019).

2.23.1 Grey Wolf Optimizer

The Grey Wolf Optimizer (GWO) was presented in 2014 by (Mirjalili, Mirjalili, & Lewis, 2014) and mimics the nature hierarchy and hunting behavior of grey wolves. Grey wolves live in naturally organized packs; the wolves' class in a pack is divided into four groups according to the level of power: alpha, beta, delta, and omega. The alpha is the most decisive wolf leader in the pack to lead for navigation and hunting. The next-level beta wolves are responsible for helping alpha wolves in decision-making and leadership. Delta and Omega wolves are the least potent wolves in the pack. The hunting behavior of GWO is presented in the figure. The GWO algorithm saves the power hierarchy of wolves, alpha, beta, and delta wolves as the three best solutions. The rest of the solutions are considered omega wolves. After defining the dominance wolves' level, the position vector of the corresponding wolf is updated as follows:

$$\vec{Y}(t+1) = \vec{Y}_p(t) - \vec{A}.\vec{D} \tag{2.1}$$

Where Y (t + 1) presented the position vector of a grey wolf in the t + 1th iteration, Y (t) shows the position vector of the grey wolf at the tth iteration, A is a coefficient, and D is the distance between the grey wolf and the location of the prey (X_p). The distance is calculated as follows:

$$\vec{D} = \left|\vec{C}.\vec{Y}_p(t) - \vec{Y}(t)\right| \tag{2.2}$$

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{2.3}$$

$$\vec{C} = 2.\vec{r}_2 \tag{2.4}$$

Where a is a parameter to balance exploration and exploitation, r_1 and r_2 are the coefficient random parameters between [0,1].

The following equations allow the update of the position of every gray wolf and make it go around in an n-dimensional search space. The parameter ‘a’ is updated in the current iteration as follows:

$$\vec{a} = 2*\left(1-\frac{\text{iter}}{\text{Maxiter}}\right) \tag{2.5}$$

The position of each wolf in each iteration is indicated using the alpha, beta, and delta wolves as follows:

$$\vec{Y}_{(\text{iter}+1)} = \frac{\vec{Y}_1+\vec{Y}_2+\vec{Y}_3}{3} \tag{2.6}$$

Where t is the current iteration, and T is the maximum number of iterations. This is presented as real grey wolves encircling prey in the 3D search space. Y_1, Y_2, and Y_3 are the new positions of a wolf and are calculated as follows:

$$\vec{Y}_1 = \vec{Y}_\alpha - \vec{R}_1*(\vec{P}_\alpha) \tag{2.7}$$

$$\vec{Y}_2 = \vec{Y}_\beta - \vec{R}_2*(\vec{P}_\beta) \tag{2.8}$$

$$\vec{Y}_3 = \vec{Y}_\delta - \vec{R}_3*(\vec{P}_\delta) \tag{2.9}$$

The three best solutions are considered alpha, beta, and delta wolf. After that, the algorithm iteratively updated the wolves' position and the time-varying parameters. In each iteration, if a new solution is better than the existing three best solutions, the existing solution is replaced by the new solution. The new solutions are now selected as the current iteration's alpha, beta, and delta wolf. This iteration process will stop when it meets the end criterion's satisfaction.

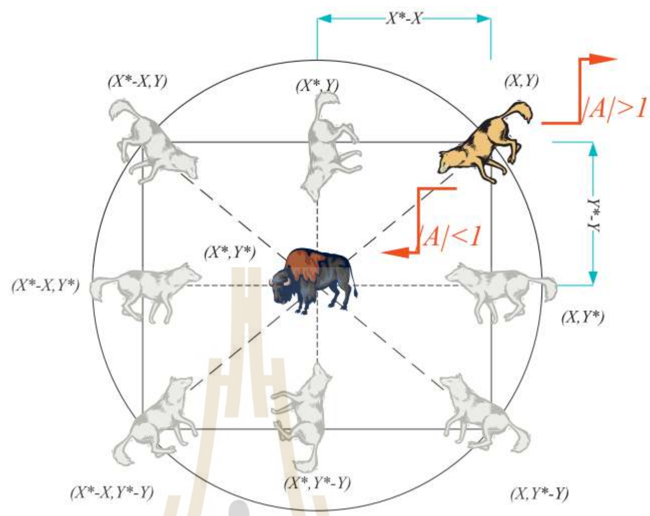


Figure 2.8 Hunting behavior of gray wolf and position updating of search agents (Mirjalili et al., 2014)

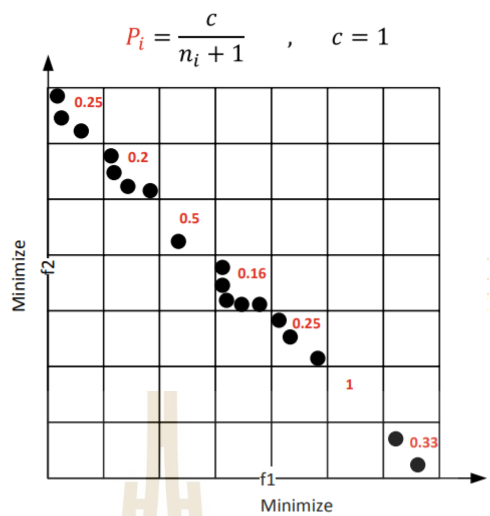
2.23.2 Multi-objective Grey Wolf Optimizer

Multi-objective Grey Wolf Optimizer (MOGWO) used the archive to store non-dominated solutions throughout the iteration process according to the following rules and conditions. The first condition, the new non-dominated wolf, will be stored in the archive if the archive is empty. The second condition is that the new non-dominated wolf will replace the existing wolf's position in the archive if the existing wolf is dominated by a new wolf outside the archive. The third condition is that the new non-dominated wolf will be stored in the archive if the new wolf is non-dominated compared to the existing wolf in the archive and the archive has enough space. The fourth condition, the most crowded grid segment in the archive, will be removed, and the new wolf will be entered. If the new wolf is a non-dominated solution compared with the existing wolf in the archive, there is also not enough space to store it (Mirjalili & Dong, 2020a). The archive mechanism has two operators to navigate the space in the maximum size: archive maintenance and leader selection. Archive maintenance is responsible for removing the existing gray wolf from crowded regions once the archive is complete. The function of the grid mechanism is to divide the objective space into segments. The number of hold gray wolves is recognized as the crowdedness of each segment (Mirjalili & Dong, 2020a). The probability of the removed segment eliminating the solution from the segment is chosen as follows. The probability of removing the solution will be high if the probability of choosing the equation shows as the crowded segment. The removing a solution is presented as low probability if the non-dominated solution does not exist it in the segment. The following equation is the probability of selecting the segment to choose a leader from the archive.

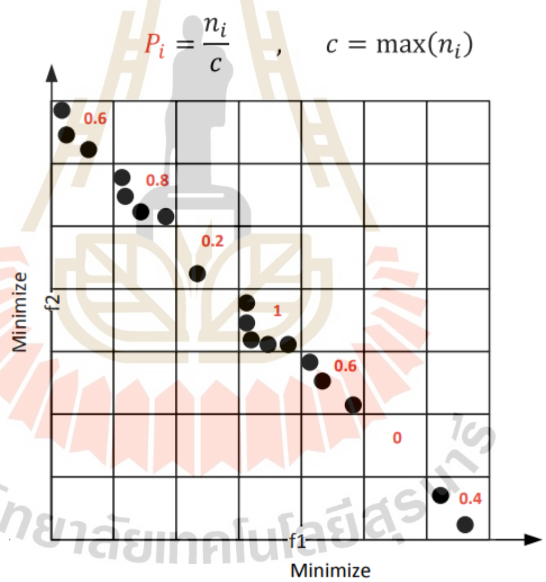
$$p_i = n_i / c \tag{2.10}$$

$$p_i = c / n_i + 1 \tag{2.11}$$

Where ni presented the number of non-dominated solutions in the i-the-segment and c represented a constant set to 1. ni indicates the number of non-dominated solutions in the i-the-segment, and c is a constant generally set to 1. This equation indicates that if the segment has few solutions, the candidate solution will have a higher potential for choosing as a leader candidate. Fig. 5.1 shows the relation of probability values for the segment and the number of solutions inside. The MOGWO search algorithm around the crowded segment areas is more likely to find the non-dominated solutions than increase overall distributions. Fig 3.2 (a) shows the potential for removing a solution from the archive according to the higher level of the crowded segment. The chosen solution from the most crowded segment will be accommodated with a new solution. In a stochastic algorithm, a small probability of crowded regions will be offered high exploration and avoided trapping in the locally optimal solutions.



(a)



(b)

Figure 2.9 (a) The probability of choosing the leader. (b) The probability values for removing segment (Mirjalili & Dong, 2020b)

The mentioned leader selection technique chooses three non-dominated solutions in every iteration step. The selected leaders are the reference points to update the solutions and position in the population, and the updated solutions and positions are inserted into the archive according to the mentioned rules (Mirjalili & Dong, 2020a). The pseudo-code of the MOGWO is taken from Goli et al. (2020).

A multi-objective is a group of vectors with more than one objective function to be minimized or maximized (Mirjalili & Dong, 2020b). The following equations represented a multi-objective minimization problem:

Minimize: $\overrightarrow{F(\vec{x})} = \left\{ f_1\overrightarrow{(\vec{x})}, f_2\overrightarrow{(\vec{x})}, \ldots, f_0\overrightarrow{(\vec{x})} \right\}$ (2.12)

Subject to: $g_i(\vec{x}) \geq 0, i = 1, 2, \ldots m$ (2.13)

$h_i(\vec{x}) = 0, i = 1, 2, \ldots, p$ (2.14)

$lb_i \leq x_i \leq ub_i, i = 1, 2, \ldots, n$ (2.15)

Where x presented a vector of objective function involving all variables in the problem, n showed the number of variables, and m and p presented the number of inequality and equality constraints, respectively. lb_i represented the lower bound of the i_{th} variable, and ub_i is the upper bound.

The Pareto optimal front, a vital dominance operator, must compare the conflict solutions among multiple solutions under multiple objectives function. The mathematical formulation of Pareto dominance and Pareto optimality for the minimization problem is defined as follows:

Two vectors, such as $\vec{x} = (x_1, x_2, \ldots, x_k)$ and $\vec{y} = (y_1, y_2, \ldots, y_k)$. Vector $\vec{x}$ dominates vector $\vec{y}$ (denote as $\vec{x} \prec \vec{y}$) if:

$\forall i \in (1, 2, \ldots, 0)$ (2.16)

$[f_i(\vec{x}) \leq f_i(\vec{y})] \wedge [\exists i \in 1, 2, \ldots, 0 : f_i(\vec{x}) < f_i(\vec{y})]$ (2.17)

A solution x ∈ X is called Pareto-optimal if:

$\left\{ \nexists \vec{y} \in X \mid \vec{y} \prec \vec{x} \right\}$ (2.18)

In such conditions, thousands of reasonable choice solutions are available with different quality. The Pareto optimal solution set is to represent this condition; this is the set of all nondominated solutions for a given problem. This set usually includes thousands of reasonable choice solutions, representing the best trade-offs between the objectives. The Pareto optimal set is represented as follows:

Pareto-optimal solutions set for all solutions in a minimization problem:

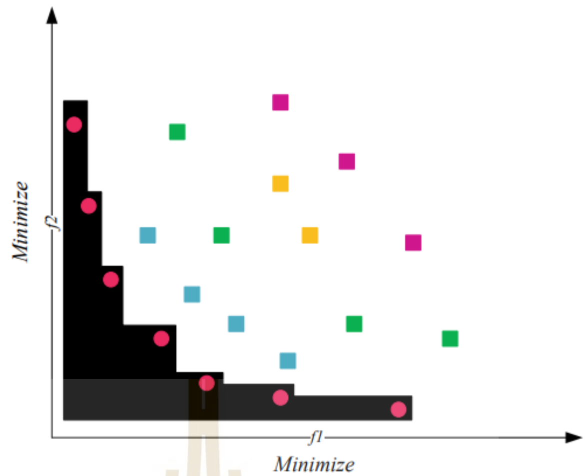
Pareto-optimal solutions set (P S) := $\{\vec{x}, \vec{y} \in X \mid \nexists \vec{y} \prec \vec{x}\}$ (2.19)

The Pareto optimal front is an essential set of multi-objective optimization processes. This set has the exact solutions as the Pareto optimal set. The Pareto optimal front is selected to store the best solutions of specific objectives for all objectives from the optimal solution set. The Pareto optimal front is the projection from the optimal solution, which only considers specific objectives. Figure 2.10 presents four possible cases of Pareto's optimal front for minimization and maximization problems.

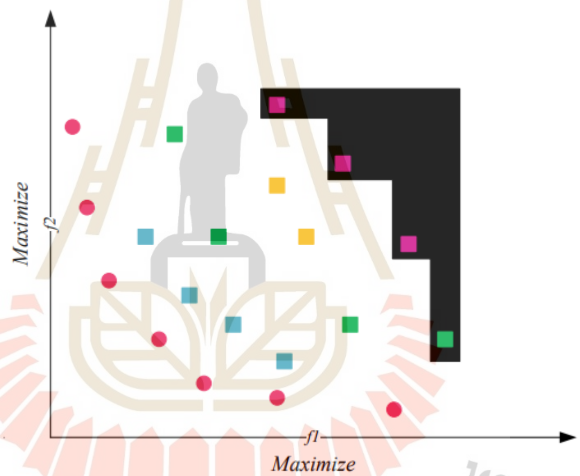
This set is presented as follows:

$\forall i \in (1, 2, \ldots, 0)$ (2.20)

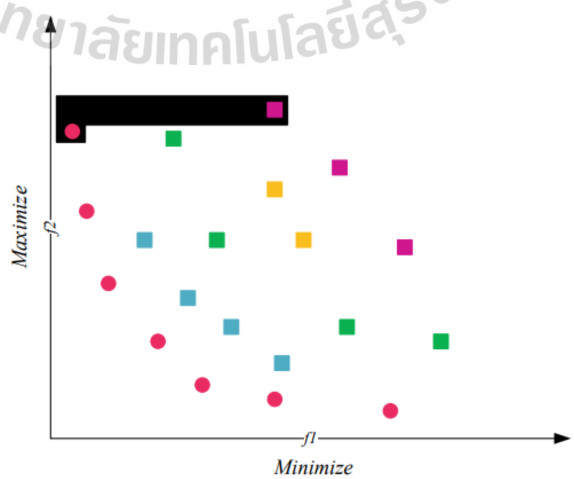
Pareto optimal front (P F) := $\{f_i(\vec{x}) \mid \vec{x} \in PS\}$ (2.21)



1. Pareto front: { ●, ●, ●, ●, ●, ●, ● }



2. Pareto front: { ■, ■, ■, ■ }



3. Pareto front: {●, ■}

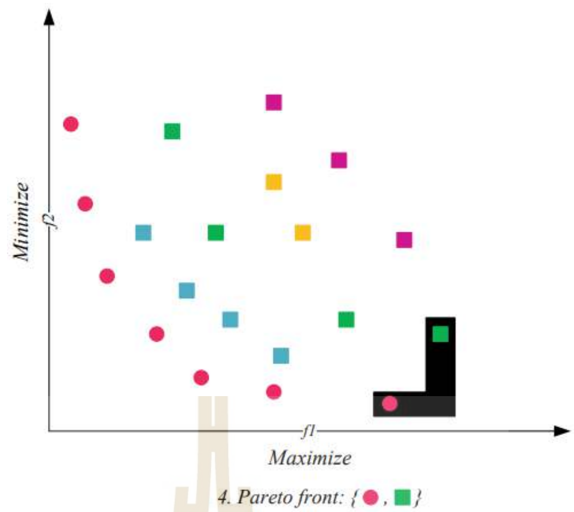


Figure 2.10 Location of Pareto optimal fronts for a bi-objective function in four cases that were considered minimized or maximized (Mirjalili & Dong, 2020b)

Algorithm: Pseudo-code Multi-objective Gray Wolf Optimizer (MOGWO)

1. Initialize wolf solutions Si (i=1,..., N_wolf)

2. Generate vectors of movement coefficient

3. Evaluate the fitness of each wolf

P_α=the position of the best wolf (alpha) P_β=the position of the second wolf (gamma) P_δ=the position of the third best wolf (delta)

4. iter=1

5. repeat

6. for n=1:N_wolf

Reposition the wolves based on Equations (8)- (14)

7. End for

8. Estimate the fitness value of wolves

9. Update P_α, P_β, P_δ

10.Update the vectors of movement coefficient

(Equtions (12)-(13))

11. Specify the non-dominate solution (P) (Update Archive)

12. iter=iter+1

13. Until iter>=Max_iter

14. Return Archive

2.23.3 Priori Multi-objective Optimization

In prior multi-objective optimization, multiple objectives are aggregated using a set of weights to form a single objective. This simple method has low computational time due to aggregated single-objective algorithms without storing non-dominated solutions. However, the algorithm required running several times to search multiple Pareto optimal solutions (Mirjalili & Dong, 2020b). The following equation presented priori multi-objective minimization problem:

Minimize : $$f(\vec{x}) = \sum_{i=1}^{0} w_i f_i(\vec{x}) \tag{2.22}$$

Subject to: $$g_i(\vec{x}) \geq 0, i = 1, 2, \ldots m \tag{2.23}$$

$$h_i(\vec{x}) = 0, i = 1, 2, \ldots, p \tag{2.24}$$

$$lb_i \leq x_i \leq ub_i, i = 1, 2, \ldots, n \tag{2.25}$$

Where x shows a vector of all variables in the problem, n represents the number of variables, and m and p represent the number of inequality and equality constraints, respectively. lb_i is the lower bound of the i_{th} variable, and ub_i is the upper bound.

2.23.4 Posteriori Multi-objective Optimization

In this algorithm, the multiple objectives of the problem are maintained and optimized simultaneously (Mirjalili & Dong, 2020b). Maintaining multi-objective formulation for a minimization problem is formulated as follows:

Minimize: $\overrightarrow{F(\vec{x})} = \left\{ f_1(\overrightarrow{\vec{x}}), f_2(\overrightarrow{\vec{x}}), \ldots, f_0(\overrightarrow{\vec{x}}) \right\}$ (2.26)

Subject to: $g_i(\vec{x}) \geq 0, i = 1, 2, \ldots m$ (2.27)

$h_i(\vec{x}) = 0, i = 1, 2, \ldots, p$ (2.28)

$lb_i \leq x_i \leq ub_i, i = 1, 2, \ldots, n$ (2.29)

Where x shows a vector of all variables in the problem, n represents the number of variables, and m and p are the number of inequality and equality constraints, respectively. lb_i is the lower bound of the ith variable, and ub_i is the upper bound.

Since the posterior method has applied the rules of Pareto optimal dominance to compare solutions, this method is required to store non-dominated solutions as the best solutions. This method can accurately approximate the Pareto optimal solutions, and the solutions' distribution is uniform across all objectives. The uniformly distributed Pareto optimal solutions supported the decision maker to choose different applications and purposes from many different solutions (Mirjalili & Dong, 2020b).

2.23.5 Interactive Multi-objective Optimization

Interactive multi-objective optimization is the human interactive input operation that implements decision-making during optimization to guide the search process to obtain desired regions. The random solution is first generated from the algorithm, and then the process is evaluated and continued to find desirable solutions (Mirjalili & Dong, 2020b).

2.24 Best compromise solution

The best compromise solution (BCS) is provided for searching for the best solution from the Pareto optimal set. This method is derived from the Euclidean distance technique. The minimum value of the corresponding objective function is set as the reference point (f_{imin}, f_{jmin}, f_{kmin}) available from the corresponding solution from all objective functions. The best solution is evaluated based on the minimum distance (d) between the specific and reference points (Khan et al., 2019). The following equation expresses the formulation of the minimum distance calculation:

$$D = [(f_{ai} - f_{i,min})^2 + (f_{bj} - f_{j,min})^2 + (f_{ck} - f_{k,min})^2]^{1/2} \tag{2.30}$$

$$d = \min(D) \tag{2.31}$$

2.25 Energy Management Systems Based on Bio-Inspired Algorithms

The concept of efficient EMS has attention recently due to demand growth and environmental issues. Autonomous and intelligent EMS is decision-making on scheduling generation and demand requirements to minimize energy utilization within a certain period. The function of computer-aided EMS is to monitor, supervise, optimize, and manage the consumer's consumption pattern, network configuration, and generation facilities. Its primary function is to make an efficient and cost-effective structure with supply/demand balancing under operational constraints, RE resources uncertainties, energy costs uncertainties, and energy demand uncertainties.

In this scenario, demand-side management (DSM) and demand response (DR) are two essential concepts of EMS. The function of DSM is demand control, such as planning, executing, and monitoring, influencing consumer energy usage patterns. DSM systematically disperses energy usage to minimize emissions and peak demand with the DR model and chooses preferred energy sources. DR is the model of incentive-based schemes or time-based pricing schemes, such as Time-of-Use (ToU), Real-time Pricing (RTP), Critical Peak Pricing (CPP), and Inclining Block Rate (IBR). Optimization and energy usage can be achieved when the EMS controller obtains the DR data and price tariff for energy from the service providers.

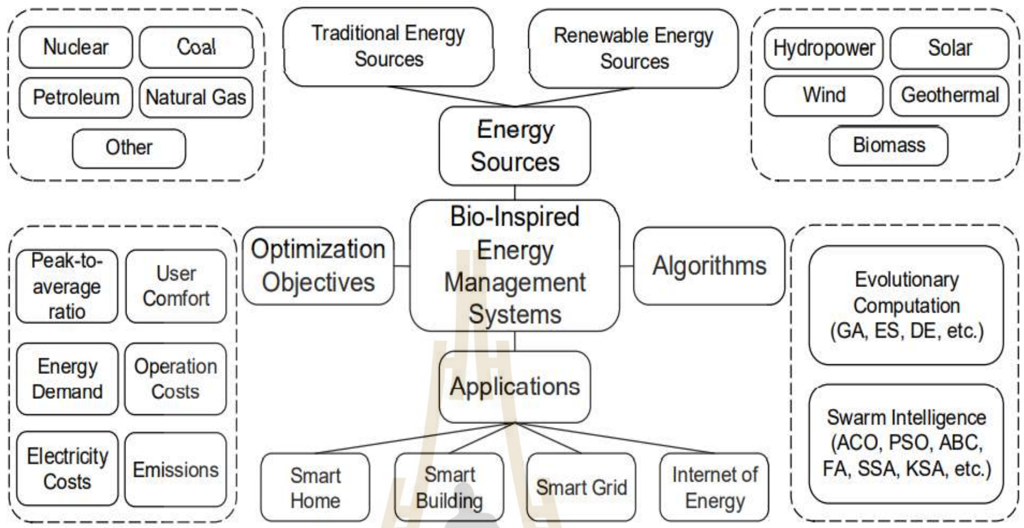


Figure 2.11 EMS using bio-inspired approaches (Nguyen et al., 2020).

The EMS with bio-inspired optimization technique is shown in Fig. 4.2. Generally, types of energy suppliers are traditional and renewable energy sources. Factors such as peak-to-average ratio, energy demand, electricity cost, emission cost, operation cost, and user-comfortable lifestyle must be considered in the planning process. These factors can influence the system's combined use of energy sources. The controlling process is executed with EMS, which performs as a decision-maker to schedule optimally according to received information and these factors in a specified time horizon.

Therefore, the responsibility of EMS is intelligently to handle and manage all information from the specified system. Applying bio-inspired searching algorithms in the EMS modeling can enhance exploration and exploitation to provide global optimization search results. This algorithm is a more powerful tool than an exact algorithm to solve optimization problems due to its effective search in the feasible region to provide optimal results (Nguyen et al., 2020).

2.26 Multi-objective Optimization Method for microgrid operation

Multi-objective optimization is the problem with conflict problems with multi-criteria objectives with multiple solutions as an optimum solution. The feasible region is formulated from the group of optimal solutions known as the Pareto optimal front to provide a solution amongst the conflicting objectives. Meta-heuristic techniques provide a Pareto optimal front in a single run, while mathematical techniques perform multiple steps to get an optimal front (Khan et al., 2019). This work implements a power system optimization problem dealing with three conflicting objectives: operation cost, PAR reduction, and consumer comfort, with and without coordination. The difference between with and without coordinate optimization impacts the decision-making step in day-ahead scheduling. The solution from the Pareto front solution set is selected using the best compromise solution (BCS) method. In the coordinate day-ahead optimization, the optimal solution is chosen first from the Pareto optimal front, and then the decision solution is generated after coordination among the conflict objective's function. During the scheduling process, although the operation cost is the main target to focus on from the upstream aspect, it is necessary to involve another conflict objective that can affect the flexible operation system. An efficient, optimal solution is required to satisfy conflicting objectives for implementing the optimization work in the natural environment. This work considers the optimal day-ahead load scheduling process equally crucial in a multi-objective framework (Khan et al., 2019).

The participation of distribution generations and responsive components in the reconfigurable microgrid will pose challenges in optimal day-ahead scheduling. To this end, this work presents active microgrid distribution network management for day-ahead scheduling of existing active components and uncertainty. In the optimal day-ahead scheduling process, the continuous real-time supervision of active structure, such as real-time forecasted REs information, real-time aggregate load profile, and available power generation from system generation units, is required. The optimization process performs as a decision-maker to evaluate the optimal set-points of system generation units and active, responsive load. The multi-objective optimizer defines the optimal generation dispatch and responsive load participation according to multi-criteria and related system constraints: wholesale market purchases and RCSs status (Esmaeili, Anvari-Moghaddam, Jadid, & Guerrero, 2019).

The optimal day-ahead scheduling is performed for a day at one h time step; its task is to evaluate the optimal dispatch of available resources in real-time. Due to the possibility of error in REs prediction, it is necessary to consider the worst-case scenario that can adjust the robustness of system performance to improve system security during optimal scheduling. Based on the robustness principle, the robust optimization model applies the interval prediction information wind/PV power output using the obtained power from the hourly real-time predicted interval. Due to the high penetration of REs, the accuracy of RE prediction becomes essential for management systems dealing with marginal operation costs and unexpected system contingencies. To avoid such shortcomings, it is required to plan the optimal scheduling with uncertainty and the predicted error to ensure the reliability and economic dispatch of the real-world system. The previous research explores the day-ahead scheduling process with mathematical formulation to capture the uncertainty; it does not consider the temporal characteristics of prediction accuracy (Xu et al., 2023).

The management and planning of microgrids is a problem commonly solved with optimization methods. The optimization methods can be divided into math and meta-heuristic approaches. Math optimization is a simplification approach that can be achieved to simplify the linear model and solve the problem with a specific model. The meta-heuristic optimization inspired the nature of the ecosystem. The multi-objective optimization provides multi-optimal points that satisfy the different criteria of the system requirement. Therefore, a suitable method for selecting the optimal solution is required (Hajiamoosha et al., 2021).

In this work, a multi-objective optimization model is applied to solve the problem of microgrid energy management. The proposed model is to handle the operation cost, peak demand, and consumer satisfaction simultaneously. Moreover, the demand response program has cooperated to elevate the microgrid performance under uncertainty due to RES' resources. The proposed model is considered energy management from the upstream aspect; the typical grid-connect model consists of PV, wind, and fuel-based distributed generation. This planning stage considers uncertain parameters due to PV and wind generation. A multi-objective gray-wolf optimizer is a powerful tool for solving multi-objective problems with three different criteria. The different case studies simulation results and comparative studies validated the effectiveness of the proposed method.

2.27 Types of Time-series Forecasting

The forecasting method can be classified according to iterative way, direct way, point forecasts, and probabilistic forecasts. Different types of forecasts are utilized depending on the desire for different situations, applications, and scenarios. The following presented the standard time-series forecasting method as groupings (Haben, Voss, & Holderbaum, 2023).

2.27.1 Point or Probabilistic forecasting

The point and probabilistic forecasts provided multiple estimation values in each time step to describe the outspread form of future values. Point forecasting is a fast estimation method with fewer learning and training data parameters. This can easily be embedded in applications, such as energy storage controlling models that utilize a single point value per time step rather than a range of values. The point forecasts reflected the uncertainty and volatile data. In such cases, the applications of probabilistic forecasting are more utilizing models for volatile data. The drawback to probabilistic methods is that they are complex and computationally expensive to produce and store (Haben et al., 2023).

2.27.2 Statistical and Machine Learning Methods

Statistical-based time series forecasting has been implemented using statistical methods, such as ARMA, ARIMA, and exponential smoothing. These methods are easy to implement and interpret and computationally inexpensive. Recently, machine- learning techniques have become applied in time series forecasting, such as neural networks and random forests. The statistical models preferred clear and linear relations in the data, such as daily/weekly, seasonality, and clear links to external influences such as weather. Since model assumptions directly learn the relationships from the data, failed model assumptions will lead to inaccurate results. Machine learning is an excellent choice for complicated nonlinear data and unclear probability relationships. This method is suited for learning many time series data and hierarchical time series forecasting (Haben et al., 2023).

2.28 Time Series: Basic Definitions and Properties

Time series data are the consecutive sequence data set that chronologically increases the discrete time index. The critical feature of time series data is stationary and autocorrelation. The stationary time series is the expected value and the variance, and each data point comes with an equal distribution of fixed mean and variance. Autocorrelation can be described as the one-point changes in the time series data related to the lagged points time series data. Autocorrelations are essential for identifying historical values to estimate future points. Non-stationary time series are the values from a distribution with time-varied mean and variance. Stationarity is essential for traditional time series forecasting models like ARMA and ARIMA. Trends and seasonality are features that often occur in non-stationary data. The trend is the macroscopic low-frequency changes in the data with the linear trend, gradual linear growth in the time series. Seasonality is the changes in the time series occurrence at fixed regular intervals or fixed periods, such as daily, weekly, and annual levels.

The fundamental function of forecasting is trying to get approximate or accurate function describing the future behavior of a time series. Accuracy is generally defined based on error measures and optimizes the application of interest. Various forecasting methods that are suited for different applications are available and have advantages and disadvantages. The context of point forecasting is to provide a single estimate for each time step tn+1, tn+2, . . . , tn+h in the forecasting horizon. Probabilistic forecasting generally provides multiple values for each time step and is usually the better description of the uncertainty of future values. The drawback of probabilistic forecasting is the high computational costs and the large amount of training data to generate an accurate estimate. The probabilistic models with sufficient computational resources and data can provide a better descriptive and informative estimation of the uncertainty in future values (Haben et al., 2023).

The traditional statistical methods assume that the relative between the dependent and independent variables is the way of linear trends autoregressive behaviors. The performance of statistical methods is quite successful and accurate, and this method is easy to forecast even with few available data. However, this method is not suited for highly complex nonlinear models. Therefore, increased monitoring has increasingly allowed machine learning methods to solve complicated patterns in the data. This model can be trained to learn the complex relationship of the data with some features. Recently, artificial neural networks become increasingly popular for time series tasks and forecasting. Sophisticated Deep learning variants, such as recurrent neural networks, long-short-term memory (LSTM), and gated recurrent unit (GRU), are the successful models for time series tasks due to the availability to model the autoregressive relationships. Recurrent architectures convolutional neural networks (CNN) also provide the best results, and this can be trained efficiently in large time series data for distribution-level networks (Haben et al., 2023).

2.29 Statistical Time series forecasting methods

There are five statistical-based forecasting methods: Artificial Neural Network (ANN), Support Vector Machine (SVM), Markov Chain, Autoregressive, and Regression models. All statistical-based models require historical data to execute time- series forecasting and do not require internal system states to model the process according to the parameter assessed at the current points (Sobri, Koohi-Kamali, & Rahim, 2018).

2.29.1 Regression

The regression method is a model for determining the functional relationship between response and predictor parameters. This method is a repetitive process where the output parameters are applied to analyze, verify, criticize, and modify the input parameter. Univariate regression analysis refers to one response parameter, and multivariate regression considers two or more parameters. The univariate linear regression approach determined the correlation parameters by fitting a proper linear equation to the data. The linear fitting kept all response parameters constant in the multiple linear regression but not for predictor parameters. These two regression methods are commonly used with the complex correlation between the parameters. The forecasted data are obtained for any predictor values that diverge from the observed data (Sobri et al., 2018).

2.29.2 Autoregressive (AR)

Autoregressive is to measure the correlations between dependent and independent parameters. The categorization process depends on the conduction of stationary/non-stationary and linear/nonlinear processes. The stationary time series is the time series that fluctuates in the region of the static mean (Sobri et al., 2018). The equation is expressed as follows:

$$\overline{x}_t = \sum_{i=1}^{m} \phi_i x_{t-i} + \omega_t \tag{2.32}$$

$$\overline{x}_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \phi_3 x_{t-3} + \ldots + \phi_m x_{t-m} + \omega_t \tag{2.33}$$

Where, ϕ_i is the ith AR coefficient. x_{t-i} is the time series values. ω_t is the white noise with zero mean and constant variance

2.29.3 Moving average (MA)

The moving average (MA) model uses a weighted factor of historical data to create a time-series representation. Then, it combines with past noise data to develop a time-series process (Sobri et al., 2018). The MA of order n is described as:

$$\bar{x}_t = \sum_{j=0}^{n} \theta_t \omega_{t-j} \tag{2.34}$$

$$\bar{x}_t = \omega_t + \theta_1 \omega_{t-1} + \theta_2 \omega_{t-2} + \ldots + \theta_n \omega_{t-n} \tag{2.35}$$

Where θ_t is the jth MA coefficient. ω_{t-j} is the white noise that is uncorrelated with random parameters with zero mean and constant variance.

2.30 Autoregressive Moving average (ARMA)

The ARMA has emerged as an adoption model that extracts from statistical and Box-Jenkins methods. The general form of the ARMA prediction model is shown in Fig 4.2. ARMA model, commonly applied in autocorrelated stationery time-series data, was a superior tool to predict the following values of particular stationary time-series (Sobri et al., 2018).

$$\bar{x}_t = \sum_{i=1}^{m} \phi_i x_{t-i} + \sum_{j=0}^{n} \theta_j \omega_{t-j} \tag{2.36}$$

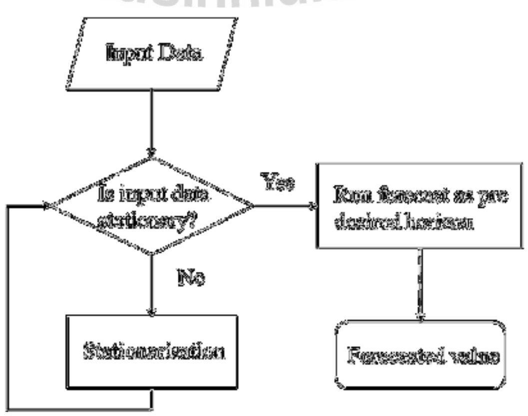


Figure 2.12 Process of ARMA forecasting method (Sobri et al., 2018).

It required a series of measure data sets for the particular site to forecast the output of an RE generation with statistical methods. The enormous amount of applied data set can be reduced without losing the information by employing statistical data treatment. Generating accurate synthetic data for a typical year represents the actual statistics of multi-year measure data (Nfaoui, Buret, & Sayigh, 1996). The following articles are the treatment process for historical data series.

2.30.1 Stationarity

The ARMA model is suited for use as a prediction tool for stationary historical time series. Stationary is the statistical properties of the time series model, which have equal mean, variance, and autocorrelations over all-time horizons. Therefore, statistical forecasting techniques applied the assumption time-series, which statistical transformations can change stationaries. The stationeries of times series data make it easier to implement the prediction process using historical data. Therefore, the time-series sequence needed to transform stationery provides a clue-searching process for the forecasting model (B. Singh & Pozo, 2019).

2.30.2 Gaussian transformation

Hourly wind data cannot be directly applied due to its non-Gaussian distribution. This problem is solved by the Dubey method that modifies shape parameters of the Weibull random variable close to 3.6 (J. L. Torres, Garcia, De Blas, & De Francisco, 2005). The Weibull probability distribution function (PDF) is given as;

$$PDF_v = k/c\,(v/c)^{k-1}\exp(-(v/c))^k \tag{2.37}$$

Time series of the particular month of the year are transformed into Gaussian distribution;

$$x = k/3.6 \tag{2.38}$$

Where k and c are the shape and scale parameters of wind speed.

2.30.3 Elimination of the seasonal variation and daily variation

The issue of non-stationary seasonal set down the year segment into monthly periods at the outset. Daily non-stationarity can be removed by subtracting the hourly mean value from the actual data set. It was also needed to divide with the standard deviation to decrease the data to a normal process with a mean of 0 and variance of 1 (Brown, Katz, & Murphy, 1984; Nfaoui et al., 1996). The time series of the particular month of the year is standardized velocity to remove diurnal non-stationarity;

$$V^*(n,y) = \frac{V'_{n,y} - \mu(t)}{\sigma(t)} \tag{2.39}$$

With the following period function:

$$\mu(t) = \frac{\sum_{i=0}^{d.Y-1} V'_{24i+t}}{d.Y}, 1 \le t \le 24 \tag{2.40}$$

$$\sigma(t) = \left[\frac{\sum_{i=0}^{d.Y-1} (V'_{24i+t} - \mu(t))^2}{d.Y}\right]^{1/2}, 1 \le t \le 24 \tag{2.41}$$

Where $V^*(n,y)$ is the standardized hourly average wind speed. $V'_{n,y}$ is hourly average wind speed. $\mu(t)$ and $\sigma(t)$ are the sample mean and the standard deviation of all transformed wind speeds in 24 hours.

