Coordinated Scheduling and Optimization of Networked Microgrids in Active Distribution Systems

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Abstract

The global shift towards renewable energy sources, such as solar and wind power, along with the increasing adoption of electric vehicles (EVs), is driving transformative changes in modern power systems. These developments are essential for reducing greenhouse gas emissions and advancing the transition towards a sustainable energy future. However, the decentralized and intermittent nature of renewable energy, coupled with the growing demand for EV charging, presents significant challenges in maintaining stability, reliability, and cost-effectiveness within active distribution networks. Traditional power systems, designed for centralized and predictable energy generation, struggle to adapt to these changes, necessitating innovative approaches to energy management.

This thesis develops a comprehensive framework for the coordinated scheduling of networked microgrids, with a focus on the economic and environmental impacts of integrating hydrogen refueling stations and EV charging infrastructure. Microgrids, as localized energy systems that can operate independently or alongside the main grid, offer a promising solution to the challenges of integrating renewable energy. However, managing these microgrids, particularly in the context of EVs and hydrogen refueling stations, requires advanced optimization techniques to ensure that they operate reliably and efficiently while minimizing costs and environmental impacts.

The proposed framework employs a two-stage stochastic programming approach to optimize microgrid operations under varying conditions. The first stage focuses on defining microgrid service areas, taking into account security constraints during emergency scenarios such as grid outages. The second stage addresses energy management, optimizing the integration of renewable energy sources, EV and fuel cell vehicle (FCV) charging stations, and flexible loads. The goal is to balance operational costs, maximize the use of renewable energy, and reduce emissions.

The optimization model is implemented using the GUROBI solver within the GAMS (General Algebraic Modeling System) environment, enabling efficient computation of complex, multi-objective optimization problems. By balancing economic and environmental objectives, the framework provides a robust solution for managing microgrids under diverse conditions.

To validate the framework, simulations were conducted using the IEEE 118-bus test system. This well-established benchmark represents a large-scale power grid and allows for rigorous testing of the framework's performance in real-world scenarios. Simulation results demonstrate significant improvements in both economic and environmental performance. Specifically, the integration of flexible loads and smart EV and FCV charging strategies reduced operating costs by approximately 4.77% and emissions by 49.13%.

These findings underscore the potential of the proposed framework to contribute to sustainable energy management by providing a scalable approach for optimizing microgrid operations. By promoting economic efficiency and supporting the integration of clean energy technologies, this research aligns with global efforts to decarbonize power systems and reduce reliance on fossil fuels. Additionally, the integration of hydrogen refueling stations within microgrids offers new opportunities for energy storage and management, further supporting the transition to a low-carbon transportation sector.

In conclusion, this thesis makes a significant contribution to sustainable energy management by developing a robust framework for the coordinated scheduling of networked microgrids. The integration of hydrogen refueling and EV charging infrastructure enhances grid flexibility and resilience, while advanced optimization techniques ensure that economic and environmental goals are achieved. Validation of the framework using the IEEE 118-bus test system confirms its applicability to real-world power systems. The findings highlight the critical role of microgrids in the global transition to cleaner, more sustainable energy systems.

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Finally, I dedicate this thesis to my family, whose love, patience, and unwavering belief in me have been my greatest source of strength. This work is a testament to their support and sacrifices.

Co-authorship Statement

I am the principal author of all the research papers used in the preparation of this thesis. My thesis supervisor, Dr. Ashraf Ali Khan, and my co-supervisor, Dr. Mohsin Jamil, are co-authors. As the principal author, I conducted the majority of the research, performed literature reviews, carried out the designs, simulations, and result analysis for each manuscript. I also prepared the original manuscripts and revised them based on feedback from my supervisors and peer reviewers throughout the review process. Dr. Mohsin supervised the entire research project, reviewed and corrected each manuscript, provided research components, and contributed ideas throughout the research and manuscript preparation. The primary contribution of this thesis lies in developing a comprehensive framework for the coordinated scheduling of networked microgrids, with a focus on the integration of hydrogen refueling stations and electric vehicle (EV) charging infrastructure.

List of Publications

- R. Parsibenehkohal, M. Jamil, and A. A. Khan, "A Multi-Stage Framework for Coordinated Scheduling of Networked Microgrids in Active Distribution Systems with Hydrogen Refueling and Charging Stations," International Journal of Hydrogen Energy, vol. 71, pp. 347-356, 2024.
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List of Abbreviations

AC	Alternating Current
DC	Direct Current
EMS	Energy Management System
EV	Electric Vehicle
FCV	Fuel Cell Vehicle
GHG	Greenhouse Gas
HEV	Hybrid Electric Vehicle
LCL	Inductor-Capacitor-Inductor
LCC	Inductor-Capacitor-Capacitor
MG	Microgrid
MILP	Mixed-Integer Linear Programming
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PMS	Power Management System
SOC	State of Charge
TOU	Time of Use
VSC	Vehicle Stability Control
WTG	Wind Turbin Gearboxes
DG	Distributed Generation
PV	Photovoltaic
DC-OTS	DC Optimal Transmission Switching
CTS	Corrective AC Transmission Switching

TVA	Tennessee Valley Authority
ERCOT	Electric Reliability Council of Texas
RTCA	Real-time Contingency Analysis
DRP	Demand Response Program
PEV	Plug-in Electric Vehicle
RTS	Reliability Test System
SDP	Semidefinite Program
VSC	Voltage Source Converter
TCR	Thyristor Controlled Reactor
TSR	Thyristor Switched Reactor
IGBT	Insulated-Gate Bipolar Transistor
CCGT	Combined Cycle Gas Turbine
GUROBI Solver	Gurobi Optimizer is a Prescriptive Analytics Platform
GAMS	General Algebraic Modeling System

List of Symbols

$I_{n,k}^{Bus}$	Busbar number n in Grid K
$I_{m,n,k}^{Line}$	Line Between busbar m & n in Grid K
$\tilde{P}_{i,t,s}^{Load}$	The predicted amount of load for active and reactive power
$P_{n,t,s}^{Flex}$	Flexible load
$I_{b,n,t,s}^{Block}$	Load change blocks
P_{g}^{DG}	utilization of power plants
$P_{w,t,s}^{Wind}$	Wind generation
$P_{pv,t,s}^{Pv}$	Solar generation
$E_{e,t,s}$	Energy levels that can be charged in the battery of the storage system
$H_{s,t}^{El}$	The quantity of hydrogen produced by these small-scale P2H units
$P_{s,t}^{El}$	Electrolyzer's power consumption
$E_{s,t}^{H}$	The hydrogen levels during station operations within predefined thresholds,
$P_{l,t,s}^{Line}$	Power that can pass through the lines
$P_{k,t,s}^{Grid}$	Power exchange with the main grid
$I_{k,t,s}^{Buy}$	Purchasing power from the main grid
$I_{k,t,s}^{Sell}$	Selling power to the main grid
$B_{l,k}$	State variable of the lines
$V_{n,t,s}$	Voltage magnitude
$\theta_{n,t,s}$	Voltage angle

Chapter 1: Introduction and Literature Review

1-1 Introduction

Nowadays, significant changes are emerging in power systems. The presence of solar resources, wind farms, and geothermal resources at the transmission level, and small renewable energy sources like fuel cells and solar cells at the distribution level, is increasing day by day. This growing presence of renewable resources in distribution systems has created a new network structure called microgrids [1]. Microgrids are small power networks composed of several renewable energy sources and local loads. Microgrids are generally connected to one of the distribution network buses under normal conditions; however, in emergencies, in case of major disturbances, they disconnect from the power network and supply some loads (important loads). The energy sources used in microgrids are connected to the main bus via power electronic converters, and the injected power to the main bus is controlled through these converters [2].

With the increasing use of renewable energy sources in microgrids, the coordination of these sources with electronic power raises major concerns regarding network stability and reliability issues [3]. Considering recent developments in the energy industry and the significant increase in installed capacity worldwide, reliability and availability have become crucial factors for renewable energy sources to be cost-effective and competitive with conventional technologies. The increase in installed capacity and the development of wind farms have raised significant concerns in various areas to achieve the goals of asset and equipment maintenance of wind farms and ensure long life cycles. Maintenance and repairs performed on a system are important and effective factors in its reliability and availability and play a key role in the production capacity achieved by wind farms [4]. The concept of reliability is the probability that components, equipment, products, or systems will perform their predetermined tasks without failure in a specified environment for a period of time under a certain number of cycles or stresses [5]. On the other hand, to develop investment in renewable energy in microgrids, investors' income to cover investment costs is of high importance. Given the change in electricity consumption peaks, investors may not have the necessary income during some consumption peaks and may be forced to increase electricity prices suddenly, leading to customer dissatisfaction. Therefore, investment in production development needs incentives to cover investment and fixed costs, providing a basis for improving system reliability and load supply. Thus, precise planning is needed to provide the required capacity to supply customers' loads with appropriate reliability indices through competitive mechanisms, creating favorable conditions for both investors and customers. The capacity market, in addition to power plant capacity, can also consider load management and control programs (demand-side management resources) as complementary solutions for capacity provision. Therefore, by signing long-term contracts with distribution companies and large industries to reduce or cut their loads to ensure capacity provision, the high costs of building power plants can be reduced, and desirable reliability indices can be achieved.

In recent years, power system research has shifted towards evaluating reliability and security due to the increasing occurrence of natural disasters such as earthquakes, storms, and floods caused by climate change. Therefore, new indices have been proposed to enhance the flexibility and reliability of power systems, and the issue of flexibility has been widely examined by integrating smart grid technologies to improve network flexibility. Hence, indices such as analyzing the number of lines removed due to faults and system recovery after faults have been introduced to examine the possibility of islanding operation for critical conditions [6,7].

1-2 Motivation

The rapid proliferation of renewable energy sources, such as solar and wind power, has significantly transformed the landscape of modern power systems. These energy sources are becoming increasingly prevalent due to their environmental benefits and their ability to reduce dependence on fossil fuels. However, the shift towards renewable energy is not without its challenges. One of the most significant obstacles in the widespread adoption of renewable energy is the inherent variability and intermittency of resources like wind and solar. Unlike traditional energy sources, which can be dispatched according to demand, renewable energy production is highly dependent on weather conditions and time of day. As a result, maintaining the stability, reliability, and efficiency of power distribution networks has become increasingly complex. This transformation has created a pressing need for new strategies and technologies capable of managing the fluctuating nature of renewable energy resources.

Traditional centralized power systems were designed to accommodate large, controllable power plants that generate electricity in a predictable and consistent manner. These systems are often ill-equipped to manage the decentralized and unpredictable nature of renewable energy sources. In a centralized grid, power flows from a few large plants to consumers, but with the rise of distributed renewable generation, electricity is produced at many smaller sites scattered across a wider geographical area. This decentralized structure creates additional strain on the grid, which must now balance energy production and consumption dynamically, often on a second-to-second basis. These challenges highlight the need for innovative energy management solutions that can accommodate the growing share of renewable energy in modern power systems.

One promising solution to these challenges is the deployment of microgrids. Microgrids are localized energy systems that can operate independently or in conjunction with the main power grid. Their ability to function autonomously during grid outages or instability makes them a valuable tool for enhancing grid reliability and resilience. Microgrids can integrate various energy resources, including renewable sources like solar and wind, energy storage systems, and traditional generators. By generating power close to the point of consumption, microgrids can reduce transmission losses, enhance system efficiency, and improve the overall integration of renewable energy resources into the grid.

Despite their benefits, the effective management and coordination of microgrids remain complex, particularly in active distribution systems. The variability of renewable resources introduces significant challenges in balancing supply and demand within a microgrid. On sunny or windy days, renewable energy production may exceed demand, leading to potential energy curtailment or the need for storage solutions. On cloudy or calm days, renewable output may fall short of demand, necessitating backup generation or power imports from the main grid. The dynamic nature of renewable energy requires advanced control strategies to ensure that microgrids can operate efficiently under varying conditions.

Additionally, the growing adoption of electric vehicles (EVs) adds another layer of complexity to the management of microgrids. As EVs become more popular, the demand for electricity to charge these vehicles increases, placing additional strain on the power grid. EV charging, particularly if done without coordination, can lead to significant peaks in electricity demand, exacerbating the challenges of integrating renewable energy. On the other hand, EVs also present opportunities for enhanced energy management. Vehicle-to-grid (V2G) technology, for example, allows EVs to act as mobile energy storage units, discharging electricity back into the grid during peak demand periods. This capability can provide valuable flexibility to the grid, helping to smooth out fluctuations in renewable energy production.

Hydrogen refueling stations also introduce new opportunities for microgrids. Hydrogen is increasingly seen as a key component of the future low-carbon energy system due to its potential for long-term energy storage and its applications in sectors such as transportation and industry. Hydrogen refueling stations, when integrated into microgrid systems, can store excess renewable energy in the form of hydrogen during periods of surplus production. This stored hydrogen can later be converted back into electricity or used directly as a fuel, thus providing a flexible energy reserve that can help balance supply and demand in the microgrid. The integration of hydrogen technology into microgrids aligns with global efforts to reduce greenhouse gas (GHG) emissions and promote sustainable energy practices, particularly in sectors that are harder to electrify, such as heavy transport and industry.

The motivation for this research stems from the critical need to develop robust frameworks that can efficiently manage the operation of networked microgrids in the face of these challenges. The increasing penetration of renewable energy sources, the growing demand for EV infrastructure, and the potential of hydrogen as a clean fuel source all create complex, dynamic systems that require advanced optimization strategies. Existing energy management systems are often inadequate to handle the complexities introduced by these new technologies, particularly in distributed, decentralized networks where local energy resources must be carefully coordinated to maintain system stability and reliability.

The complexity of managing networked microgrids lies in the need to balance multiple, often competing, objectives. On the one hand, there is the economic imperative to minimize operational costs, maximize the use of renewable energy, and reduce the reliance on expensive, carbon-intensive backup generation. On the other hand, there is the environmental imperative to minimize GHG emissions, which often requires prioritizing renewable energy even when it may not be the most cost-effective option. Achieving a balance between these objectives is no easy task, particularly given the variability and uncertainty inherent in renewable energy production. The development of optimization frameworks that can navigate these trade-offs is therefore essential for the future of microgrid management.