2.30.4 Parameter Estimation

The Yule-Walker estimator is used to calculate the sample autocorrelation coefficient (Patterson, 2011);

$$\hat{\sigma}^2 = \hat{\gamma}(0)(1 - \hat{\rho}_2^T \hat{R}_2^{-1} \hat{\rho}_2) \tag{2.42}$$

Where,

$$\hat{\gamma}(k) = \sum_{t=k+1}^{24T} V^*(t-k)V^*(t), k = 0,1,...,p \tag{2.43}$$

$$\hat{\phi} = \hat{R}_2^{-1}\hat{\rho}_2 \tag{2.44}$$

$$\hat{R}_2 = \begin{pmatrix} \hat{\rho}(0) & \hat{\rho}(1) \\ \hat{\rho}(1) & \hat{\rho}(0) \end{pmatrix} \tag{2.45}$$

$$\hat{\rho}_2 = \left[\hat{\rho}(1) \quad \hat{\rho}(2)\right]^T \tag{2.46}$$

$$\hat{\phi} = \left[\hat{\phi}_1 \quad \hat{\phi}_2\right]^T \tag{2.47}$$

$$\hat{\phi}_{11} = \hat{\rho}(1) = \frac{\hat{\phi}_1}{1-\hat{\phi}_2} \tag{2.48}$$

$$\hat{\phi}_{22} = \hat{\phi}_2 = \frac{\hat{\rho}(2)-\hat{\rho}^2(1)}{1-\hat{\rho}(1)} \tag{2.49}$$

$$\hat{\phi}_{21} = \hat{\phi}_1 = \hat{\rho}(1)[1-\hat{\phi}_{22}] \tag{2.50}$$

For first-order moving average model, MA(1);

White-noise series distributed with constant variance.

$$\omega_{t-j} = \sum_{j=0}^{\infty}(-\theta)^j y_{t-j} \tag{2.51}$$

Where,

$$\theta(0) = \frac{\gamma(0)}{\gamma(0)} = 1 \tag{2.52}$$

$$\theta(1) = \frac{\gamma(1)}{\gamma(0)} = \frac{b}{1+b^2} \tag{2.53}$$

$\theta(k) = 0$ for all k> (2.54)

2.31 Performance metrics

The performance index of the forecasting methods can be measured by different metrics related to the forecast error. The higher percentage of errors index corresponds to fewer accuracies. This section provides the commonly used definitions and equations for error calculation metrics (Ghofrani & Alolayan, 2018). Many metrics can be defined as the validation for forecasting results. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Bias Error (MBE) are commonly used error metrics for forecasting (David et al., 2016). The formulation of performance metrics is as follows:

Root Mean Square Error $$(\mathrm{RMSE}) = \sqrt{1/n\sum_{i=1}^{n}(\bar{x}_i - x_i)^2} \qquad (2.55)$$

Mean Absolute Error $$(\mathrm{MAE}) = 1/n\sum_{i=1}^{n}|\bar{x}_i - x_i| \qquad (2.56)$$

Mean Bias Error $$(\mathrm{MBE}) = 1/n\sum_{i=1}^{n}(\bar{x}_i - x_i) \qquad (2.57)$$

Where, x_i is the forecasted time series values

$\bar{x}_i$ is the observed time series values

n is the total number of samples

2.32 Modern Recurrent Neural Networks

RNN networks have only been capable of modeling short-term dependencies and numerical instability issues. Therefore, gated recurrent units (GRUs) and long short-term memory (LSTM) are the popular extensions of RNNs. In feedforward networks, recurrent neural networks work the input data of the input layer X_t , a hidden state of the activation signal from the last time step Z_{t-1}. LSTMs involve a second hidden state called the cell state. The function of cell state is to memorize the current state and previous cell state where the training determines memorized for long- and short-term values. LSTMs also involve the forget gate to control the forget function of the input and output state. Weights and activation functions are needed to activate since the gates are made up of ANN layers. The forget gate controls keep data from the previous cell state and add data from the current input of the previous activation. The activation of the input and output is evaluated with a sigmoid function (between 0 and 1), in which the choice cell state “forgets” when the values are close to 0 or the choice cell state “kept” when the values are close to 1 (Huawei Technologies Co., 2022).

2.33 Deep Neural Network

Deep learning is a group of stacked perceptrons used to build multi-layer artificial neural networks based on human neural networks. The artificial neural network is a computing system of highly interconnected artificial neuron networks that processes information with dynamic responses to external inputs. Artificial neural networks possess the same feature as the human brain, such as parallel information processing, learning, association, classification, and memorizing.

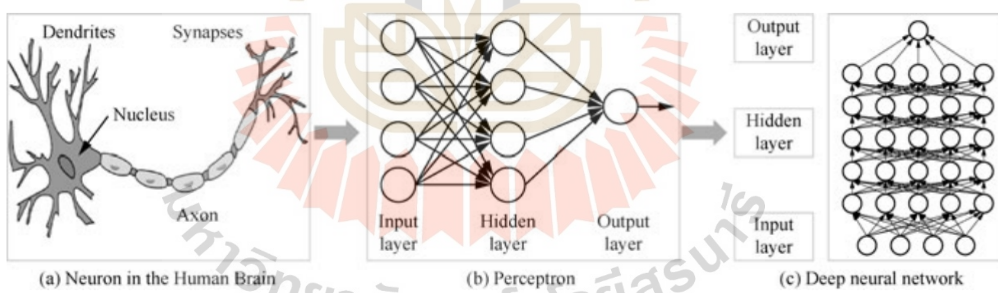


Fig. 2.13 Neurons in the human brain and artificial neural network (Huawei Technologies Co., 2022)

In single-layer perceptron, the input vector X ¼ [x0, x1,•••, xn] T is the dot product with the weight net W ¼ [w0, w1,•••,wn]T. The net is activated to take an output function by an activation function called Sgn(net). The single-layer perceptron is a linear model and can only implement linear classification. The multilayer perceptron, the fastest-growing artificial feedforward neural network, is the structure of a hierarchical neuron arrangement to process non-linear data. The inner layer neuron of nodes is the computing unit that performs the computing function. The neurons are to receive the previous values and transmit the value to the subsequent layer neurons. The same layer neurons are not internally connected, and the data transmission is one-way between the layers (Huawei Technologies Co., 2022).

2.33.1 Optimizer

The optimizer is the gradient descent algorithm term, often encapsulating into one object when implemented in an object-oriented language. The popular optimizers are SGD, Momentum, Nesterov, Adagrad, Adadelta, RMSprop, Adam, Adamax, Nadam, etc. The optimizers are used to improve the convergence speed of the algorithm, the stability to a local extremum, and the efficiency of the hyperparameters. The following presented the most commonly used optimizers (Huawei Technologies Co., 2022).

2.33.2 Adam Optimizer

Adagrad and Adadelta developed the Adaptive Moment Estimation (Adam) optimizer. Adam is to identify the adaptive learning rate of the parameter in a complex neural network. This is also used as weight adjustment of the network's different sensitivity parts, which is a complicated process to calculate the specific learning rate of the sensitive parts. The optimizer is generally a lower value. Identifying the sensitive parts manually and calculating the specific learning rate was challenging. The learning rate of the Adam optimizer setup is 0.0001. The gradient update equation is shown below:

$$\Delta w = -\frac{\eta}{e + \sqrt{v(n)}} m(n) \qquad (2.58)$$

Where m and v are the past gradients' first moment (mean) and second moment (uncentered variance), respectively. m and v can be defined as:

$$m(n) = am(n-1) + (1-a)g(n) \qquad (2.59)$$

$$v(n) = bv(n-1) + (1-b)g^2(n) \qquad (2.60)$$

2.33.3 Activation Function

The activation function is essential in neural network learning models to interpret complex nonlinear functions. The activation function implements nonlinear characteristics in the neural network. Without the activation function, the neural network can be represented as a linear function even with many layers. The sigmoid function is most frequently adopted in the study of feedforward neural networks. The sigmoid function is monotonic and derivative continuous to compute output bounded, used in the output layer for binary classification. This function facilitates the convergence of the network (Huawei Technologies Co., 2022).

2.33.4 Regularization

Regularization is the practical measure parameter to reduce generalization error and overfitting in machine learning. There are several proper techniques to prevent overfittings, such as parameter norm penalty, dataset expansion, dropout, and early stopping. Dropout is comprehensive and straightforward in the computation regularization method. The dropout function has discarded some parts of the output of neurons randomly and does not update the discarded neurons during the training phase. During the training, The random dropout process makes constant shield parameters and generates competitive models (Huawei Technologies Co., 2022).

2.33.5 Loss Function

Error detection function of the target classification is needed during the training of a deep neural network. This function is presented as a loss function or an error function. The loss function is to reflect the error between the target value and the actual value of the network perceptron. The commonly used loss function is the root mean square error (RMSE), as follows:

$$J(w) = \frac{1}{2n} \sum_{x \in X, d \in D} (t_d - o_d)^2 \tag{2.61}$$

Where, w is the model parameter, X is the training examples set, n is the size of X, D is the gathering of neurons in the output layer, t is the target output, and o is the actual output (Huawei Technologies Co., 2022).

2.34 Long short-term memory

The deep learning neural network was introduced, and the performances of such an approach have been assessed in several fields, such as language modeling, machine translation, image captioning, handwriting generation, image generation, and time series forecasting. RNNs can connect previous data with the present task, but their performance is poor in some applications when facing long-term dependencies. LSTMs are designed to solve the long-term dependency problem by removing or adding information in a single cell. LSTMs are constructed with several layers, and different types of layers are connected internally. (1) The Sequence Input layer sets the dimension of the input sequence at each time step. (2) The LSTM layer has several hidden units described as long-term dependencies, relying on a recurrent dynamical model. (3) The Fully Connected layer is a feedforward layer that connects the hidden units with the output layer in the LSTM layer. This layer acts independently and statically at every step. (4) The Regression Output layer is the computing layer that evaluates the mean squared error loss to solve the regression problem during training time.

The basic structure of RNNs has the vanishing gradient problem: the gradient decreases when the number of layers increases. The gradient problem is practically null and prevents the network training process of the deep RNNs with many layers. The networks with short-term memory do not provide good results dealing with long sequences. Therefore, the network demanded memorization of all the information in a complete sequence. Long short-term memory (LSTM) recurrent networks have been introduced to solve the vanishing gradient problem. LSTM uses three gate units, namely forget gate, update gate, and output gate, to keep relevant information and discard irrelevant information. Forget Gate decided to discard and save the information using binary numbers (0 and 1), whereas 0 means the information is forgotten and 1 means the information remains. The update gate decided the update and memory state condition of new information. The output gate generates the output value of a specific hidden unit, the input of the following hidden unit. The dot product of the previously hidden unit and the x_t current input is passed through the r sigmoid activation function to compute the current gate values. The tanh activation function computes the ~ct update values (Torres et al., 2021). The following equations define such condition:

$$\tilde{c}_t = \tanh(W_c[a_{t-1}, x_t] + b_c) \tag{2.62}$$

$$\Gamma^u = \sigma(W_u[a_{t-1}, x_t] + b_u) \tag{2.63}$$

$$\Gamma^f = \sigma(W_f[a_{t-1}, x_t] + b_f) \tag{2.64}$$

$$\Gamma^o = \sigma(W_o[a_{t-1}, x_t] + b_o) \tag{2.65}$$

$$c_t = \Gamma^u \tilde{c}_t + \Gamma^f \tilde{c}_{t-1} \tag{2.66}$$

$$a_t = \Gamma^o \tanh c_t \tag{2.67}$$

Where W_u, W_f, and W_o present the weights function of the update gate, forget gate, and output gate, respectively. b_u, b_f, and b_o are biases that govern the behavior of update, forget, and output gates, respectively. W_c and b_c show the weights and bias of the memory cell.

2.35 Gated recurrent units

Gated recurrent unit (GRU) is a simple version of LSTMs as long- term memory networks with low computational cost than LSTM networks. This unit is a widely used version with high convergence and robustness for many problems. GRU is the improved RNN network version that captures long-range dependencies and effectively uses the

RNN network. GRU is a simple model with less computational time, and it only uses two gates, namely the update gate and the Gr relevance gate. The update gate decides the condition of the memory state to be updated or not updated according to the memory state candidate. The relevance gate decides the relevance of c_t 1 to compute the next candidate for c_t (Torres et al., 2021). The following equations presented such conditions:

$$\Gamma^{u} = \sigma(W_{u}[c_{t-1}, x_{t}] + b_{u}) \tag{2.68}$$

$$\Gamma^{r} = \sigma(W_{r}[c_{t-1}, x_{t}] + b_{r}) \tag{2.69}$$

$$\tilde{c}_{t} = \tanh(W_{c}[\Gamma^{u}\tilde{c}_{t-1}, x_{t}] + b_{c} \tag{2.70}$$

$$c_{t} = \Gamma^{u}\tilde{c}_{t} + (1-\Gamma^{u})c_{t-1} \tag{2.71}$$

$$c_{t} = \Gamma^{u}\tilde{c}_{t} + \Gamma^{f}\tilde{c}_{t-1} \tag{2.72}$$

$$a_{t} = c_{t} \tag{2.73}$$

where W_u and W_r, show the weights function of the update gate and relevance gate, respectively. b_u and b_r are the bias that governs the behavior of the update gate and relevance gate, respectively. W_c and b_c are the weights and bias of the memory cell candidate.

CHAPTER III
RESEARCH METHODOLOGY

The common objective of the energy planning system has been to address the cost minimization problem (Gamarra & Guerrero, 2015). The planning process needs other essential objectives to be taken into account, such as environmental cost, power quality, system reliability, fuel consumption cost, total voltage variation, voltage stability enhancement, voltage profile improvement, transmission active and reactive power loss reduction (Gamarra & Guerrero, 2015; Guoping Zhang et al., 2020). The following chapter describes the common optimization problem in the microgrid planning process and also discusses techniques to solve energy management problems:

3.1 Research Methodology

The previous section summarizes the methodology for forecasting solar power, wind power, and demand using the stochastic base scenario and ARMA models. Renewable power prediction differs from demand due to its inherent non-stationary, diurnal nature and seasonal ramps. Solar power forecasting is generally divided into physics-based models, which apply numerical weather forecasting and solar radiation data, and statistical models that directly predict historical data. Many research articles point out that both techniques have their strength and weaknesses. This work uses statistical methods alone, specifically auto-regressive moving average (ARMA) models developed for the forecasting model. Although it has some limitations, the ARMA model is widely applied as a forecasting tool due to its ease of implementation.

Accurate forecasting is vital to guarantee reliable operations conditions and planning for generation capacities. To solve the problem, uncertainty modeling is typically executed by statistics base stochastic process. The former is evaluated by modeling synthetic samples or scenarios in the input model for decision-making optimization. The latter model applied a simple stochastic process in the sophisticated decision-making model. However, it is hard to interface the complex scenario base forecasting models and the sophisticated decision-making model. This work highlights the interfacing of the time-series forecasting model with decision-making models. In the proposed method, the system operation is further incorporated with DR, which does not require predefined constrain parameters to tackle the deviation from the forecasting (B. Singh & Pozo, 2019).

Energy efficiency and renewable resources provided guidelines for the minimization of the environmental impact of the network (Gamarra & Guerrero, 2015). However, renewable resources have volatile production energy and are unavailable at their peak power. Forecasting is implemented with optimization problems due to the uncertain nature of demand and renewable generation, the seasonal availability of power generation, and the demand for the microgrids forecasted in this system.

The proposed microgrid combines responsive loads, RESs, and non-RESs. Due to environmental concerns, modern microgrids focus on elevating the integration of RES resources. Therefore, combining different generation technologies requires optimal management and planning of the system's resources. Moreover, analyzing a suitable approach for the system’s uncertainties caused by the energy resources is also essential. Many research articles have been concerned with uncertainties in microgrids' energy management in recent years. The demand response program is a topic to address in managing microgrids. The impact of demand response can effectively solve the uncertainties in the renewable energy-based microgrid.

The proposed multi-objective framework is formulated for the minimization problem of operation cost, peak demand, and consumer comfort factor while satisfying network constraints and demand response. This multi-objective optimization is a problem that handles multi-criteria complex problems with multiple optimal points (Pareto-optimal front). The conventional optimization techniques do not have sufficient capabilities to solve such a problem. In this work, a deterministic multi-objective optimization problem is solved iteratively over time by the most updated and accurate available RE information at each time step. The demand response program is integrated as an ancillary service to provide reliable operation and consider uncertainty impact. From the previous research, the estimation of day-ahead parameters is scheduled based on the predicted system information with a specific probability function. The proposed work further investigates combining deep learning and multiple objectives optimization for the microgrid dispatch problem. Due to the intermittent nature of RE resources and demand, uncertainty becomes a significant concern related to microgrid energy management systems. In general, the uncertainty can be described as the divergence probability of the predicted values and the actual data. As illustrated in Figure 3.1, microgrid energy management is the optimization problem, which determines the optimal dispatching of resources according to system objectives. After that, the management system also creates an active distribution network by providing control commands for responsive loads. This work has executed the function with relevant technical information, network constraints, grid characteristics, and forecasted information.

The first step is forecasting in the microgrid environment, which can support the required information to evaluate the scheduling of generation capacities and demand requirements for the next day. Various forecasting data can be available based on different time horizons, from more than a few hours to quite a few days ahead. The proposed system developed 24-hour-ahead prediction results with a deep neural network. Secondly, the scheduling scheme was assessed before the next day. The scheduling of generating capacities is optimized by forecasting results from the first step, PV/wind power and load profile. As a result, the proposed system controls the operational status of optimal economic dispatch power from the various energy resources. Finally, the controllable responsive loads program can be dispatched to ensure reliability in the system based on the optimal generation scheduling results.

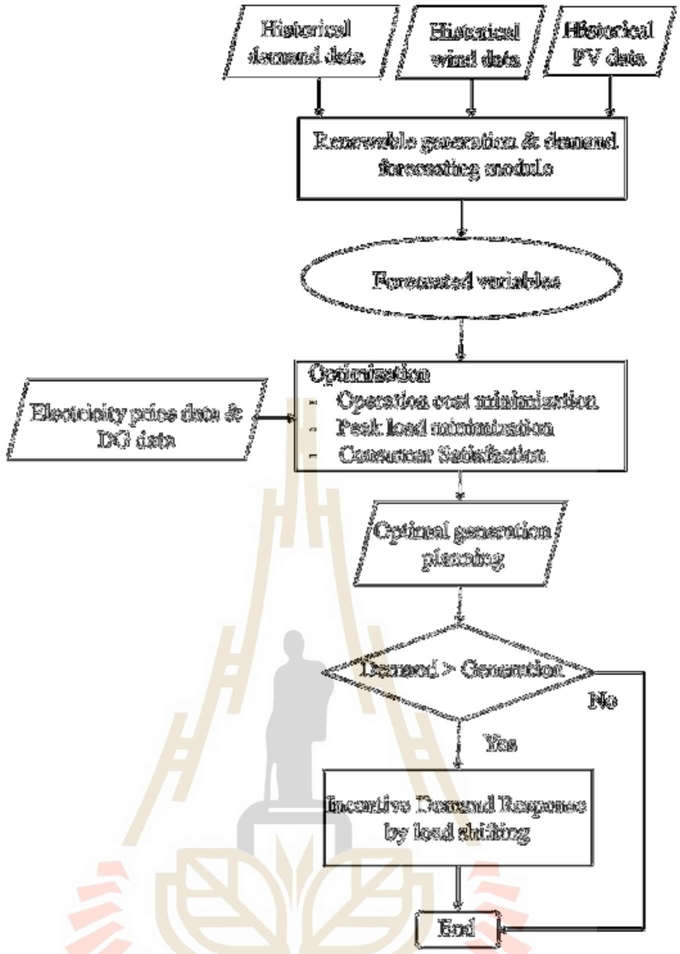


Figure 3.1 Flowchart of proposed EMS

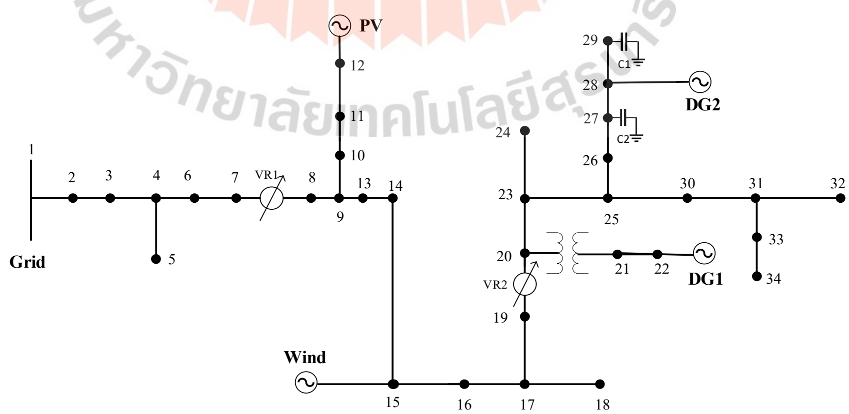


Figure 3.2 IEEE 34 node test system (Abdelmotteleb, San Roman, & Reneses, 2016)

3.2 System Modelling for the economical operation of a microgrid

The microgrid is a small-scale distribution network combining renewable and non-renewable sources to provide local demand optimally. This is a part of the active distribution networks in which consumers can participate in power sharing to reduce electricity costs (Chamandoust, Bahramara, & Derakhshan, 2020). The economical operation is the power system dispatch operation issues, where the system operator tries to minimize generation costs. Therefore, economical operation cost has become a dispatching objective in power system operation (Y. Li et al., 2019). This work presented the uncertainty of power generation and load demands required to balance effectively by grid operators in the day-ahead dispatch microgrid. In the smart microgrid, day-ahead scheduling and demand-side management are used to solve the challenges of the system's contingencies due to rising uncertainty. The demand side management interacts with the consumer to encourage consumption patterns to change to minimize the upstream side's total operation cost and the consumer's electricity payment. The changing pattern includes load shifting regarding the availability of output power from generation units, load curtailment according to the high energy price, and reduced fossil fuel utilization to minimize the operation cost. Many studies have analyzed the optimal scheduling problem from the economic, environmental, and technical aspects.

Due to the high penetration of RE resources, energy waste, and operation cost increment are the issues dealing with intensified uncertainty. The energy management system is the option that can effectively be performed as an economic benefit flexible network (Qiu et al., 2022). On the other hand, the intermittent nature of REs is a disturbance to implementing effective microgrid energy management. Microgrids are a part of the electricity market in which proper scheduling of local resources is essential to perform an economically operated system. Although economic operation is the main issue for microgrids, many discrete factors still exist in the microgrids' optimization problem. This work uses the IEEE 34 node test system with dispatch and non-dispatch DG units as a model for solving the multi-objective day-ahead scheduling problem. Due to the randomness of RE generation, the proposed system considers uncertain conditions. A microgrid is a distribution network with bidirectional power flow; the generated power can be exchanged with the upstream network (Gazijahani, Hosseinzadeh, Abadi, & Salehi, 2017). The specifications of DG units, such as capacity and construction, can be found in Figure 3.7. The proposed model's multi-criteria have been handled by a multi-objective gray wolf optimizer (MOGWO) to minimize the objective function simultaneously. Conventional balancing techniques fail to recover from uncertainty problems. With the emergence of microgrid advanced communication systems, modern techniques are the option for balancing, such as day-ahead scheduling, energy storage, and demand side management. The ongoing research work in the microgrids field is the application of modern techniques for solving operational control problems (Kumar & Saravanan, 2019). Demand response (DR) is a part of the Demand-Side Management (DSM) technique; this is the method of modifying the consumption patterns of consumers to respond to electricity market prices or the system's emergency condition. The purpose of such a program is to utilize downstream control schemes to monitor the effective utilization of energy during peak hours.

The first objective function is the operation cost minimization problem. The generation unit in this model involves PV, wind, fuel-base distribution generator, and grid power exchange:

$$\min C^{t}_{operation} = \sum_{t=1}^{T} P^{t}_{PV}\lambda_{PV} + P^{t}_{wind}\lambda_{wind} + [aP^{2}_{DG} + bP_{DG} + a] + P^{t}_{grid}\lambda_{grid}(u^{t}_{grid} - u^{t}_{sell}) \quad (3.1)$$

The second optimization problem is the minimization of peak load at each time. PAR is peak demand at particular hours, presented as the ratio of preferred peak and average demand at each time. PAR is expressed as follows:

$$\min \Pi^{t}_{PAR} = \frac{P^{max}_{L}}{\sum_{t\in T} P^{avg}_{L}} \quad (3.2)$$

The third objective function is minimizing consumer dissatisfaction, considering the time and power gaps. In the consumer comfort problem, operation time delay and demand gap are considered the metrics of consumer satisfaction level in the optimization problem. The power gap is defined as the ratio of the preferred and scheduled power, and the time gap is presented as the ratio of the waiting time to total operation time, which is expressed as follows:

$$\min \Gamma_{dissatisfaction} = \frac{T^{t}_{shift}}{T^{total}_{operation}} + \frac{P^{t}_{shift}}{P^{total}_{operation}} \tag{3.3}$$

Demand elasticity: $$\mu^{t}_{elasticity} = \frac{P^{t}_{shift}}{P^{total}_{operation}} \tag{3.4}$$

Subject to,

Power balance constraint:

$$\sum_{t=1}^{T} P^{t}_{PV} + P^{t}_{wind} + P^{t}_{DG} + P^{t}_{grid} = P^{t}_{d} \tag{3.5}$$

Power exchange constraints:

$$lb \le u^{t}_{grid} \le ub \tag{3.6}$$

The spinning reserve is considered to protect the system from unexpected conditions, power outages, and sudden load changes:

$$\sum_{g=1}^{G} [P^{g}_{max} - P^{t}_{g}] - P^{t}_{d} \ge P^{t}_{Rev} \tag{3.7}$$

Generation capacities:

$$P^{min}_{PV} \le P_{PV} \le P^{max}_{PV} \tag{3.8}$$

$$P^{min}_{wind} \le P_{wind} \le P^{max}_{wind} \tag{3.9}$$

$$P^{min}_{DG} \le P_{DG} \le P^{max}_{DG} \tag{3.10}$$

$$P_{grid}^{min} \leq P_{grid} \leq P_{rid}^{max} \tag{3.11}$$

Constraints to prevent new peak:

$$P_{min}^{t} \leq P_{L}^{max} \leq P_{max}^{t} \tag{3.12}$$

Dissatisfaction level constraints (Time gap and power gap constraints for dissatisfaction index):

$$T_{shift}^{t} = T_{start}^{shift} - T_{stop}^{shift} \leq 6 \tag{3.13}$$

$$5\%P_{d,total}^{t} \leq P_{shift}^{t} \leq 20\%P_{d,total}^{t} \tag{3.14}$$

3.3 Study area and Data collection

The study area is the Nakhon Ratchasima district. The Nakhon Ratchasima district is one of the districts in Thailand located at 14.979900 latitudes and 102.097771 longitudes. Collection and preparation data include three years of historical wind speed, solar radiation, and historical load profile for a particular region. This data is used for static modeling purposes by ARMA techniques. The historical wind speed and solar radiation are downloaded from the Historical Weather Dashboard and National Climatic Data Center (NCDC) website. Specify that the region's daily load data are collected from Provincial Electricity Authority (PEA) load research.

CHAPTER IV

RESULTS AND DISCUSSION

This chapter presents simulation results and discusses the microgrid energy management system. The discussion parts are regarded with the following aspects: simultaneous multi-objective implementation, comparison of single and multi-objective optimization related to generation costs, impacts of demand response implementation, and impacts of uncertainty on the proposed system. The simulation results are summarized as five different case studies.

4.1 Problem description

The proposed system combines different generation technologies with different marginal production costs for different generation technologies. The proposed multi- objective optimization determined the optimal conditions of energy generation to provide microgrids with the least cost and the best decisions. The generation schedule is the combined utilization of different units according to the cost order. Since the MG is a grid-tied system, the power has been imported and exported from the main grid. The simulation is performed based on the data from Thailand's power system, Nakhon Ratchasima City, in 2022 for the operating days. The typical working day with high power demand during working hours is due to a significant space cooling and operation system requirement. The power generation is shared and represented in the system with 20% from REs production, 50% from the main grid, and 30% power generation from DG units. In this model, the utilization of generation resources is according to the order of lower electricity production cost. The highest priority of resources is renewable generation resources (REs), which are non-dispatchable generation with negligible marginal production costs. DG units are dispatched when the lower marginal costs are fully utilized. Therefore, the generation cost to satisfy demand indicates the power generation system efficiency.

Moreover, the proposed energy management method forms an active distribution network in which demand-side flexibility investigates the influence on the generation cost. Based on the hourly generation in the reference condition, demand response is implemented at a 5%-20% percentage of the hourly consumption and shifted over 24 hours. Although consumers and system operators practically activate the level of load shift participation, the flexibility approach is outside the scope of the study.

4.2 Forecasting performance analysis and discusses

With rapidly growing capability dealing with big data and computing power, deep learning is applied in the power system energy management to improve the accuracy of renewable energy and load profile prediction. The deep learning-based forecasting model has been developed for deterministic, probabilistic forecasting of 24-hour ahead renewable energy and load profiles. This section discusses the deep learning model's performance and potential research application in the challenges of the power system field. Due to the uncertainty of the forecasted data negatively impacting the daily operation of power systems, current uncertainty assessments have received sufficient attention to solve the management of power systems. The proposed model solves the energy management problem with the received deterministic forecasted data. Five case studies were performed for uncertainty assessment. Regarding higher accuracy, GRU is used as a forecasting module for the energy management system where uncertainty assessment is continuously improved.

Although the performance accuracy of the hybrid model provided a better solution than the conventional single model, it was recommended that this work use three years of historical time series data length for the prediction process. This work suggested that conventional deep learning models, convolutional neural networks, and long short-term memory neural network models are reasonable choices under certain circumstances, such as preferring processing time for a specific model and the historical time series data available from the specific geographic location. In the PV power prediction, the GRU model implemented the prediction process using solar irradiation from the National Climatic Data Center (NCDC) website for Nakhon Ratchasima City, Thailand, over five months of data (April 1, 2022, to September 30, 2022). In the wind power prediction, the model used wind speed data from the Historical Weather Dashboard for Nakhon Ratchasima City, Thailand, over five months of data (April 1, 2022, to September 30, 2022). In the demand power prediction, the model used a historical load profile of load research of the Provincial Electricity Authority (PEA) over five months of data (April 1, 2022, to September 30, 2022). This input data set was split into training and test sets. The training data is used to train the data in the learning process, and the test data is used to test the results in the learning process.

MATLAB (R2022b) software was used to train input data for the LSTM prediction process. The GRU process is a developed RNN architecture to predict the values of the next time steps of a time-series sequence. The regression network was trained to the GRU sequence, where responses are training sequences with changing values in one step. That is, for each time step of the input sequence, the GRU network learns to predict the value of the next time step. The GRU and LSTM model training sets have 500 Epochs and 200 hidden layers. The data collected from the selected site location was collected 24 hours daily for one month, from 6 am to 5 am. The solar irradiation data were collected at 1-hour intervals for 5 months, including $5 \times 30 \times 24 = 3600$ measurements. The missing value is filled by the average value of the last 3 hr. After completion of the training process, the forecasting results obtained from the models are compared with the test data set. The number of past values in the data set requirement of the series is not dependent on the target vector's size but on the problem's nature. In this regard, a single execution of the algorithm with a few historical data will be enough to predict the necessary results in the future time step with the necessary horizon. This algorithm considers the day-ahead predicting PV, wind, and demand power at 1-hour intervals. To evaluate the performance and correctness, the results of the GRU deep learning algorithm were compared using the extensively used statical technique ARMA model. Two types of time series prediction models were implemented in the proposed methodology in this work.

The simulation results show that the deep-learning model has a competitive prediction performance compared to conventional statistical models. Whether the length and non-linear characteristic of the collected historical data, such as wind speed data, solar radiation, and historical load, does not matter upon the performance of the deep-learning model. Furthermore, Figures 4.1 to 4.6 illustrate that the deep learning GRU model performed better than the statistical ARMA models. Deep learning is a less straightforward process than ARMA models to extract the inherent nonlinear features and high-level invariant structures in time-series data. The deterministic forecasting of REs and load profiles are predicted with GRU and LSTM deep learning algorithms. The performance of forecasting methods is tabulated in Table 4.1 using root-mean-square error (RMSE). The main feature of LSTM and GRU is the internal memory function layers connections between the processing neural units, which is suited for REs time-series prediction. The deterministic 24-hour ahead short-term forecasting performance of GRU and LSTM models are statistically presented in terms of mean absolute error (MAE) and root-mean-square error (RMSE). It can be seen from the table that the performance index of the GRU model in specified location random error ranges from 0.1192 to 0.6841. Similarly, the LSTM and ARMA model indexes are between 0.1718-0.8342 and 6.9427-9.3878, respectively. It has been observed from the results that the deterministic prediction performance differs in different forecasting methods, and the single variant prediction method exhibited different error ranges according to different forecasting methods.

Table 4.1 Comparison of random error for forecasting methods

Items	GRU	LSTM	ARMA
PV	0.1337	0.1718	2.6349
Wind	0.6841	0.8342	2.6723
Load profile	0.1192	0.1759	3.0640

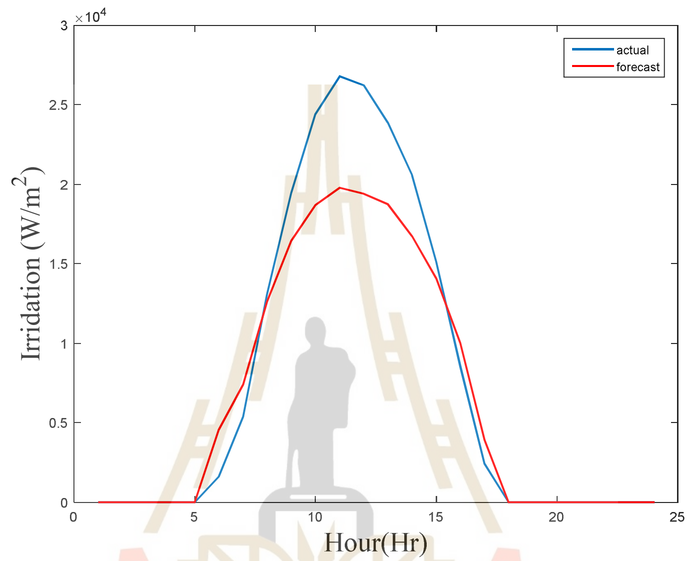


Figure 4.1 Monthly solar irradiation (April) with ARMA

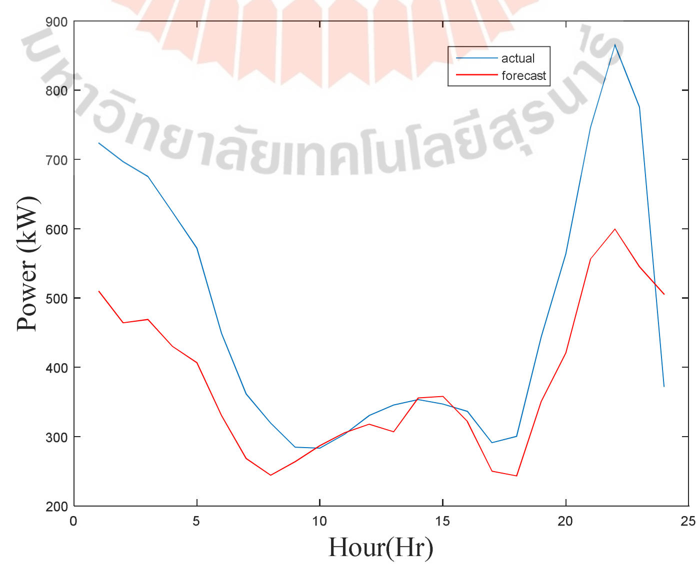


Figure 4.2 Monthly Average Load Profile (April) with ARMA

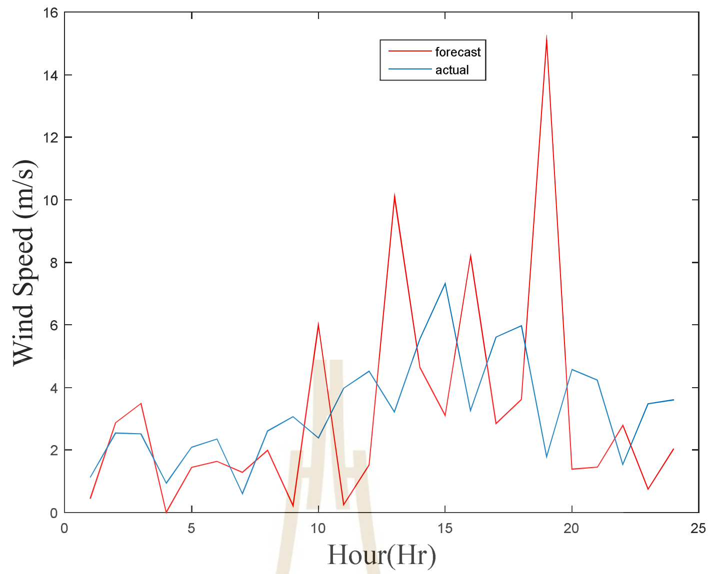


Figure 4.3 Monthly average Wind Speed (April) with ARMA

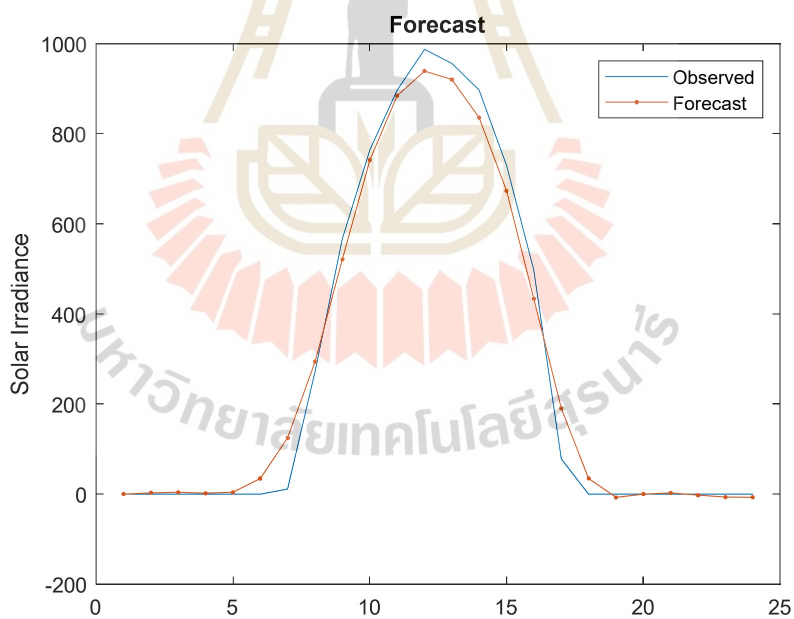


Figure 4.4 Forecasted and observed day-ahead solar irradiation with GRU.

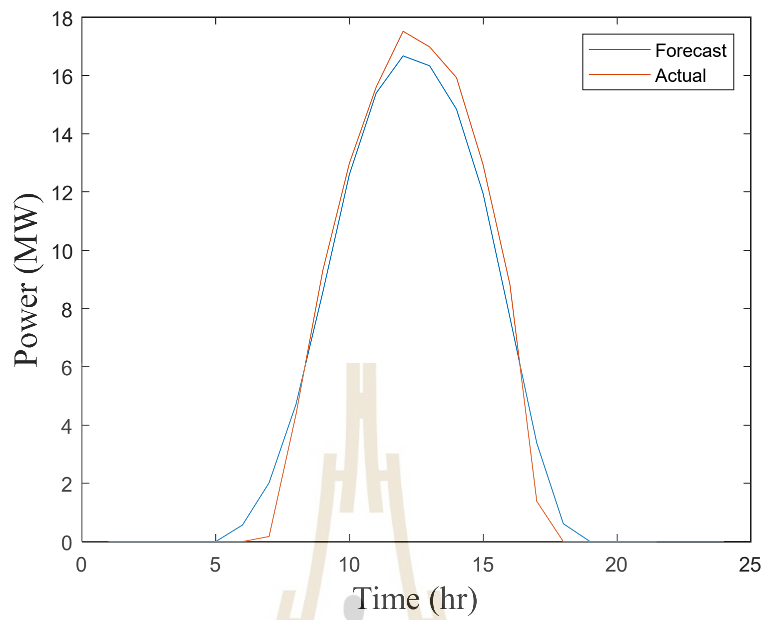


Figure 4.5 Forecasted and observed day-ahead solar power with GRU.