Furthermore, microgrids must also be designed to handle emergency scenarios, such as natural disasters or grid failures, where they may need to operate in island mode for extended periods. In these situations, ensuring the reliability and security of the microgrid becomes paramount, as it may be the sole source of electricity for critical infrastructure and services. The framework developed in this research addresses these concerns by considering the security constraints of microgrids in emergency conditions, ensuring that they can maintain reliable operation even when isolated from the main grid.

In addition to addressing these technical challenges, this research is also motivated by the broader context of global efforts to transition to cleaner, more sustainable energy systems. Governments and organizations around the world are increasingly recognizing the importance of reducing GHG emissions to combat climate change. The integration of renewable energy, electric vehicles, and hydrogen technologies into microgrid systems offers a pathway to achieving significant emissions reductions while also improving energy security and system resilience. By developing frameworks that optimize the operation of networked microgrids, this research contributes to the ongoing transition to sustainable energy systems that are capable of meeting the demands of a rapidly changing energy landscape.

In conclusion, the motivation for this research is rooted in the need to address the challenges posed by the increasing integration of renewable energy sources, electric vehicles, and hydrogen refueling stations into modern power systems. Microgrids offer a promising solution to these challenges, but their effective management requires sophisticated optimization strategies that can balance economic, environmental, and security objectives. By developing robust frameworks for the coordinated scheduling of networked microgrids, this research aims to contribute to the development of sustainable, resilient energy systems that are equipped to handle the complexities of the future energy landscape.

1-3 Literature Review

In recent years, there has been an increasing focus on developing modern and flexible distribution systems that can support renewable energy sources. In the literature review [8], the importance of infrastructure development in the production, transmission, distribution, and consumption sectors has been highlighted, and a research and development plan focusing on modernizing the distribution network and supporting renewable energies while maintaining reliability and availability has been presented [8].

In [9], the flexibility of microgrids to achieve a flexible distribution system has been proposed in a conceptual approach. The analysis presented in this paper includes three practical examples of increasing flexibility using microgrids, showing that communities can use the power system in more modern distribution systems without losing operational capabilities in case of faults and quickly returning to normal conditions.

In [10], the role of microgrids in enhancing system reliability during severe events has been discussed. This paper suggests that microgrids can increase system flexibility and robustness against fluctuations. Various approaches to increasing the flexibility of distribution systems have also been proposed.

In [11], hardware solutions and smart grid ideas for improving system flexibility through network reconfiguration, microgrids, and distribution automation have been discussed. In [12], a decision-making framework for network modernization and system performance improvement during restoration operations has been presented. In [13], a method for measuring resilience has been proposed, and various methods have been compared in terms of feasibility. In [14], cost and demand planning in the power system through an optimization model based on a mixed-integer linear program has been prepared, and an optimal development plan considering the installation of each large-scale power plant and DG sources has been presented.

In [15], the improvement of reliability and wind power production based on real-time has been addressed. This research examines a fuzzy artificial method for evaluating real-time conditions of wind turbine gearboxes (WTG). In [16], relative development and transmission planning considering system reliability and line maintenance have been addressed. This research examines the economic and reliability effects of line maintenance in transmission and production planning, considering the reliability of transmission and production systems.

In [17], a new stochastic super fuzzy framework for managing renewable microgrid energy based on the maximum deployment of electric vehicles has been presented. This paper attempts to formulate, model, and operate renewable microgrids considering various renewable sources, including solar units, wind units, and storage in the presence of electric vehicles. In [18], the effects of integrating electric vehicles on protection coordination in microgrids have been evaluated. The main contribution of this paper is the precise assessment of the impact of EVs on short-circuit levels and protection coordination schemes in microgrids. For this purpose, a method for measuring the impact of EVs on protection coordination schemes in microgrids using various evaluation indices has been proposed.

In [19], the optimal coordination of protective devices in distribution networks with distributed energy resources and microgrids has been evaluated. This paper proposes a mathematical model for the optimal coordination of protective devices in distribution networks with distributed energy resources operating in both grid-connected and islanded modes. However, these studies mainly discuss the topological structure of distribution systems and do not consider the electrical characteristics or the potential and nature of incidents appearing in the system.

Ref. [20] uses graph theory to evaluate the flexibility of the distribution system in a multi-criteria decision-making problem. In [21], microgrids with free production capacity were used to supply sensitive demand in feeders after a severe event. In [22], the optimization of support services in smart distribution networks has been examined to determine how the frequency reduction settings of distributed generation resources should be adjusted to restore maximum load. In [23], optimal scheduling for energy management in microgrids has been studied, while [24] proposes an approach for flexible scheduling of stationary microgrids. Reference [25] discusses the use of microgrids in the dynamic state of distribution systems.

In [26], a new structure of microgrids was introduced to simplify their proper scheduling. Finally, a new framework for daily scheduling of a smart distribution system based on robust optimization was examined in [27] to secure system operations under uncertainty. In [28], a conceptual approach for making changes to achieve a flexible distribution system through microgrids was presented. This review refers to three practical examples of resilience enhancement concepts and their practical results. The obtained results show that communities can use the power system in modern distribution systems without losing operational capabilities during faults and quickly return to normal conditions.

In [29], the resilience evaluation of the distribution system was modeled as a multi-criteria decision-making problem and calculated using graph theory. However, the method presented in this review mainly discusses the structural features of distribution networks and cannot adequately represent the electrical characteristics, existing capabilities, and nature of events in this part of the power network. In [30], the optimal scheduling problem for energy management in microgrids was examined. The objective function considered in this review is to minimize net operational costs considering the uncertainty of renewable energy sources. However, the possibility of severe events is not considered in this review.

In [31], an effective approach for flexible scheduling of static microgrids was presented. However, this study did not examine the geographical status of the distribution network and its limitations. In [32], the issue of constructing microgrids in dynamic distribution networks from the perspective of energy management and optimal use of renewable energy sources was discussed.

In [33], a new framework for microgrids was proposed to simplify optimal scheduling, and demand response programs were used to reduce consumer costs and adjust peak loads. Additionally, a new framework for daily scheduling of a smart distribution network based on a robust optimization approach to secure system performance against the worst conditions of uncertain variables was presented in [34].

In [35], the strategic integration of battery energy storage systems with distributed ancillary services in active distribution systems was examined. This paper presented a two-level optimization framework for the optimal allocation of wind energy generation units and energy storage systems with central and distributed ancillary services in distribution systems.

In [36], the reduction of power losses through the optimal placement of batteries in a distributed network with high photovoltaic system penetration was examined. This paper reviewed system losses and power quality issues related to high PV deployment in a distribution network, and using a genetic algorithm, the placement of BESS capacity was performed, and a brief step-by-step analysis was provided to show the effectiveness and robustness of the proposed method in reducing incremental system losses with increasing PV penetration. In [37], an optimal model for improving the reliability of radial distribution systems by determining the optimal location and capacity of energy storage systems using the TLBO algorithm was presented. The formulation of this problem includes the cost of unserved energy (CENS), additional costs such as investment and operational costs of ESS (lifecycle cost), and power losses in the distribution system.