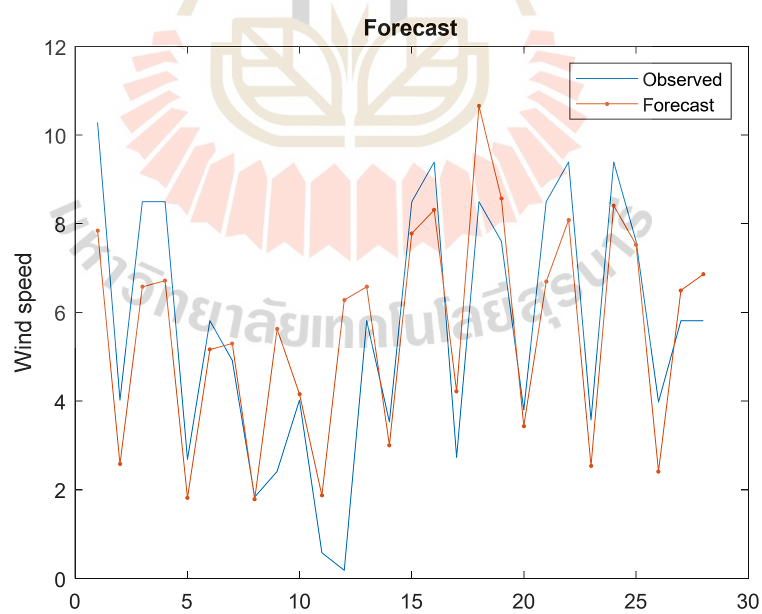


Figure 4.6 Forecasted and observed day-ahead wind speed with GRU.

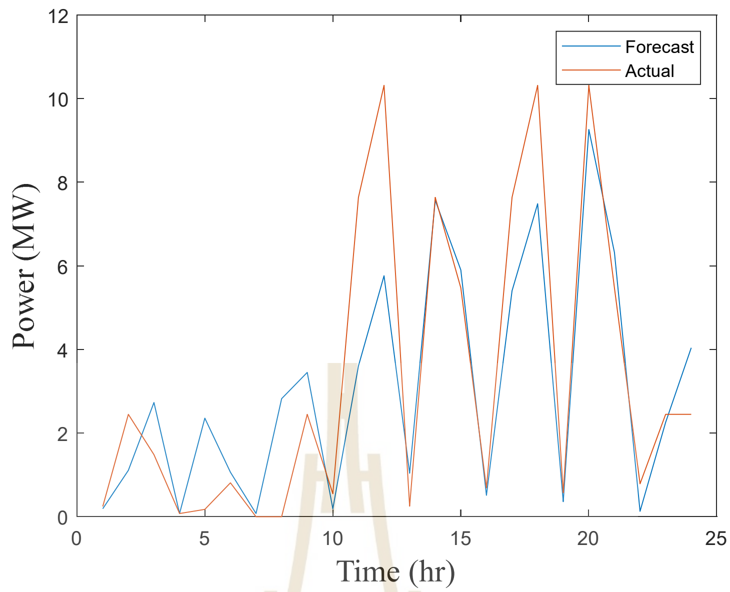


Figure 4.7 Forecasted and observed day-ahead wind power with GRU.

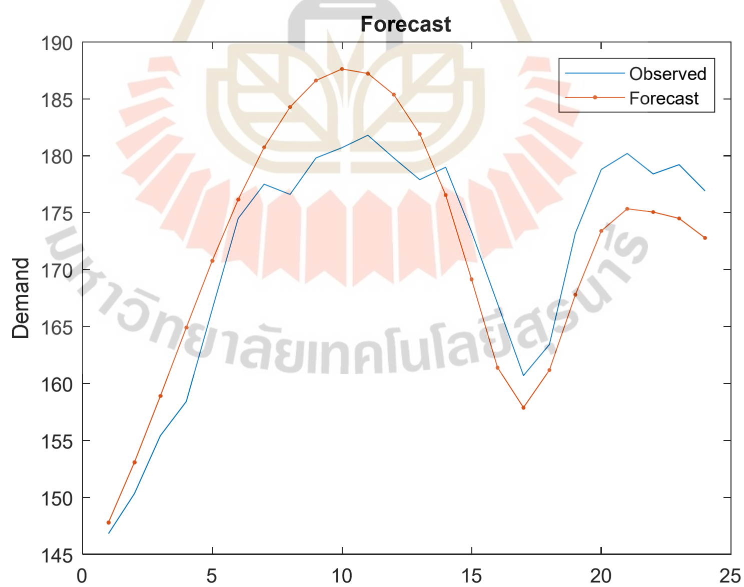


Figure 4.8 Forecasted and observed day-ahead load profile with GRU.

Although deep-learning models provided different performances, the results indicated that they performed better than the statistical ARMA model. Probabilistic and deterministic forecasting based on deep learning has paid attention to RE forecasting. The proposed model provides accurate prediction and reliable data, allowing for efficient power sharing at future upstream and downstream side operations. The combined application of artificial intelligence with the optimal energy efficiency concept appears to have boosted the digitization of the electrical sector, particularly with energy sustainability and decarburization. The importance of time series data processing in optimization models is highlighted in this section. A deep-learning-based LSTM, GRU time series prediction performs as a better time-series model, while the statistical ARMA model performs poorly in time series prediction. The reason suggests this work focuses on the development of a prediction module in order to arrive at high suitability in the advanced energy management system. While comparing prediction methods, artificial intelligence algorithms have demonstrated less error and superiority in obtaining favorable outcomes. Obtaining favorable results necessitates adjusting a certain amount of hyperparameter adjustment. The quality and quantity of the input data impact the prediction model's performance.

4.3 Parameters and Case Studies

Three power generation technologies are considered: wind, PV, and fuel-fired distributed generators. The proposed system developed 24-hour ahead-generation scheduling for microgrids as an active distribution network where end-users can participate in periodic responsive load programs. The proposed model is considered a microgrid system on the IEEE test system and tested for five case studies on a standard IEEE node system. The location and the links of available resources of MG are from (Abdelmotteleb et al., 2016). It is assumed that the uncertainty of the variable parameter, such as wind speed, solar radiation, and the load profile, is based on the random error of forecasted information. Since the MG has flexible and inflexible loads, a responsive load program is only considered for flexible load change. The responsive load change is implemented between 5%- 20% of the average load demand. The main grid's power delivery is between 50 and 100 MW. The minimum and maximum generation capacity of two DG units are 25MW and 125MW, respectively. The grid electricity prices are considered according to Thailand's Time of use (TOU). Since the PVs and WTs technologies only have operation and maintenance costs (O&M), the O&M cost for PVs and WTs is 0.10954 $/kWh. The O&M costs for WT and PV are obtained from (Karimi & Jadid, 2020), and these resources' hourly generation costs are set as zero. The risks concerned with uncertainty management are considered in this work. The coefficients of the DG cost function are tabulated in Table 4.2 (Gao Zhang et al., 2017). Due to their continuous operation, DGs' startup and shutdown costs are not considered. In case studies II-V, the multi-objective optimization of the MG is considered for cost minimization, peak load reduction (PAR), and consumer satisfaction. In all case studies, the MG participates in demand response (DR) programs; the maximum DR is 20% of the average load demand.

The proposed model is utilized for forecasting scenarios for the microgrid energy management design to achieve a cost-effective active distribution network. The renewable sources considered in this study are wind power and photovoltaic solar power generation. The power capacity for each generation scenario is determined by considering the power demand of the target region. The optimal scenarios are evaluated by economic, peak demand reduction, and consumer comfort aspects. In this work, the cheapest generation from the RESs scenario provided their total capacity to the optimal dispatch system. To evaluate the effectiveness of the proposed model, four case studies are considered as follows:

Case study I: In this case study, the single objective optimization of the MG is considered only for cost minimization. In order to prove the effectiveness of the multi-objective proposed system, case study I is to be compared with the following case studies.

Case study II: In this case study, the multi-objective optimization of the MG is considered for cost minimization, peak load reduction (PAR), and consumer satisfaction simultaneously. In order to prove the effectiveness of the proposed system, case II does not consider the uncertainty effect related to the system's parameter variable.

Case study III: The MG solves the same optimization problem as case study II. This case study considers the scheduling problem for wind and PV power uncertainties. The load profile is considered to be accurately forecasted by the operator. This case study is proven to solve multi-objective optimization with generation uncertainty.

Case study III: Multi-objective optimization is solved for the MG scheduling problem under demand uncertainty. This case study is considered to prove the MG multi-criteria problem under demand uncertainty.

Case study IV: This case study is the same as case II; the proposed model is solved for the MG energy management, while the MG experience in REs generation and demand uncertainty. In order to prove the robustness of the proposed system, this case considered and solved all uncertainty simultaneously.

Table 4.2 The characteristic of distributed generator

Items	a	b	P_{min} (MW)	P_{max} (MW)
DG1	0.02	10	25	125
DG2	0.015	10.75	25	125

4.4 Performance Comparison of Optimal microgrid dispatch

This section discussed the optimal operation of different case studies based on single and multi-objective problems to analyze different uncertainty levels that affect the system and highlight the achievement of multi-objective over single objectives in optimal dispatch. Figure 4.7-Figure 4.11 demonstrated the optimal power generation for five case studies from the wind, PV, DGs, and main grid to the demand through the 24-hour horizon. The Figures show that most of the electricity at night and early morning is supplied from the main grid and local DG generation due to the insufficient power from wind turbines and lack of power from PV generation. The peak load started in the morning at 07:00 hr, coinciding with an increasing time of use tariff. The surplus demand is shifted when there is an inefficient way to generate it. Thus, the peak load occurs during working hours between 7:00- and 16:00, so the dispatch units are required to generate expensive hours. Currently, the demand response is used to balance the demand when local generation is insufficient to provide high demand. The demand response program allows the hourly consumption to shift 20% of demand power within the day, and the lack load is moved to demand response agreement hours. The conjunction of PV from 8:00 a.m. to 6:00 p.m. and wind generation is frustrating all day. The high wind and PV power can be observed in the daytime between 9:00 a.m. and 6:00 p.m. When the PV is not generated, and wind power is at low capacity than other hours, the high power is imported from the grid between 19:00 hr-20:00 hr and 1:00 hr -6:00 hr. The optimal planning results also indicate that DGs reduced the generated power at high PV generation. This is the way of elevating wind and fully utilizing PV power. According to Table 4.2, although the generated power is higher than the total demand, the production costs are not raised at a specific time. At 15:00 hr, the total power generated in case II is 269.3175MW, and the generation cost is 863.4912 $/hr. In other words, the optimal scheduling process is planned to generate more power at a specific time without detaching the system's objective function and contents. The optimization algorithm is implemented for optimal search for the multi-decision variables while satisfying the load demand.

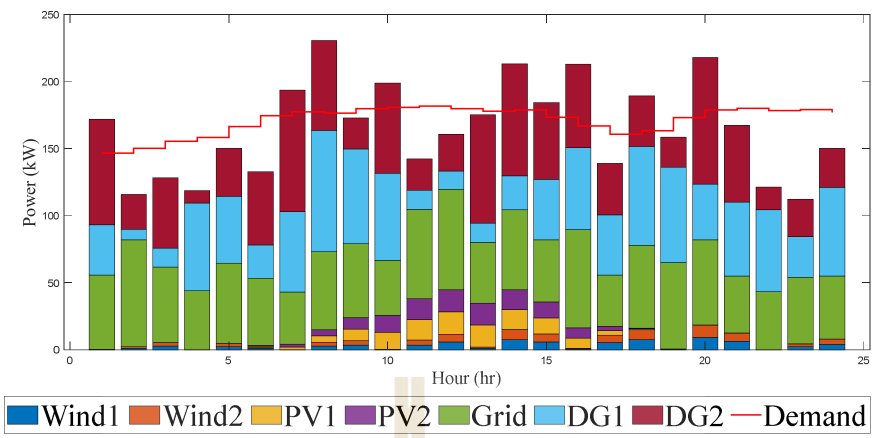


Figure 4.9 Optimal generation scheduling (Case I)

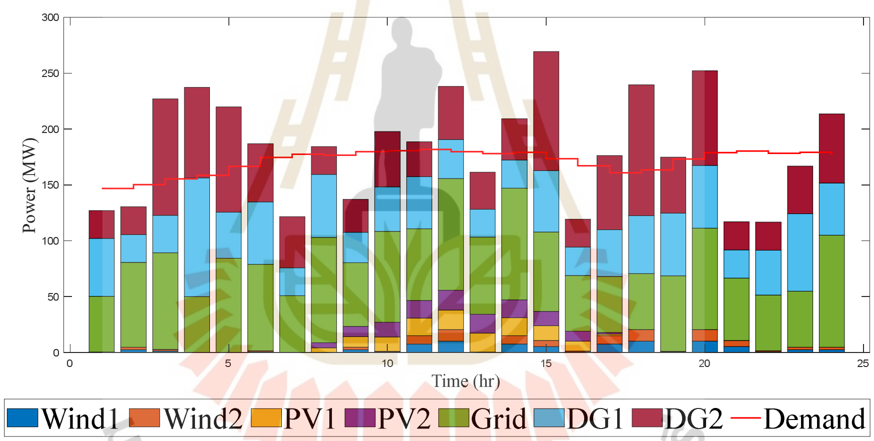


Figure 4.10 Optimal generation scheduling (Case II)

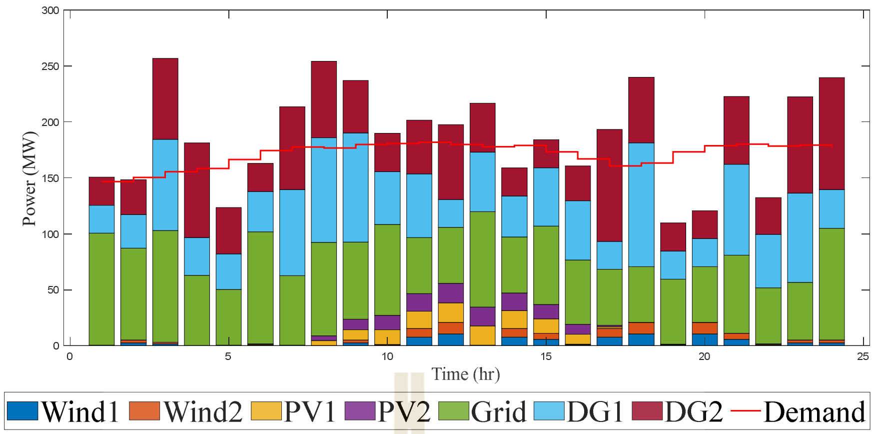


Figure 4.11 Optimal generation scheduling (Case III)

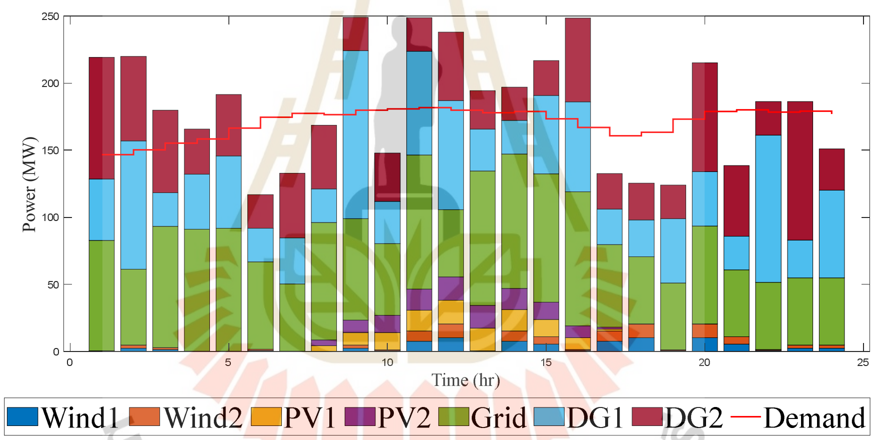


Figure 4.12 Optimal generation scheduling (Case IV)

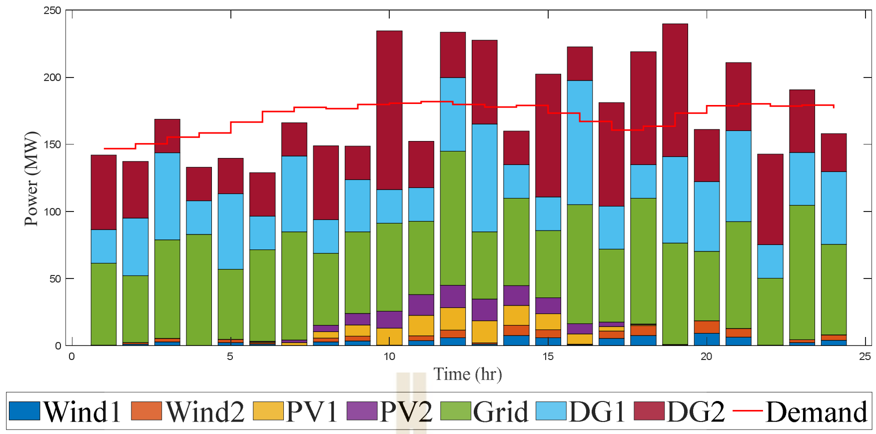


Figure 4.13 Optimal generation scheduling (Case V)

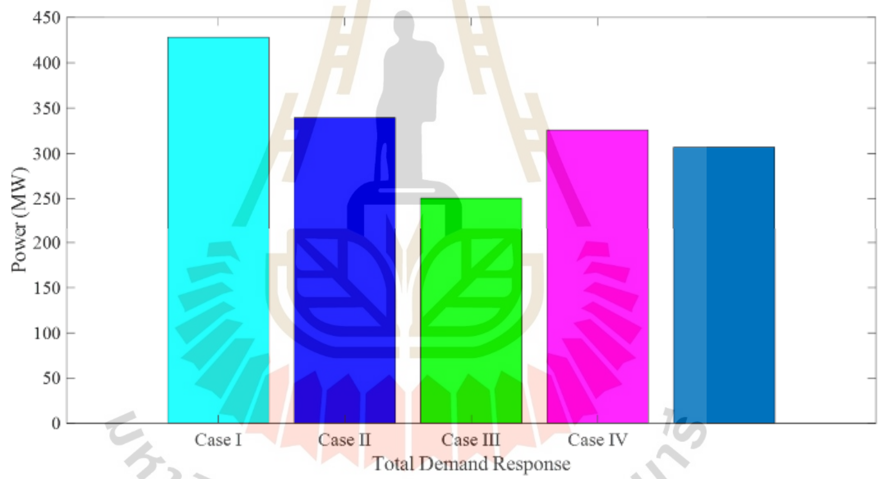


Figure 4.14 Demand Response Comparison

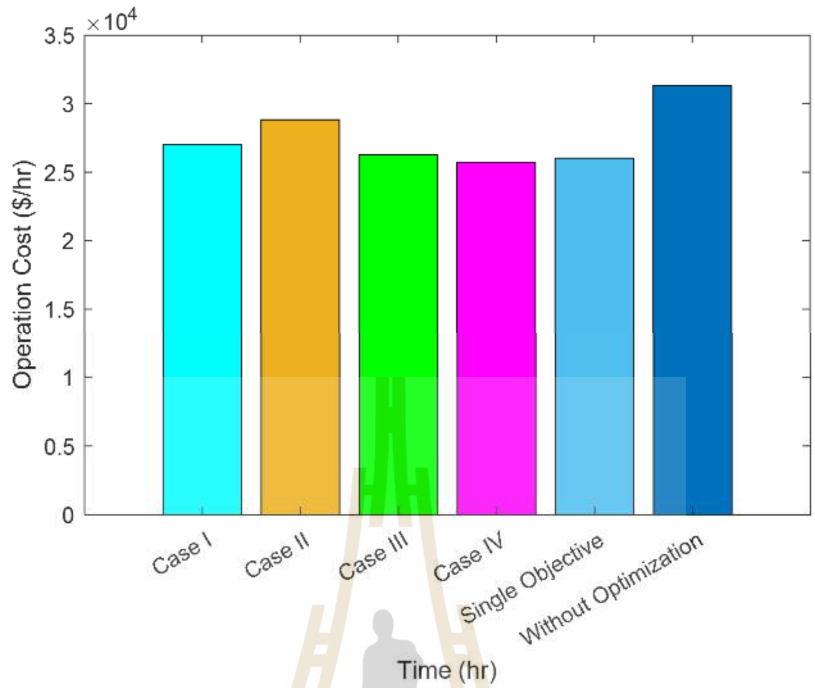


Figure 4.15 Operation Cost Comparison

In case V, the worst scenario occurs when the system suffers REs and demand uncertainty at certain hours. The worst case obtained from the prediction results allows for determining the necessary reserves for a microgrid. The results in case study III-V indicated that the uncertainty by REs resources and demand influence the microgrid operation schedule costs. Moreover, the uncertainty also impacts the demand response program, as shown in Figure 4.12. Figure 4.13 demonstrates the total generation cost of each scenario. While comparing the rate of cost of optimal scenarios I-V to the without optimization scenario, the performance of optimal scenarios is better than that of the without optimization scenario.

Table 4.3 Operation Cost Comparison

Time	Case I ($/hr)	Case II ($/hr)	Case III ($/hr)	Case IV ($/hr)	Single Objective Optimization	Without Optimization
1	850.3547	548.7659	1602.6038	909.8174	1348.8052	1178.3895
2	546.8354	675.4061	1881.3554	950.3468	375.8713	1166.4242
3	1647.7591	1814.2025	986.5724	1014.8482	755.3541	1262.6394
4	2260.2045	1382.8665	830.3685	546.8436	844.131	1343.1749
5	1597.4741	810.7412	1128.6224	925.2776	955.6905	1454.7519
6	1228.4864	674.5382	545.6983	633.1734	896.9522	1551.3196
7	789.8557	1772.5758	922.2043	911.4865	1771.578	1613.097
8	915.1626	1927.3184	816.1838	906.4845	1860.017	1480.4041
9	623.0207	1710.0389	1848.8694	702.5314	1070.0432	1318.4219
10	1007.2585	911.5002	750.1332	1753.1033	1528.6164	1281.7748
11	871.0221	1196.8271	1181.8888	658.9685	414.443	1034.9343
12	931.4334	1057.7202	1543.7718	1003.4643	456.2641	889.1053
13	643.6643	1099.922	665.0263	1671.819	1121.2631	1142.985
14	693.4364	681.9297	553.2851	550.4119	1278.3009	989.6244
15	1935.8251	863.4912	954.7437	1382.0845	1164.2192	1049.4357
16	550.6114	941.7813	1499.6155	1382.839	1420.9453	1203.1379
17	1239.8446	1491.7396	580.3995	1266.3497	929.4854	1130.5521
18	2041.085	2041.5774	601.8911	1282.7158	1279.9121	1132.3403
19	1205.234	548.5494	806.3561	1943.9574	1066.5643	1539.488
20	1651.4888	546.6343	1413.8903	1020.5354	1605.2763	1344.3061
21	550.4086	1659.43	873.4584	1359.1564	1281.3776	1500.249
22	714.4964	897.854	1618.5924	1058.807	877.6257	1608.6235
23	1280.2971	1966.8542	1571.219	969.86	635.1677	1572.3436
24	1242.2974	1604.3582	1089.0291	922.9465	1078.5599	1539.1209
Total	27018	28827	26266	25728	26016	31327

Table 4.4 Peak load Limit

Time	Case II	Case III	Case IV	Case V
1	45.3820	50	50	1.2372
2	1.5866	9.6227	50	8.4500
3	5.7101	3.5861	9.5415	30.2988
4	20.0023	50	5.7829	2.3446
5	38.4223	23.3173	26.8279	7.0604
6	3.5374	0	3.3282	0
7	50	42.0055	50	24.4368
8	50	23.7297	0	50
9	21.6324	48.5468	24.2745	50
10	1.9812	31.8058	12.7375	5.4831
11	0	31.3314	9.5113	50
12	8.8724	50	28.2874	26.2175
13	7.8348	22.1608	0	50
14	0	30.3119	11	50
15	50	5.2005	30.8079	3.9629
16	0	50	50	32.6861
17	1.0917	50	50	26.9262
18	0	2.8050	43.6707	50
19	50	0	48.1903	17.9828
20	11.7004	26.0738	42.9103	7.5695
21	44.7376	50	50	17.8145
22	14.4537	13.9775	10.0359	25.4472
23	0.7616	0	50	50
24	45.3820	50	50	17.5532

Table 4.5 Percentage Demand Elasticity

Time	Case II (%)	Case III (%)	Case IV (%)	Case V (%)
1	6	29	10	13
2	19	20	3	8
3	6	9	12	7
4	24	13	24	12
5	3	22	23	28
6	28	4	20	4
7	23	28	15	29
8	19	7	14	25
9	5	11	11	27
10	20	4	8	14
11	15	12	18	7
12	10	6	3	3
13	6	6	17	6
14	29	8	18	3
15	24	21	9	3
16	5	8	29	14
17	26	13	12	29
18	20	28	29	20
19	12	8	9	14
20	12	28	3	18
21	4	3	3	17
22	3	11	10	21
23	23	13	4	27
24	14	6	29	3

Table 4.6 Demand Response Comparison

Case Studies	Case I	Case II	Case III	Case IV	Single Objective Optimization
Total Demand Response (MW)	339	251	326	307	428

Table 4.7 Total Generation Capacity in Microgrid

Item	Case I	Case II	Case III	Case IV	Case V	With Optimization
Grid Power (MW)	1314	1674	1634	1723	1630	2400
Local Generation (MW)	2267	2346	2492	2279	2242	2424

The local generation capacity and gird power of microgrid (MG) for all case studies is tabulated in Table 4.6. This table shows that the local generation increased due to the optimal generation scheduling process in single and multi-objective case studies. The proposed system is the model of the active distribution network to reduce energy importation from the main grid, and local resources mainly generate energy requirements. The results summarized in Table 4.6 showed the power imported from the main grid. The results revealed the facts of microgrid independence. The proposed model entirely consumes local wind and PV generation energy. It can be observed that the power from the main grid is decreased purchasing during improved REs capacity in the daytime (8:00hr-18hr). The case studies showed that the proposed model minimized the main grid dependency and elevated RE generation regardless of peak and off-peak periods. The fuel-based DGs are applied as dispatchable generation units and serve unfulfilled power from non-dispatchable units such as local wind and

PV generation. Due to high production costs, the DG generation can use total capacity over other resources in this model. By comparing the case studies in Tables 4.2 and 4.6, it can be observed that the operation costs of the proposed model depend on DG generation. The operation cost from the fuel generation unit in the microgrid is a key factor to expense the whole operation—the optimization algorithm searches for a better objective function solution. When the microgrid is without optimization, the total operation cost is 31327$. The dependence performance indices of case studies II-V are 55%, 70%, 68%, 71%, and 62% without optimization, respectively.

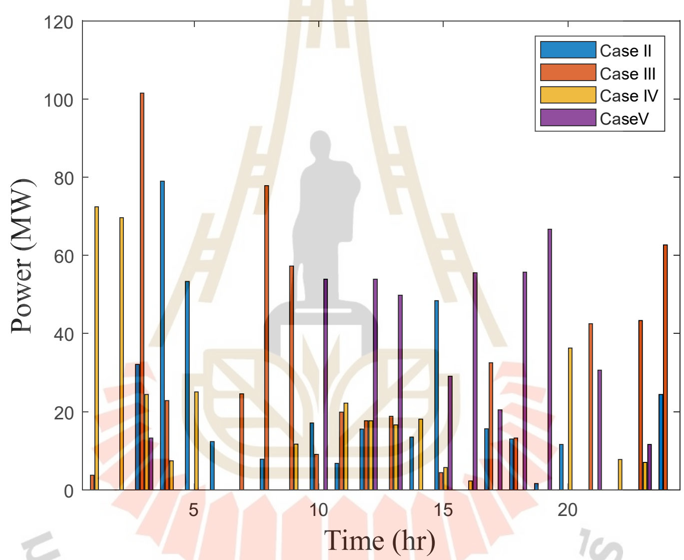


Figure 4.16 Power Trading to Main Grid

Figure 4.23 shows the surplus power of case studies after performing the optimization. The surplus power is traded back to the upstream network at different hours. It can be observed from case studies II-V that all generation resources are running at optimal production levels, and surplus electricity is traded to the network to gain more profit. This is also the way of natural profit maximization for the overall interconnected microgrid. Regarding responsive load, the trade power depends on the combination of total power demand in MW at this hour and shifted load in MW from nearby hours. In case I, the available generating units produced maximum electric power at 15:00 hours, which is about 269.3175 MW, and the total cost of production is 1935.8251$/hr. Thus, the total electricity demand at this period is 173.3 MW, and the total shifted load from 16:00 hours to 48 MW. The surplus 49 MW is traded back to the main grid at 15:00hr. It was noted from Figure 4.7 that from 1:00 hr - to 5:00 hr, microgrids trade a high amount of power to the grid.

Table 4.8 Total Power Trading back to Main Grid

Item	Case I	Case II	Case III	Case IV	Case V
Sell Power (MW)	352.1016	551.9353	344.3057	440.5191	352.1016

4.5 Effect of Demand Response on the Operation Cost

Table 4.2 presents the performance comparison related to the generation costs of different case studies. The proposed multi-objective model is tested on four different scenarios based on the level of experiencing variable parameter uncertainty. In case I, the microgrid, does not participate in multi-criteria optimization, the proposed model for case I only solved for generation cost reduction. According to Table 4.6, local generation is more required to compensate and fulfill demand in case III. Besides, the energy not supply (ENS) in case I is improved by 121MW (39% improvement) compared to the worst-case scenario (case V).

The cost of microgrid operation is 31327 $ without considering optimization. After optimal operation, the cost reached 26016 $, reduced by 17% compared to without optimal operation. Besides, the ENS is increased by 428MW due to DR participation in case study I. In case I, the optimal generation scheduling problem is only based on cost minimization. In other words, the optimization process is not limited to maximum DR participation. The ENS in Case III is lower at 26%, 23%, and 18% than in Cases I, II, and IV. In this case study, the optimal scheduling is implemented with the uncertainty related to RE generation. The uncertainty related to wind speed is 0.68 % more forecasted than actual wind speed. In other words, the forecasted power from RE resources significantly impacts the generation costs. By implementing optimal energy management, DR provided the loads shifting program to shift the load from the energy not supply (ENS) period to the off-peak periods. This way, the peak load and energy requirement are reduced based on the economical operation. The results revealed that the proposed multi-objective model reduces the ENS and generation costs more than single objectives without optimal operation models. In this regard, the proposed model significantly improves the usage of RE resources, lessens independence on the main grid, and reduces the generation cost by 17% compared to without optimal operation.

The case studies in Table 4.3 show that the uncertainty effects related to RE generation and load profile are significantly mitigated by introducing DR in the microgrid. This table also compared the impact of DR on multi-objective and single-objective optimization problems. According to Figure 4.14-Figure 4.17, load shifting commonly occurs when the demand exceeds the total generation capacity due to insufficient power from RE resources. The load shifting DR is more likely to favor working hours due to surplus total generated power. Figure 4.18 to Figure 4.22 compares the existing load profile with the load profile after DR participation for five case studies. The optimal situation for case studies varied the load change pattern at different hours. It can be observed from this Figure that the daily load profile of the microgrid is removed from peak load by implementing multi-objective optimization with the DR program. Participating in the DR program shifts the peak load from on-peak to off-peak periods.

Moreover, multi-objective is considered to prevent the creation of a new peak at the on- peak and off-peak periods. It can also be observed that demand response significantly improves the MG load profile. Figure 4.18 shows the new peak load created at 70 MW in peak time by DR programs. Although DR reduces system peak load at peak and off- peak times, a new peak load is created at peak time due to the

DR program. This is the cause of over-DR after implementing a single objective demand response model. The new demand is higher than the existing demand after implementing DR, leading to the extra load at the peak time. Therefore, DR programs increased peak load by about 29% at peak time. The performance of load shifting demand response in case I improved peak load at 8:00 hr, 10:00 hr, and 14:00 hr.

In this work, multi-objective optimization is considered an objective function to avoid DR problems. In this regard, case II-V considered multi-objective optimization for optimal scheduling problems. In the proposed model, multi-objective implemented optimal generation scheduling regarding cost minimization, simultaneously preventing peak load creation and consumer comfort. Table 4. shows the Peak to Average Rates (PAR) in cases II-IV. The optimization results are the tolerance level of peak load each hour to prevent new peak creation after load shifting demand response participation. After DR programs, overall PAR in cases II-V is improved and reaches 1.14 (18%), 1.12 (16%), 1.16 (18%) and 1.24 (18%), respectively. In Figure 4.19 to Figure 4.22, cases II - III load profiles are the results of multi-objective dealing with peak prevention, cost reduction, and consumer satisfaction simultaneously. Implementing multi-objective optimization and DR programs prevents the system's peak load from being created in the new load profile. It can be seen that the day-ahead load shifted by multi-objective-based DR was reduced over DR after DR implementation, and the proposed model has a better performance than the traditional single objective-based DR program.

According to simulation results, the flexibility load change reduced the generation cost and mitigated system uncertainty, especially from non-dispatchable generation resources and load profiles. RE generation significantly affects the operation schedule, which depends on the values of RE uncertainty. Similarly, the increment of REs' power significantly reduced the grid dependency. According to the facts from this work, since the uncertainty in REs generation and demand impacts the scheduling process and total operation cost, it can be considered a factor for predicting a 24-hour bidding price in a day-ahead pricing market.