The shift towards clean energy alternatives has accelerated in recent years due to increasing concerns about pollution emissions. Many organizations and countries have implemented initiatives to reduce their carbon footprint, leading to increased adoption of green energy sources and optimal planning practices [38]. One example of this approach is the hybrid wind turbine and photovoltaic system, which in [39] shows the potential share of renewable energies in operator profits. Another approach is the reconfiguration of energy networks, which was examined in [40] with the aim of increasing the share of renewable energies.

As a multifunctional complementary system, in [41], a multi-objective framework for electric and natural gas infrastructure, along with a hybrid biogas-solar renewable system, was presented to create thermodynamic connections and interactions with electrical, gas, and thermal consumption. In [42], the issue of energy supply planning in the presence of distributed wind and solar generation, electric energy storage systems, and demand response programs on an 83-bus distribution network was examined in a three-objective model.

According to the results of [43], photovoltaic arrays installed on customer rooftops can offer benefits such as return on investment and reduced electricity prices. In addition to solar and wind energy, other complementary systems are being examined to meet energy demand while reducing pollution emissions. For example, a hybrid electricity-gas-biomass system was proposed in [44] as a multifunctional approach to energy production.

Meanwhile, optimal scheduling in the day-ahead market to minimize costs was examined in [45], focusing on the potential of renewable energies. In [46], comprehensive coordination of the resilience of radial distribution networks in the presence of distributed generation sources using fault current limiters was examined. This paper proposed a coordination algorithm to adjust the time multiplier settings (TMS) and current settings of protective devices, such as overcurrent relays, reclosers, and fuses, to overcome common issues with SMDG installations, such as disturbance interruptions and fuse blowing.

In [47], an analytical method for evaluating reliability in smart grids, including renewable and non-renewable distributed sources and plug-in hybrid electric vehicles, was presented. The main contribution of this paper is the proposal of a new state matrix method (S-matrix) including a new model for examining the operational states of the smart grid using partitioning concepts and graph theory. In [48], the challenge of integrating renewable energies into power system protection and reducing it for reliable operation was examined. This paper introduces an alternative protection scheme that can operate regardless of the connected or islanded state of the distribution network and updates relay settings and trip currents based on shared connection information.

In [49], optimal distributed oscillation control based on data in islanded AC microgrids without the need for precise model parameters to enhance their reliability was examined. According to this model, the frequency controller quickly restores the frequency and ensures accurate active energy sharing. This paper presented a dual dynamic programming model using a neural network that increases system stability. Additionally, the convergence of the proposed algorithm and system stability, data-based error analysis, is examined.

In [50], the evaluation and review of investment in renewable energy sources and green financing for the deployment of solar energy in residential buildings was examined. This paper, using the wavelet power spectrum approach, shows that IRE, REEO, and GFi fluctuate more compared to GDP and EIPP during the selected time period. In [51], the environmental and economic analysis of grid-connected photovoltaic power systems with silicon solar panels, in line with Iran's new energy policy, was examined. This work aims to provide a comprehensive review of the use of renewable sources from an energy perspective and its prominent policies.

In [52], the replacement of hard coal with wind and nuclear energy in Finland and its impact on electricity and district heating markets was examined. This paper models the impacts of this transition in electricity markets and DH systems and develops scenarios with large-scale transitions to wind and nuclear heat pumps and heat pumps in DH systems. In [53], the economic analysis of integrating a network of variable solar and wind energy with the conventional power system was examined. This paper quantitatively examines the costs of integrating wind and solar energy on both the demand and supply sides using an economic energy model along with Monte Carlo simulation.

In [54], the impact of replacing thermal power plants with renewable energies on the power system was examined. This paper examines the impacts of increasing renewable energy sources up to 20% after sudden changes in production on the frequency control of Egypt's power system. In [55], the power system production planning scenarios of Croatia, including the integration of renewable and traditional power plants until 2030, were simulated using DIgSILENT software.

Simulations show that the load-frequency control system may not perform adequately. In [56], a hybrid wind-solar-tidal system was developed using the Multi-Objective Adaptive Guided Differential Evolution method. In [57], the optimization of a multi-objective hybrid system with a hybrid energy storage source using MOEA-DM optimization was addressed. Thermal energy and battery sources were used for energy storage in this system. The objectives of this study are cost, reliability, and storage.

In [58], the optimization of the size of an off-grid hybrid system considering the uncertain amount of energy produced from renewable sources and the uncertain amount of load consumption was addressed. This paper used Monte Carlo simulation based on the particle swarm optimization algorithm.

In [59], the optimization of a hybrid wind-solar system with battery support using a multi-objective genetic optimization algorithm was addressed. The objectives considered in this study are cost, reliability, and the probability of losing energy sources. In [60], the optimization of a grid-connected hybrid wind-solar-battery system using the energy reliability-constrained (ERC) method with the aim of reliability and cost was addressed. The study area is a residential building in a Mediterranean climate. In [61], the optimization of an off-grid hybrid solar-wind-battery system using the genetic-particle swarm algorithm and the multi-objective particle swarm algorithm was addressed. The objectives considered in this study are minimizing cost and maximizing reliability.

In [62], the optimization of a grid-connected hybrid solar-wind system considering the objectives of minimum cost, pollution, and maximum reliability was addressed. The solution method used in this study is the multi-objective particle swarm optimization algorithm. The study area in this paper is a village in the Ismailia province of Egypt. Overall, these studies highlight the significant potential of renewable energies to reduce pollution emissions and improve sustainability in the energy sector.

Shukla et al. [63] proposed an integrated approach for using electric vehicles and energy storage devices to efficiently control load frequency in isolated hybrid microgrids. They introduced a fractional-order proportional-integral-derivative (FOPID) controller for frequency regulation in hybrid microgrids (HMG). Additionally, they suggested a modified virtual rotor (MVR) concept to enhance system inertia. The study utilized particle swarm optimization (PSO) to fine-tune the controller gains. The proposed controller was compared with several fixed control strategies, including PID, PI-PD, and PIDF controllers. The performance of electric vehicles (EVs) integrated with various energy storage systems, such as superconducting magnetic energy storage (SMES), capacitive energy storage (CES), and redox flow batteries (RFB), was evaluated under both steady and variable load profiles. The study showed that the FOPID controller significantly improved settling time, peak reduction, and performance indices compared to PID, PI-PD, and PIDF controllers.

Mohamad et al. [64] introduced a new load frequency control scheme for a multi-microgrid power system using electric vehicles and supercapacitors. They proposed a centralized fractional-order proportional-integral controller combined with a virtual inertia simulator (C.FOPI + VI). The virtual inertia simulation was achieved using a supercapacitor (SC) along with electric vehicles (EVs) controlled by a virtual inertia controller. The control system was applied to three interconnected microgrids, each containing a thermal power plant, a supercapacitor, and an electric vehicle aggregator. The proposed control technique was compared with five different inertia simulation topologies: virtual inertia (VI), virtual synchronous generator (VSG), distributed fractional-order proportional-integral with virtual inertia (D.FOPI+VI), distributed fractional-order proportional-integral with virtual synchronous generator (D.FOPI+VSG), and without artificial inertia. The transit search optimization algorithm (TS) was used to optimize the controller parameters. The C.FOPI+VI demonstrated superior performance in providing fast frequency recovery, reducing stress on conventional generating units, and minimizing disturbance propagation. It also increased the gain margin (G.M) compared to other methods.