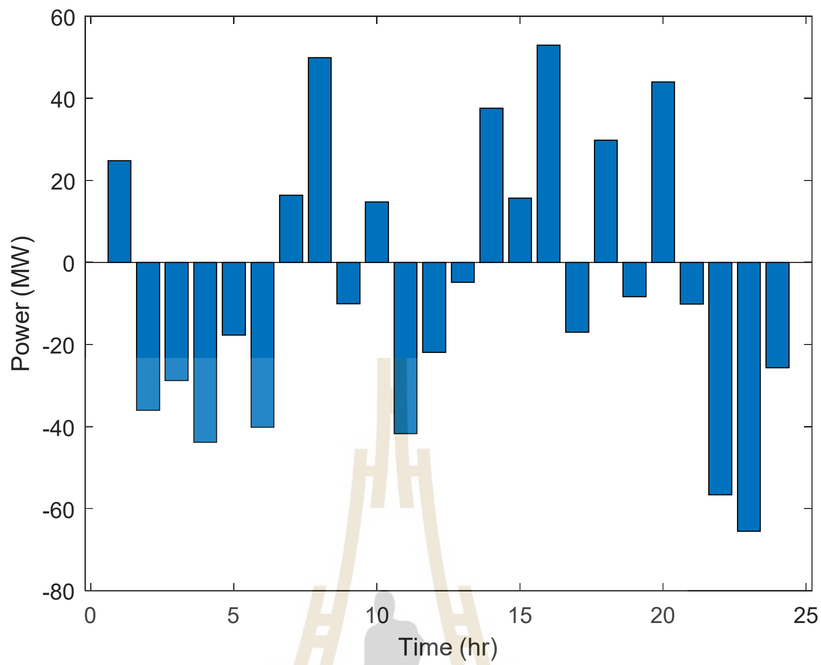


Figure 4.17 Load Shifting demand response program (Case I)

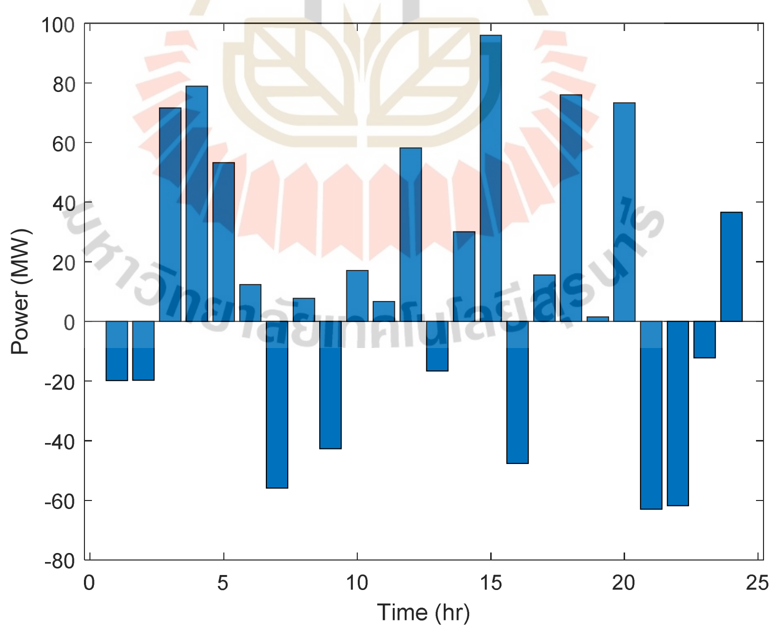


Figure 4.18 Load Shifting demand response program (Case II)

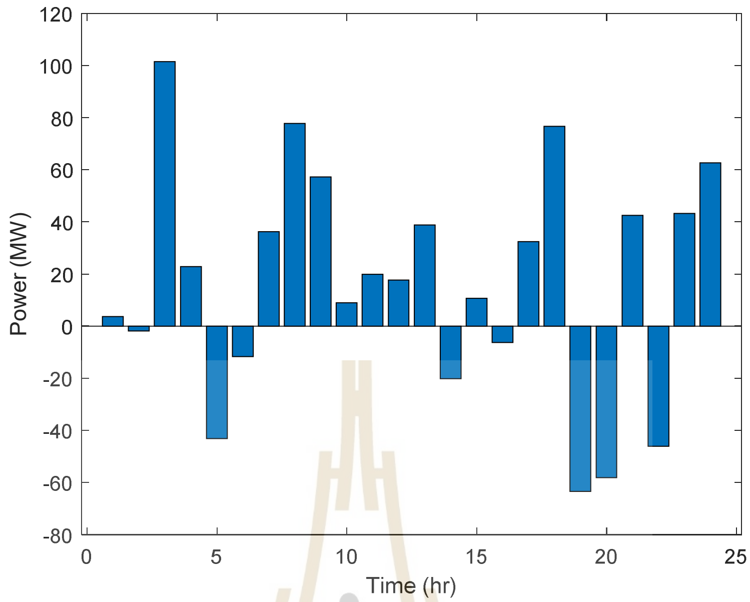


Figure 4.19 Load Shifting demand response program (Case III)

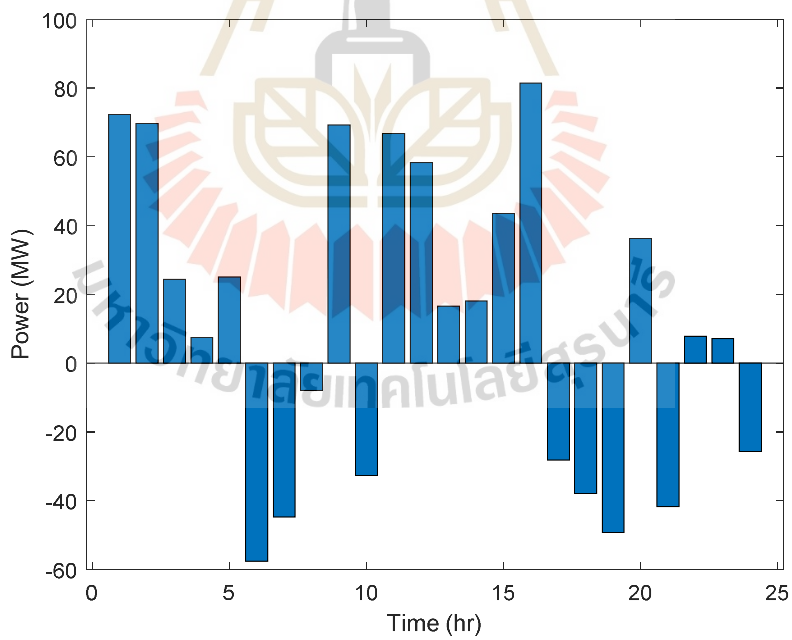


Figure 4.20 Load Shifting demand response program (Case IV)

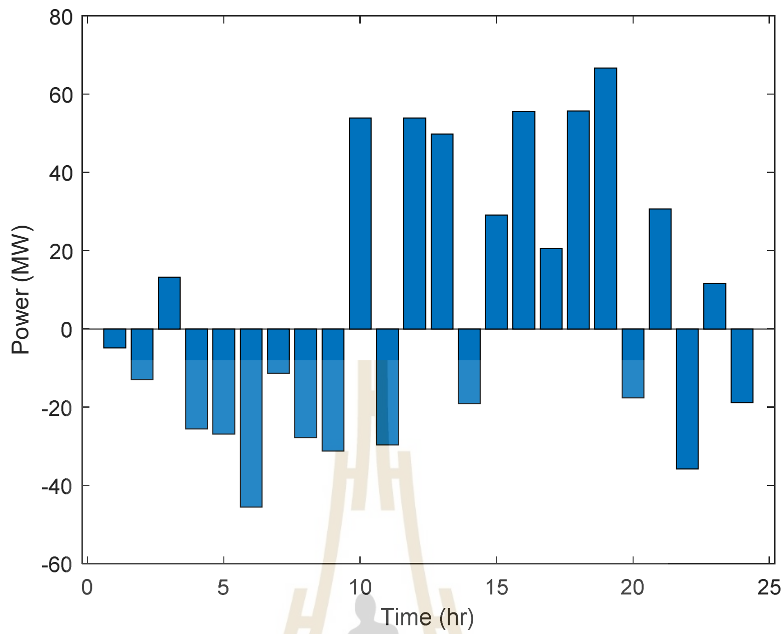


Figure 4.21 Load Shifting demand response program (Case V)

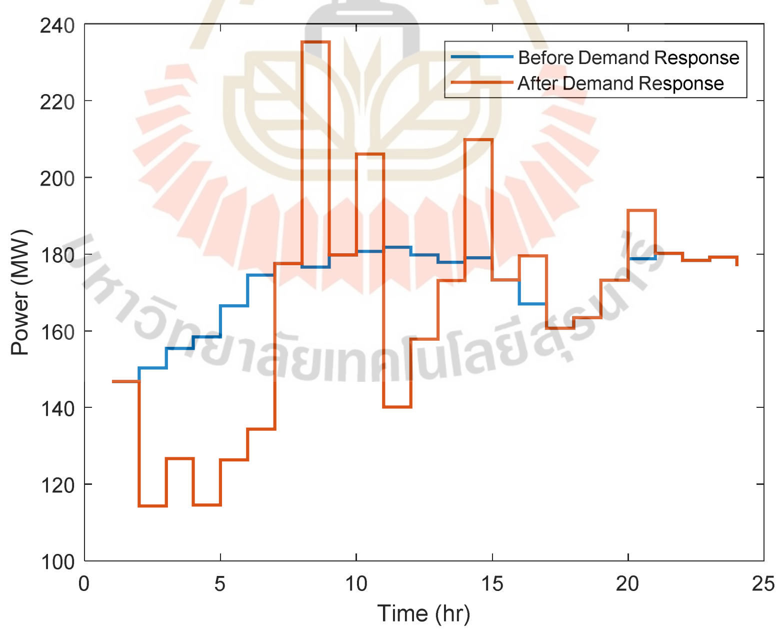


Figure 4.22 Comparison of load pattern before and after demand response in Case I single objective

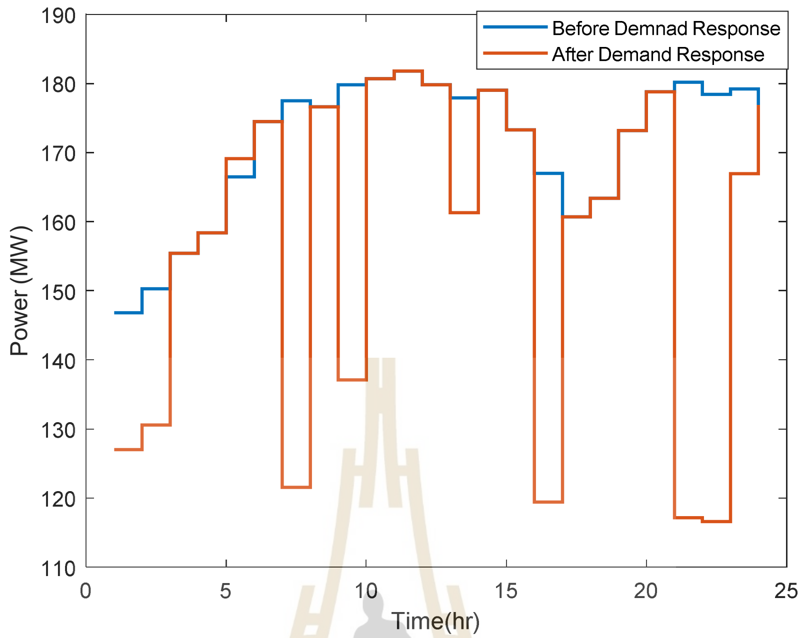


Figure 4.23 Comparison of load pattern before and after demand response in Case II

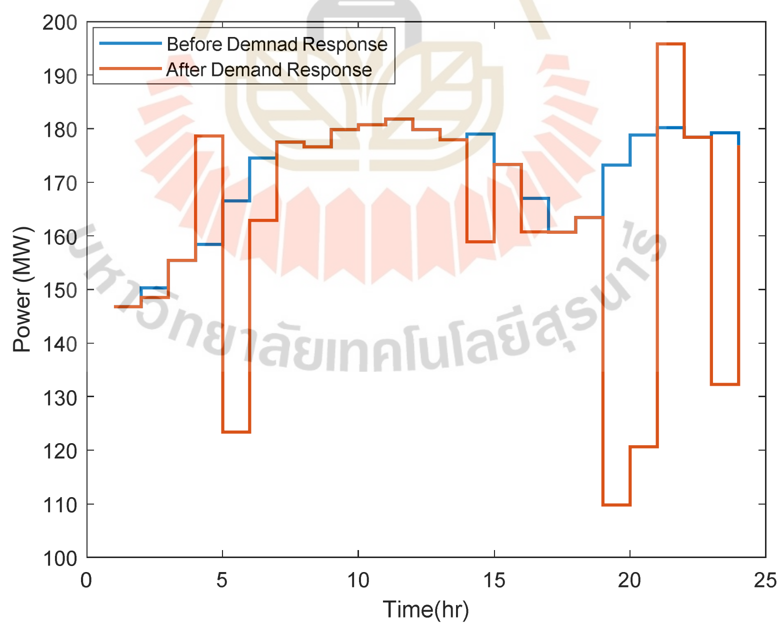


Figure 4.24 Comparison of load pattern before and after demand response in Case III

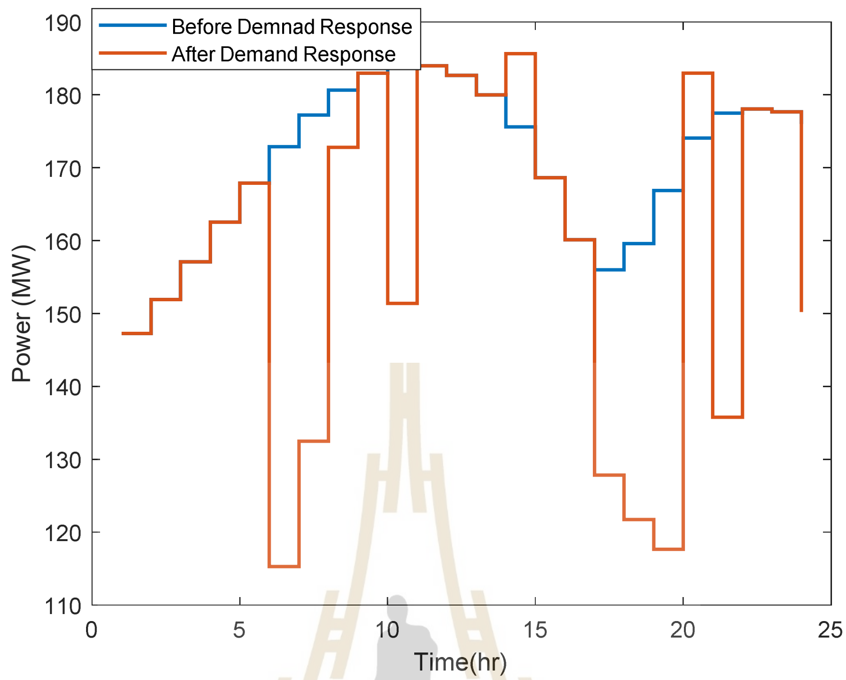


Figure 4.25 Comparison of load pattern before and after demand response in Case IV

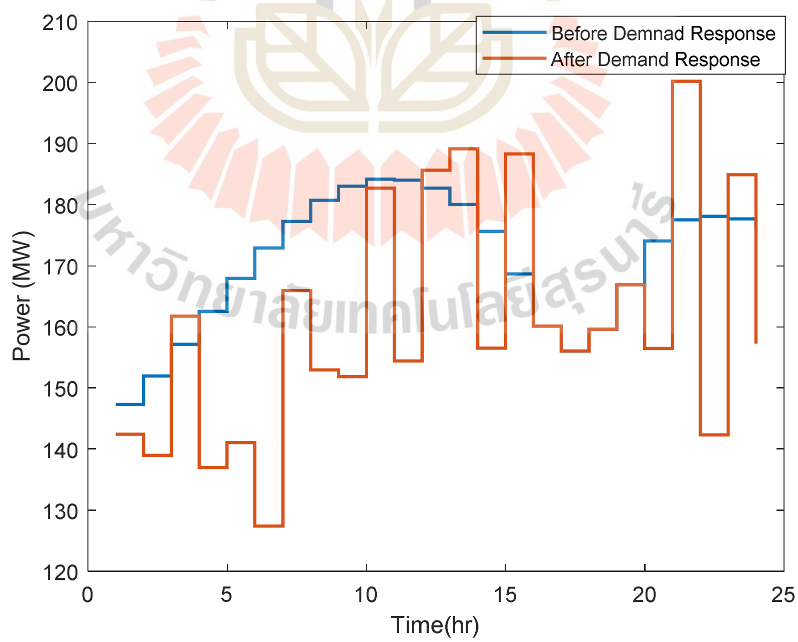


Figure 4.26 Comparison of load pattern before and after demand response in Case V

4.6 Simulation results and discussion of multi-objective optimization

The Pareto optimal fronts obtained from the algorithms are provided in Figure 4.25-Figure 4.27. Since the proposed method is a multi-objective minimization problem, the shape of the Pareto optimal fronts is a convex function, explained in section 3.4.2. The Figure shows the dominated and non-dominated solutions in a particular iteration process. The non-dominated solution is stored in the archive based on the mentioned rules in section 3.4.2 for each iteration process. The best optimal solution is the choice with the best compromise solution (BCS) method. The optimal results are shown in the Figure. According to the figures, the optimal solutions were selected close to the Pareto optimal front.

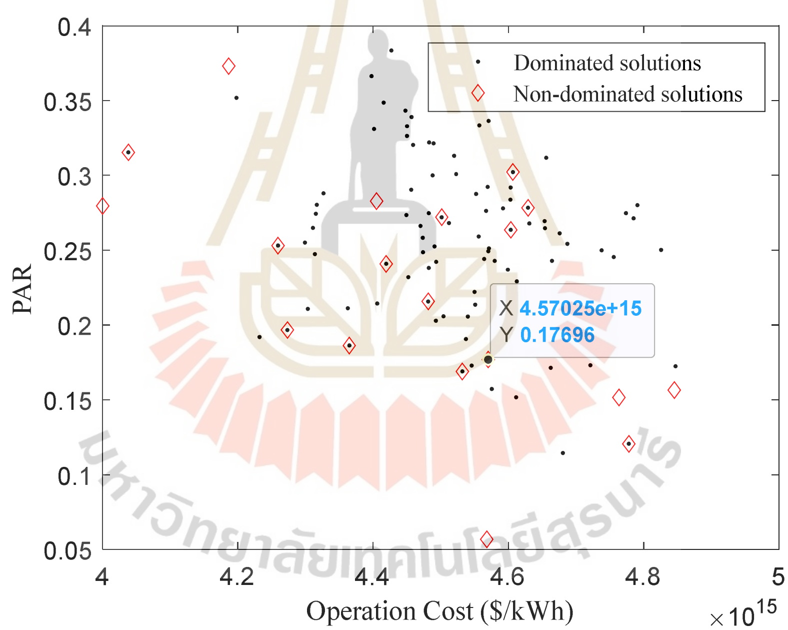


Figure 4.27 Dominated and Non-dominated wolves in the archive for the bi-objective minimization problem

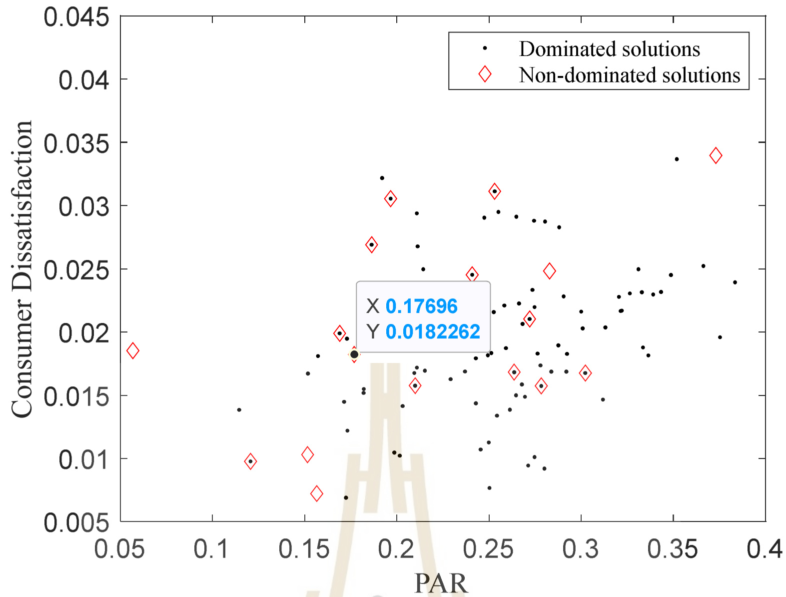


Figure 4.28 Dominated and Non-dominated wolves in the archive for the bi-objective minimization problem

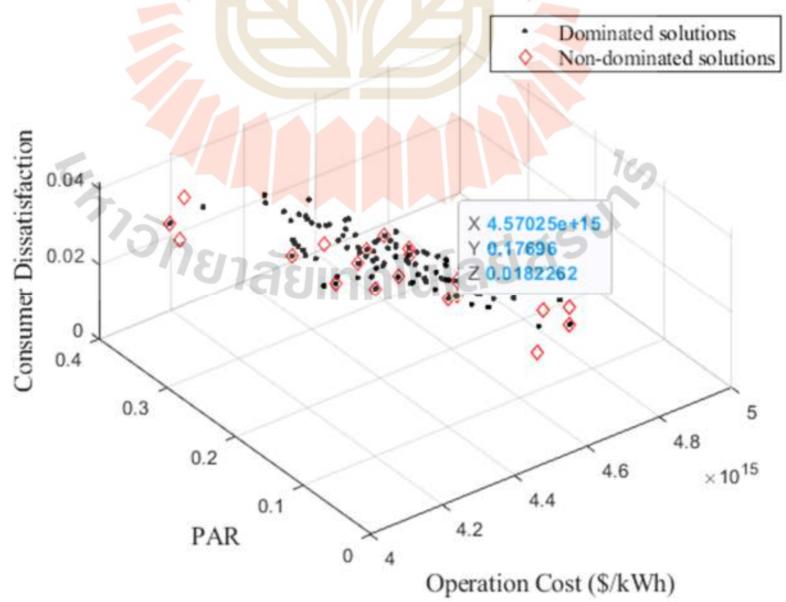


Figure 4.29 Dominated and Non-dominated wolves in the archive for the tri-objective minimization problem

CHAPTER V

CONCLUSION AND RECOMMENDATION

5.1 Concluding summary and recommendation

In this work, operation cost is formulated as the combination of RES, power exchange from the grid, and fuel cost. The fuel cost is usually represented as the quadratic function of output power. With the high penetration of RE resources, it is essential to maintain energy balancing, secure generating a scheduling, and make effective dispatch choices. The adequate forecast information minimizes generation costs, reduces demand shortage due to RE capacity variation, and enhances power operation. Due to its unpredictable and unstable nature, it is challenging to forecast accurate RE capacity over time. Due to the uncertainty and variability of renewable energy, modern electric power systems need to change flexible networks with adequate management in short- term operations. Regarding this aspect, most work has not considered the flexibility needed to meet economic investment decisions for generation purposes related to renewables generation and demand uncertainty.

The increased penetration of RE resources increases the network's randomness, volatility, and uncertainty. Such uncertainty challenges network security, such as safety, reliability, and economic operation generation systems. Therefore, the upstream power network can control and manage a reliable dispatch of generation units from the predicted REs generation and demand information. The optimal day-ahead scheduling of the distribution with REs generation systems is proposed in this work, and the proposed model also considers the demand response program to capture REs uncertainty. This problem is described as a multi-criteria optimization problem, a solved multi-objective gray wolf optimizer. At the same time, It compares and analyzes the impact of multi-objective day-ahead scheduling with the existing works. The simulation result presented the effectiveness of the proposed model in terms of operation cost, peak load reduction, and consumer comfort. The uncertainty is the challenge of dealing with the scheduling problem of distribution systems with highly integrated renewable energy. To deal with this problem, the proposed system analysis is a multi-objective day-ahead scheduling problem under the renewable energy uncertainty problem.

The day-ahead unit scheduling was to manage the generation unit optimally 24 hours in advance, with a one-hour time scale. Integrated demand response is introduced after the day-ahead scheduling process to adjust the aggregate load profile. In order to perform optimal day-ahead scheduling, the local day-ahead wind, PV, and load forecasting is vital information for the microgrid EMS system. Optimal day-ahead scheduling is the optimization problem to minimize operation cost, peak load, and consumer comfort.

The decision-making ability is to control the risk caused by the system's unbalanced condition, as reflected by the confidence level. In the day-ahead optimal scheduling model, the risk usually comes from the insecure forecast information, which will destroy system balancing. The simulation results reveal that the proposed model allocates the maximum power sharing from the cheaper generation units in the total generation capacity. PV and wind are the cheapest resources, and the proposed algorithm is preferred to the extent of 100% utilization of these resources. The power exchange from the grid is the high-paid source at 24 h and the sparing power capacity. The optimal scheduling is to extend maximum capacity from cheaper sources and spare the extent of extensive generation. Moreover, the optimization problem can effectively implement a demand response program to manage the excess load from the aggregate load profile.

Regarding the possibility of the proposed model extension, the following points are mentioned as future work. The proposed system is a step-by-step approach to energy management, and the implementation process has not been solved in a single optimization problem. Further work in this field is expanding and improving the energy management method suited to dynamic environments. In order to improve the planning model, it can incorporate different generation technologies and electric vehicles, which can be unpredictable and economically irrational.

REFERENCES

Abdelmotteleb, I., San Roman, T. G., & Reneses, J. (2016). *Distribution network cost allocation using a locational and temporal cost reflective methodology.* Paper presented at the 2016 Power Systems Computation Conference (PSCC).

Aghajani, G. R., Shayanfar, H. A., & Shayeghi, H. (2015). Presenting a multi-objective generation scheduling model for pricing demand response rate in micro-grid energy management. *Energy Conversion and Management, 106*, 308-321. doi:10.1016/j.enconman.2015.08.059

Ahmadi, A., Charwand, M., & Aghaei, J. (2013). Risk-constrained optimal strategy for retailer forward contract portfolio. *International Journal of Electrical Power & Energy Systems, 53*, 704-713.

Akhter, M. N., Mekhilef, S., Mokhlis, H., & Mohamed Shah, N. (2019). Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques. *IET Renewable Power Generation, 13*(7), 1009-1023. doi:10.1049/iet-rpg.2018.5649

Albadi, M. H., & El-Saadany, E. F. (2008). A summary of demand response in electricity markets. *Electric power systems research, 78*(11), 1989-1996.

Alilou, M., Nazarpour, D., & Shayeghi, H. (2018). Multi-Objective Optimization of demand side management and multi DG in the distribution system with demand response. *Journal of Operation and Automation in Power Engineering, 6*(2), 230-242.

Arias, L. A., Rivas, E., Santamaria, F., & Hernandez, V. (2018). A review and analysis of trends related to demand response. *Energies, 11*(7), 1617.

Azizipanah-Abarghooee, R., Niknam, T., Roosta, A., Malekpour, A. R., & Zare, M. (2012). Probabilistic multiobjective wind-thermal economic emission dispatch based on point estimated method. *Energy, 37*(1), 322-335. doi:10.1016/j.energy.2011.11.023

Bacher, P., Madsen, H., & Nielsen, H. A. (2009). Online short-term solar power forecasting. *Solar Energy, 83*(10), 1772-1783. doi:10.1016/j.solener.2009.05.016

Borghetti, A., & Nucci, C. A. (2016). Integration of distributed energy resources in distribution power systems. In *Integration of Distributed Energy Resources in Power Systems* (pp. 15-50): Elsevier.

Brown, B. G., Katz, R. W., & Murphy, A. H. (1984). Time series models to simulate and forecast wind speed and wind power. *Journal of Applied Meteorology and Climatology, 23*(8), 1184-1195.

Cai, M., Pipattanasomporn, M., & Rahman, S. (2019). Day-ahead building-level load forecasts using deep learning vs. traditional time-series techniques. *Applied Energy, 236*, 1078-1088. doi:10.1016/j.apenergy.2018.12.042

Chamandoust, H., Bahramara, S., & Derakhshan, G. (2020). Day-ahead scheduling problem of smart micro-grid with high penetration of wind energy and demand side management strategies. *Sustainable Energy Technologies and Assessments, 40*. doi:10.1016/j.seta.2020.100747

Chandran, V., Patil, C. K., Merline Manoharan, A., Ghosh, A., Sumithra, M. G., Karthick, A., . . . Arun, K. (2021). Wind power forecasting based on time series model using deep machine learning algorithms. *Materials Today: Proceedings, 47*, 115-126. doi:10.1016/j.matpr.2021.03.728

Conejo, A., & Carrion, M. (2006). Risk-constrained electricity procurement for a large consumer. *IEE Proceedings-Generation, Transmission and Distribution, 153*(4), 407-413.

Costianu, D. R., Arghlra, N., Fagarasan, I., & St Iliescu, S. (2012). A survey on power system protection in smart grids. *University" Politehnica" of Bucharest Scientific Bulletin, Series C: Electrical Engineering, 74*(1), 139-146.

David, M., Ramahatana, F., Trombe, P.-J., & Lauret, P. (2016). Probabilistic forecasting of the solar irradiance with recursive ARMA and GARCH models. *Solar Energy, 133*, 55-72.

De Brabandere, K., Vanthournout, K., Driesen, J., Deconinck, G., & Belmans, R. (2007). *Control of Microgrids*. Paper presented at the 2007 IEEE Power Engineering Society General Meeting.

Dietrich, K., Latorre, J. M., Olmos, L., & Ramos, A. (2011). Demand response in an isolated system with high wind integration. *IEEE Transactions on Power Systems, 27*(1), 20-29.

Du, Y., Li, Y., Duan, C., Gooi, H. B., & Jiang, L. (2020). Adjustable uncertainty set constrained unit commitment with operation risk reduced through demand response. *IEEE Transactions on Industrial Informatics, 17*(2), 1154-1165.

Du, Y., Li, Y., Duan, C., Gooi, H. B., & Jiang, L. (2021). Adjustable Uncertainty Set Constrained Unit Commitment With Operation Risk Reduced Through Demand Response. *IEEE Transactions on Industrial Informatics, 17*(2), 1154-1165. doi:10.1109/tii.2020.2979215

Elsaraiti, M., & Merabet, A. (2022). Solar Power Forecasting Using Deep Learning Techniques. *IEEE Access, 10*, 31692-31698. doi:10.1109/access.2022.3160484

Erdem, E., & Shi, J. (2011). ARMA based approaches for forecasting the tuple of wind speed and direction. *Applied Energy, 88*(4), 1405-1414. doi:10.1016/j.apenergy.2010.10.031

Esmaeili, S., Anvari-Moghaddam, A., Jadid, S., & Guerrero, J. M. (2019). Optimal simultaneous day-ahead scheduling and hourly reconfiguration of distribution systems considering responsive loads. *International Journal of Electrical Power & Energy Systems, 104*, 537-548. doi:10.1016/j.ijepes.2018.07.055

Essayeh, C., El-Fenni, M. R., & Dahmouni, H. (2016). *Load management strategy for an OFF-grid switched mode in smart MicroGrid systems.* Paper presented at the 2016 International Conference on Wireless Networks and Mobile Communications (WINCOM).

Falsafi, H., Zakariazadeh, A., & Jadid, S. (2014). The role of demand response in single and multi-objective wind-thermal generation scheduling: A stochastic programming. *Energy, 64*, 853-867. doi:10.1016/j.energy.2013.10.034

Gamarra, C., & Guerrero, J. M. (2015). Computational optimization techniques applied to microgrids planning: A review. *Renewable and Sustainable Energy Reviews, 48*, 413-424.

Gao, B., Huang, X., Shi, J., Tai, Y., & Xiao, R. (2019). Predicting day-ahead solar irradiance through gated recurrent unit using weather forecasting data. *Journal of Renewable and Sustainable Energy, 11*(4). doi:10.1063/1.5110223

Garulli, A., Paoletti, S., & Vicino, A. (2015). Models and Techniques for Electric Load Forecasting in the Presence of Demand Response. *IEEE Transactions on Control Systems Technology, 23*(3), 1087-1097. doi:10.1109/tcst.2014.2361807

Gazijahani, F. S., Hosseinzadeh, H., Abadi, A. A., & Salehi, J. (2017). *Optimal day ahead power scheduling of microgrids considering demand and generation uncertainties.* Paper presented at the 2017 Iranian Conference on Electrical Engineering (ICEE).

Ghofrani, M., & Alolayan, M. (2018). *Time series and renewable energy forecasting* (Vol. 10): IntechOpen.

Goli, A., Zare, H. K., Tavakkoli-Moghaddam, R., & Sadegheih, A. (2020). Multiobjective fuzzy mathematical model for a financially constrained closed-loop supply chain with labor employment. *Computational Intelligence, 36*(1), 4-34.

Haben, S., Voss, M., & Holderbaum, W. (2023). *Core Concepts and Methods in Load Forecasting: With Applications in Distribution Networks*: Springer Nature.

Haddadian, H., & Noroozian, R. (2017). Multi-microgrids approach for design and operation of future distribution networks based on novel technical indices. *Applied Energy, 185*, 650-663. doi:10.1016/j.apenergy.2016.10.120

Hajebrahimi, A., Abdollahi, A., & Rashidinejad, M. (2017). Probabilistic Multiobjective Transmission Expansion Planning Incorporating Demand Response Resources and Large-Scale Distant Wind Farms. *IEEE Systems Journal, 11*(2), 1170-1181. doi:10.1109/jsyst.2015.2464151

Hajiamoosha, P., Rastgou, A., Bahramara, S., & Bagher Sadati, S. M. (2021). Stochastic energy management in a renewable energy-based microgrid considering demand response program. *International Journal of Electrical Power & Energy Systems, 129*. doi:10.1016/j.ijepes.2021.106791

Hayes, B. (2017). Distribution Generation Optimization and Energy Management. *Distributed Generation Systems; Gharehpetian, GB, Agah, SMM, Eds.; Elsevier Inc.: Oxford, UK*, 415-451.

Hill, D. C., McMillan, D., Bell, K. R. W., & Infield, D. (2012). Application of Auto-Regressive Models to U.K. Wind Speed Data for Power System Impact Studies. *IEEE Transactions on Sustainable Energy, 3*(1), 134-141. doi:10.1109/tste.2011.2163324

Hong, Y.-Y., & Lin, J.-K. (2013). Interactive multi-objective active power scheduling considering uncertain renewable energies using adaptive chaos clonal evolutionary programming. *Energy, 53*, 212-220. doi:10.1016/j.energy.2013.02.070

Horri, R., & Roudsari, H. M. (2020). Adaptive under-frequency load-shedding considering load dynamics and post corrective actions to prevent voltage instability. *Electric power systems research, 185*, 106366.

Huang, C., Yue, D., Xie, J., Li, Y., & Wang, K. (2016). Economic dispatch of power systems with virtual power plant based interval optimization method. *CSEE Journal of Power and Energy Systems, 2*(1), 74-80. doi:10.17775/cseejpes.2016.00011

Huawei Technologies Co., L. (2022). Huawei MindSpore AI Development Framework. In *Artificial Intelligence Technology* (pp. 137-162): Springer.

Ibrahim, A., Mirjalili, S., El-Said, M., Ghoneim, S. S. M., Al-Harthi, M. M., Ibrahim, T. F., & El-Kenawy, E.-S. M. (2021). Wind Speed Ensemble Forecasting Based on Deep Learning Using Adaptive Dynamic Optimization Algorithm. *IEEE Access, 9*, 125787-125804. doi:10.1109/access.2021.3111408

Ji, W., & Chee, K. C. (2011). Prediction of hourly solar radiation using a novel hybrid model of ARMA and TDNN. *Solar Energy, 85*(5), 808-817. doi:10.1016/j.solener.2011.01.013

Jun Hua, Z., Zhao Yang, D., Zhao, X., & Kit Po, W. (2008). A Statistical Approach for Interval Forecasting of the Electricity Price. *IEEE Transactions on Power Systems, 23*(2), 267-276. doi:10.1109/tpwrs.2008.919309

Karimi, H., & Jadid, S. (2020). Optimal energy management for multi-microgrid considering demand response programs: A stochastic multi-objective framework. *Energy, 195*, 116992.

Khalili, T., Nojavan, S., & Zare, K. (2019). Optimal performance of microgrid in the presence of demand response exchange: A stochastic multi-objective model.

Computers & Electrical Engineering, 74, 429-450. doi:10.1016/j.compeleceng.2019.01.027

Khan, Z. A., Khalid, A., Javaid, N., Haseeb, A., Saba, T., & Shafiq, M. (2019). Exploiting Nature-Inspired-Based Artificial Intelligence Techniques for Coordinated Day-Ahead Scheduling to Efficiently Manage Energy in Smart Grid. *IEEE Access, 7*, 140102-140125. doi:10.1109/access.2019.2942813

Khoa, T. D., Dos Santos, L. T., Sechilariu, M., & Locment, F. (2016). *Load shedding and restoration real-time optimization for DC microgrid power balancing.* Paper presented at the 2016 IEEE International Energy Conference (ENERGYCON).

Khosravi, M., Afsharnia, S., & Farhangi, S. (2022). Stochastic power management strategy for optimal day-ahead scheduling of wind-HESS considering wind power generation and market price uncertainties. *International Journal of Electrical Power & Energy Systems, 134*. doi:10.1016/j.ijepes.2021.107429

Ko, M.-S., Lee, K., Kim, J.-K., Hong, C. W., Dong, Z. Y., & Hur, K. (2021). Deep Concatenated Residual Network With Bidirectional LSTM for One-Hour-Ahead Wind Power Forecasting. *IEEE Transactions on Sustainable Energy, 12*(2), 1321-1335. doi:10.1109/tste.2020.3043884

Kumar, K. P., & Saravanan, B. (2019). Day ahead scheduling of generation and storage in a microgrid considering demand Side management. *Journal of Energy Storage, 21*, 78-86. doi:10.1016/j.est.2018.11.010

Lee, W., Kim, K., Park, J., Kim, J., & Kim, Y. (2018). Forecasting Solar Power Using Long-Short Term Memory and Convolutional Neural Networks. *IEEE Access, 6*, 73068-73080. doi:10.1109/access.2018.2883330

Li, D., Chiu, W.-Y., & Sun, H. (2017). Demand side management in microgrid control systems. In *Microgrid* (pp. 203-230): Elsevier.

Li, D., Chiu, W.-Y., Sun, H., & Poor, H. V. (2018). Multiobjective Optimization for Demand Side Management Program in Smart Grid. *IEEE Transactions on Industrial Informatics, 14*(4), 1482-1490. doi:10.1109/tii.2017.2776104

Li, Y., Wang, P., Gooi, H. B., Ye, J., & Wu, L. (2019). Multi-Objective Optimal Dispatch of Microgrid Under Uncertainties via Interval Optimization. *IEEE Transactions on Smart Grid, 10*(2), 2046-2058. doi:10.1109/tsg.2017.2787790

Liu, H., Erdem, E., & Shi, J. (2011). Comprehensive evaluation of ARMA–GARCH(-M) approaches for modeling the mean and volatility of wind speed. *Applied Energy, 88*(3), 724-732. doi:10.1016/j.apenergy.2010.09.028

Logenthiran, T., & Srinivasan, D. (2009). *Short term generation scheduling of a microgrid.* Paper presented at the TENCON 2009-2009 IEEE Region 10 Conference.

Lu, X., Cheng, L., & Carli, R. (2021). Day-Ahead Scheduling for Renewable Energy Generation Systems considering Concentrating Solar Power Plants. *Mathematical Problems in Engineering, 2021*, 1-14. doi:10.1155/2021/9488222

Malakar, S., Goswami, S., Ganguli, B., Chakrabarti, A., Roy, S. S., Boopathi, K., & Rangaraj, A. G. (2021). Designing a long short-term network for short-term forecasting of global horizontal irradiance. *SN Applied Sciences, 3*(4). doi:10.1007/s42452-021-04421-x

Martín, L., Zarzalejo, L. F., Polo, J., Navarro, A., Marchante, R., & Cony, M. (2010). Prediction of global solar irradiance based on time series analysis: Application to solar thermal power plants energy production planning. *Solar Energy, 84*(10), 1772-1781. doi:10.1016/j.solener.2010.07.002

Massrur, H. R., Niknam, T., & Fotuhi-Firuzabad, M. (2018). Investigation of carrier demand response uncertainty on energy flow of renewable-based integrated electricity–gas–heat systems. *IEEE Transactions on Industrial Informatics, 14*(11), 5133-5142.

Mirjalili, S., & Dong, J. S. (2020a). Multi-objective Grey Wolf Optimizer. In *Multi-Objective Optimization using Artificial Intelligence Techniques* (pp. 47-58).

Mirjalili, S., & Dong, J. S. (2020b). *Multi-objective optimization using artificial intelligence techniques*: Springer.

Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in engineering software, 69*, 46-61.

Mokryani, G. (2015). Active distribution networks planning with integration of demand response. *Solar Energy, 122*, 1362-1370. doi:10.1016/j.solener.2015.10.052

Moradi, H., Esfahanian, M., Abtahi, A., & Zilouchian, A. (2018). Optimization and energy management of a standalone hybrid microgrid in the presence of battery storage system. *Energy, 147*, 226-238. doi:10.1016/j.energy.2018.01.016

Mortaji, H., Ow, S. H., Moghavvemi, M., & Almurib, H. A. F. (2017). Load shedding and smart-direct load control using internet of things in smart grid demand response management. *IEEE Transactions on Industry Applications, 53*(6), 5155-5163.

Nam, K., Hwangbo, S., & Yoo, C. (2020). A deep learning-based forecasting model for renewable energy scenarios to guide sustainable energy policy: A case study of Korea. *Renewable and Sustainable Energy Reviews, 122*. doi:10.1016/j.rser.2020.109725

Nfaoui, H., Buret, J., & Sayigh, A. (1996). Stochastic simulation of hourly average wind speed sequences in Tangiers (Morocco). *Solar Energy, 56*(3), 301-314.

Nguyen, T.-H., Nguyen, L. V., Jung, J. J., Agbehadji, I. E., Frimpong, S. O., & Millham, R. C. (2020). Bio-inspired approaches for smart energy management: State of the art and challenges. *Sustainability, 12*(20), 8495.

Nikmehr, N., & Najafi Ravadanegh, S. (2016). Reliability evaluation of multi-microgrids considering optimal operation of small scale energy zones under load-generation uncertainties. *International Journal of Electrical Power & Energy Systems, 78*, 80-87. doi:10.1016/j.ijepes.2015.11.094

Nikoobakht, A., Aghaei, J., Shafie-Khah, M., & Catalao, J. P. S. (2019). Assessing Increased Flexibility of Energy Storage and Demand Response to Accommodate a High Penetration of Renewable Energy Sources. *IEEE Transactions on Sustainable Energy, 10*(2), 659-669. doi:10.1109/tste.2018.2843161

Noor, S., Guo, M., van Dam, K. H., Shah, N., & Wang, X. (2018). Energy demand side management with supply constraints: game theoretic approach. *Energy Procedia, 145*, 368-373.