Aslam et al. [65] presented a new multi-level dynamic decomposition-based coordinated control scheme for electric vehicles in multi-microgrids. They proposed a four-level dynamic decomposition-based control approach for the coordinated operation of electric vehicles in multi-microgrids. This approach is comprehensive, general, modular, and secure, aiming to maximize the use of renewable energy sources while meeting load demands. Each microgrid consists of several renewable energy sources, energy storage systems, non-renewable energy sources, electric vehicles, and loads, all controlled by micro-source controllers. The proposed control scheme was validated through simulation-based case studies.

Pan et al. [66] proposed a coordinated energy control scheme for an integrated DC microgrid including PV, energy storage, and EV charging. They investigated a coordinated energy control strategy for an independent DC microgrid integrated with PV, energy storage, and EV charging. The study proposed maximum power point tracking (MPPT) control strategies using a variable step perturb and observe method to shorten the PV unit's settling time. An improved droop control based on the state of charge (SOC) of the batteries was designed, along with secondary voltage bus recovery and power equalization controls to enhance DC bus voltage regulation. Simulation results showed that the proposed coordination control strategy effectively improved the stability of the DC microgrid system and reduced the redundancy of the energy storage device capacity.

Mohammed et al. [67] proposed an accurate reactive power sharing strategy for islanded AC microgrids based on droop control. They suggested an optimal tuning of the virtual complex impedance for each inverter to address disproportionate feeder impedances. The proposed strategy established an explicit relationship between the mismatched values of the actual resistive-inductive feeders and the assigned values for the virtual complex impedance. It did not require prior knowledge of the actual feeder impedances, as they were estimated online. The proposed control was reliable and fault-tolerant, ensuring accurate reactive sharing even in primary control. Simulation results and experimental validation confirmed the performance of the proposed technique.

Alzahrani et al. [68] investigated power loss reduction through optimal battery placement in a distributed network with high photovoltaic penetration. They examined system losses and power quality issues associated with high PV deployment in an IEEE 33-bus distribution network. Using a genetic algorithm, they optimized the placement of battery energy storage systems (BESS). The study demonstrated the effectiveness and robustness of the proposed method in reducing system losses with increasing PV penetration. A comparative study quantified the impact and effectiveness of centralized and distributed BESS placement, showing significant system loss reduction, especially for distributed BESS placement.

Santi Mari Anthony et al. [69] evaluated dynamic model predictive controllers for frequency regulation of an isolated microgrid with electric vehicles and ESS integration. They presented two innovative control techniques: model predictive control (MPC) and dynamic droop control

(D2C) to address frequency regulation in an independent microgrid. The combined MPC and D2C settings were tuned using a complex evolutionary technique. The study modeled and evaluated a single microgrid using MATLAB/Simulink, validating the integration of D2C and MPC. Comparison results showed that MPC outperformed fuzzy proportional-integral (FPI) and proportional-integral (PI) controllers.

Singh et al. [70] presented a frequency regulation strategy for a two-area microgrid system supported by electric vehicles using a novel fuzzy-based two-stage controller and a modified dragonfly algorithm. The research aimed to develop a new frequency regulation (FR) approach for biogas (wind) diesel engines, organic Rankine cycle (ORC), and two-area islanded microgrids based on solar energy with EVs in both areas. This paper introduces a fuzzy logic controller (FLC) for FR with scaling factors as proportional-integral (PI) and proportional-derivative with filter (PDF), forming an FLC-SF-PI-PDF controller. The modified dragonfly algorithm was used to determine the optimal values for the controller parameters. The effectiveness of the proposed controller was demonstrated with and without the presence of EVs. The paper also examines various uncertain conditions, nonlinearities, and eigenvalue stability analysis to confirm the superiority of the proposed approach.

Salama et al. [71] presented an adaptive coordination control strategy for renewable energy sources, hydrogen production units, and fuel cells for frequency regulation in a hybrid distributed power system. This paper proposes an adaptive coordination control strategy for renewable energy sources (RES), an electrolyzer (AE) for hydrogen production, and a fuel cell-based energy storage system (ESS) to enhance frequency stability in hybrid generation systems (HGS). In the proposed system, excess energy from RES is used to power the electrolyzer through an AE to store hydrogen energy in FCs. The proposed method is based on a proportional-integral (PI) controller optimally designed using the grey wolf optimization (GWO) algorithm to estimate excess energy from RES. The studied HGS includes various generation systems such as diesel generators, wind turbines, photovoltaic (PV) systems, AE with FCs, and ESSs (e.g., batteries and flywheels). The proposed method adjusts Kn with variable frequency deviation values to achieve the best benefits from RES while reducing frequency fluctuations. The proposed method is validated under different loading conditions and compared with other studies that consider Kn as a fixed value. Simulation results show that the proposed method, which adjusts Kn and subsequently stores the extracted power from RES in hydrogen energy storage according to frequency deviation changes, performs better than methods using a fixed Kn. Statistical analysis for frequency deviation in HGS with the proposed method shows the best values and achieves significant improvements in minimum, maximum, difference between maximum and minimum, mean, and standard deviation compared to the existing method.

Kaur et al. [72] presented a frequency control scheme in microgrids based on a coordinated fuzzy electric vehicle charging station. This study proposes an intelligent controller based on fuzzy logic systems (FL) to effectively reduce frequency deviations in microgrids. The proposed controller is applied to plug-in electric vehicles (PEV) to tightly control their charging/discharging power at all times. In this study, PEVs are considered dynamic energy storage elements participating in the frequency control process in the microgrid. Each PEV is connected to the microgrid through a dedicated frequency control unit (FCU). The FCU mainly consists of an FL controller, a battery management system (BMS), and frequency detection links. The FL controller acts as the main decision-making agent, determining the reference charging/discharging power for each PEV. Two important aspects were considered when designing the FL controller. The obtained simulation results demonstrate the effectiveness of the FL-controlled fleet of PEVs in regulating microgrid frequency even during severe contingencies.

Li et al. [73] presented a distributed secondary frequency control method based on consensus for AC microgrids using the ADRC technique. This paper proposes a new distributed secondary frequency control approach for islanded microgrids, aiming to eliminate frequency deviation under droop control with better disturbance rejection performance. Unlike many traditional approaches that rely on an accurate control model, the proposed method requires minimal model information due to the model-independent nature of the active disturbance rejection control (ADRC) technique. A linear extended state observer is introduced to estimate the unmodeled dynamics (including unknown disturbances, unmodeled dynamics, and nonlinear dynamics), which are then compensated in the control input. After active compensation, the nonlinear frequency control model can be transformed into a quasi-linear model, based on which a distributed proportional control algorithm is developed for frequency recovery and active power sharing among DGs. Simulation results based on a four-inverter microgrid show that the proposed approach achieves satisfactory frequency recovery, active power sharing, and disturbance rejection performance.