Nourollahi, R., Salyani, P., Zare, K., & Razzaghi, R. (2022). A two-stage hybrid robust-stochastic day-ahead scheduling of transactive microgrids considering the possibility of main grid disconnection. *International Journal of Electrical Power & Energy Systems, 136*. doi:10.1016/j.ijepes.2021.107701

Pan, J., Nuqui, R., Srivastava, K., Jonsson, T., Holmberg, P., & Hafner, Y.-J. (2008). *AC grid with embedded VSC-HVDC for secure and efficient power delivery.* Paper presented at the 2008 IEEE Energy 2030 Conference.

Paoli, C., Voyant, C., Muselli, M., & Nivet, M.-L. (2010). Forecasting of preprocessed daily solar radiation time series using neural networks. *Solar Energy, 84*(12), 2146-2160. doi:10.1016/j.solener.2010.08.011

Pappas, S. S., Ekonomou, L., Karamousantas, D. C., Chatzarakis, G. E., Katsikas, S. K., & Liatsis, P. (2008). Electricity demand loads modeling using AutoRegressive Moving Average (ARMA) models. *Energy, 33*(9), 1353-1360. doi:10.1016/j.energy.2008.05.008

Paterakis, N. G., Gibescu, M., Bakirtzis, A. G., & Catalao, J. P. S. (2018). A Multi-Objective Optimization Approach to Risk-Constrained Energy and Reserve Procurement Using Demand Response. *IEEE Transactions on Power Systems, 33*(4), 3940-3954. doi:10.1109/tpwrs.2017.2785266

Patterson, K. (2011). An introduction to arma models. In *Unit Root Tests in Time Series: Key Concepts and Problems* (pp. 68-122): Springer.

Peng, Q., Liu, W., Zhang, Y., Zeng, S., & Graham, B. (2023). Generation planning for power companies with hybrid production technologies under multiple renewable energy policies. *Renewable and Sustainable Energy Reviews, 176*. doi:10.1016/j.rser.2023.113209

Phani Raghav, L., Seshu Kumar, R., Koteswara Raju, D., & Singh, A. R. (2022). Analytic Hierarchy Process (AHP) – Swarm intelligence based flexible demand response management of grid-connected microgrid. *Applied Energy, 306*. doi:10.1016/j.apenergy.2021.118058

Poggi, P., Muselli, M., Notton, G., Cristofari, C., & Louche, A. (2003). Forecasting and simulating wind speed in Corsica by using an autoregressive model. *Energy Conversion and Management, 44*(20), 3177-3196. doi:10.1016/s0196-8904(03)00108-0

Qiu, S., Chen, J., Mao, C., Duan, Q., Ma, C., Liu, Z., & Wang, D. (2022). Day-ahead optimal scheduling of power–gas–heating integrated energy system considering energy routing. *Energy Reports, 8*, 1113-1122. doi:10.1016/j.egyr.2022.08.147

Rajagukguk, R. A., Ramadhan, R. A. A., & Lee, H.-J. (2020). A Review on Deep Learning Models for Forecasting Time Series Data of Solar Irradiance and Photovoltaic Power. *Energies, 13*(24). doi:10.3390/en13246623

Reddy, S. S. (2016). Optimizing energy and demand response programs using multi-objective optimization. *Electrical Engineering, 99*(1), 397-406. doi:10.1007/s00202-016-0438-6

Rosato, A., Panella, M., Araneo, R., & Andreotti, A. (2019). A Neural Network Based Prediction System of Distributed Generation for the Management of Microgrids. *IEEE Transactions on Industry Applications, 55*(6), 7092-7102. doi:10.1109/tia.2019.2916758

Rozinajová, V., Ezzeddine, A. B., Lóderer, M., Loebl, J., Magyar, R., & Vrablecová, P. (2018). Computational intelligence in smart grid environment. In *Computational Intelligence for Multimedia Big Data on the Cloud with Engineering Applications* (pp. 23-59): Elsevier.

Saez, D., Avila, F., Olivares, D., Canizares, C., & Marin, L. (2015). Fuzzy Prediction Interval Models for Forecasting Renewable Resources and Loads in Microgrids. *IEEE Transactions on Smart Grid, 6*(2), 548-556. doi:10.1109/tsg.2014.2377178

Santamaría-Bonfil, G., Reyes-Ballesteros, A., & Gershenson, C. (2016). Wind speed forecasting for wind farms: A method based on support vector regression. *Renewable Energy, 85*, 790-809. doi:10.1016/j.renene.2015.07.004

Shen, Y., Ma, Y., Deng, S., Huang, C.-J., & Kuo, P.-H. (2021). An Ensemble Model based on Deep Learning and Data Preprocessing for Short-Term Electrical Load Forecasting. *Sustainability, 13*(4). doi:10.3390/su13041694

Shewale, A., Mokhade, A., Funde, N., & Bokde, N. D. (2020). An Overview of Demand Response in Smart Grid and Optimization Techniques for Efficient Residential Appliance Scheduling Problem. *Energies, 13*(16). doi:10.3390/en13164266

Shi, Z., Liang, H., & Dinavahi, V. (2018). Direct Interval Forecast of Uncertain Wind Power Based on Recurrent Neural Networks. *IEEE Transactions on Sustainable Energy, 9*(3), 1177-1187. doi:10.1109/tste.2017.2774195

Shi, Z., Liang, H., Huang, S., & Dinavahi, V. (2019). Multistage robust energy management for microgrids considering uncertainty. *IET Generation, Transmission & Distribution, 13*(10), 1906-1913.

Shokooh, F., Dai, J., Shokooh, S., Taster, J., Castro, H., Khandelwal, T., & Donner, G. (2005). *An intelligent load shedding (ILS) system application in a large industrial* *facility.* Paper presented at the Fourtieth IAS Annual Meeting. Conference Record of the 2005 Industry Applications Conference, 2005.

Shyh-Jier, H., & Kuang-Rong, S. (2003). Short-term load forecasting via ARMA model identification including non-gaussian process considerations. *IEEE Transactions on Power Systems, 18*(2), 673-679. doi:10.1109/tpwrs.2003.811010

Silva, V. A., Aoki, A. R., & Lambert-Torres, G. (2020). Optimal Day-Ahead Scheduling of Microgrids with Battery Energy Storage System. *Energies, 13*(19). doi:10.3390/en13195188

Singh, A. K., Ibraheem, Khatoon, S., Muazzam, M., & Chaturvedi, D. K. (2012). *Load forecasting techniques and methodologies: A review*. Paper presented at the 2012 2nd International Conference on Power, Control and Embedded Systems.

Singh, B., & Pozo, D. (2019). *A guide to solar power forecasting using ARMA models.* Paper presented at the 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe).

Soares, J., Fotouhi Ghazvini, M. A., Silva, M., & Vale, Z. (2016). Multi-dimensional signaling method for population-based metaheuristics: Solving the large-scale scheduling problem in smart grids. *Swarm and Evolutionary Computation, 29*, 13-32. doi:10.1016/j.swevo.2016.02.005

Sobri, S., Koohi-Kamali, S., & Rahim, N. A. (2018). Solar photovoltaic generation forecasting methods: A review. *Energy Conversion and Management, 156*, 459-497.

Solanki, B. V., Raghurajan, A., Bhattacharya, K., & Canizares, C. A. (2015). Including smart loads for optimal demand response in integrated energy management systems for isolated microgrids. *IEEE Transactions on Smart Grid, 8*(4), 1739-1748.

Su, W., & Wang, J. (2012). Energy management systems in microgrid operations. *The Electricity Journal, 25*(8), 45-60.

Succetti, F., Rosato, A., Araneo, R., & Panella, M. (2020). Deep Neural Networks for Multivariate Prediction of Photovoltaic Power Time Series. *IEEE Access, 8*, 211490-211505. doi:10.1109/access.2020.3039733

Tabar, V. S., Jirdehi, M. A., & Hemmati, R. (2017). Energy management in microgrid based on the multi objective stochastic programming incorporating portable renewable energy resource as demand response option. *Energy, 118*, 827-839. doi:10.1016/j.energy.2016.10.113

Tan, Q., Mei, S., Dai, M., Zhou, L., Wei, Y., & Ju, L. (2020). A multi-objective optimization dispatching and adaptability analysis model for wind-PV-thermal-coordinated operations considering comprehensive forecasting error distribution. *Journal of cleaner production, 256*. doi:10.1016/j.jclepro.2020.120407

Tavakoli Ghazi Jahani, M. A., Nazarian, P., Safari, A., & Haghifam, M. R. (2019). Multi-objective optimization model for optimal reconfiguration of distribution networks with demand response services. *Sustainable Cities and Society, 47*. doi:10.1016/j.scs.2019.101514

Torres, J. F., Hadjout, D., Sebaa, A., Martinez-Alvarez, F., & Troncoso, A. (2021). Deep Learning for Time Series Forecasting: A Survey. *Big Data, 9*(1), 3-21. doi:10.1089/big.2020.0159

Torres, J. L., Garcia, A., De Blas, M., & De Francisco, A. (2005). Forecast of hourly average wind speed with ARMA models in Navarre (Spain). *Solar Energy, 79*(1), 65-77.

Tostado-Véliz, M., Rezaee Jordehi, A., Icaza, D., Mansouri, S. A., & Jurado, F. (2023). Optimal participation of prosumers in energy communities through a novel stochastic-robust day-ahead scheduling model. *International Journal of Electrical Power & Energy Systems, 147*. doi:10.1016/j.ijepes.2022.108854

Vahedipour-Dahraie, M., Rashidizadeh-Kermani, H., Anvari-Moghaddam, A., & Guerrero, J. M. (2019). Stochastic risk-constrained scheduling of renewable-powered autonomous microgrids with demand response actions: Reliability and economic implications. *IEEE Transactions on Industry Applications, 56*(2), 1882-1895.

Vivekananthan, C. (2014). *Demand Response for Residential Appliances in a Smart Electricity Distribution Network: Utility and Customer Perspectives.* Queensland University of Technology,

Voyant, C., Muselli, M., Paoli, C., & Nivet, M.-L. (2012). Numerical weather prediction (NWP) and hybrid ARMA/ANN model to predict global radiation. *Energy, 39*(1), 341-355. doi:10.1016/j.energy.2012.01.006

Voyant, C., Randimbivololona, P., Nivet, M. L., Paoli, C., & Muselli, M. (2014). Twenty four hours ahead global irradiation forecasting using multi-layer perceptron. *Meteorological Applications, 21*(3), 644-655. doi:10.1002/met.1387

Wang, C., Song, G., Li, P., Ji, H., Zhao, J., & Wu, J. (2016). Optimal Configuration of Soft Open Point for Active Distribution Network Based on Mixed-integer Second-order Cone Programming. *Energy Procedia, 103*, 70-75. doi:10.1016/j.egypro.2016.11.251

Wang, F., Zhou, L., Ren, H., Liu, X., Talari, S., Shafie-khah, M., & Catalao, J. P. S. (2018). Multi-Objective Optimization Model of Source–Load–Storage Synergetic Dispatch for a Building Energy Management System Based on TOU Price Demand Response. *IEEE Transactions on Industry Applications, 54*(2), 1017-1028. doi:10.1109/tia.2017.2781639

Wang, H., Lei, Z., Zhang, X., Zhou, B., & Peng, J. (2019). A review of deep learning for renewable energy forecasting. *Energy Conversion and Management, 198*. doi:10.1016/j.enconman.2019.111799

Wang, K., Qi, X., & Liu, H. (2019). A comparison of day-ahead photovoltaic power forecasting models based on deep learning neural network. *Applied Energy, 251*. doi:10.1016/j.apenergy.2019.113315

Wang, L., Li, Q., Ding, R., Sun, M., & Wang, G. (2017). Integrated scheduling of energy supply and demand in microgrids under uncertainty: A robust multi-objective optimization approach. *Energy, 130*, 1-14. doi:10.1016/j.energy.2017.04.115

Wang, Y., Huang, Y., Wang, Y., Zeng, M., Li, F., Wang, Y., & Zhang, Y. (2018). Energy management of smart micro-grid with response loads and distributed generation considering demand response. *Journal of cleaner production, 197*, 1069-1083.

Wang, Y., Xia, Q., & Kang, C. (2011). Unit Commitment With Volatile Node Injections by Using Interval Optimization. *IEEE Transactions on Power Systems, 26*(3), 1705-1713. doi:10.1109/tpwrs.2010.2100050

Wen, L., Zhou, K., Yang, S., & Lu, X. (2019). Optimal load dispatch of community microgrid with deep learning based solar power and load forecasting. *Energy, 171*, 1053-1065. doi:10.1016/j.energy.2019.01.075

Wu, L., Shahidehpour, M., & Li, Z. (2012). Comparison of Scenario-Based and Interval Optimization Approaches to Stochastic SCUC. *IEEE Transactions on Power Systems, 27*(2), 913-921. doi:10.1109/tpwrs.2011.2164947

Xu, H., Chang, Y., Zhao, Y., & Wang, F. (2023). A new multi-timescale optimal scheduling model considering wind power uncertainty and demand response. *International Journal of Electrical Power & Energy Systems, 147*. doi:10.1016/j.ijepes.2022.108832

Yang, Y., Wang, Y., Gao, Y., & Gao, C. (2022). Peak Shaving Analysis of Power Demand Response with Dual Uncertainty of Unit and Demand-Side Resources under Carbon Neutral Target. *Energies, 15*(13). doi:10.3390/en15134588

Yang, Z., Ghadamyari, M., Khorramdel, H., Seyed Alizadeh, S. M., Pirouzi, S., Milani, M., . . . Ghadimi, N. (2021). Robust multi-objective optimal design of islanded hybrid system with renewable and diesel sources/stationary and mobile energy storage systems. *Renewable and Sustainable Energy Reviews, 148*. doi:10.1016/j.rser.2021.111295

Yong, L., Zhi-Jian, H., & Chuan-Wen, J. (2005). *Unit commitment by binary particle swarm optimization.* Paper presented at the 7th WSEAS Int. Conf. on mathematical methods and computational techniques in electrical engineering.

Yu, M., Hong, S. H., & Kim, J. B. (2016). *Incentive-based demand response approach for aggregated demand side participation.* Paper presented at the 2016 IEEE International Conference on Smart Grid Communications (SmartGridComm).

Zhang, G., Jiang, C., Wang, X., Li, B., & Zhu, H. (2017). Bidding strategy analysis of virtual power plant considering demand response and uncertainty of renewable energy. *IET Generation, Transmission & Distribution, 11*(13), 3268-3277.

Zhang, G., Wang, W., Du, J., & Liu, H. (2020). A Multiobjective Optimal Operation of a Stand-Alone Microgrid Using SAPSO Algorithm. *Journal of Electrical and Computer Engineering, 2020*, 1-16. doi:10.1155/2020/6042105

Zheng, S., Sun, Y., Li, B., Qi, B., Shi, K., Li, Y., & Tu, X. (2020). Incentive-based integrated demand response for multiple energy carriers considering behavioral coupling effect of consumers. *IEEE Transactions on Smart Grid, 11*(4), 3231-3245.

Zhong, H., Xie, L., & Xia, Q. (2012). Coupon incentive-based demand response: Theory and case study. *IEEE Transactions on Power Systems, 28*(2), 1266-1276.

APPENDIX A

MATLAB Codes

Main MOGWO

```
clear all
clc
drawing_flag = 1;

fobj=@(x)objective_function3DG_forecast_mo(x);
nVar=11;
VarSize=[1 nVar];
% Lower bound and upper bound
lb=[     0.2406    0      50    25   25   0       0   0    0    5
0.05];
ub=[     0.2406    0      100   125  125   100    1    1     5   50
0.2];

GreyWolves_num=100;
MaxIt=10;  % Maximum Number of Iterations
Archive_size=20;   % Repository Size

alpha=0.1;  % Grid Inflation Parameter
nGrid=11;   % Number of Grids per each Dimension
beta=4; %=4;    % Leader Selection Pressure Parameter
gamma=2;    % Extra (to be deleted) Repository Member Selection
Pressure

% Initialization

GreyWolves=CreateEmptyParticle(GreyWolves_num);

for i=1:GreyWolves_num
    for j=1:nVar
    GreyWolves(i).Velocity=0;
    GreyWolves(i).Position=zeros(1,nVar);

        %GreyWolves(i,j).Position=unifrnd(lb,ub);
    GreyWolves(i).Position=unifrnd(lb,ub);
    GreyWolves(i).Cost=fobj(GreyWolves(i).Position);
    GreyWolves(i).Best.Position=GreyWolves(i).Position;
    GreyWolves(i).Best.Cost=GreyWolves(i).Cost;
    end
end

GreyWolves=DetermineDomination(GreyWolves);

Archive=GetNonDominatedParticles(GreyWolves);

Archive_costs=GetCosts(Archive);
Grid=CreateHypercubes(Archive_costs,nGrid,alpha);

for i=1:numel(Archive)
    Archive(i)=GetGridIndex(Archive(i),Grid);
end

% MOGWO main loop
```

```
 y=zeros(3*MaxIt,Archive_size);
 q=zeros(MaxIt,nVar);

for it=1:MaxIt
    a=2-it*((2)/MaxIt);
    for i=1:GreyWolves_num

        clear rep2
        clear rep3

        % Choose the alpha, beta, and delta grey wolves
        Delta=SelectLeader(Archive,beta);
        Beta=SelectLeader(Archive,beta);
        Alpha=SelectLeader(Archive,beta);

        % If there are less than three solutions in the least crowded
        % hypercube, the second least crowded hypercube is also found
        % to choose other leaders from.
        if size(Archive,1)>1
            counter=0;
            for newi=1:size(Archive,1)
                if sum(Delta.Position~=Archive(newi).Position)~=0
                    counter=counter+1;
                    rep2(counter,1)=Archive(newi);
                end
            end
            Beta=SelectLeader(rep2,beta);
        end

        % This scenario is the same if the second least crowded
hypercube
        % has one solution, so the delta leader should be chosen from
the
        % third least crowded hypercube.
        if size(Archive,1)>2
            counter=0;
            for newi=1:size(rep2,1)
                if sum(Beta.Position~=rep2(newi).Position)~=0
                    counter=counter+1;
                    rep3(counter,1)=rep2(newi);
                end
            end
            Alpha=SelectLeader(rep3,beta);
        end

        % Eq.(3.4) in the paper
        c=2.*rand(1, nVar);
        % Eq.(3.1) in the paper
        D=abs(c.*Delta.Position-GreyWolves(i).Position);
        % Eq.(3.3) in the paper
        A=2.*a.*rand(1, nVar)-a;
        % Eq.(3.8) in the paper
        X1=Delta.Position-A.*abs(D);


        % Eq.(3.4) in the paper
```

```
        c=2.*rand(1, nVar);
        % Eq.(3.1) in the paper
        D=abs(c.*Beta.Position-GreyWolves(i).Position);
        % Eq.(3.3) in the paper
        A=2.*a.*rand(1, nVar)-a;
        % Eq.(3.9) in the paper
        X2=Beta.Position-A.*abs(D);


        % Eq.(3.4) in the paper
        c=2.*rand(1, nVar);
        % Eq.(3.1) in the paper
        D=abs(c.*Alpha.Position-GreyWolves(i).Position);
        % Eq.(3.3) in the paper
        A=2.*a.*rand(1, nVar)-a;
        % Eq.(3.10) in the paper
        X3=Alpha.Position-A.*abs(D);

        % Eq.(3.11) in the paper
        GreyWolves(i).Position=(X1+X2+X3)./3;

        % Boundary checking

GreyWolves(i).Position=min(max(GreyWolves(i).Position,lb),ub);

        GreyWolves(i).Cost=fobj(GreyWolves(i).Position);
        fnew=fobj(GreyWolves(i).Position);

        f=fobj(GreyWolves(i).Best.Position);
        if fnew<=f
    f(:,:)=fnew(:,:);
    GreyWolves(i).Best.Position=GreyWolves(i).Position;
    %GreyWolves(i).Cost=fobj(GreyWolves(i).Best.Position);
    end

    end
      [optval,optind]=min(f(:,:));
   bestfx(MaxIt)=optval;
   %bestpos=position(optind,:);

    GreyWolves=DetermineDomination(GreyWolves);
    non_dominated_wolves=GetNonDominatedParticles(GreyWolves);

    Archive=[Archive
        non_dominated_wolves];

    Archive=DetermineDomination(Archive);
    Archive=GetNonDominatedParticles(Archive);

    for i=1:numel(Archive)
        Archive(i)=GetGridIndex(Archive(i),Grid);
    end

    if numel(Archive)>Archive_size
        EXTRA=numel(Archive)-Archive_size;
        Archive=DeleteFromRep(Archive,EXTRA,gamma);
```

```
        Archive_costs=GetCosts(Archive);
        Grid=CreateHypercubes(Archive_costs,nGrid,alpha);

    end

    %disp(['In iteration ' num2str(it) ': Number of solutions in the
archive = ' num2str(numel(Archive)) ':Best Cost ='
num2str(GreyWolves(i).Cost) ':Best position ='
num2str(GreyWolves(i).Position)]);


    save results

    %[optval,optind]=min(f(:,:));
   %bestfx=optval;
   %bestpos=position(optind,:);
    % Results

    costs=GetCosts(GreyWolves);
    Archive_costs=GetCosts(Archive);
    Archive_position=Archive.Position;


     %disp(['In iteration ' num2str(it) ': Number of solutions in the
archive = ' num2str(numel(Archive))]);
    %selsect min from Archive
if drawing_flag==1
    hold off
        plot(costs(1,:),costs(2,:),'k.');
        hold on
        plot(Archive_costs(1,:),Archive_costs(2,:),'rd');
        legend('Dominated solutions','Non-dominated solutions');
        xlabel('Operation Cost
($/kWh)','FontSize',28,'FontName','Times New Roman');
         ylabel('PAR','FontSize',28,'FontName','Times New Roman');
        figure;
        plot(costs(2,:),costs(3,:),'k.');
        hold on
        plot(Archive_costs(2,:),Archive_costs(3,:),'rd');
        legend('Dominated solutions','Non-dominated solutions');
        xlabel('PAR','FontSize',28,'FontName','Times New Roman');
         ylabel('Consumer
Dissatisfaction','FontSize',28,'FontName','Times New Roman');
        figure;
       plot3(costs(1,:),costs(2,:),costs(3,:),'k.');
       hold on

plot3(Archive_costs(1,:),Archive_costs(2,:),Archive_costs(3,:),'rd');
        %legend('Grey wolves','Non-dominated solutions');
        legend('Dominated solutions','Non-dominated solutions');
         xlabel('Operation Cost
($/kWh)','FontSize',28,'FontName','Times New Roman');
         ylabel('PAR','FontSize',28,'FontName','Times New Roman');
         zlabel('Consumer
Dissatisfaction','FontSize',28,'FontName','Times New Roman');
```

```
          grid on
          figure;
         drawnow

end

    bestfx_1(it)=f(:,1);
    bestfx_2(it)=f(:,2);
    bestfx_3(it)=f(:,3);
    %disp([   '' num2str(Archive_costs)  ]);

    disp([  '' num2str(Archive_position) ]);

y(it,:)=[Archive_costs(1,:)];

  y(it+MaxIt,:)=[Archive_costs(2,:)];

  y(it+MaxIt*2,:)=[Archive_costs(3,:)];
    filename=['bcs_cost_1_adfr_2','.xlsx'];
    xlswrite(filename,y)   ;

    q(it,:)=Archive_position(:,:);
      filename= ['bcs_G_1_adfr_2','.xlsx'];

      xlswrite(filename,q);


    %disp([  '' num2str(Archive_position) ]);
    %disp([ 'In iteration ' num2str(it) ':Cost'
num2str(GreyWolves(i).Cost) ':Best position ='
num2str(GreyWolves(i).Best.Position)]);
    %disp(['' num2str( f(:,:)) ':'
num2str(GreyWolves(i).Best.Position) ]);
   % if drawing_flag==1
      % hold off
       %plot(GreyWolves(i).Cost(:,1),GreyWolves(i).Cost(:,2),'*r');
       %plot(Archive_costs(:,:),'*r');
      %xlabel('Obj 1');
         %ylabel('Obj 2');
    %end
    %plot(bestfx_3,'Linewidth',2);
    %xlabel('Iteration');
    %ylabel('Best Cost (First Objective)' );
end
```

Objective Function

```
function [f] = objective_function3DG_forecast_mo(x)
data1=[ 147.2607       146.8
    151.9281       150.3
    157.119          155.4
    162.5461        158.4
    167.9063         166.5
    172.8989         174.5
```

```
    177.2422         177.5
    180.6783        176.6
    183.008         179.8
    184.1255        180.7
    184.016          181.8
    182.6872        179.8
    180.031         177.9
    175.6149        179
    168.6586        173.3
    160.1163        167
    156.0161        160.7
    159.5986        163.4
    166.8815        173.2
    174.0677        178.8
    177.511         180.2
    178.0595        178.4
    177.6684        179.2
    176.0256        176.9];         % demand forecast & actual
(gru)//// wholesale price

pv=[0          0
         0         0
         0         0
         0         0
         0         0
    0.5750         0
    2.0133    0.1747
    4.7038    4.3580
    8.5583    9.3070
   12.6055   12.9876
   15.4040   15.6100
   16.6730   17.5211
   16.3370   16.9766
   14.8364   15.9214
   11.9471   12.9440
    7.6976    8.8252
    3.3794    1.3812
    0.6151         0
         0         0
         0         0
         0         0
         0         0
         0         0
         0         0];  %%% PV power/gru/forecast &actual / MW


 wind=[0.1918    0.2406
    1.1077    2.4474
    2.7287    1.4827
    0.0715    0.0768
    2.3577    0.1754
    1.0640    0.8121
    0.0752    0.0024
    2.8232    0.0001
    3.4542    2.4474
    0.1901    0.5492
    3.6018    7.6409
```

```
    5.7626   10.3165
    1.0430    0.2528
    7.5667    7.6409
    5.9023    5.4731
    0.5123    0.6841
    5.4016    7.6409
    7.4826   10.3165
    0.3566    0.5704
    9.2593   10.3165
    6.3229   5.4731
    0.1295    0.7853
    2.2546    2.4474
    4.0447    2.4474];%%% wind power/gru/forecast&actual/MW
data3=[  0     0
    2.664108        0
    3.739684      0
    1.696395      0
    3.758407      0
    34.54576      0
    124.7138      10.82
    520.8635     272.24
    741.4423      566.43
    884.3228     763.92
    939.1666     896.15
    920.2418     986.94
    835.7125      956.27
    672.9625      896.83
    433.595       729.12
    293.8441        497.11
    190.3563      77.82
    34.64856      0
    0    0
    0     0
    0      0
    0      0
    0       0
    0          0];         %PV irradiation gru forecast/actual
data4=[ 2.4871   2.6822
    4.462       5.8115
    6.0261      4.9174
    1.7895      1.8329
    5.7396      2.414
    4.4025      4.0234
    1.8206      0.58115
    6.0949      0.17882
    6.5188      5.8115
    2.4794      3.5316
    6.6104     8.4938
    7.7314     9.3878
    4.3733     2.7269
    8.4662     8.4938
    7.7934     7.5997
    3.4506     3.7998
    7.5665     8.4938
    8.4347     9.3878
    3.0581     3.5763
    9.0555     9.3878
    7.9743     7.5997
```

```
    2.1816     3.9787
    5.6547     5.8115
    6.8709      5.8115];       % wind gru forecast/actual

X1=x(:,1);           %%%wind
X2=x(:,2);           %%%PV
X3=x(:,3);           %%%grid
X4=x(:,4);           %%%DG1
X5=x(:,5);           %%%DG2
X6=x(:,6);           %%%PAR
X7=x(:,7);           %%%waiting time
X8=x(:,8);           %%% demand limit
X9=x(:,9);         %%%DR elasticity
%1st objective function
z_1=[X1.*0.1095]+[X2.*0.1095]+[X3.*0.075]+[(
0.02.*X4.^2+10.*X4)+(0.015.*X5.^2+10.75.*X5)];
z_2=((X6)./(data1(1,2)));                          %PAR min
%z_2=exp([(24.*X6)./data1(3,1)]).*data1(3,2);

%3nd objective function              %Dissatification min
z_3=X7./24+(X8./data1(1,2)).*X9;

%3st Constraints
g(:,4)=abs(X7-5);
%g(:,5)=[X11-data1(3,1).*0.005];
%1st Constraint
g(:,1)=X1+X2+X3+X4+X5-data1(1,2)-(10^(5));         %power balance
constraints
g(:,2)=-[50-X1]-[50-X2]-[100-X3]-[125-X4]-[125-
X5]+data1(1,2)+data1(1,2).*0.1;          %spinning resereve constraint
%define pently term
pp=10^(15);
for i=1:size(g,1)
   for j=1:size(g,2)
       if g(i,j)>0

           penalty(i,j)=pp.*g(i,j);
       end
   end

end
%compute objective function

Z_1=z_1+sum(penalty,2);
%Z_2=z_2+sum(penalty,2);
Z_2=z_2;
Z_3=z_3;
f=[Z_1  Z_2  Z_3];
```

Create Empty Particle

```
function particle=CreateEmptyParticle(n)

    if nargin<1
        n=1;
    end
```

```
    empty_particle.Position=[];
    empty_particle.Velocity=[];
    empty_particle.Cost=[];
    empty_particle.Dominated=false;
    empty_particle.Best.Position=[];
    empty_particle.Best.Cost=[];
    empty_particle.GridIndex=[];
    empty_particle.GridSubIndex=[];

    particle=repmat(empty_particle,n,1);

end
```

Create Hyper Cubes

```
function G=CreateHypercubes(costs,ngrid,alpha)

    nobj=size(costs,1);

    empty_grid.Lower=[];
    empty_grid.Upper=[];
    G=repmat(empty_grid,nobj,1);

    for j=1:nobj

        min_cj=min(costs(j,:));
        max_cj=max(costs(j,:));

        dcj=alpha*(max_cj-min_cj);

        min_cj=min_cj-dcj;
        max_cj=max_cj+dcj;

        gx=linspace(min_cj,max_cj,ngrid-1);

        G(j).Lower=[-inf gx];
        G(j).Upper=[gx inf];

    end

end
```

Delete From Cubes

```
function rep=DeleteFromRep(rep,EXTRA,gamma)

    if nargin<3
        gamma=1;
    end

    for k=1:EXTRA
        [occ_cell_index occ_cell_member_count]=GetOccupiedCells(rep);
```

```
        p=occ_cell_member_count.^gamma;
        p=p/sum(p);

selected_cell_index=occ_cell_index(RouletteWheelSelection(p));

        GridIndices=[rep.GridIndex];

        selected_cell_members=find(GridIndices==selected_cell_index);

        n=numel(selected_cell_members);

        selected_memebr_index=randi([1 n]);

        j=selected_cell_members(selected_memebr_index);

        rep=[rep(1:j-1); rep(j+1:end)];
    end

end
```

Determine domination

```
function pop=DetermineDomination(pop)

    npop=numel(pop);

    for i=1:npop
        pop(i).Dominated=false;
        for j=1:i-1
            if ~pop(j).Dominated
                if Dominates(pop(i),pop(j))
                    pop(j).Dominated=true;
                elseif Dominates(pop(j),pop(i))
                    pop(i).Dominated=true;
                    break;
                end
            end
        end
    end

end
```

Dominates solution

```
function dom=Dominates(x,y)

    if isstruct(x)
        x=x.Cost;
    end

    if isstruct(y)
```

```
        y=y.Cost;
    end

    dom=all(x<=y) && any(x<y);

end
```

Get costs function

```
function costs=GetCosts(pop)

    nobj=numel(pop(1).Cost);
    costs=reshape([pop.Cost],nobj,[]);

end
```

Get gris index function

```
function [Index SubIndex]=GetGridIndex(particle,G)

    c=particle.Cost;

    nobj=numel(c);
    ngrid=numel(G(1).Upper);

    str=['sub2ind(' mat2str(ones(1,nobj)*ngrid)];

    SubIndex=zeros(1,nobj);
    for j=1:nobj

        U=G(j).Upper;

        i=find(c(j)<U,1,'first');

        SubIndex(j)=i;

        str=[str ',' num2str(i)];
    end

    str=[str ');'];

    Index=eval(str);

end
```

Get non-dominated solution

```
function nd_pop=GetNonDominatedParticles(pop)

    ND=~[pop.Dominated];

    nd_pop=pop(ND);
```

```
end
```

Occupied cells

```
function [occ_cell_index occ_cell_member_count]=GetOccupiedCells(pop)

    GridIndices=[pop.GridIndex];

    occ_cell_index=unique(GridIndices);

    occ_cell_member_count=zeros(size(occ_cell_index));

    m=numel(occ_cell_index);
    for k=1:m
        occ_cell_member_count(k)=sum(GridIndices==occ_cell_index(k));
    end

end
```

Roulette Wheel Selection

```
function i=RouletteWheelSelection(p)

    r=rand;
    c=cumsum(p);
    i=find(r<=c,1,'first');

end
```

Select Leader

```
function rep_h=SelectLeader(rep,beta)
    if nargin<2
        beta=1;
    end

    [occ_cell_index occ_cell_member_count]=GetOccupiedCells(rep);

    p=occ_cell_member_count.^(-beta);
    p=p/sum(p);

    selected_cell_index=occ_cell_index(RouletteWheelSelection(p));

    GridIndices=[rep.GridIndex];

    selected_cell_members=find(GridIndices==selected_cell_index);

    n=numel(selected_cell_members);

    selected_memebr_index=randi([1 n]);
```

```
    h=selected_cell_members(selected_memebr_index);

    rep_h=rep(h);
end
```

BCS selection

```
clc
clear all
%select = readtable('bcs_cost_1.xlsx');
data = xlsread('bcs_cost_17_fdar_1.xlsx');
y=zeros(300,1);
for i=1:300
f_1=min(data(i,:));

disp([num2str(f_1) ]);
y(i,:)=f_1(:,:);
      filename= ['bcs_min_select_17_fdar_1','.xlsx'];

      xlswrite(filename,y);
end
```

BCS main

```
clc
clear all
data=xlsread('bcs_min_select_17_fdar_1.xlsx');
f_1=min(data(1:100,:));
f_2=min(data(101:200,:));
f_3=min(data(201:300,:));

for i=1:100
   D=sqrt((data(i,:)-f_1).^2+(data(i+100,:)-f_2).^2+(data(i+200,:)-
f_3).^2);
   disp(['Distance ' num2str(D)]) ;

end
```

GWO main

```
format short
clc
clear all
%initialize the parameter
CostFunction=@(x)objective_function3DG_arma_peakday_1(x);
N=10;                   %no. of wolf
D=5;                     %no. of paramater
d=[5 D];
lb=[2.7287    0      50    25   25    ];
ub=[2.7287    0      100   125  125   ];

itermax=100;
wolf.pos=[];
```

```
pop=repmat(wolf,D);
%generating the initial population
%for i = 1:N
   %pop(i).pos = unifrnd(lb, ub, d);
  % pop(i).fx = CostFunction(pop(i).pos);

 %end
position=zeros(5,5);

for i=1:N

     pop(i).pos =unifrnd(lb, ub);

position(i,:)= pop(i).pos ;

end

fx=CostFunction(position);
[fminval,ind]=min(fx);      %find minimum value
gbest=position(ind,:);

iter=1;

    fgbest=fminval;

   a=2-(2.*(iter./itermax));
   while iter<=itermax
 for j=1:N
     position_1=position;
     %pos1=pop(i).pos;
     x=position(j,:);
   A1=(2.*a.*rand(1,D))-a;             %alpha wolf
   C1=2.*rand(1,D);
   fx=CostFunction(position_1);
   [alphaval,alphaind]=min(fx);
   alphapos=position_1(alphaind,:);
   Dalpha=abs((C1.*alphapos)-x);
   X_1=(alphapos-(A1.*Dalpha));


   position_1(alphaind,:)=[];            %beta wolf
   fx=CostFunction(position_1);
   [betaval,betaind]=min(fx);
   A2=(2.*a.*rand(1,D))-a;
   C2=2.*rand(1,D);
   %[betaval,betaind]=min(fx);
   betapos=position_1(betaind,:);
   Dbeta=abs((C2.*betapos)-x);
   X_2=(betapos-(A2.*Dbeta));


   position_1(betaind,:)=[];       %delta wolf

   fx=CostFunction(position_1);
   [deltaval,deltaind]=min(fx);
```

```
    A3=(2.*a.*rand(1,D))-a;
   C3=2.*rand(1,D);
   %[deltaval,deltaind]=min(fx);
   deltapos=position_1(deltaind,:);
   Ddelta=abs((C3.*deltapos)-x);
   X_3=(deltapos-(A3.*Ddelta));

   Xnew=((X_1+X_2+X_3)./3);           %new solution
   %check bond
   %Xnew=min(Xnew,lb);
   %Xnew=max(Xnew,ub);
   %fnew=CostFunction(Xnew);
   if Xnew>ub
      Xnew= ub;
   end
    if Xnew<lb
           Xnew=lb;
    end

    fnew=CostFunction(Xnew);
f=CostFunction(position(i,:));
if fnew<f
    f=fnew;
    position(i,:)=Xnew;

end
 end

   %update gbest
   [fmin,find]=min(fx);
   if fmin<fgbest
       fgbest=fmin;
       gbest=position(find,:);
   end

   [optval,optind]=min(f);
   bestfx(iter)=optval;
   bestpos=position(optind,:);
   disp(['iteration:'   num2str(iter)   'Best Cost:'
num2str(bestfx(iter))  'best position:'  num2str(bestpos)]);
    %disp([ num2str(f)]);
   iter=iter+1;
    plot(bestfx,'Linewidth',2);
   xlabel('Iteration Number');
   ylabel('Best Cost');
    grid on

 end
```

GRU load prediction

```
jean_data = readtable('load_5.csv');                     %Purifyadditional
data for analysis
```

```
%   Fill the NaN value with the Nearest value.
jean_data.irradiance = fillmissing(jean_data.P, 'nearest');
lenofdata = length(jean_data.P);


%for i=1 : length(jean_data.collect_day)
   % jean_data.collect_day(i) = strip(jean_data.collect_day(i),',');
%end

Y = jean_data.irradiance;
data = Y';

%   2015.01.01 ~ 2019.05.06 (90%) : Training Data Set
%   2019.05.07 ~ 2019.10.31 (10%) : Test Data Set
numTimeStepsTrain = floor(0.9933*numel(data));
dataTrain = data(1:numTimeStepsTrain+1);
dataTest = data(numTimeStepsTrain+1:end);

%   Normalize sales_price to a value between 0 and 1 (Training Data
Set)
mu = mean(dataTrain);
sig = std(dataTrain);
dataTrainStandardized = (dataTrain - mu) / sig;
XTrain = dataTrainStandardized(1:end-1);
YTrain = dataTrainStandardized(2:end);

%LSTM Net Architecture Def                                   %Model
Selection for Prediction
numFeatures = 1;
numResponses = 1;
numHiddenUnits = 200;
layers = [ ...
    sequenceInputLayer(numFeatures)
    gruLayer(numHiddenUnits,'OutputMode','sequence')
    fullyConnectedLayer(numResponses)
    regressionLayer];
options = trainingOptions('adam', ...
    'MaxEpochs',500, ...
    'GradientThreshold',1, ...
    'InitialLearnRate',0.005, ...
    'LearnRateSchedule','piecewise', ...
    'LearnRateDropPeriod',125, ...
    'LearnRateDropFactor',0.2, ...
    'Verbose',0, ...
    'Plots','training-progress');

%   Train LSTM Net
net = trainNetwork(XTrain,YTrain,layers,options);

%   Normalize sales_price to a value between 0 and 1 (Testing Data
Set)         %Data prediction
dataTestStandardized = (dataTest - mu) / sig;
XTest = dataTestStandardized(1:end-1);
net = predictAndUpdateState(net,XTrain);
[net,YPred] = predictAndUpdateState(net,YTrain(end));
```

```
%   Predict as long as the test period (2019.05.07 ~ 2019.10.31)
numTimeStepsTest = numel(XTest);
for i = 2:numTimeStepsTest
    [net,YPred(:,i)] = predictAndUpdateState(net,YPred(:,i-
1),'ExecutionEnvironment','cpu');
end

%   RMSE calculation of test data set
%Predictive evaluation (RMSE)
YTest = dataTest(2:end);
YTest = (YTest - mu) / sig;
rmse = sqrt(mean((YPred-YTest).^2))

%   Denormalize Data                                %Result and
semantic analysis
YPred = sig*YPred + mu;
YTest = sig*YTest + mu;

%   X Label : Collect Day
x_data = datetime(jean_data.collect_date_time, 'InputFormat' ,'yyyy-
MM-dd-hh:mm:ss');
%x_data = (jean_data.collect_day);
x_train = x_data(1:numTimeStepsTrain+1);
x_train = x_train';
x_pred =
x_data(numTimeStepsTrain:numTimeStepsTrain+numTimeStepsTest);
%xx=x_train(1:end-1);
%yy=dataTrain(1:end-1);
%   Train + Predict Plot
figure
%plot(xx,yy)
plot(x_train(1:end-1),dataTrain(1:end-1))
%plot(x_train,dataTrain)
hold on
plot(x_pred,[data(numTimeStepsTrain) YPred],'.-')
hold off
xlabel('Collect Day')
ylabel('Sales Price')
title('Forecast')
legend('Observed', 'Forecast')

%  RMSE Plot : Test + Predict Plot
disp([':pre ' num2str(YPred) ':test '  num2str(YTest)]);
figure
%subplot(2,1,1)
plot(YTest)
hold on
plot(YPred,'.-')
hold off
legend('Observed', 'Forecast')
ylabel('Demand')
title('Forecast')

%subplot(2,1,2)
%stem(YPred - YTest)
%xlabel('Collect Day')
%ylabel('Error')
```

```
%title('RMSE = ' + rmse)

%   Train + Test + Predict Plot
figure
plot(x_data,Y)
hold on
plot(x_pred,[data(numTimeStepsTrain) YPred],'.-')
hold off
xlabel('Collect Day')
ylabel('Sales Price')
title('Compare Data')
legend('Raw','Forecast')
```

APPENDIX B

Lists of Publications

Lists of Publications

Wynn, S. L. L., Boonraksa, T., Boonraksa, P., Pinthurat, W., & Marungsri, B. (2023). **Decentralized Energy Management System in Microgrid Considering Uncertainty and Demand Response**. ***Electronics***, 12(1), 237.

Wynn, S. L. L., Pinthurat, W., & Marungsri, B. (2022). **Multi-Objective Optimization for Peak Shaving with Demand Response under Renewable Generation Uncertainty**. ***Energies***, 15(23), 8989.

Wynn, S. L. L., Boonraksa, T., & Marungsri, B. (2021, March). **Optimal generation scheduling with demand side management for microgrid operation.** *In 2021 9th International Electrical Engineering Congress (iEECON)* (pp. 41-44). IEEE.

Wynn, S. L. L., Boonraksa, T., Boonraksa, P., & Marungsri, B. (2021, October). **Optimal Distribution Level of Energy Management Considering Generation Uncertainties and Demand Response.** *In 2021 International Conference on Power, Energy and Innovations (ICPEI)* (pp. 29-32). IEEE.

electronics

MDPI

Article

Decentralized Energy Management System in Microgrid Considering Uncertainty and Demand Response

Sane Lei Lei Wynn [1], Terapong Boonraksa [2], Promphak Boonraksa [3], Watcharakorn Pinthurat [4] and Boonruang Marungsri [1,*]

[1] School of Electrical Engineering, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand
[2] School of Electrical Engineering, Rajamangala University of Technology Rattanakosin, Nakhon Pathom 73170, Thailand
[3] School of Electrical Engineering, Faculty of Engineering and Architecture, Rajamangala University of Technology Suvarnabhumi, Nonthaburi 11000, Thailand
[4] School of Electrical Engineering and Telecommunications, The University of New South Wales, Sydney 2052, Australia
* Correspondence: bmshvee@sut.ac.th; Tel.: +66-089-717-7065

Abstract: Smart energy management and control systems can improve the efficient use of electricity and maintain the balance between supply and demand. This paper proposes the modeling of a decentralized energy management system (EMS) to reduce system operation costs under renewable generation and load uncertainties. There are three stages of the proposed strategy. First, this paper applies an autoregressive moving average (ARMA) model for forecasting PV and wind generations as well as power demand. Second, an optimal generation scheduling process is designed to minimize system operating costs. The well-known algorithm of particle swarm optimization (PSO) is applied to provide optimal generation scheduling among PV and WT generation systems, fuel-based generation units, and the required power from the main grid. Third, a demand response (DR) program is introduced to shift flexible load in the microgrid system to achieve an active management system. Simulation results demonstrate the performance of the proposed method using forecast data for hourly PV and WT generations and a load profile. The simulation results show that the optimal generation scheduling can minimize the operating cost under the worst-case uncertainty. The load-shifting demand response reduced peak load by 4.3% and filled the valley load by 5% in the microgrid system. The proposed optimal scheduling system provides the minimum total operation cost with a load-shifting demand response framework.

Keywords: microgrid; demand response; autoregressive moving average; particle swarm optimization; generation scheduling

Citation: Wynn, L.L.S.; Boonraksa, T.; Boonraksa, P.; Pinthurat, W.; Marungsri, B. Decentralized Energy Management System in Microgrid Considering Uncertainty and Demand Response. *Electronics* **2023**, 12, 237. https://doi.org/10.3390/electronics12010237

Academic Editor: Adel M. Sharaf, Ragab A. El-Sehiemy, Mohamed Talaat

Received: 25 November 2022
Revised: 28 December 2022
Accepted: 29 December 2022
Published: 3 January 2023

1. Introduction

Over the last decades, renewable energy resources (RESs) have been encouraged to reduce dependency on fuel-based generation and greenhouse gas (GHG) emissions [1–3]. Renewable energy resources are one of the solutions to the above issues and an option for future clean energy. Higher renewable penetration, such as wind and solar, in the power grid can significantly raise uncertainties in the systems and has adverse effects on the proper operation of the power systems. As a result, efficient forecasting of the RES generation has become necessary for the power systems with high RES penetration, and it has the potential to improve power efficiency and system reliability. Some critical aspects of power generation forecasting included high RES penetration rates, power supply and demand imbalances, and optimal system operation. In recent years, time-series statistical models have been the most commonly applied forecasting technique [4]. The mathematical formulation of the time-series method was developed and can be applied to observe near-future predictions based on available historical data [5]. Moreover, an accurate demand forecasting can help the utility with decisions in various aspects, such as purchasing and generating electricity, load switching, and improving system infrastructure. In addition, demand variation was a significant issue for system management in electricity markets. This variation created the distribution network's vulnerability and had an economic effect on the electricity spot price, at which decisions were made based on the existing plants' expanded investment. Thus, demand forecasting has also become an essential aspect of the emergence of competitive electricity markets [6,7].

The distribution network is being deregulated and changed to open a new window of a competitive electricity market by increasing system efficiencies, reducing operation costs, and minimizing utilities' financial losses. The restructured design has been mainly partitioned into two sectors: the generation side and the load aggregator or end-user side [8]. While the conventional system has generated energy to meet total power demand requirements every time-step, the restructured system becomes more effective way for supply–demand balancing that keeps power fluctuation within the threshold level. Moreover, balancing in the conventional system cannot be achieved quickly due to several limitations, such as unexpected production outages, power transferring system failures, and unpredictable system load changing [9]. For this reason, the demand response (DR) has been changed for a sustainable electricity service system by changing consumers' behavior which is responding to the real-time price tariffs program or the incentives offered by the program and also responding to the jeopardy of the system's reliability circumstances [10]. Therefore, the new power system infrastructure with a demand response (DR) strategy was the more effective and lower investment for reliable power system operation. DR programs did not need more capital investment for system updating for more production units and power transferring capacities [9]. With the high penetration of distributed generation resources into the system, the reliable design function of DR provided positive impacts for the whole system through level-up system security and economic benefit [11]. The DR program has participated as a role in the active distribution network. The DR also plays as a chance to mitigate the system fluctuations due to the ability of fast action to meet system balancing in the event of resource shortage. It offered adjustment to the demand side rather than power procurement from the generation side. In this way, the electric consumer can fully participate in the active distribution network [12].

The microgrid EMS monitors and controls the operational status of optimal power allocation from the various energy resources to the controllable and critical loads. In advanced restructured design, controllable loads can be dispatched to ensure system reliability and stability. The EMS was designed to collect load profiles and forecast the energy resource information, consumer preference, policy and electricity market price for optimal power flow (OPF), energy price, load dispatching and generation scheduling [13]. Decentralized EMS is the autonomous intelligence controller considering several local controllers. Because local controllers only need to make decisions and communicate locally, communication congestion and computational burden are much lower than that in a centralized EMS system [14]. The uncertainties of RES and demand can cause difficulty managing optimal generation. All entities in distribution networks with microgrid clusters are interconnected systems and have different operational objectives and decision variables due to the impact of the local operating environment. Therefore, the centralized energy management system is no longer an option for the generation scheduling of the distribution networks with the MG cluster. The decentralized EMS has become a solution to tackle the microgrid operation [15]. In this scheme, local controllers must determine the optimal power output locally. Therefore, the decentralized EMS will significantly reduce the computational power requirement in the entire microgrid. Because local controllers have local authority, troubleshooting security issues could be difficult [14].

Generation scheduling is a common problem in feasible microgrid planning. It was usually solved by the optimization process. The optimal planning techniques can be applied to both renewable energy allocation and energy management systems. The energy management systems applied different optimization methods based on technical, environmental, and economic constraints and uncertainties [16]. In recent years, optimal planning techniques have become popular in the energy management systems in smart homes, smart buildings, and smart grids. Decision-making-based energy modeling has become a sustainable design for planning and controlling optimization issues [17]. Uncertainties of the RES generation exacerbated the balancing between generation and demand [2]. Therefore, it is required to schedule generation units in the microgrid planning stage to closely match with the forecasted demand profile between generation and demand. The problem of optimal appliance scheduling with the DR program and the uncertainty of rooftop PV were analyzed in [18]. In this work, the uncertainty of solar radiation was tackled with the Weibull probability density function (PDF). This system can reduce computation time with high computational accuracy. The result showed that the proposed model provided an economically feasible microgrid operation under solar uncertainty. The work in [19] presented the optimization of hybrid DG while taking demand and supply uncertainties into account. The model of demand variation was investigated by the probability density function. Controllable and uncontrollable DG mitigated the uncertainty of the supply side. The results demonstrated that the optimal combination of hybrid DG captured the demand uncertainty in the reconfigurable microgrid. The bi-level algorithm for decentralized energy management systems in microgrids was presented in [2]. The first step predicted generation set-points, while the second step adjusted generation outputs based on various scenarios. The simulation results provided the stable operation of networked and islanded modes under the stochastic nature of DG's output power. The work in [20] put forward the ideas of a decentralized framework with DR from the point of view of a system operator who wanted to balance supply and demand and changed generation curves to match changes in demand. The results showed that the proposed algorithm minimized the suppliers' operation cost, the consumers' discomfort, and the transmission system's congestion. The work in [21] was to demonstrate the active disturbance rejection control (ADRC) paradigm to ensure the effect of exogenous disturbances on the PV generation uncertainty. In this work, the performance of modified ADRC was compared with linear ADRC (LADRC), conventional ADRC, and improved ADRC (IADRC). The results showed that the proposed model provided high performance in the tracking system to capture PV uncertainty. The risk-seeking stochastic optimization was proposed to coordinate electricity markets with wind generation in [22]. The results showed that the procurer profit maximization can be provided by adjusting the parameters of the risk-seeking stochastic optimization model. A two-stage optimization model was implemented for profit maximization scenarios, and a probabilistic statistical perspective was used to capture wind power uncertainty. The risk-averse two-stage stochastic model was proposed for short-term schedules for the pool electricity market in [23]. The results showed that contracts with withdrawal penalty (CWP) and contracts with option (CWO) were the new options that provided retailers profit maximization in the pool electricity market. The electricity tariffs and demand uncertainties were considered to show the effect on the retailer profits/risk and retail price. The previous model applied a stochastic process that was embedded in the sophisticated decision-making model [15,20,24–26].

Although the stochastic model was applied in the operation and planning of the electrical power system, this model generated different scenarios to achieve optimal solutions and required a significant amount of computation time [27]. Moreover, the stochastic model is difficult to interface with the complex scenario-based forecasting models and the sophisticated decision-making model. The work in [28] proposed a decentralized multi-agent control scheme to manage the power sharing of the distribution network with RESs. However, the nature of RE resources uncertainty and the role of demand response were not considered in this work. The results presented that the proposed model provided a balanced active/reactive power sharing during stable/unstable demand events. The decentralized multi-agent robust optimal model with integrated demand response was presented in [29] for the electricity–gas–heat systems. The integrated demand response was used to handle the uncertainty of RESs. This work showed the effectiveness of the multi-agent decentralized robust optimal dispatching compared with the centralized robust optimal dispatching. The simulation results showed that the demand response market can handle the nature of RE resources uncertainty. The Benders decomposition technique is introduced for networked microgrid energy management in [30] to address the unbalanced condition. Probabilistic scenarios was generated to capture RE resources and demand uncertainty. The simulation results showed that the increased use of expensive generation resources constantly increased the operation cost. The proposed model provided a cost-effective interaction of operators and distributors. Nowadays, the use of electricity is increasing, and the electricity is generated from various renewable sources such as wind, hydro and solar power. Therefore, it is very important to plan and manage the power generation for effectively supplying power systems. This paper focuses on managing power generation systems to reduce the peak load of the microgrid system using an optimization method.

Three options are available to handle uncertainty problems: generating more power or buying more energy from the main grid, using energy storage systems, and participating in a demand response program [31]. Due to economic operation and environmental concerns, the first conventional solution has the drawback of power reserving [32]. The previous work did not highlight common possible uncertainties in the power network, especially the intermittent nature of wind and solar generations and demand variation. The concept of DR cooperation in the microgrid energy management system is to reduce operating costs and to mitigate the intermittent nature of RE resources. To ensure a certain amount of uncertainty, energy management from the generation side is an option to maintain system security. To [illegible], this article proposes a decentralized energy management model by considering RE uncertainty and demand response. The proposed [illegible] system [illegible] to manage the generation sources from the [illegible]. [illegible] by introducing the local energy management system with demand response.

The major contributions of this article are summarized as follows:

- The Autoregressive moving average (ARMA) model is introduced to predict wind and PV generations as well as load demand for the proposed decentralized energy management system, which [illegible] the computational burden.
- The particle swarm optimization (PSO) technique is applied to implement the optimal generation scheduling based on the forecast data of wind, PV, and load demand to reduce the operation costs of the microgrid system.
- The proposed method incorporates the demand response (DR) which does not require probability constraint parameters to tackle the deviation from the forecasting data.

The rest of the paper is organized as follows. Section 2 presents the proposed methodology of the paper. In this section, the forecast technique, well-known particle swarm optimization technique, and problem formulation are introduced and discussed. Section 3 presents verification simulation results and discussions. Finally, Section 4 concludes the paper.

2. Methodology

The proposed strategy consists of three stages. In the first stage, hourly average energy demand and hourly average WT and PV power generations are predicted by using an ARMA (2,1) for a particular month. This work used two-year historical data to forecast the present-time RE generation and demand profile. The second step is scheduling available generation resources with the system's constraints, such as power balance constraints, generation capacities, and spinning reserves. This step requires the information [illegible] necessary for the system, such as forecasting RE and power demand, electricity price, and distributed generation characteristics. A particle swarm optimization algorithm was used for optimal scheduling to minimize system operating costs. All available generation resources are scheduled optimally by the PSO optimizer according to actual and forecast data for a particular month. The final step is generating a demand response program from optimally scheduled results. If the generation capacities are less than the power demand or a particular time, the required power demand is suggested to shift the valley period. Finally, the network operators provided the demand decision information to the demand side to respond to the load in a particular hour. The proposed framework is shown in Figure 1. The decentralized forecasting and optimization model are implemented using MATLAB 2021. The simulation is performed with an Intel(R) Core(TM) i7-6500U, 2.50 GHz CPU speed, and 8.00 GB RAM. A flowchart of the proposed decentralized energy management system is given in Figure 2.

In the next subsections, the forecasting technique used to predict WT and PV generations and load demand based on historical data is presented. Then, the problem formulation based on the particle swarm optimization technique is given and discussed.

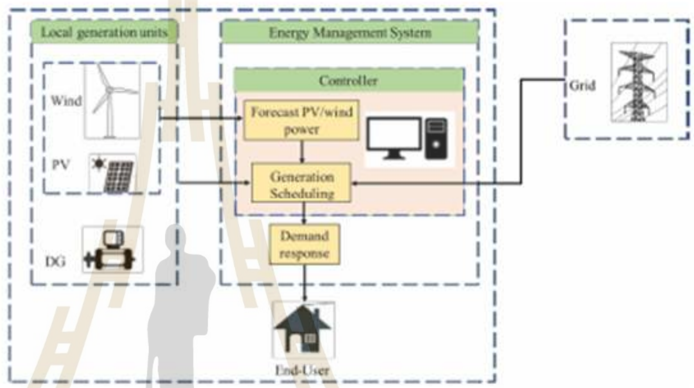


Figure 1. The proposed framework of the decentralized energy management system.

2.1. Forecasting Technique

An ARMA model based on statistical and Box–Jenkins methods was adopted. The ARMA model is commonly applied to stationary time-series data as it is a superior tool to predict the future values of stationary time-series [33]. The Yule–Walker estimator was used to estimate the sample autocorrelation coefficient [34] which is expressed by,

$$\hat{x}_t = \sum_{i=1}^{m} \phi_i x_{t-i} + \sum_{j=0}^{n} \theta_j \omega_{t-j}, \tag{1}$$

where ϕ_i is the i-th AR coefficient; x_{t-i} is the time series value; ω is the white noise with zero mean and constant variance; and θ_j is the j-th MA coefficient.

A series of measurement data sets for the specific site is required to forecast the output of a RES generation using statistical methods. The selected site for obtaining the historical data is Nakhon Ratchasima Province (14.979900 latitudes, 102.097771 longitudes), Thailand. The historical wind speed, solar irradiation data, and load profile were taken from the selected site location [35–37]. The enormous amount in the applied data set can be reduced without losing information by employing statistical data treatment. Synthetic data for a typical year that represent the actual multi-year measured data statistics can be generated [38].

The ARMA model is a suitable prediction tool if the historical time-series is stationary. The stationary time-series have statistical properties such as all mean, variance and autocorrelations that are constant or meaningful over all time horizons. Therefore, a statistical forecasting technique in which the stationary time-series is changed by statistical transformations will be applied.

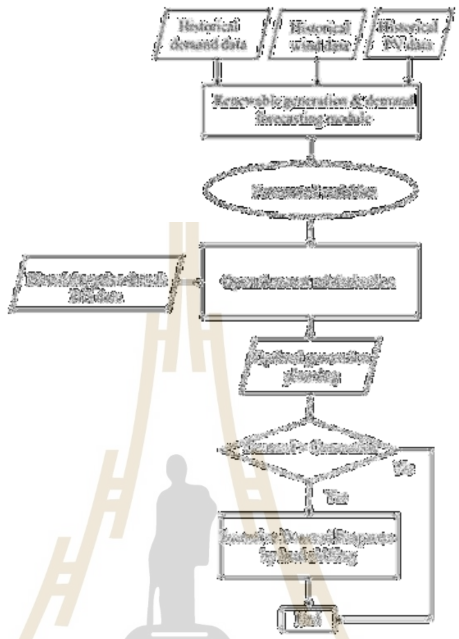


Figure 2. Flowchart for implementation of the proposed decentralized energy management system.

The stationary time-series provided an easy implementation process that gave the predicted results according to the historical data. Thus, the time-series sequence can provide a clue to the search process for the forecasting model [39].

For seasonally non-stationary data, the yearly data set is divided into the seasonal monthly segments. Daily non-stationary data are removed by subtracting the hourly mean value from the actual data set and dividing it by the standard deviation to reduce the data to a normal process with a mean of 0 and a variance of 1 [3,40]. The time-series of the particular month of the year is the standardized velocities for removing diurnal non-stationary and it can be denoted as

$$V^*(n,y) = \frac{V'_{n,y} - \mu(t)}{\sigma(t)}, \tag{2}$$

with the period function as

$$\mu(t) = \frac{\sum_{n=1}^{N-1} V'_{n,y}}{N-1}, \quad 1 \le t \le 24, \tag{3}$$

$$\sigma(t) = \left[\frac{\sum_{n=1}^{N-1} (V'_{n,y} - \mu(t))^2}{N-1}\right]^{\frac{1}{2}}, \quad 1 \le t \le 24, \tag{4}$$

where $V^*(n,y)$ is the standardized hourly average wind speed; $V'_{n,y}$ is the hourly average wind speed; $\mu(t)$ and $\sigma(t)$, respectively, are the sample mean and standard deviation of N transformed wind speeds in 24 h; d and Y are the number of days considering for a month and year, respectively.

Then, the statistic series is compared with the measured data series by mean absolute error (MAE) to show the performance index as given by

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\bar{X}_i - X_i|, \tag{5}$$

where X_i represents the forecast time-series values; $\bar{X}_i$ represents the observed time series values and n is the total number of samples.

2.2. Optimal Generation Scheduling

In general, demand shifting and peak shaving that response from the demand side significantly impacted the whole system context under stringent operating conditions. The demand-shifting function removes the demand from peak time to an off-peak time interval to mitigate operation stress in the design and reduce energy costs for end-users. The system operator's perspective is to minimize system operation costs by replacing more expensive energy production with cheaper production [41]. Metaheuristic is a powerful technique to search feasible solutions from the discrete large search space, while classical methods cannot find optimal points from a large search space. The metaheuristic is a robust optimization technique with high exploring and exploiting. The classical method cannot solve all types of the optimization problem, and it requires extensive computation time to obtain the optimum points [16]. Bio-inspired optimization is an emerging metaheuristic technique inspired by the nature of biological evolution. Swarm intelligence and evolutionary computing are two main types of bio-inspired optimization methods. Particle swarm optimization (PSO) is a popular swarm intelligence bio-inspired optimization method [17]. The PSO is a robust technique and can search the global optimum points with fast convergence speed [42]. The PSO method is an easy-to-understand optimization method with few parameters and efficient global best solutions. So, this method has been chosen by the several researchers.

In this section, optimal generation scheduling is implemented by employing the particle swarm optimization technique. The working principle of the particle swarm optimization is inspired by the behavior of swarm species that worked cooperatively and search their requirement in the search space. The local best experience (P_{best}) and global best experience (G_{best}) were used to search for the next movement to guarantee the best solution. c_1 and c_2 factors accelerate the best searching positions, and the random numbers are generated between w_{min} and w_{max} [43]. The velocity of the particle and the particle's position are expressed by

$$V_{i,j}^{k+1} = \omega V_{i,j}^{k} + c_1 r_1 (Pbest_{i,j}^{k} - X_{i,j}^{k}) + c_2 r_2 (Gbest_{i,j}^{k} X_{i,j}^{k}), \tag{6}$$

$$X_{i,j}^{k+1} = X_{i,j}^{k} + V_{i,j}^{k+1}, \tag{7}$$

where $X_{i,j}^{k}$ is the position of particles i and j with iteration k; $V_{i,j}^{k}$ is the velocity of particles i and j with iteration k; ω is the inertial factor; $c_1 are c_2$ are the acceleration factors; $r_1 are r_2$ are the random number [0, 1]; P_{best} is the best particle and G_{best} is the best global solution.

2.3. Proposed Objective Function

In this section, an energy management system is implemented with the optimal generation scheduling. The objective function of the optimization is the operation cost minimization with system constraints. The system constraints included power balance constraints, spinning reserves constraints, and generation capacities constraints. The spinning reserves protect the system from unexpected power outages and sudden load changes in this work. The system's objective function includes the operation cost of the two-generation units, PV and wind generations, and required power from the main grid. The operation cost of the generation unit is taken from [31]. The power purchasing price from the main grid considered in this study is a time of use (TOU) from [44]. The operating costs are defined as follows: the purchase price of electricity from the grid is based on the Thai TOU electricity trading rate on-peak = 0.17 $/kWh and off-peak = 0.076 $/kWh. The PV and WT only have the operation and maintenance costs [24,45]. The operation and maintenance costs of PV and WT are 0.1095 $/kWh [24]. Therefore, the purpose of cost reduction is manage the DGs during on-peak periods where the operating costs are high. The PSO technique is used for optimizing the arrangement of DGs to generate the energy at peak load times. The optimization problem formulations of the DR program are defined by

$$\text{Min } C_{operation} = \sum_{t=1}^{T} P_{wind}^{t}\lambda_{wind} + P_{PV}^{t}\lambda_{PV} + P_{grid}^{t}\lambda_{grid} + [aP_{g}^{2} + bP_{g}], \tag{8}$$

where $C_{operation}$ is the total operation of the system; P_{PV}^{t}, P_{wind}^{t}, P_{grid}^{t} and P_{g}^{t} are the power delivered from the PV, wind, grid and the generator at time t, respectively; a, b are the cost coefficients of DG units. $\lambda_{wind}, and \lambda_{PV}$ represent the coefficient of the operation and maintenance cost of wind and PV. λ_{grid} represents the prices of operation costs.

The proposed objective function of the optimization problem is subject to the following constraints.

Power balance constraint:

[illegible] (9)

[illegible]

[illegible] (10)

[illegible]

[illegible] (11)

[illegible] (12)

[illegible] (13)

[illegible] (14)

3. Results and Discussion

[illegible] proposed strategy is introduced. Then, the output powers of the wind, PV, and load for the demand forecasting module are given. Finally, simulation results obtained from the proposed strategy are provided and discussed.

3.1. Test System

The test system that is used for verification of the proposed strategy is illustrated in Figure 3. As seen in the figure, there are two DG units connected to Buses 22 and 28, respectively. All information of the test system can be found in [46]. The characteristics of the cost function of the two DG units are given in Table 1. In addition, there is one wind turbine unit and one PV source connected at Buses 15 and 12, respectively. The microgrid system is connected to the main grid at Bus 1.

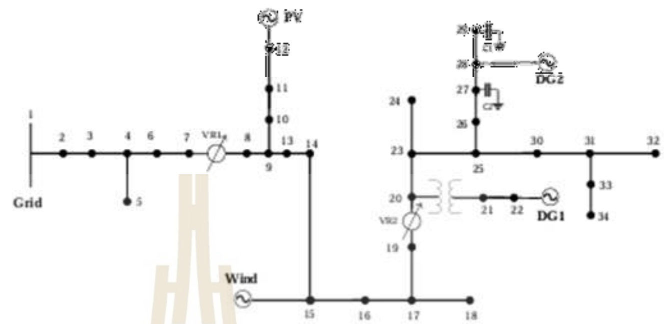


Figure 3. Microgrid test system [46].

Table 1. Generation characteristics of the two DGs.

DGs	a	b	P_{min}, (kW)	P_{max}, (kW)
1	0.000430	21.60	30	33
2	0.000394	20.81	125	143

3.2. Forecasting Output Powers of Average Hourly Wind, PV and Load

ARMA (2,1) is implemented in the process of time-series analysis for PV and demand forecasting. The technique applied two-year hourly wind speed data of a particular month. ARMA (3,1) is applied for forecasting wind speed. The historical data set of the seasonally selected data set is used for future average hourly prediction series. Figures 4–6 show the simulation results obtained based on average solar irradiance, wind speed, and load profile, respectively. Renewable energy has a capacity limit that changes with time due to environmental disturbances [47]. The irradiation, temperature, and unexpected weather condition have a considerable deviation effect on the efficiency and power generation of the PV system [21,48]. The nature of time-varying is due to exogenous disturbance, which will affect power generation, and demand. This limitation is known as uncertainty [32,47]. When the system operates with high penetration of RE resources, this system is required to ensure the balance of generation and demand [49]. In this work, it was assumed that the error percentage is the percentage of uncertainty. In generation forecasting, the forecast (MAE) errors of WT and PV were 11.43% and 10.45%, respectively, while in load predicting, the percentage (MAE) error of the peak day was 17.71%. In this paper, it is assumed that the error percentage obtained here is the percentage of uncertainty in the microgrid system.

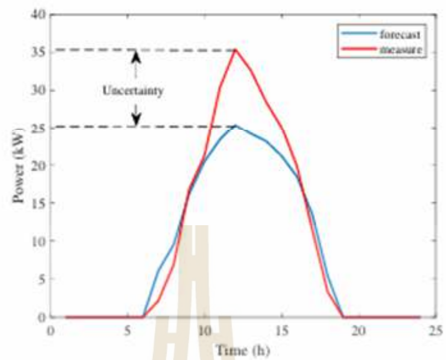


Figure 4. Forecast and actual PV power data.

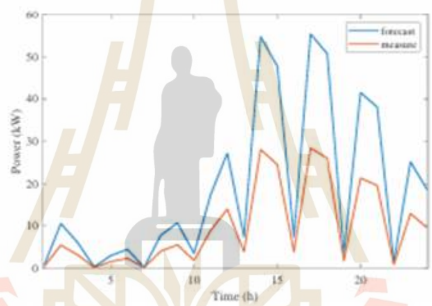


Figure 5. Forecast and actual wind power data.

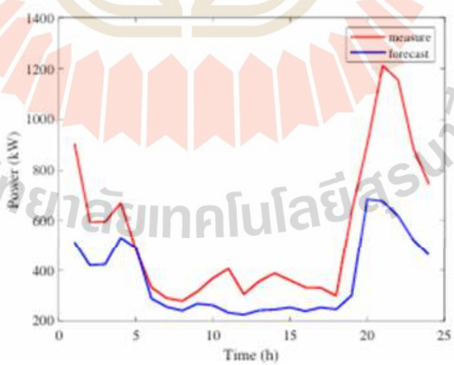


Figure 6. Forecast and actual of load profile data for peak day.

3.3. Generation Scheduling and Demand Response Program

This section provides simulation results of the optimal generation scheduling and load-shifting demand response program. The effectiveness of the proposed strategy is evaluated in three cases as follows.

- Case I: Cost minimization of the microgrid system with forecast PV, wind, and load demand data without considering uncertainty.
- Case II: Cost minimization of the microgrid system considering uncertainty, the uncertainty of PV 10.45%, the wind of 11.43%, and the load demand of 17.71%.
- Case III: Cost minimization of the microgrid system for the day-ahead forecast PV and wind uncertainty (PV of 10.45% and wind of 11.43%) as well as the actual load demand requirement.

It is assumed that the microgrid system participates in the DR program in all cases. The amount of maximum power that can be exchanged by the main grid is 300 kW.

The load shifting changed the required amount of load from peak-demand time to off-peak time to reshape the load profile. In the case studies, the two distributed generators (DG1 and DG2) are working as the dispatchable generation while the PV and WT units are non-dispatchable generations.

In Case I, when the PV and wind generated maximum power during the daytime, the two DG units and the grid provided less power, as seen in Figure 6. All generation sources are not able to provide the required demand at peak days. Hence, the DR program will be applied to solve the power requirements. The option of the proposed strategy is to provide priority to the DG units while maximizing RES generations. The available resources such as DG units and the main grid are planned to optimally schedule in the microgrid system. Figures 6–8 show the simulation results of the optimal generation scheduling with actual and forecast data.

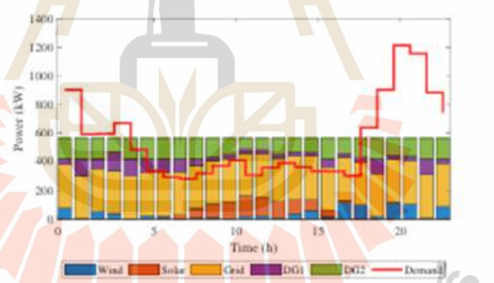


Figure 7. Case I: Microgrid generation scheduling for peak day with forecast data.

The objective function and system constraints are the standard parameters used in the microgrid scheduling process to achieve cost–benefit under a RES uncertain environment. According to Figures 7 and 8, optimal generation scheduling with a demand response program can reduce the peak load on peak days at 19–24 h and 1–5 h. Load shifting occurred in the off-peak period when the total loads are less than the generation capacity at 6–18h. Figures 8 and 9 compare the load demand and the available generation capacity of Case II and Case III. The capacity difference is high when the PV and wind had not provided sufficient generation. Moreover, in Cases II and III, as the actual demand is more than the forecast demand, the power requirement is more dependent on the local dispatchable generation units and the main grid.

Based on Figures 7–9, the loads of the microgrid test system from the three case studies can be shifted by using the proposed decentralized EMS, as illustrated in Figure 10. According to Figure 10, the optimization method provided the stable best solution for Cases

I, II, and III, although the microgrid has RE generation and demand uncertainties. After the optimal generation schedule program has been implemented, the simulation results provided the preferred amount of power that must be shifted to a particular period.

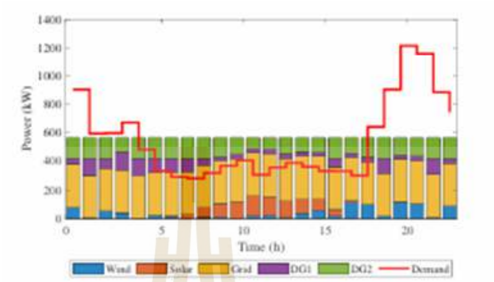


Figure 8. Case II: Microgrid generation scheduling for peak day with actual data.

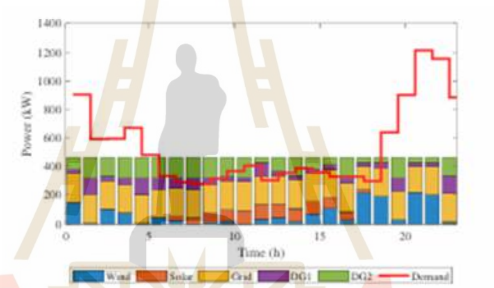


Figure 9. Case III: Microgrid generation scheduling for peak day with PV and wind forecast data and actual demand.

In Case I, the power is planned to receive from the cheaper generation such as wind, solar, and the main grid, and the power is supplied from expensive DG generation during the [illegible]. Therefore, the total operation cost is saving by [illegible] compared to that without optimal scheduling. The demand response program is less than Cases II and [illegible]. However, the possible uncertainty effect is not considered in this case. The operation costs for the microgrid with and without optimal scheduling are [illegible] $ and [illegible] $, respectively.

In Case II, the robustness of the EMS is tested with the worst-case uncertainty of RESs. The PV generation uncertainty increased to [illegible], wind power decreased to [illegible], and the total demand changed to [illegible]. The available wind output power is lower than the forecast value, and the available PV power and the actual load demand level are higher than the forecast value. Therefore, the local generation and operation costs are higher than that of Cases I and III. This is because the proposed system properly considered the higher system's uncertainty that will impact the distribution system. Therefore, Case II needs more generations to immunize against a higher level of uncertainty. Table 2 shows that production costs increased significantly to cover worst-case RES uncertainties. From Table 3, the powers from the DG increase with growing uncertainty, and load shift DR also increases to compensate for the worst case. The optimal scheduling has effectively controlled more power generation without violating the objective function and system constraints. The operation costs for the microgrid with and without optimal scheduling are 131,020 $ and 137,020 $, respectively. Although the scheduling is implemented with possible system uncertainty (RE and demand), the operation cost is 42% less than the operation cost without optimal scheduling.

Case III only considered RE generation uncertainty to evaluate the system's supply and demand balance. This is because the proposed system elevated the use of RE resources. The results show that the scheduling process retained 22% of cost savings. The operation costs for the microgrid with and without optimal scheduling are 104,060 $ and 137,020 $, respectively. Due to generation uncertainty, the power requirement is more dependent on the local dispatchable generation units and the main grid. From Figures 8 and 9, the total generation from available local resources is stable for 24 h. This is because the optimal schedule process provided the stable operation cost for Cases II, and III, although the microgrid has RE and demand uncertainties. However, in Case II, the total power from the main grid and local generation are 7200 kW and 4452 kW, respectively. In Case III, the total power from the main grid and local generations are 4732 kW and 3767kW, respectively. Therefore, the grid and local generation's dependency decreased by 52% and 18%, respectively. However, the DR program of Case III is 38% more than that of Case II. Thus, the total operational cost is reduced by optimal generation scheduling. The cost-saving results in the three case studies are 55%, 4%, and 22%, respectively.

The system operation cost minimization is the objective function in case studies, and demand response is to mitigate system uncertainty by shifting demand. It is noteworthy that the total RES power is available more at the off-peak time. The possible demand response after applying the optimal generation scheduling is shown in Figure 10. The positive power is the required amount of power to shift at the peak time period, while the negative power is the extra generation capacities at the off-peak time period. The load at the peak time period of 19–4h can be transferred to the off-peak time of 6–18h. In Case II, the demand response decreased the peak load by 4.3%, and the valley load filled by 5.0%. In Case III, the peak load reduced by 7.2%, and the valley load filled by 7.3%.