Wan et al. [74] presented an improved second-order consensus-based distributed secondary frequency controller for virtual synchronous generators in isolated AC microgrids. This paper proposes a second-order consensus-based distributed secondary frequency controller by introducing second-order consensus control of active power and demonstrates the oscillation suppression capability of the second-order consensus algorithm in depth. Since there are no specific control requirements for second-order variables, i.e., the rate of change of active power and MG frequency in the steady state, the proposed controller can be simplified by replacing the integral control of second-order variables with proportional control of first-order variables, i.e., active power and frequency. Therefore, the communication data volume does not increase compared to traditional first-order consensus-based controllers. This paper also presents a small-signal model of the MG with the proposed controller to evaluate the system's dynamic performance and design parameters. Finally, simulation results confirm the effectiveness of the proposed controller.

Eydi et al. [75] presented a novel communication-free control method for voltage and frequency regulation in DC microgrids based on AC signal injection. This paper proposes a new communication-free control method to address voltage and frequency regulation concerns in microgrids. Energy storage units are controlled by local parameters to ensure system stability. In this method, one unit (the transmitter unit) estimates the DC bus voltage deviation and injects an AC signal into the DC bus. The droop curves of the units are shifted based on the AC signal and their SOC. The shifted values are determined so that units with higher SOC inject (absorb) more (less) power, and the DC bus voltage is restored. Stability analysis and system step response show that the proposed method has acceptable stability and satisfactory speed. Simulation results confirm that the proposed method can regulate the DC bus voltage and reduce SOC imbalance among units without any communication links or central controller.

Khan et al. [76] presented an advanced distributed voltage regulation scheme for radial feeders in islanded microgrids. This paper proposes an improved distributed control strategy to restore load voltage levels and achieve proportional power sharing in islanded microgrids. The study considers voltage regulation at the load node instead of the inverter terminal. Additionally, a supervisory control layer is implemented to monitor and correct load voltage deviations and system frequency. The goal of this method is to replace the parallel inverter control methods used so far. Stability analysis using systematic small-signal models and experimental results obtained with conventional and proposed control schemes confirm the effectiveness of the proposed method. Khemok et al. [77] presented a microgrid control model using robust data-driven controllers for distributed electric vehicles. This paper proposes an approach for voltage and frequency regulation in microgrids using data-driven controllers for distributed EVs. Without requiring any microgrid parameters, uncertainty information is monitored based on operational changes so that key stability indices, namely damping and robustness, can be automatically calculated. Considering these indices, adaptive control techniques are used to design the controllers. The proposed adaptive data-driven controller is compared with a controller designed considering the full dynamics of converter models. Simulation results in a microgrid with renewable energy sources and distributed EVs under various operational points and uncertainties confirm the effectiveness of the proposed approach.

Baharifard et al. [78] discussed smart charging scheduling for commercial electric vehicle parking lots and its impact on distribution network imbalance indices. This paper proposes a two-stage framework where the first stage involves several technical parameters such as battery conditions, charge/discharge specifications, and transportation parameters including daily travel distance, arrival and departure times at the CPL, and the number of EVs. Consequently, the sales and profitability of the EV charge/discharge schedule for EV users and CPL owners are calculated in the optimal CPL scheduling. In the second stage, the effect of CPLs is examined by calculating imbalance indices in a standard IEEE unbalanced distribution network. Additionally, the results confirm that the average profit for EV users increased by 23% compared to the total cost paid for charging the vehicle. Finally, it was found that without changing the distribution network structure and connecting the CPL to active commercial loads of the distribution network, the network imbalance could be improved by about 30% during EV charging. Table 1-1 shows the summary of all of these methods in a window.

Table 1-1: Comparison of different methods

Approach/Method	Advantages	Disadvantages
Microgrids for Distribution Flexibility	Increases reliability and operational flexibility during faults; enables quick return to normal conditions	May not account for electrical characteristics and incident nature in system planning
Hardware Solutions and Smart Grids	Enhances system flexibility through automation and network reconfiguration	Implementation complexity and high costs
Decision-Making Framework for Network Modernization	Supports effective restoration operations, improving overall system performance	Limited adaptability to various incident scenarios
Fuzzy Artificial Methods for Wind Power Production	Enables real-time reliability assessment of wind turbines, improving fault response	Requires advanced algorithms and real-time data collection
Stochastic Super Fuzzy Framework for Renewable Microgrids	Accommodates diverse renewable sources, maximizes EV deployment	Complex to manage due to stochastic elements and multiple sources
Optimization Models for Cost and Demand Planning	Optimizes development plan for power systems, minimizes costs	Inflexible to sudden severe events
Battery Energy Storage System (BESS) Optimization	Reduces system losses, improves PV integration, and enhances power quality	Expensive initial setup and dependency on precise modeling
Hybrid Renewable Energy Systems (Wind, Solar,	Reduces pollution emissions, increases renewable integration,	May have high setup costs

Biogas)	and optimizes resource use	and complex maintenance
Frequency Regulation with Model Predictive Control (MPC)	Achieves accurate frequency regulation in isolated microgrids	May require high computational resources
Droop Control for Reactive Power Sharing in Microgrids	Ensures reliable, fault-tolerant power sharing	Can be ineffective without precise impedance knowledge
Communication-Free Control in DC Microgrids	Eliminates need for central controller, maintains voltage stability	May struggle with large-scale applications
Frequency Regulation in EV Integrated Microgrids	Utilizes EVs as dynamic energy storage, improves frequency stability	High reliance on EV availability and user compliance
Data-Driven Adaptive Control for EVs in Microgrids	Adapts to uncertainty, enhances robustness	Requires real-time data processing and complex modeling

1-4 Research Objectives

The primary objective of this research is to develop a comprehensive multi-stage framework for the coordinated scheduling of networked microgrids in active distribution systems, with a particular focus on the economic and environmental impacts of electric vehicles and flexible loads. This framework aims to address several key challenges and objectives:

1. **Enhance Microgrid Reliability and Resilience under Uncertainty**

Develop robust strategies to improve microgrid reliability, especially during grid outages or emergencies, through the delineation of service areas and integration of security constraints, enabling autonomous operation if disconnected from the main grid.

2. **Optimize Economic and Environmental Outcomes in Microgrid Operations**

Formulate a multi-objective optimization model that balances cost-efficiency with environmental sustainability, focusing on reducing operational costs and emissions through smart EV charging strategies, hydrogen refueling integration, and flexible load management.

3. **Integrate Advanced Energy Storage and Distribution Technologies**

Incorporate EV charging stations and hydrogen refueling stations into the microgrid framework to enhance energy storage and distribution, allowing for efficient management of supply-demand fluctuations and supporting renewable energy utilization.

4. **Develop a Stochastic Programming Framework for Uncertainty Management**

Establish a two-stage stochastic programming model to address uncertainties in renewable energy sources, EV charging patterns, and load demand. This approach seeks to provide adaptable, reliable solutions for dynamic energy management in microgrids.

5. **Validate the Practical Application and Scalability of the Framework**

Validate the proposed framework's effectiveness through simulations using real-world data, aiming to achieve significant reductions in operating costs and emissions, and to assess scalability across diverse geographic and grid configurations.

By achieving these objectives, this research contributes to the growing body of knowledge in the field of sustainable energy management, offering practical solutions for the efficient operation of networked microgrids. The outcomes of this study are expected to have significant implications for the design and implementation of future power distribution systems, particularly in the context of increasing renewable energy integration and the widespread adoption of electric vehicles.

In conclusion, the rapid integration of renewable energy sources, electric vehicles, and flexible loads has fundamentally transformed traditional power systems, highlighting the critical need for innovative energy management frameworks. Microgrids emerge as a promising solution to address these challenges by providing localized, resilient, and environmentally sustainable power. However, as the literature underscores, effective operation of microgrids demands advanced optimization techniques capable of balancing economic, environmental, and reliability objectives under conditions of uncertainty. This thesis, therefore, aims to contribute to this evolving field by developing a multi-stage framework for the coordinated scheduling of networked microgrids, incorporating emerging energy technologies and addressing real-world complexities in active distribution systems. Chapter 1 has laid the groundwork, identifying the research objectives and challenges that the subsequent chapters will address in depth.

Chapter 2: Sustainable Energy Management for Microgrids

2-1 Microgrid

The concept of microgrids is a new one introduced with smart grids. A microgrid is an electric energy distribution system with voltage levels corresponding to conventional distribution networks, where distributed energy resources and various loads are located within a defined electrical boundary. The configuration of a microgrid is island-like in distribution systems and near local loads, encompassing a set of loads. Microgrids are active low or medium voltage distribution networks of various sizes and shapes, including renewable energy sources like PV, wind turbines, batteries, loads, and control devices. Microgrids can connect to the main grid or operate independently, and when connected to the grid, they can facilitate bidirectional power exchange. The primary goal of these networks is to address technical issues related to enhancing the reliability and quality of power delivered to consumers.

Microgrids offer significant advantages for consumers, including improved reliability and power supply during stress conditions through independent operation and enhanced power quality. Additionally, microgrids shorten the distance between production and consumption, leading to reduced losses and better outage management, and they simplify maintenance processes. Furthermore, the expansion of renewable energy use in microgrids helps prevent excessive greenhouse gas emissions, which is a major concern today.

Microgrids have become a central topic in recent research due to their potential to improve energy efficiency, reliability, and sustainability. A review in the journal *Sustainability* highlights the numerous benefits of microgrids, such as increased reliability, reduced energy costs, enhanced energy security, and environmental advantages. However, the review also identifies several challenges, including high capital costs, technical complexity, regulatory hurdles, and maintenance requirements. The study emphasizes the need for strategic planning and technological advancements to overcome these challenges and fully harness the potential of microgrids. By examining the current state of microgrid development in various regions, the research underscores the unique opportunities microgrids offer for addressing energy poverty, reducing greenhouse gas emissions, and promoting sustainable economic growth.

Another significant area of research focuses on energy management systems (EMS) within microgrids. According to a paper in the journal *Energies*, effective EMS are crucial for optimizing the performance of microgrids by ensuring the optimal use of distributed energy resources (DERs) and energy storage systems (ESS). The paper discusses various control strategies and optimization techniques that enhance the efficiency and reliability of microgrids. It highlights the importance of integrating renewable energy sources and advanced storage solutions to create more resilient and intelligent energy systems. The ongoing advancements in EMS and control strategies are pivotal in addressing the growing energy demands and integrating renewable energy sources more effectively [79].

There are numerous successful microgrid implementations worldwide. For instance, the Brooklyn Microgrid project in New York City is a community-based microgrid utilizing solar panels, battery storage, and backup generators to provide reliable and affordable electricity to residents. Similarly, the Alamosa Solar Generating Project in Colorado is a hybrid microgrid that combines a large-scale solar power plant with battery storage and natural gas backup generators to deliver reliable and cost-effective electricity to the local grid.

In addition to these examples, ongoing research and development efforts aim to enhance the performance and cost-effectiveness of microgrids. Researchers are investigating new battery chemistries and storage technologies to improve the energy density and longevity of microgrid batteries. They are also developing advanced control and monitoring systems to boost the reliability and efficiency of microgrids, as well as exploring new renewable energy sources such as wave energy and geothermal power. The structure of a microgrid, as shown in Figure 2-1, illustrates these advancements [80].

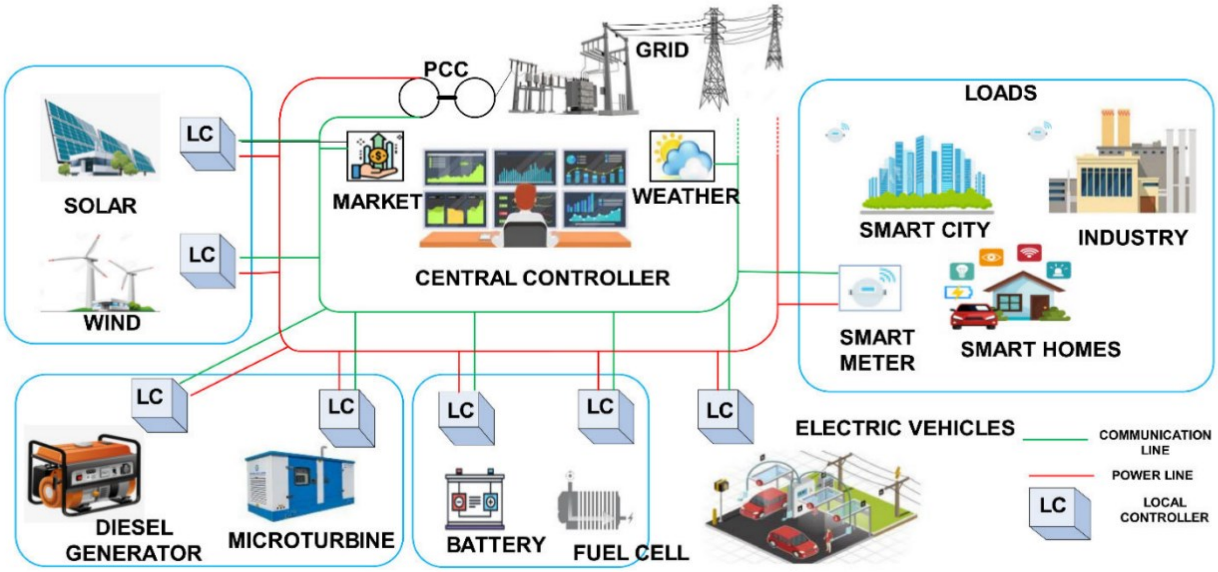


Figure 2-1: A schematic of a microgrid [80]

2-2 Types of Microgrids

2-2-1 DC Microgrid

The 20th century witnessed a strong debate on how to generate, transmit, and use electricity, known as the War of Currents, between Westinghouse and Tesla on the AC side and Edison as the main proponent of DC. Naturally, this debate ended with the broader implementation of AC distribution in most power networks for reasons that were more logical at the time. One of the most important factors for this dominance was the invention of the transformer, a simple and excellent tool for increasing voltage levels, thereby covering larger areas with the distribution system. In contrast, changing DC voltage levels was a significant obstacle. Additionally, the invention of multiphase AC machines helped people find an alternative to DC machines, which were the only option at the time. However, DC systems have not disappeared from distribution. For example, an old system using gas and electricity in San Francisco feeds DC motors for elevators in several historic buildings. Advances in power electronics, which have made DC voltage regulation simple, along with the increasing penetration of DC loads and sources, have encouraged researchers to consider DC distribution in at least parts of today’s power systems to enhance overall efficiency [80].