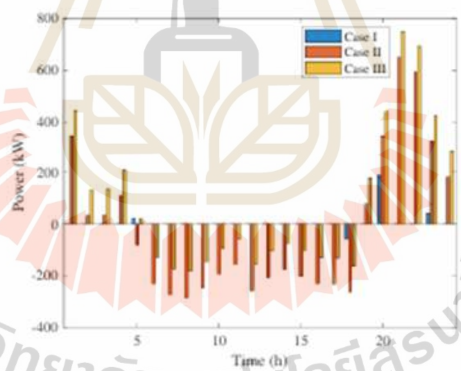


Figure 10. Hourly–shiftable demand response program in peak day.

According to Figure 11, the optimization method provided the economic costs for Cases I, II, and III at peak time (20–23 h), although the microgrid has wind and demand uncertainties. The optimal operation process maintained the system's operational security under 11% PV generation, 10% wind power uncertainty and 17% demand uncertainties. In all case studies, the dispatch of the DG units and the grid power was able to balance the generation and demand under uncertainty. In the economic aspect, the optimization results can provide an economic cost interval of (1355 $/h, 7075 $/h). Table 2 shows the optimization results of the operation cost over 24 h for the three case studies.

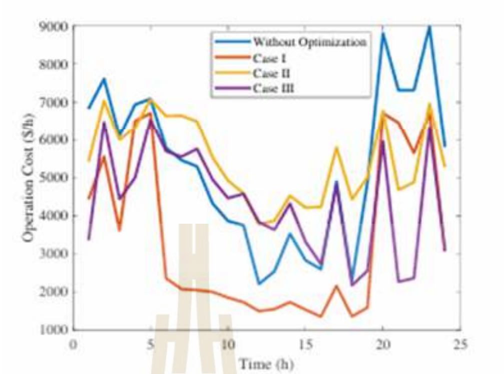


Figure 11. Comparison of operation cost of case studies and without optimization.

Table 2. Total operation cost of generation units.

Time (h)	w/o Optimization, ($/h)	Case I, ($/h)	Case II, ($/h)	Case III, ($/h)
1	[illegible]	[illegible]	[illegible]	[illegible]
2	[illegible]	[illegible]	[illegible]	[illegible]
3	[illegible]	[illegible]	[illegible]	[illegible]
4	[illegible]	[illegible]	[illegible]	[illegible]
5	[illegible]	[illegible]	[illegible]	[illegible]
6	[illegible]	[illegible]	[illegible]	[illegible]
7	[illegible]	[illegible]	[illegible]	[illegible]
8	[illegible]	[illegible]	[illegible]	[illegible]
9	[illegible]	[illegible]	[illegible]	[illegible]
10	[illegible]	[illegible]	[illegible]	[illegible]
11	[illegible]	[illegible]	[illegible]	[illegible]
12	[illegible]	[illegible]	[illegible]	[illegible]
13	3543	1553	3867	3631
14	4524	1734	4520	4312
15	3831	1537	4210	3317
16	3596	1355	4227	2727
17	5891	2162	5790	4797
18	2305	1362	4427	2174
19	4871	1593	5000	2558
20	8806	6717	6775	5950
21	7318	6463	4675	2269
22	7319	5639	4874	2362
23	8983	6715	6960	6326
24	5804	3069	5270	3069
Total	137,020	80,287	131,020	104,060

Table 3 shows the impact of system uncertainties on the DR program and generation resources. After introducing system uncertainties, the load was cut and shifted more than the load in Case I, and more energy was exchanged from the main grid. It is observed that Case II mainly depended on the grid, and local generation was the second option to meet the peak demand. The DR program was a less desirable option than that of Case III. In Case II, the optimization method provided optimal energy management and distributed the peak load among the DR, local generation, and the main grid. When the uncertainty increased in the microgrid system, the electricity generation also increased in the local generation capacity to meet demand variation from 12,197.1 to 14,330.7 kW.

Table 3. Power requirements for each case study.

Case Studies	DR_{Total} (KW)	Local Generation (KW)	Grid Power (KW)
Case I	248	3009	3974
Case II	2678	4452	7200
Case III	3697	3767	4734

To evaluate the performance of the proposed strategy, the energy management system presented in [48,50–52] is compared with the proposed system in terms of operation cost minimization. The works in existing and proposed methods considered load-shifting demand response in the distribution network. The method's effectiveness is demonstrated by operation cost reduction with the system's uncertainty. The comparison results are shown in Table 4. The work in [50] proposed multi-agent generation scheduling and demand-side management without considering system uncertainty. In this work, the proposed system provided 5% cost savings by shifting the load. The work in [51] investigated the impact of high penetration of wind power on the operation cost savings with the introduction of demand response. In this work, the wind uncertainty was assumed at 10%, and the operation cost is saved by 27%. The article [52] optimized the network–load interaction framework to capture market price DR uncertainty. The results showed that the optimization method can reduce the network operation cost by 16.9%. The work in [48] represented the PV power on a sunny and cloudy day, potentially impacting the operation cost. The demand response with battery energy storage was introduced for industrial microgrid facilities. The results in this work showed that the proposed model provided a 15.6% cost saving on a cloudy day and 12.8% on a sunny day.

In the proposed system, the cost saving is 22% with the optimal scheduling method. This is because the objective of the local EMS system is to use full power from RE generation and expensive DG power used as a dispatchable generation. Consequently, the proposed method properly considers higher system uncertainties than the existing works. By comparing with the results obtained by the existing works, the proposed method provided higher cost savings than the existing methods under the worst uncertainty. It is shown that the optimal generation scheduling with demand response can effectively manage local generation under uncertainties to achieve operational cost savings.

Table 4. Results comparison with existing works.

Articles	System's Uncertainty	Operation Cost Reduction
[48]	PV uncertainty	15.6%
[50]	Not consider	5%
[51]	Wind uncertainty (10%)	27%
[52]	Price uncertainty	16%
Propose method	11% PV uncertainty, 10% wind uncertainty	23%

4. Conclusions

The energy management system has been used to provide advanced load management techniques and control facilities. This paper proposed a decentralized energy management [illegible] result, the proposed strategy was able to increase the utilization rate of the RESs and to reduce the system's uncertainty with minimum operating cost. In the proposed strategy, the customers can participate in the active distribution network by changing demand patterns. Moreover, the proposed strategy also provided the balance of robustness and cost benefits of the microgrid operation. The proposed system managed power sharing among RE and dispatchable generation units in the microgrid system to provide operational cost minimization. The demand response program was introduced in the system to cope with the 17% PV generation uncertainty, 10% wind power uncertainty, and 17.71% demand uncertainty. The simulation results showed that the optimal generation scheduling can minimize the operating cost under the worst-case uncertainty. Using the demand response model, the customers can participate in the active distribution network by changing the load pattern to respond to the system's uncertainties. The load-shifting demand response reduced the peak load by 4.5% and filled the valley load by 5%. There are several benefits of accurate generation forecasting, such as alleviating generation uncertainties, increasing in system stability, allowing more renewable penetration into the system, and minimizing maintenance costs.

In future work, the day-ahead generation scheduling integration with the deep learning techniques may extend this work. The deep learning model can provide more accurate forecasting results and perform short-time predictions of RESs for network energy management.

Author Contributions: Conceptualization, S.L.L.W., W.P. and B.M.; methodology, S.L.L.W.; software, S.L.L.W., T.B., and P.B.; validation, S.L.L.W. and B.M.; formal analysis, S.L.L.W., W.P. and B.M.; investigation, S.L.L.W., W.P. and B.M.; data curation, S.L.L.W.; writing—original draft preparation, S.L.L.W.; writing—review and editing, W.P. and B.M.; supervision, B.M.; funding acquisition, B.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Suranaree University of Technology, Thailand (ว่าด้วยทุนปี 2562-2).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: Sane Lei Lei Wynn gratefully acknowledges the scholarship from Suranaree University of Technology, Thailand.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ARMA	Autoregressive Moving Average
DNO	Distribution Network Operator
EMS	Energy Management System
LC	Local Controller
MAE	Mean Absolute Error
MGCC	Microgrid Central Controller
MO	Market Operator
PDF	Probability Density Function
RES	Renewable Energy Resource
TOU	Time of Use
ϕ_i	The i-th AR coefficient
X_{t-i}	Time-series values
θ_j	The j-th MA coefficient
ε_{t-j}	White noise
$\overline{Y}^{s}_{(t,d)}$	Standardized hourly average value

energies

MDPI

Article

Multi-Objective Optimization for Peak Shaving with Demand Response under Renewable Generation Uncertainty

Sane Lei Lei Wynn [1], Watcharakorn Pinthurat [2,*] and Boonruang Marungsri [1,*]

[1] School of Electrical Engineering, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand
[2] School of Electrical Engineering and Telecommunications, The University of New South Wales, Sydney 2052, Australia
[*] Correspondence: w.pinthurat@unsw.edu.au (W.P.); bmshvee@sut.ac.th (B.M.); Tel.: +66-089-717-7065 (B.M.)

Abstract: With high penetration of renewable energy sources (RESs), advanced microgrid distribution networks are considered to be promising for covering uncertainties from the generation side with demand response (DR). This paper analyzes the effectiveness of multi-objective optimization in the optimal resource scheduling with consumer fairness under renewable generation uncertainty. The concept of consumer fairness is considered to provide optimal conditions for power gaps and time gaps. At the same time, it is used to mitigate system peak conditions and prevent creating new peaks with the optimal solution. Multi-objective gray wolf optimization (MOGWO) is applied to solve the complexity of three objective functions. Moreover, the best compromise solution (BCS) approach is used to determine the best solution from the Pareto-optimal front. The simulation results show the effectiveness of renewable power uncertainty on the aggregate load profile and operation cost minimization. The results also provide the performance of the proposed optimal scheduling with a DR program in reducing the uncertainty effect of renewable generation and preventing new peaks due to over-demand response. The proposed DR is meant to adjust the peak-to-average ratio (PAR) and generation costs without compromising the end-user's comfort.

Keywords: multi-objective gray wolf optimization; demand response; generation scheduling; microgrid; renewable energy uncertainties

Citation: Wynn, S.L.L.; Pinthurat, W.; Marungsri, B. Multi-Objective Optimization for Peak Shaving with Demand Response under Renewable Generation Uncertainty. *Energies* **2022**, *15*, 8989. https://doi.org/10.3390/en15238989

Academic Editor: Nicu Bizon

Received: 2 November 2022
Accepted: 18 November 2022
Published: 28 November 2022

1. Introduction

Recently, the awareness of sustainable renewable energy development, increments in power demand and the use of advanced communication technology have altered microgrid infrastructures [1,2]. The aim of microgrids in both grid-tied and stand-alone modes is to manage renewable and nonrenewable power generation and load aggregation [3]. Microgrids boost the adoption of renewable energy resources (RESs) to transform sustainable electricity networks [2]. The inherent nature of the RESs brings intermittence and fluctuation problems to power generation, to a high penetration level in the power systems [4,5]. The intermittency of RESs can be mitigated by several technical approaches, such as grid integration, spinning reserves, energy storage (ES) and distributed generation (DGs), modern forecasting techniques and demand-side management (DSM) or demand response (DR). The aim of these technical approaches is to dynamically maintain balance of power supply and demand at all times [3].

The topics of grid operation, energy resources and optimal demand management have become crucial. In the conventional power networks, the system operator adjusts the supply and demand with standby generation units and brings the power from third parties [5]. Moreover, it is difficult to schedule and manage generation units to compensate for the intermittence problems. In modern power distribution networks and microgrids, the uncertainty problems of high RES penetration can be mitigated by the active DSM scheme [3]. The microgrid can provide an energy management model locally, which can optimally control the performance of available resources at the generation level and load aggregation at the demand level with the DSM [3]. Thus, the DSM is a helpful method to improve the efficiency of the distribution systems and microgrids [6].

The DSM is an active management option in a smart distribution network. Basically, the DSM controls and monitors consumer consumption patterns. Consumers can modify their consumption patterns to mitigate negative impacts on system stability during peak demand periods [7]. Rather than attempting to generate more power, the DSM takes demand variation action with the available power level. In this regard, the DSM can significantly reduce the network's new installation cost and the impacts of peak load problems. A powerful DSM program was achieved by aggregate load profile improvement [8]. According to the previous analysis, a smooth load profile provided a high-efficiency generation profile and network stability [9].

Additionally, DR is a helpful demand-side management technology. The DR encourages consumers to reduce and change energy usage during peak demand periods [6]. Two types of the DR are generally offered to consumers: (i) incentive-based and (ii) time-based DR programs. The incentive-based DR gives rewards to the consumers who adjust their load profiles or allow some level of control over their apparatus. Direct load control, uninterruptible service, demand bidding, capacity market programs, and ancillary service markets are classified as incentive-based DR. On the country, in the time-based DS, the price of electricity is changed over time according to the generation and demand conditions. Critical-peak pricing, time-of-use (TOU) pricing, real-time pricing and peak-load-reduction credits are some approaches to the time-based DR [5].

Furthermore, the DR has become an option for smart microgrids in critical situations, such as inadequate spinning reserves and expensive power exchange from tie-line capacity to compensate for lost or insufficient local generation and sudden load changes. In this regard, optimal generation resource scheduling with the DR becomes the topic of the microgrid planning stage during network contingency to guarantee particular operation conditions [10]. Different possible issues are involved in the planning stage while solving optimization in the power systems [11,12]. Thus, the microgrid resource scheduling model can be considered as a multi-objective and multi-constrained optimization problem [13].

Recently, many research articles have focused on a multi-objective and multi-constrained optimization problem. Moreover, the DS can be widely used for the residential, commercial and industry sectors from the economic ancillary service and technical perspectives. The work in [14] presented a multi-objective stochastic optimization method with a price-based DS program for the operation cost and emission minimization. The multi-objective model was handled by the augmented epsilon constraint method. The article in [15] analyzed the effects of optimal spinning reserve (SR) approaches to recover wind power and net demand uncertainties. The optimal work provided economic benefit and can reduce unexpected interruption. The day-ahead actual power scheduling in stand-alone microgrid mode was carried out with weighting factors in multi-objective non-linear programming. The objectives of this work were to minimize fuel and emission costs [16].

The modified teaching–learning algorithm (MTLA) used to solve the economic load dispatch problem was presented in [17]. This optimization problem focuses on the uncertainties of fuel and emission cost minimization under wind and load demand. The optimal distributed generation management with demand response was analyzed in [6]. The non-dominated sorting firefly algorithm (NSFA) was applied for the test system, in which the objectives were technical index enhancement, considering power losses and voltage stability [6]. The problem of DG planning with demand response for virtual power players (VPPs) considering profit maximization analysis with meta-heuristic multi-dimensional signaling was examined by the authors of [18]. The work in [19] highlighted the light daily scheduling of a microgrid with two types of DR programs considering intermittent RESs and demands. This optimization problem was executed by the PSO algorithm to minimize network operation costs. The authors of [20] proposed a demand-response-based home energy management system to reduce electricity costs and the peak-to-average ratio (PAR).

The proposed system applied an enhanced differential evolution (DE) harmony search technique. A multi-objective building energy management system (BEMS) with DR was analyzed in [21]. This work provided the effective performance of the DR for the smart house regarding security, economy, and efficiency.

Although DSM can provide system stability, along with technical and economic benefits, the effective implementation of the DSM programs still affects consumer comfort [22]. The DSM or DR can disturb the convenience to consumers [3,5]. Operation-cost minimization and consumption bill reduction are no longer advanced infrastructure solutions. The electricity service's qualities and the power communities' satisfaction level have become challenges in power networks. The consideration factors can promote the role and achievement of the DSM in practical situations [5]. The variability in wind and solar resources created issues in scheduling to meet the hourly demand in one setting [23]. The work in [24] highlighted the effective deployment of demand response with heterogeneous energy storage. The risk-averse stochastic method was applied to maximize profit, minimize risk, and handle the RES and environmental uncertainty.

Although the peak demand at peak time can be avoided, the peak demand will increase at valley times due to a nonuniform demand shift toward the troughs. Therefore, this condition could create a loss of network diversity. Thus, in this work, we propose a multi-optimization-based method to control this over-demand response using peak-to-average ratio minimization at each time interval without adverse effects on consumer satisfaction. The target of the proposed work focuses on the generation scheduling with various generation units considering operation cost minimization, peak load controlling, and end-user comfort.

The main contributions of this paper are summarized as follows:

1. The meta-heuristic-based multi-objective gray wolf optimizer (MOGWO) is proposed to simultaneously solve three multi-objective problems to achieve the Pareto-optimal solution.
2. A demand response (DR) program is designed to reshape the flexibility of load profiles under the uncertainty of RES.
3. The optimal generation scheduling problem is resolved by considering multi-objective optimization.
4. The optimal uniform demand shifting program is applied to adjust the peak to average ratio (PAR) and generation cost without compromising the end-user comfort to prevent new peaks at valley time.

The rest of the paper is organized as follows. Section 2 presents the proposed methodology of the paper. In this section, the multi-objective optimization technique and problem formulation are comprehensively discussed. Section 3 presents verification results and discussions. Finally, Section 4 concludes the paper.

2. Proposed Methodology

In this section, an overview of multi-objective optimization is briefly described, followed by an introduction to the multi-objective gray wolf optimization (MOGWO) technique. Then, the best compromise solution and mathematical model of the optimization problem are proposed.

2.1. A Brief Introduction to Multi-Objective Optimization

The multi-objective optimization problem is used to find the optimal solution to handle different criteria with different sets of inequality and equality constraints. Single-objective optimization was developed to solve a single problem, and multi-objective optimization to handle more than one optimization problem simultaneously [6]. The problems involve different criteria that conflict with each other and must be considered simultaneously. Therefore, multi-criteria optimization searches for optimal solutions to different problems rather than the best solution for a particular problem, i.e., Pareto-optimal front [3]. The general formulation of the multi-objective optimization problem can be written as

$$\text{Min } F(\mathbf{x}) = \left[f_1(\mathbf{x}), f_2(\mathbf{x}), ..., f_N(\mathbf{x})\right]^T, \tag{1}$$

Subject to,

$$g_i(\mathbf{x}) \leq 0, i = 1, 2, \ldots, N_{neq}, \tag{2}$$

$$g_i(\mathbf{y}) \leq 0, i = 1, 2, \ldots, N_{eq}, \tag{3}$$

$$\mathbf{x} = (x_1, x_2, \ldots, x_k), \tag{4}$$

$$\mathbf{y} = (y_1, y_2, \ldots, y_k), \tag{5}$$

$$\forall_i \in \{1, 2, \ldots, k\}, f(x_i) \geq f(y_i) \wedge \exists i \in 1, 2, \ldots, k : f(x_i)], \tag{6}$$

$$P_f := \{F(x) | x \in P_s\}, \tag{7}$$

where $\mathbf{x}$ and $\mathbf{y}$ are the vectors representing Equations (4) and (5), respectively. $\mathbf{x}$ is the dominated vector and is shown in Equation (6). Here, no vector can dominate the other vector solution, so it is the non-dominated solution. A set of all non-dominated solutions is called the Pareto-optimal set. A set with Pareto-optimal solutions in the Pareto-optimal set is the Pareto-optimal front. The Pareto-optimal front allows for a better solution for the conflicting objectives [12]. Unlike the single-objective problems, large and highly complex searching are the limitations to accurately solving the majority of multi-criteria problems. The multi-objective optimization provided a non-dominated solutions set as an approximation method [10].

Different methods have been used to solve the multi-objective problem. Classical and meta-heuristic methods are the two possible optimization approaches for the multi-objective functions [17]. Usually, the classical approaches transform the multi-objective optimization problem into a single-objective optimization problem [13]. Currently, the meta-heuristic techniques are more capable of searching for optimal solutions than the classical methods for the advanced microgrid problem because of their fast convergence and high accuracy. The meta-heuristic optimization also provides a more accurate Pareto-optimal solution than the classical methods [17]. In the next subsection, the proposed multi-objective gray wolf optimizer is introduced.

2.1.1. Multi-Objective Gray Wolf Optimization

The multi-objective gray wolf optimizer (MOGWO) was developed by the authors of [12]. It was inspired by gray wolves' hunting behavior. The top three tiers of wolves lead this algorithm to search for the best solution. The leader wolf is donated as alpha (α), which is the wolf nearest to the prey. The beta (β) is an alpha follower responsible for maintaining harmony in the hunting group. In the hierarchy, delta (δ) wolves are in the third position and act as scapegoats. The remaining wolves in the hunting group are donated as delta (δ). The position updating of the MOGWO algorithm is mathematically represented by

$$\mathbf{Y}_1 = \mathbf{Y}_\alpha - \mathbf{R}_1 \mathbf{P}_\alpha, \tag{8}$$

$$\mathbf{Y}_2 = \mathbf{Y}_\beta - \mathbf{R}_1 \mathbf{P}_\beta, \tag{9}$$

$$\mathbf{Y}_3 = \mathbf{Y}_\delta - \mathbf{R}_1 \mathbf{P}_\delta, \tag{10}$$

$$Y_{(iter+1)} = \frac{Y_1 + Y_2 + Y_3}{3}, \tag{11}$$

$$R_1 = 2ar_1 - a, \tag{12}$$

$$Q = 2r_2, \tag{13}$$

$$a = 2 \cdot \left(1 - \frac{iter}{Max_{iter}}\right), \tag{14}$$

where Y_1, Y_2, and Y_3 are the positions of the wolves; R_1, Q, and a are the coefficient vectors; and r_1 and r_2 are the random vectors in [0, 1].

The MOGWO algorithm consists of two new items: (i) archive and (ii) leader selection. The first component is applied to store the non-dominated Pareto-optimal solutions throughout the process. The second is used to choose leaders' (alpha, beta, and delta) solutions for the hunting process from the existing solution in the archive. The archive serves as a storage unit in which non-dominated Pareto-optimal solutions can be saved and retrieved with the help of the archive controller. During the iteration process, the archive controller controls and compares the new solution with existing solutions that try to enter into the archive. Four different non-dominated sorting cases are given as follows:

- The archived solution will not be updated if the new solution dominates the archive's residences.
- The archived solution will be replaced with the new solution if the former is dominated by the new solution.
- The new non-dominated solution will be allowed to enter the archive if the archive has enough space.
- The grid mechanism will rearrange the segmentation and search for the most crowded solution to omit it if the new non-dominated solution has to enter and the archive is full.

The MOGWO algorithm is superior in coverage speed because of the new archiving and leader-selection processes. The obtained solutions are continually removed from the most crowded segments of the archive, and the leaders are selected from the most-populated solution of the archive. The MOGWO algorithm is suitable for solving problems with three objectives [12]. The pseudo-code of the MOGWO adopted from [25] is given as Algorithm 1.

Algorithm 1 Pseudo-code of MOGWO.

Initialize wolf solutions as $S_i(i = 1, 2, \ldots, N_{woft})$, in which N_{wolf} is the number of the gray wolf population
Generate vectors of the movement coefficients
Evaluate the fitness of each wolf as $\mathbf{P}_\alpha$, $\mathbf{P}_\beta$ and $\mathbf{P}_\delta$
iter = 1
Repeat
for $i = 1$ to N_{woft} **do**
    Repositioning the wolves based on Equations (8)–(11)
end for
Estimate the fitness value of the wolves
Update $\mathbf{P}_\alpha$, $\mathbf{P}_\beta$ and $\mathbf{P}_\delta$
Update the vectors of movement coefficients considering Equations (12)–(14)
Specify the non-dominate solution P: Update Archive
iter = iter + 1
Until iter $\geq$ Max iter
Output P: Archive

2.1.2. Best Compromise Solution

Our method applies the best compromise solution (BCS) to find the best solution from the Pareto-optimal set. The BCS method is based on the Euclidean distance technique. The reference point ($f_{i,min}$, $f_{j,min}$ and $f_{k,min}$) from the corresponding objective function is selected as the minimum value of the available solution for all objectives. The best solution is obtained as the point which is the minimum distance (d) from the reference point in the Pareto-optimal set [26]. The following expression is minimum distance formulation.

$$D = \sqrt{\left[(f_{ai}) - f_{i,min})^2 + (f_{bj}) - f_{j,min})^2 + (f_{ck}) - f_{k,min})^2\right]}, \tag{15}$$

$$d = \min(D), \tag{16}$$

where f_{1i}, f_{2i}, and f_{3i} are the points of corresponding objective functions in the feasible region.

3.1.3. Mathematical System Modeling

In the power network, the proposed algorithm will optimize power generation and responsive loads locally to meet peak power demand for 24 h. The peak power demand is planned for the day ahead (24 h) using the combination of dispatchable and non-dispatchable power generation resources. This paper considers the combination of PV and wind, grid power, and fuel-base generation units. The system's optimization problems are the minimization of generation costs, peak-to-average ratio (PAR), and consumer dissatisfaction with equality and inequality constraints. The operation cost includes operation cost, spinning reserves, and energy exchange costs. The optimal resource scheduling, [illegible], is implemented based on PV and wind forecast values. Based on the forecast wind speed and solar irradiance values, the multi-objective problem is solved by employing the multi-objective grey wolf optimization (MOGWO). The following are the three defined objectives of the paper.

The first objective is the system's operation cost minimization, which involves wind, PV, fuel-base generations, and grid power exchange costs as

$$\text{Min } C_{operation} = \sum_{t=1}^{T} P_{PV}^{t}\lambda_{PV} + P_{wind}^{t}\lambda_{wind} + (a(P_{G}^{t})^{2} + bP_{G}^{t} + c) + P_{grid}^{t}\lambda_{grid}(\delta_{grid}^{t} - \delta_{grid}^{t}) \quad (17)$$

where $C_{operation}^{t}$ is the total cost of generation at time t [illegible]; P_{PV}^{t} and P_{wind}^{t} are the output power of PV and wind at time t, respectively; P_{G}^{t} and P_{grid}^{t} are total power generation and power exchange with grid at time t, respectively; a, b, c are the generation coefficients; δ_{grid}^{t} and δ_{grid}^{t} are the power exchange coefficients at time t; and λ_{PV}, λ_{wind} and λ_{grid} are the prices of generation costs.

The second objective is peak demand minimization for a particular hour. Therefore, PAR of a particular time is the ratio of preferred peak to demand at a particular time. The second objective is given as

$$\text{Min } PAR = \frac{P_{L}^{max}}{\sum_{t=1}^{T} P_{L}^{avg}} \quad (18)$$

where P_{L}^{max} is the target peak demand at time t and P_{L}^{avg} the average demand at time t.

The third objective is to minimize consumer dissatisfaction concerning the time and power gaps. In consumer comfort, operation delay and power gap are the metrics for measuring consumer satisfaction in the scheduling problem. The power gap is defined as the preferred and scheduled power ratio, and the time gap is the waiting time ratio to total operation time. The third objective is expressed by

$$\text{Min } I_{dissatisfaction} = \frac{T_{delay}^{t}}{T_{operation}^{total}} + \frac{P_{delay}^{t}}{P_{operation}^{total}} \cdot \rho_{elasticity}^{t} \quad (19)$$

where $I_{dissatisfaction}$ is the consumer dissatisfaction index; T_{delay}^{t} and P_{delay}^{t} are the shiftable time and power at time t, respectively; $T_{operation}^{total}$ and $P_{operation}^{total}$ are the total shiftable time and power at time t, respectively; and $\rho_{elasticity}^{t}$ is the demand elasticity coefficient at time t.

The following are equality and equality constraints that are used in the optimization problem.

Power balance constraint:

$$\sum_{t=1}^{T} P_{PV}^{t} + P_{wind}^{t} + P_{G}^{t} + P_{grid}^{t} - P_{sh}^{t} = P_{L}^{t} \quad (20)$$

Power exchange constraints:

$$u^t_{grid} + u^t_{sell} \le 1. \quad (21)$$

The spinning reserve is to protect the system from unexpected conditions, power outages, and sudden load changes:

$$[illegible] \quad (22)$$

Generation capacities:

$$P^{min}_{PV} \le P^t_{PV} \le P^{max}_{PV}, \quad (23)$$
$$P^{min}_{wind} \le P^t_{wind} \le P^{max}_{wind}, \quad (24)$$
$$P^{min}_{DG} \le P_{DG} \le P^{max}_{DG}, \quad (25)$$
$$P^{min}_{grid} \le P^t_{grid} \le P^{max}_{grid}. \quad (26)$$

Constraints to prevent new peaks:

$$[illegible] \quad (27)$$

[illegible]

$$[illegible] \quad (28)$$
$$[illegible] \quad (29)$$

4. Results and Discussion

[illegible]

3.1. Test System

The test system that was used for verification of the proposed technique is illustrated in Figure 1. As can be seen in the figure, two DGs were connected to buses 22 and 28, respectively. Additionally, there were PV and wind sources connected to buses 12 and 15, respectively. The test system was connected to the main grid at bus 1. All information of the test system can be found in [27]. The forecast's PV and wind power generation are shown in Figure 2a,b, respectively. The figures clearly show that there were uncertainties between measurement and forecast data of the PV and wind sources. The characteristics of the two DGs were taken from [14] and are given in Table 1. The electricity prices were assumed as the time of use (TOU). All points in the feasible region represent the non-dominated solution store in the archive, as seen in Figure 3. The concept of a non-dominated solution is according to Equations (4)–(7). In this study, the non-dominated solution was chosen with the BCS method.

Table 1. Generation characteristics of the two DGs.

DGs	a	b	c	P_{min} (KW)	P_{max} (KW)
1	[illegible]	[illegible]	[illegible]	5	100
2	[illegible]	[illegible]	[illegible]	5	100

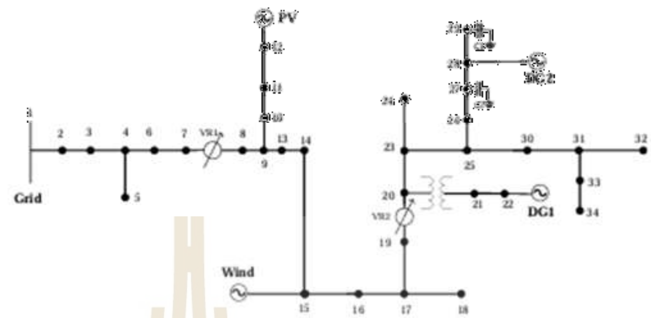


Figure 1. Test system [27].

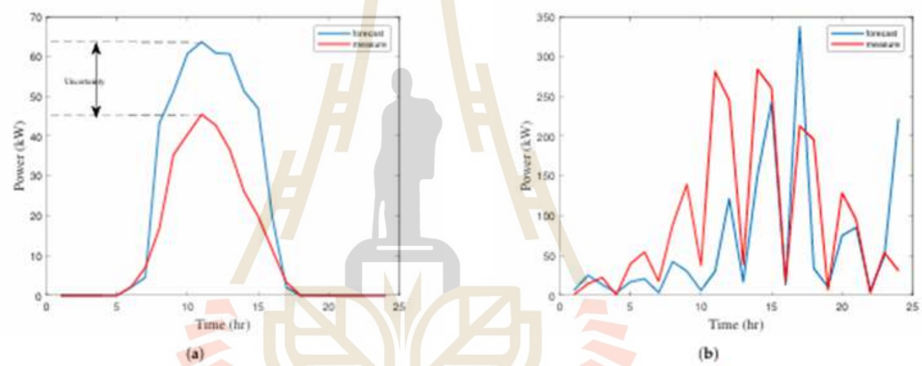


Figure 2. Forecast and actual power generation of PV and wind units [28]. (a) PV power generation. (b) Wind power generation.

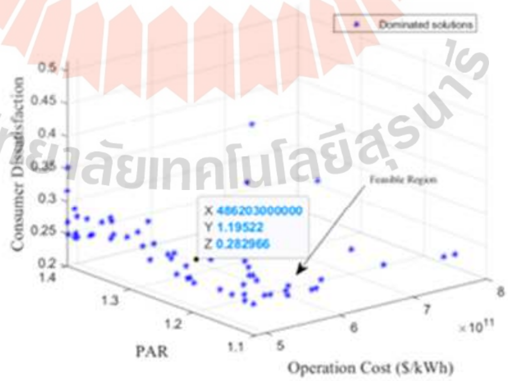


Figure 3. Pareto-optimal solutions for operation cost, PAR and consumer dissatisfaction.

3.2. *Simulation Results*

In this section, two case studies are given. In *Case Study 1*, the optimal scheduling process is implemented for uncertainties of the RES data considering the minimization of operational costs . *Case Study 2* analyzes the multi-objective optimal demand response program. The simulation results were obtained using MATLAB 2021 software.

3.2.1. Case Study 1: Multi-Objective Operation Costs Optimization under RES Uncertainties

In this case study, the simulation results of the optimal generation scheduling are given for forecast and actual data. The optimal resource scheduling considering optimal operation cost curves of all the system's generating units are shown in Figures 4 and 5. According to the minimum cost problem, DG1 and DG2 are the most expensive generation units which are scheduled with minimum capacities in the system. The PV and wind units are more likely to schedule their maximum generation capacities according to cost minimization. The PV and wind generated more power in the daytime. Therefore, total generation capacities are higher during the off-peak period (daytime). The participation of load-response programs according to the uncertainty effect are illustrated in Figures 6 and 7. As shown in Figures 8 and 9, the proposed DR program shifted the load from peak periods of 1–5 h and 20–24 h to the valley time of 6–20 h. Therefore, the system scheduling altered the shape of the load profile after DR participation.

Table 2 shows the operational cost under the RES uncertainty based on actual and forecast data of PV and wind units. The PV generation was scheduled with higher output. The demand response requirements increase, and the operational cost is high. The wind output was scheduled with lower output, so the demand response decreases, and the operation level is low. In *Case Study 1*, it is essential to engage uncertainties of the RES units and the DR effect, which provide energy in new peak leads to the off-peak time. Figures 8 and 9 show the statement of new peak creation. Peak-to-average ratio describes the stability of the system. In *Case Study 1*, the PAR is at 41% with actual RESs and at 44% with the forecast RESs.

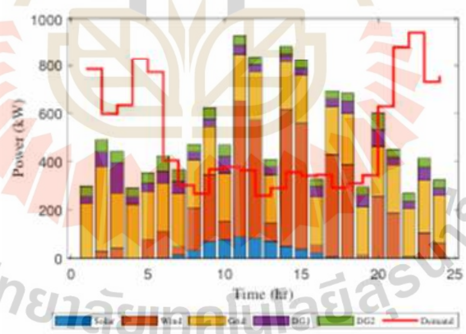


Figure 4. Optimal generation scheduling with PV and wind actual data.

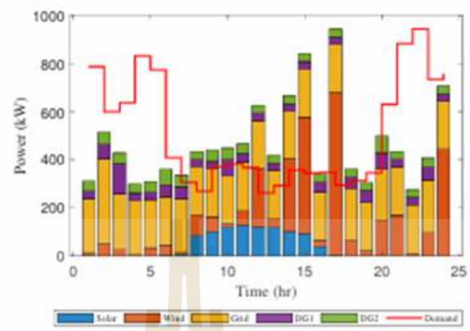


Figure 5. Optimal scheduling with forecast PV and wind data.

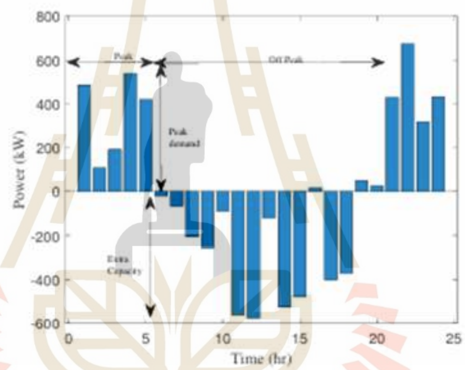


Figure 6. Demand−response schedule with actual PV and wind data.

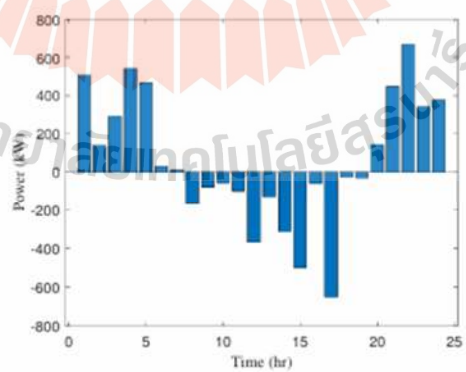


Figure 7. Demand−response schedule with forecast PV and wind data.

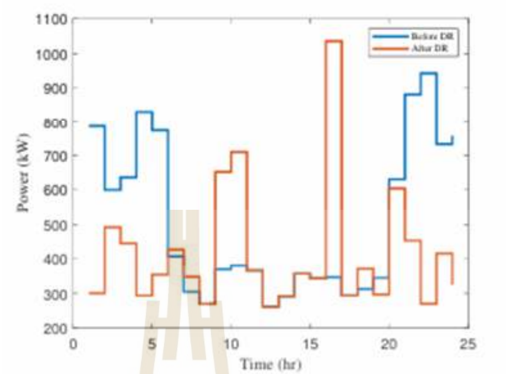


Figure 8. Demand−response schedule with actual PV and wind data.

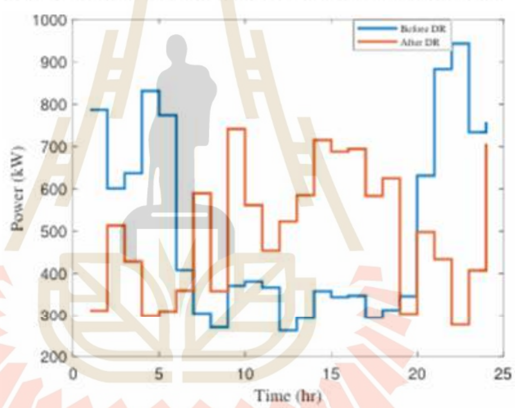


Figure 9. Aggregate load reshapes with forecast PV and wind data.

Table 2. Comparison of operational cost with RES uncertainty.

Time (h)	Operation Cost (Actual, $/kWh)	Operation Cost (Forecast, $/kWh)
7	3509	3339
8	3439	3232
9	4419	3467
10	4258	4144
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]

4.2.2. Case Study 2: Multi-Objective Peak Reduction Problem

This work analyzes the flexible demand response to reshape the aggregated demand profile with multi-criteria decisions. The target of this work is to prevent the creation of a new peak in the off-peak time. In this part, the simulation results of [illegible] are shown in Figures 10–13. The participation of responsive loads in the DR programs for *Case Study 2* is shown in Figures 10 and 12. Since the PV and wind powers are scheduled with uncertainty, the capacity of the DR created a new peak according to *Case Study 1*. In *Case Study 2*, and as shown in Figure 11, the amount of demand that is more than the optimal generation capacity is moved to an off-peak time based on the optimal hourly peak (less than 600 kW). The numerical information of the load shifting can be found in Table 3. According to Table 3, however, the total waiting time of the optimal peak reduction case is more than that of *Case Study 1* (6 h), due to optimal demand distribution. The term peak-to-average ratio refers to the the quantitative measurement for load profile and the stability of the system. The system stability metric of the PAR is lower than that of *Case Study 1* when considering the optimal peak load minimization (44% to 43%).

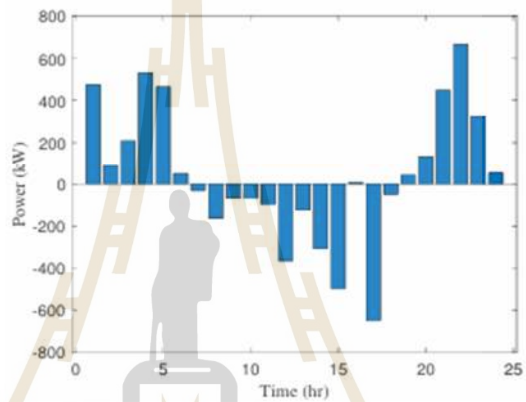


Figure 10. Optimal demand−response schedule considering peak load reduction.

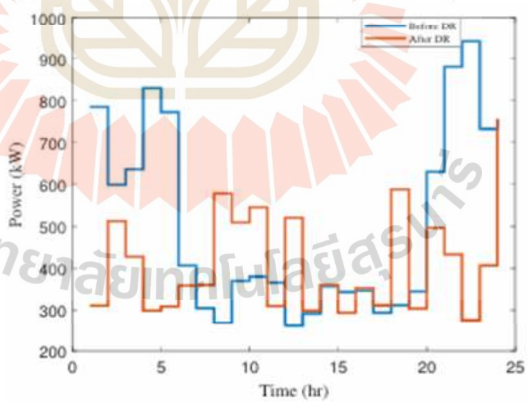


Figure 11. Optimal aggregate load reshapes considering peak load reduction.

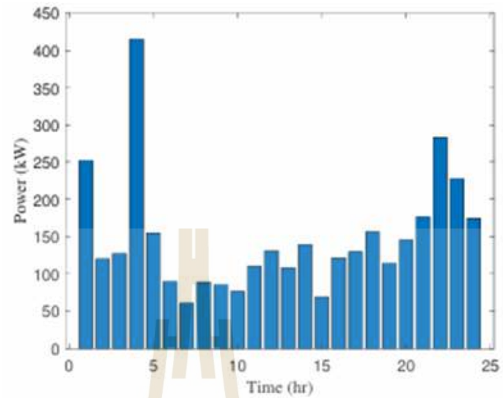


Figure 12. Optimal demand−response schedule considering peak load reduction and user comfort.

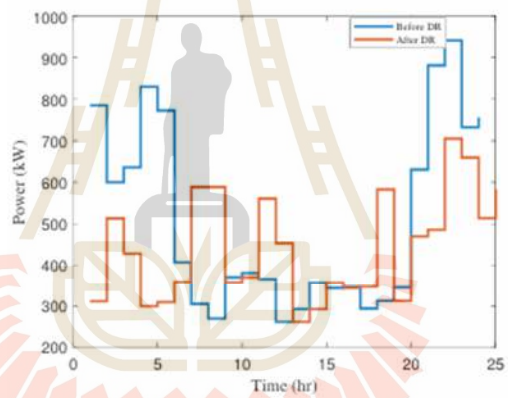


Figure 13. Optimal aggregate load reshapes considering peak load reduction and user comfort.

Uniform optimal load shifting considering consumer comfort is shown in Figures 12 and 13. The dissatisfactory optimization index is the difference between actual and reference consumption at a particular period. The increase in the different levels described increases the discomfort. Therefore, the dissatisfaction should be a convex function, as shown in Figure 3. In this case, extra loads were changed to off-peak time according to optimal power-gap and time-gap information. The allowable DR is between 20% and 30% of hourly demand. The detailed information of the optimal load response for 24 h is presented in Table 4. The index of the PAR was reduced to 37%, and the total waiting time was 6 h. As observed from simulation results, the peak shaving and load-profile reshaping had advantages for the proposed renewable energy of the microgrid system. It also prevented a new peak due to RES uncertainty and load response. Figures 11 and 13 present the results related to the statements above. When the total generation capacity exceeded the optimal demand response, it can sell power back to the grid. The capacities of power exchanged from and sold to the grid were 200–300 kW and 100 kW, respectively. After the power moves from peak time to off-peak time, the extra power form off-time can be sold back to the main grid. The results in Figure 14 indicate that the power surplus at 12–17 h is sold back to the main grid. The total amounts of power shifted by the DR and the user comfort DR that can go back to the main grid are 1028 kW and 1287 kW, respectively. The profits resulting from exchanging power covering the production cost and the consumer comfort case are illustrated in Figures 11 and 13. As the shiftable DR was adjusted between 20% and 30% for the user comfort, the extra power of user comfort DR was more than the shift by DR at off-peak time. The demand elasticity factor ($\mu_{elasticity}$) represents the simulation results of optimal DR based on power gap and time-gap constraints in each hour. Numerical results for 0.2200 of the demand elasticity factor at 6 h were related to the case of 22% of DR. Results in Figure 13 illustrate that when the optimal DR programs were implemented at peak time, the level of the end-user dissatisfaction index had improved between 0.45 and 0.7. The level of the end-user dissatisfaction index decreased from 0.45 to 0.19 at an off-peak time. It is indicated that end-user dissatisfaction had better performance based on the lower waiting time (time gap) and allowable DR (20–30% power gap).

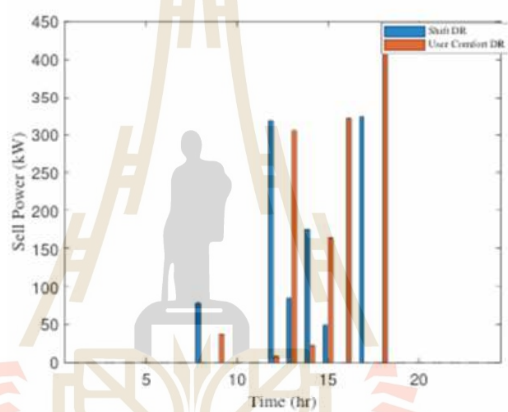


Figure 14. The amount of power sold to the grid.

Figure 15 shows the end-user dissatisfaction index with DR over 24 h. A summary of the results of the three objective functions is provided in Table 5.

Table 3. Load shifting considering peak load reduction.

Time (h)	Power (kW)	Waiting Time (h)
7	360.4108	5
8	578.5112	7
9	509.8774	6
10	545.7373	8
11	309.7874	8
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]

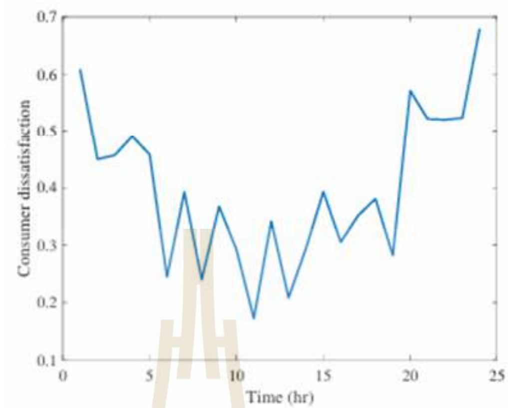


Figure 15. End – user dissatisfaction index with DR.

Table 6. Optimal percentage of DR considering uncertainties.

Time (h)	Demand Flexibility Factor [illegible]
[illegible]	[illegible]
[illegible]	[illegible]
[illegible]	[illegible]
[illegible]	[illegible]
[illegible]	[illegible]
[illegible]	[illegible]
[illegible]	[illegible]
[illegible]	[illegible]
[illegible]	[illegible]
10	[illegible]
11	[illegible]
12	0.3000
13	0.3000
14	0.3000
15	0.2000
16	0.3000
17	0.3000
18	0.3000
19	0.3000
20	0.2300
21	0.2000
22	0.3000
23	0.3000
24	0.2300

For comparison, the work in [29] was implemented using adaptive stochastic programming to cope with 10% of wind power uncertainty. From the optimal planning with DR, it has 30% of overall PAR. Moreover, the work in [30] presented optimal allocation resources with DR and day-ahead real-time pricing (DARTP). The total RES uncertainty of this work was reduced from 9.93% to 7.20% with the DARTP demand response model. The overall PAR for this method was 42.6156%. From Table 6, our proposed optimal DR system guaranteed the RES uncertainty increment up to 27.0136%. Additionally, it is noted that the configurations of power networks may affect the performance of our proposed method due to different locations of RESs and line losses from a different network topology.

Table 5. A summary of results of three objective functions.

Time (h)	Operation Cost ($/kWh)	PAR	Dissatisfaction Index
1	2716	1.3570	0.6083
2	4389	1.7672	0.4497
3	4984	1.8890	0.4568
4	[illegible]	[illegible]	[illegible]
5	[illegible]	[illegible]	[illegible]
6	[illegible]	[illegible]	[illegible]
7	[illegible]	[illegible]	[illegible]
8	[illegible]	[illegible]	[illegible]
9	[illegible]	[illegible]	[illegible]
10	[illegible]	[illegible]	[illegible]
11	[illegible]	[illegible]	[illegible]
12	[illegible]	[illegible]	[illegible]
13	[illegible]	[illegible]	[illegible]
14	[illegible]	[illegible]	[illegible]
15	[illegible]	[illegible]	[illegible]
16	[illegible]	[illegible]	[illegible]
17	[illegible]	[illegible]	[illegible]
18	[illegible]	[illegible]	[illegible]
19	[illegible]	[illegible]	[illegible]
20	4762	1.1677	0.5713
21	3230	1.0939	0.5221
22	2422	1.1061	0.5207
23	3555	0.9568	0.5236
24	4621	1.7299	0.6792

Table 6. Comparison with existing strategies.

Refs.	PAR (%)	RES Uncertainty (%)
[29]	30	10
[30]	42.6156	9.93
Proposed strategy	37	27.0136

4. Conclusions

In recent years, there has been increased attention in DR programs to address the problem of the peak load in the power distribution systems and microgrids. Moreover, owing to a significant amount of RES penetration and integration in power networks, advanced microgrid planning cannot consider the signal objective function. This paper proposed the optimal power resource management based on three objective functions with network constraints. The objective functions of the proposed method include the minimization problems of the operation cost, peak-to-average ratio (PAR), and consumer dissatisfaction over a 24 h period. Meta-heuristic MOGWO was applied to handle the multi-decision problem. Moreover, the MCS method was applied as a decision maker to search for the optimal solution from the conflicting objective functions. The performance of the proposed method was justified for two scenarios. First, the results illustrated the possible peak load at off-peak time due to the effects of RES uncertainty and over-demand response. Second, the simulation results showed that the performance of the proposed system was advantageous for generation scheduling due to the uncertainty effect. The power gap and then gap minimization were also considered through the index of cost-user comfort. Peak-to-average ratio reduction was provided to show the effectiveness of the proposed method on the test system. For consumer's comfort, the DI set the range between 30% and 60%. Multi-objective optimization can be solved via multi-decision variable simultaneously. The obtained results showed that the proposed strategy can handle RES uncertainty increment with less overall PAR.

Future work will focus on expanding our strategy of multi-objective planning to microgrid clusters.

Author Contributions: Conceptualization, S.L.L.W., W.P. and B.M.; methodology, S.L.L.W.; software, S.L.L.W.; validation, S.L.L.W., W.P. and B.M.; formal analysis, S.L.L.W., W.P. and B.M.; investigation, S.L.L.W., W.P. and B.M.; data curation, S.L.L.W.; writing—original draft preparation, S.L.L.W.; writing—review and editing, W.P. and B.M.; supervision, B.M.; funding acquisition, B.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Suranaree University of Technology, Thailand ([illegible] 2562-2).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: S.L.L.W. gratefully acknowledges the scholarship from Suranaree University of Technology, Thailand.

Conflicts of Interest: The authors declare no conflict of interest.

Sample Availability: Not applicable.

Abbreviations

The following abbreviations are used in this manuscript:

N_{eq}, N_{ineq}	Number of equality and inequality constraints
N_{pop}	Number of grey wolf population
Y_1, Y_2, Y_3	Positions of wolves
R_1, Q, a	Coefficient vectors
r_1, r_2	Random vectors in range [0, 1]
$Y_{p,t}$	Updating the position of wolf
[illegible]	Best compromise solution index
f_1, f_2, f_3	Points of corresponding objective function in feasible region.
$f_{1,min}, f_{2,min}, f_{3,min}$	Reference points of corresponding objective function in feasible region
$C_{operation}$	Total operation cost from [illegible] (THB/kWh)
P_{PV}	Output power of PV at time t (kW)
P_{wind}	Output power of wind unit at time t (kW)
P_{grid}	Power exchange from the grid at time t (kW)
P_{ESS}	Output power of ESS at time t (kW)
P_{ch}, P_{dch}	Power exchange of the ESS at time t
[illegible]	Prices of generation cost ($)
W_{peak}	Peak [illegible] at time t
P^{peak}	Target peak demand at time t
P^{avg}	Average demand at time t
P_{min}, P_{max}	Minimum and maximum band of allowable peak demand at time t
[illegible]	[illegible] classification index
t_{shift}	Shifting time (h)
$t_{operation}$	Total operation time (h)
P_{shift}	Shiftable power at time t (kW)
$P^{total}_{operation}$	Total power at time t (kW)
$E_{elasticity}$	Demand elasticity coefficient at time t
P_D^t	Total power demand at time t (kW)
P_{SR}^t	Spinning reserve power at time t (kW)
P_G^t	Total generation power at time t (kW)
P_{max}	Maximum output power of generation (kW)
$p_{min,j}, p_{max,j}$	Generation capacity of the j-th unit (kW)

2022 International Electrical Engineering Congress (iEECON2022)
March 10-12, 2022, Pattaya, THAILAND

OPTIMAL GENERATION SCHEDULING WITH DEMAND SIDE MANAGEMENT FOR MICROGRID OPERATION

[illegible] Lei Lei Wynn
[illegible]

Terapong Boonraksa
[illegible]

Boonruang Marungsri
[illegible]

Abstract— [illegible]

Keywords— [illegible]

I. INTRODUCTION

[illegible]

2021 International Electrical Engineering Congress (iEECON2021)
March 10-12, 2021, Pattaya, THAILAND

meet system demand. Therefore, peak shaving can be reduced energy consumption at peak hours. A microgrid viewpoint can be minimized system operation costs by replacing more expensive energy production with cheaper production [5]. Demand Response (DR) gave economic benefits to interactive customers, electricity market development, and potential benefits for system efficiency improvement. It can also minimize the capital investment need for system or generation plant upgrades. [illegible]

[illegible]

[illegible]

appliances' operation and the stress back to the whole system.

Therefore, the generation resources can be regulated and optimized based on the system's economic operation. Generally, local renewable generation is more economic resources than the utility grid. Therefore, the objective of microgrids is to extract the maximum amount of power from RE based resources. [illegible]

II. [illegible]

[illegible]

[illegible]

[illegible]

$$[illegible] \quad (1)$$

[illegible]

$$[illegible] \quad (2)$$

2020 International Electrical Engineering Congress (iEECON2020)
March 4-6, 2020, Pattaya, THAILAND

Power balance constraint for island operation mode,

$$\sum_{i=1}^{N} P^{t}_{wind} + P^{t}_{PV} + P^{t}_{storage} + P^{t}_{DG} = P^{t}_{D} \quad \text{[illegible]}$$

Spinning reserve constraint

$$\sum_{i=1}^{N} P^{t}_{i} \geq P^{t}_{D} + R_{t} \quad \text{[illegible]}$$

Capacity limits of generating unit

[illegible]

The objective for demand side management,

[illegible]

The profit formulation for DSM,

[illegible]

Where [illegible] are the amount of power sent to the demand side from RE, grid, and generator. [illegible] represents the amount of total power demand from customers. P_L and P_G are the parameter for the power losses and total power generation. C_{cost} and C_{DR} are the parameters of selling price to the customer and the cost of power purchased from the customer.

TABLE I HOURLY WHOLESALE PRICE AND HOURLY FORECASTED REGENERATION

Hour	Hourly Price	Wind	Solar
1	1.57	7.56	0
2	1.40	7.50	0
3	2.20	8.25	0
4	3.76	8.48	0
5	4.50	8.48	0
6	4.70	9.42	0
7	5.04	9.82	0
8	5.35	10.35	7.99
9	6.70	10.88	10.56
10	6.16	11.01	13.61
11	6.38	10.94	14.97
12	6.82	10.68	15
13	7.30	10.42	14.78
14	7.80	10.15	14.59
15	8.50	9.67	13.56
16	7.10	8.98	11.83
17	6.80	8.37	10.17
18	6.30	7.61	7.66
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]

TABLE II GENERATION CAPACITY OF FIVE DISTRIBUTED GENERATIONS

DGs	a	b	P_{min}	P_{max}
1	[illegible]	[illegible]	[illegible]	[illegible]
2	[illegible]	[illegible]	[illegible]	[illegible]
3	[illegible]	[illegible]	[illegible]	[illegible]
4	[illegible]	[illegible]	[illegible]	[illegible]
5	[illegible]	[illegible]	[illegible]	[illegible]

[illegible] RESULTS AND DISCUSSION

This simulation analysis was carried out [illegible] microgrids. The generation system consists a wind system, photovoltaic system, storage system, and five distributed generators. The [illegible] is shown in Table II. The maximum amount of power transfer capacity between the interconnection system was [illegible]. The generation schedule was analyzed for a day. The wholesale electricity prices and RE generation are shown in Table I. The simulation outcomes demonstrated the effectiveness of the proposed optimization methods.

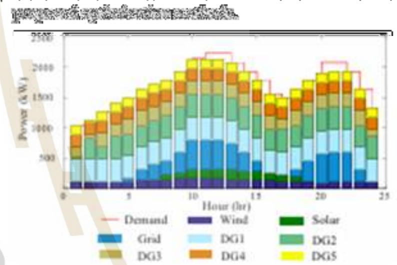


Fig. 1. Optimal generation scheduling for the grid-connected operation of the microgrid.

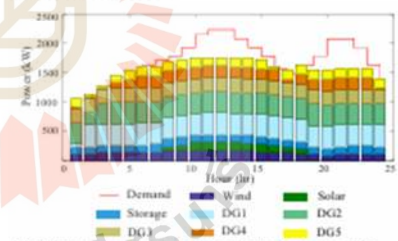


Fig. 2. Optimal generation scheduling for Island operation of the microgrid.

Fig. 1 and Fig. 2 show day-ahead generation scheduling for all resources under grid-connected mode and island mode. In this work, the maximum power transfer capacity was [illegible]. In grid-connected mode, the main grid [illegible] to the microgrid, especially at the time of lower wholesale price and high demand intervals from 5 hr to 15 hr, and [illegible] hr to [illegible] hr. This method [illegible] load shedding with incentives paid to the customer when the local generation and power transfer capacity [illegible]

2021 International Electrical Engineering Congress (iEECON2021)
March 10-12, 2021, Pattaya, THAILAND

the main grid was not enough: from 10 hr to 13 hr and 20 hr to 24 hr, and at the time of expensive the wholesale market price, such as 14 hr to 17 hr. The power generation from the DGs is not expensive as the wholesale energy prices are 16 hr to 17 hr; therefore, it is favored to supply more power from DGs than transfer power from the main grid.

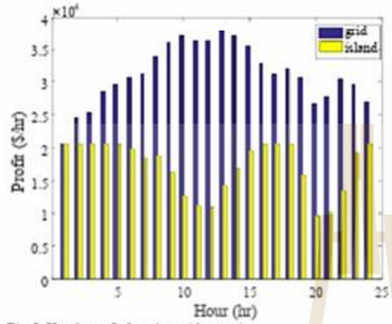


Fig. 3. Hourly profit for microgrid operation.

Fig. 3 presents the outcome of scheduling the island operation mode microgrid for the day. In this work, the energy storage systems are employed to reduce stress on local generation units, principal demand fluctuation, and the storage system's hourly discharge capacity is considered constant capacity. The capacity of the storage system was [illegible]. Within the previous case, the optimization approaches suggested achieving more DSM options for enabling demand shedding with incentives paid to meet the hourly demand requirement, especially at high demand. Fig. 3 compares the profit of two operation modes. Fig. 4 shows the hourly demand response offer to customers. According to the results, the island mode's expected profit is significantly lower than the grid-connected mode when more demand response offers a period and at high demand time.

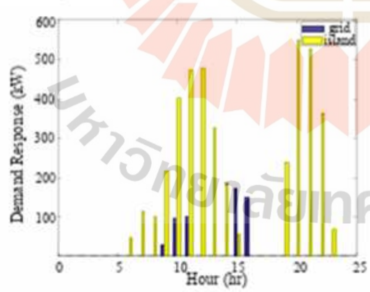


Fig. 4. Hourly Demand response offer to the demand side.

IV. Conclusion

In this paper, the combined operation of unit commitment with DSM in the microgrid is a proposed option for a microgrid management system to optimize profit and increase dependencies on local clean energy generation. The load shedding approach is more significantly effective for island operation mode to maintain supply/demand balance and reduce stress on generation resources. The generation schedule optimized the operation status of the local generation capacity for both operation modes. The proposed system's effectiveness maximized the profit for microgrid operator and the optimal power transfer from the utility grid are also considered for grid-connected mode.

References

[1] T. Logenthiran and D. Srinivasan, "Short term generation scheduling of a microgrid," TENCON 2009 IEEE Region 10 Conference, pp. 1-6, 2009.

[2] L. Trigueiro dos Santos, M. Sechilariu, F. Locment, "Optimized load shedding approach for grid-connected dc microgrid systems under realistic constraints," Buildings - December 2016.

[3] T. Logenthiran, D. Srinivasan, A. M. Khambadkone, and H. N. Aung, "Multiagent system for real-time operation of a microgrid in real-time digital simulator," IEEE transactions on smart grid, vol. 3, No. 2, pp. 925–933, June 2012.

[4] B. V. Solanki, A. Raghurajan, K. Bhattacharya, and C. A. [illegible], "Including smart loads for optimal demand response in integrated energy management systems for isolated microgrids," IEEE transactions on smart grid, vol. [illegible], No. 4, pp. [illegible], July [illegible].

[5] [illegible], "Demand response in an isolated system with high wind integration," IEEE transactions on power systems, vol. [illegible], No. 1, pp. [illegible], February [illegible].

[6] [illegible], IEEE Transactions on Industry Applications, vol. [illegible], No. 4, pp. [illegible], August [illegible].

[7] [illegible]

[8] S. Noor, M. Guo, K. H. Van Dam, N. Shah, X. Wang, "Energy demand side management with supply constraints: game theoretic approach," applied energy symposium and forum, Renewable energy integration with Mini/Microgrids, REM 2017, 18–20 October 2017.

[9] L. Yong, H. Zhi-Jian, J. Chuan-wen, "Unit commitment by binary particle swarm optimization," 7th WSEAS Int. Conf. on mathematical methods and computational techniques in electrical engineering, Sofia, pp. 372-377, 27-29 October 2005.

[10] T. D. Khoa, L. Trigueiro D. Santos, M. Sechilariu, F. Locment, "Load shedding and restoration real-time optimization for dc microgrid power balancing," IEEE International Energy Conference (ENERGYCON), pp. 1-6, 2016.

[11] F. Shokooh, J. J. Dai, S. Shokooh1, J. Tastet, H. Castro1, T. Khandelwal1, G. Donner, "An intelligent load shedding (ILS) system application in a large industrial facility," Fourtieth IAS Annual Meeting. Conference Record of the 2005 Industry Applications Conference, Vol. 1, pp. 417-425, 2005.

[12] V. Rozinajova, A. B. Ezzeddine, M. Loderer, J. Loebl, R. Magyar, and P. Vrablecova, "Computational Intelligence in Smart Grid Environment," Computational Intelligence for Multimedia Big Data on the Cloud with Engineering Applications, pp. 23-59, Academic Press, 2018.

2021 International Conference on Power, Energy and Innovations (ICPEI 2021)
October 20-22, 2021, Nakhon Ratchasima, THAILAND

OPTIMAL DISTRIBUTION LEVEL OF ENERGY MANAGEMENT CONSIDERING GENERATION UNCERTAINTIES AND DEMAND RESPONSE

Sane Lei Lei Wynn — School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima, Thailand

Terapong Boonraksa — School of Electrical Engineering, Rajamangala University of Technology [illegible], Thailand

Promphak Boonraksa — School of Electrical Engineering, Bangkok Thonburi University, Bangkok, Thailand

Boonruang Marungsri — School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima, Thailand

Abstract— Incentive base demand response was a powerful tool for supply-demand balancing in the system with renewable energy resources. However, renewable energy generation's uncertainties in the supply side become a challenge to implement energy management. This paper proposed improving the usage of renewable generation in the local distribution network among multiple energy carriers. This paper aims to solve the microgrid's renewable energy generation uncertainties and energy management problems with the network-connected structure. The stochastic Weibull distribution function and Beta distribution function are employed to solve wind and solar generation forecasting. For the optimization process, the Particle Swarm Optimization algorithm is used for optimal generation scheduling. The simulation results show that the microgrid energy management with an effective demand response model [illegible] for entire distribution networks where the demand users can be participating.

Keywords—demand response, RE generation uncertainties, optimization, grid-connected microgrid, generation scheduling

I. INTRODUCTION

[illegible]

II. METHODOLOGY

A. Uncertainty modeling

[illegible]

978-1-6654-[illegible]

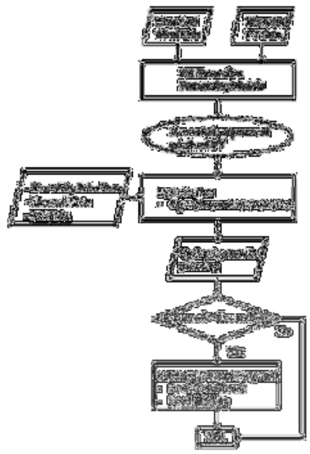


Fig. 1. [illegible]

In the stochastic process, the probability distribution function (PDF), mean, variance values of a random variable are modeled to evaluate the forecasted value [7]. For wind power forecasting, the Weibull distribution function is used in this paper. In the case of PV output, the Beta distribution function is employed to solve the uncertainty problem. The parameters estimation of Weibull PDF is executed by the method of the moment [8]. The Weibull probability distribution function (PDF) is given as

$$PDF_v = k/c\,(v/c)^{k-1}\exp(-(v/c))^k \quad (1)$$

The available wind power density from average wind speed,

$$P/A = 1/2\,\rho c^3\Gamma((k+3)/k) \quad (2)$$

Where k and c are shape and scale parameters of wind speed. ρ is the air density, and A is the area relates to the wind stream.

The output power of solar is achieved as

$$P_t^{PV} = \eta^{PV}S^{PV}I_t(1-0.005(T_t^{out}-25)) \quad (3)$$

Beta PDFs of solar variables is given by

$$PDF_{PV} = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}x^{(\alpha-1)}(1-x)^{(\beta-1)} \quad (4)$$

$$\beta = [illegible] \quad (5)$$

$$\alpha = [illegible] \quad (6)$$

Where α and β are beta distribution parameters. η is the conversion efficiency of the solar array. I_t is solar irradiance.

B. Distribution level demand response

The effect of DR on the distribution system is to improve voltage profile, reduce losses in the network, minimize network congestion, guarantee the system's voltage stability and reliability [7]. Real-time pricing, shown in Fig. 2, is one of DR implementation's required mechanisms. If the consumer knows the price information in next day in advance, the electric consumer can change their consumption pattern [illegible]

The objective function for the generation side,

$$[illegible] \quad (7)$$

Power balance constraint

$$[illegible] \quad (8)$$

Spinning reserve constraint

$$[illegible] \quad (9)$$

Generation capacities constraints

$$P_{PV}^{min} \le P_{PV} \le P_{PV}^{max} \quad (10)$$

$$P_{wind}^{min} \le P_{wind} \le P_{wind}^{max} \quad (11)$$

$$P_{DG}^{min} \le P_{DG} \le P_{DG}^{max} \quad (12)$$

$$P_{grid}^{min} \le P_{grid} \le P_{grid}^{max} \quad (13)$$

P_{RE}, P_{grid}, P_g are the power delivered from RE, grid, and generator. P_d presents the total power from the demand side. P_L and P_G are represented as the line losses and total power from the generation side.

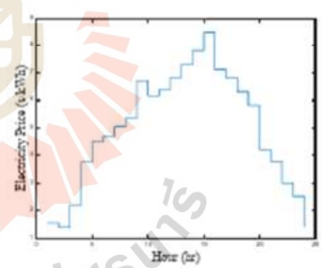


Fig. 2. Hourly Wholesale Electricity Price [11]

TABLE I PARAMETER OF THREE DISTRIBUTED GENERATIONS

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	[illegible]	[illegible]	[illegible]	[illegible]
2	[illegible]	[illegible]	[illegible]	[illegible]
3	[illegible]	[illegible]	[illegible]	[illegible]

2021 International Conference on Power, Energy and Innovations (ICPEI 2021)
October 20-22, 2021, Nakhon Ratchasima, THAILAND

C. Solving algorithm

Biologically evolution-inspired technique, genetic algorithm (GA) and particle swarm optimization (PSO), is powerful tools to handle the optimal operation microgrid due to nonlinear mapping, simplicity, and superior searching capabilities [12]. This paper uses particle swarm optimization (PSO) for optimal RE integrated microgrid operation scheduling. Particle swarm optimization (PSO) inspired the cooperative working behavior of swarm species to search their requirement in the search space. Present positions in their searching space decide the algorithm searches for the best solution to guarantee local best experience (Pbest), global best experience (Gbest), and the swarm particles' next movement. Moreover, the searching positions are accelerated by the factors c_1 and c_2, and the random numbers generated between w_{min} and w_{max} [12].

$$V_{i,j}^{k+1} = \omega V_{i,j}^{k} + c_1 r_1 (Pbest_{i,j}^{k} - X_{i,j}^{k}) + c_2 r_2 (Gbest_{j}^{k} - X_{i,j}^{k}) \quad (14)$$

$$X_{i,j}^{k+1} = X_{i,j}^{k} + V_{i,j}^{k+1} \quad (15)$$

$Pbest_{i,j}^{k}$, and $Gbest_{i,j}^{k}$ represented local best and global best solution, j^{th} component and i^{th} individual, iteration k.

III. RESULTS AND DISCUSSION

In this study, the network connection system is coupled with the demand response model. This local distribution network has three conventional generation units, one wind generation, one solar generation. The generation scheduling period is based on 24 hr advance. However, according to sunshine hours, daily solar generation scheduling interval is from 6 a.m. - 6 p.m. Table 1 shows the conventional generator parameter. The PV and wind output power is forecasted by stochastically process the historical hourly irradiation data and wind speed for a site in Bangkok, Thailand (latitude 13.736717). The forecasted generation capacity of wind and PV are shown in Figs. 3 and 4.

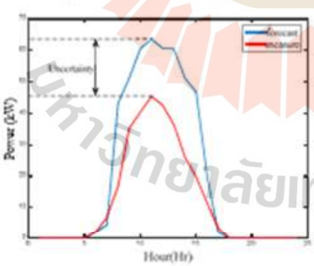


Fig. 3. Hourly forecasted and measured solar generation

Table 2 shows the uncertainty effect on the system's total operation cost at high and low demand periods. The PV and wind standard deviation results in 12.8191and 87.2950 at noon; the actual total production cost increased 30.4294% than the forecast cost. The actual operation cost is lower 31.1151% than the forecast value due to lower standard deviation at 4 p.m. The result mirrors that the generation uncertainty has impacted total production costs. Therefore, DR is an option to implement generation/demand balancing in real-time.

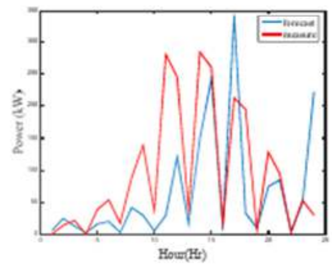


Fig. 4. Hourly forecasted and measured wind generation

Figs. 5 and 6 summarize all energy sources' optimal scheduling in the local distribution system with RE generation uncertainties. The suggested load response and therefore the grid-connected mode are shown more clearly in Figs. 7 and 8. The proposed EMS system sent the suggested information to the demand side at the peak demand time, high price period, and under generation uncertainty. From 9 a.m. - 2 p.m. and from 7 p.m. to 11 p.m., the system operator sent a specific response signal to shift or clip the load. 12 a.m.- 4 a.m. and 5 p.m.-7 p.m. In these periods, the wholesale electricity price and total demand are high and total capacity is not optimal to generate.

TABLE II STANDARD DEVIATION (σ) AND OPERATION COST VARIATIONS

Time	σ_{pv}	σ_{wind}	*Operation cost changes (%)*
12 p.m	12.8191	87.2950	30.4294
2 p.m	17.7944	94.4340	16.1571
4 p.m	5.8978	2.1596	-31.1151
5 a.m	0	15.9157	5.3043

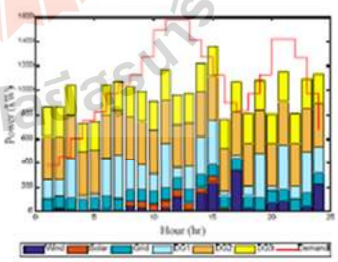


Fig. 5. Optimal scheduling of output power from all generation units with forecasted RE data

The optimal generation capacity provided more energy than total demand capacity between 12 a.m - 6 a.m and 3 p.m -5 p.m. Therefore, the EMS system suggested shifting controllable load to those periods. In this scenario, the electric user can participate in the demand clipping/shifting action with an incentive payment to reduce specific electric bills.

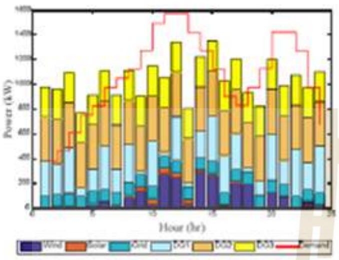


Fig. 6. Optimal scheduling of output power from all generation units with RE actual data

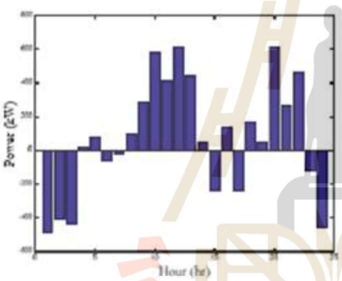


Fig. 7. Hourly generation capacity to implement DR process (from forecast RE data)

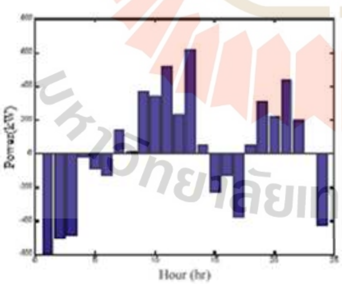


Fig. 8. Hourly generation capacity to implement DR process (from actual RE data)

IV. CONCLUSION

The work highlight in this paper is the optimal allocation of local generation capacity with a demand response model and RE uncertainty in the grid-connected system. In order to tackle RE generation uncertainty, the stochastic method is employed before the optimization process. Firstly, mathematical formulation considered a stochastic method for wind turbine (WT) and photovoltaic (PV) generation. Secondly, generation scheduling problems have been solved by the practical swarm optimization algorithm. Finally, a demand response offering has been presented in this paper. The simulation results reveal that the combination of EMS and the DR allowed the electricity user to participate in the active distribution network and maintained supply-demand balancing under RE uncertainty.

REFERENCES

[1] S. E. Ahmadi and N. Rezaei. "A new isolated renewable based multi microgrid optimal energy management system considering uncertainty and demand response". International Journal of Electrical Power & Energy Systems. vol.118, 2020.

[2] A. S. Farsangi, S. Hadayeghparast, M. Mehdinejad and H. Shayanfar. "A novel stochastic energy management of a microgrid with various types of distributed energy resources in presence of demand response programs". Energy, vol. 160, pp.257-274, 2018.

[3] E. Shahryari, H. Shayeghi, B. Mohammadi-Ivatloo and M. Moradzadeh. "A copula-based method to consider uncertainties for multi-objective energy management of microgrid in presence of demand response". Energy, vol. 175, 879-890, 2019.

[4] S. Zheng, Y. Sun, B. Li, B. Qi, X. Zhang, and F. Li. "Incentive-based integrated demand response for multiple energy carriers under complex uncertainties and double coupling effects". Applied Energy, vol. 283, 2021.

[5] Y. Wang, Y. Huang, Y. Wang, M. Zeng, F. Li, Y. Wang and Y. Zhang. "Energy management of smart micro-grid with response loads and distributed generation considering demand response". Journal of cleaner production, vol. *197*, pp. 1069-1083, 2018.

[6] I. R. da Silva, R. de AL Rabêlo, J. J. Rodrigues, P. Solic and A. Carvalho. "A preference-based demand response mechanism for energy management in a microgrid". Journal of Cleaner Production, vol. *255*, 2020.

[7] B. S. K. Patnam and N. M. Pindoriya. "Demand response in consumer-centric electricity market: mathematical models and optimization problems". Electric Power Systems Research, 2020.

[8] A. Genc, M. Erisoglu, A. Pekgor, G. Oturanc, A. Hepbasli and K. Ulgen. "Estimation of wind power potential using Weibull distribution". Energy Sources, vol. 27, No. 9, pp. 809-822, 2005.

[9] W. Xu, D. Zhou, X. Huang, B. Lou, and D. Liu. "Optimal allocation of power supply systems in industrial parks considering multi-energy complementarity and demand response". Applied Energy, vol. 275, 2020.

[10] N. I. Nwulu and X. Xia. "Optimal dispatch for a microgrid incorporating renewables and demand response". Renewable Energy, vol. 101, pp. 16-28, 2017.

[11] J. Zeng, Q. Wang, J. Liu, J. Chen and H. Chen. "A potential game approach to distributed operational optimization for microgrid energy management with renewable energy and demand response". IEEE Transactions on Industrial Electronics, vol. 66, No. 6, pp. 4479-4489, 2018.

[12] M. N. Alam. "Particle swarm optimization: algorithm and its codes in MATLAB". ResearchGate, vol. 8, pp. 1-10, 2016.

BIOGRAPHY

Ms. Sane Lei Lei Wynn was born in Shan State, Myanmar, on October 14, 1986. She received her bachelor's degree in Electrical Power Engineering from Technological University (Myeik), Myanmar, in 2007 and her Master's degree in Electrical Power Engineering from Yangon Technological University, Myanmar, in 2017. Afterward, she attended Suranaree University of Technology, Nakhon Ratchasima, Thailand, to pursue a Ph.D. in electrical engineering. Her research interests include the smart grid and electricity market.