Many of today's consumer loads are powered by DC. Household and office electronics, such as computers, laptops, tablets, mobile phones, printers, televisions, microwave ovens, and lighting, all use DC power. Newer and more efficient lighting technologies, like compact fluorescent lamps and solid-state lamps, include a DC stage, making DC distribution systems more economical for these applications. DC power is also utilized in variable speed drives for pumps, heating, purification, ventilation systems, fans, elevators, traction systems, and mills. In industrial settings, the steel industry increasingly uses DC electric furnaces due to their lower energy consumption and reduced light flicker compared to AC types. The electrochemical industry almost exclusively requires DC power.

Using AC distribution systems to supply these loads introduces conversion stages, leading to inefficiencies. Approximately 30% of AC power produced passes through power electronic converters before use, with energy losses typically ranging from 10-25%. Research suggests that power conversion efficiency can be improved by 80% with DC systems and by about 25% by eliminating converters. Given that a significant portion of renewable energy sources generate DC power, a DC bus for network connection is necessary. Additionally, modern DC loads in distribution systems have significantly increased in recent years. DC microgrids offer better protection against short circuits and lower voltage levels, enhancing performance and reducing the size and cost of the distribution network. DC microgrids have emerged due to their advantages in efficiency, cost, and the elimination of AC-DC and DC-AC power conversion stages and associated energy losses.

A recent paper highlights a research project on advances in smart DC microgrids, focusing on the latest developments in distributed generation and modern electrical loads. An example of this network is shown in Figure 2-2, where several AC and DC sources are connected to a low voltage DC network after necessary conversions and connection to the Point of Common Coupling (PCC).

DC microgrids have garnered significant attention recently due to their potential to boost energy efficiency and reliability. A review in the journal *Energies* highlights that DC microgrids are particularly beneficial because they eliminate the need for AC-DC and DC-AC conversion stages, which are typically associated with energy losses. These systems are highly compatible with renewable energy sources, such as solar photovoltaics, which naturally generate DC power.

The integration of energy storage systems, like batteries, further enhances the stability and reliability of DC microgrids. Additionally, DC microgrids offer better protection against short circuits and lower voltage levels, which can reduce the size and cost of the distribution network.

Another study emphasizes the importance of energy management systems (EMS) in optimizing the performance of DC microgrids. Effective EMS can ensure the optimal use of distributed energy resources (DERs) and energy storage systems (ESS), making the grid more secure, reliable, and intelligent. Research indicates that DC microgrids can significantly improve power conversion efficiency and reduce energy losses. These systems are particularly advantageous for residential applications, where they can help manage the increasing demand for electricity while integrating renewable energy sources. The hierarchical control strategies and advanced optimization techniques discussed in recent papers highlight the ongoing advancements in this field [81].

Several states in the USA have invested millions of dollars in promoting and advancing microgrids as part of regional resilience programs against natural disasters. Since microgrids generally include renewable sources and batteries, DC microgrids have a high capacity to enhance the overall system's efficiency. Numerous papers indicate that DC microgrids can play a more effective role in solving some operational issues on the main grid. Additionally, solar cells and batteries can be used to mitigate the severe effects of nonlinear loads. Consequently, these factors have led to extensive research to raise the question: "Does DC distribution offer the highest efficiency for electric energy distribution, or is it time to consider developing DC distribution as an alternative?" Research has shown that DC power systems are no longer obsolete. They seem more aligned with today's needs than they were 100 years ago. The figure below shows a real and laboratory-scale DC microgrid at Aalborg University. Figure 2-3 shows a real laboratory-scale DC microgrid used at Aalborg University [82]. This microgrid is also a real-life network example. The laboratory-scale DC microgrid is a single-phase laboratory system designed by the National Technical University of Athens (NTUA), including microgrid operations at scales and laboratory simulations for providing renewable energies like solar and wind, designed and built by the University of Manchester [83].

Architectures and Configurations

One aspect that remains unstandardized is the type of architecture that should be adopted or is most suitable for a specific application. In reality, several possible architectures can be used to establish a DC microgrid. These different structures include:

1. **Single Bus Topology**

This is the simplest topology, consisting of a single DC bus. All generators, storage systems, and loads are connected to the same point (bus). Figure 2-2 shows two typical examples of this topology: one connected to the electrical grid and the other operating in islanded mode. Besides its simplicity, this topology is characterized by low maintenance requirements and low costs.

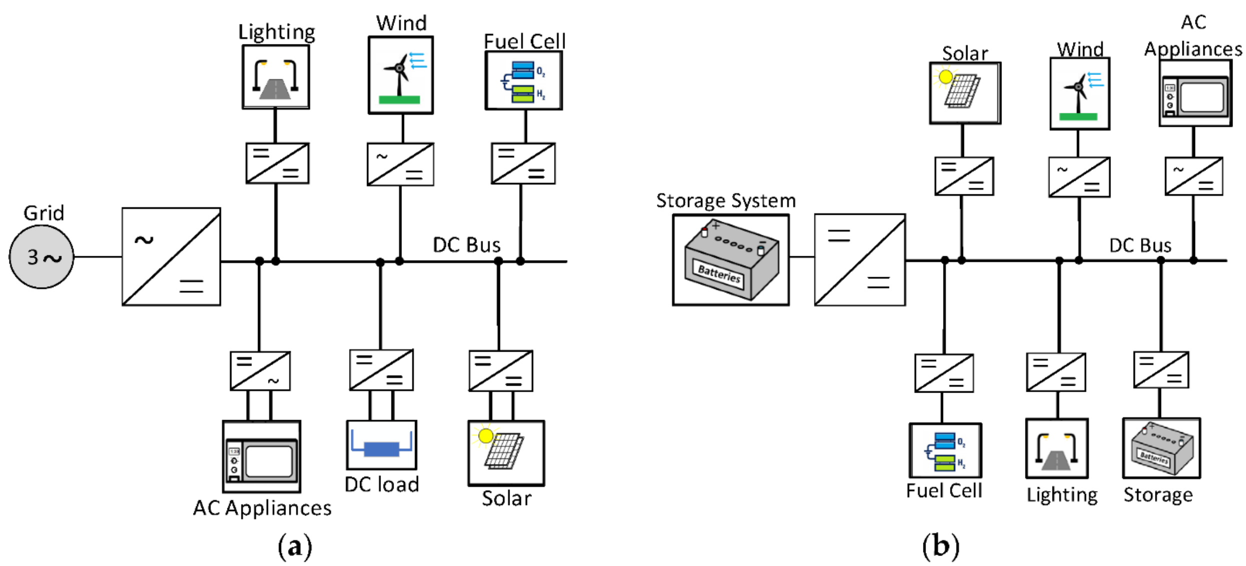


Figure 2-2: A schematic of a typical example of the single bus topology: (a) connected to the grid mode (b) island mode.

2. **Radial Topology**

This topology can be seen as an extension of the single bus. As shown in Figure 2-3, it provides more than one DC bus, each used to connect generators, storage systems, and loads. There are typically two possible configurations: series and parallel. In the series configuration (Figure 2-3a), two or more DC microgrids are interconnected in series, while in the parallel configuration (Figure 2-3b), they are interconnected in parallel. This topology maintains some simplicity, allows for different voltage levels, and increases reliability. However, it may experience some instability during islanding mode.

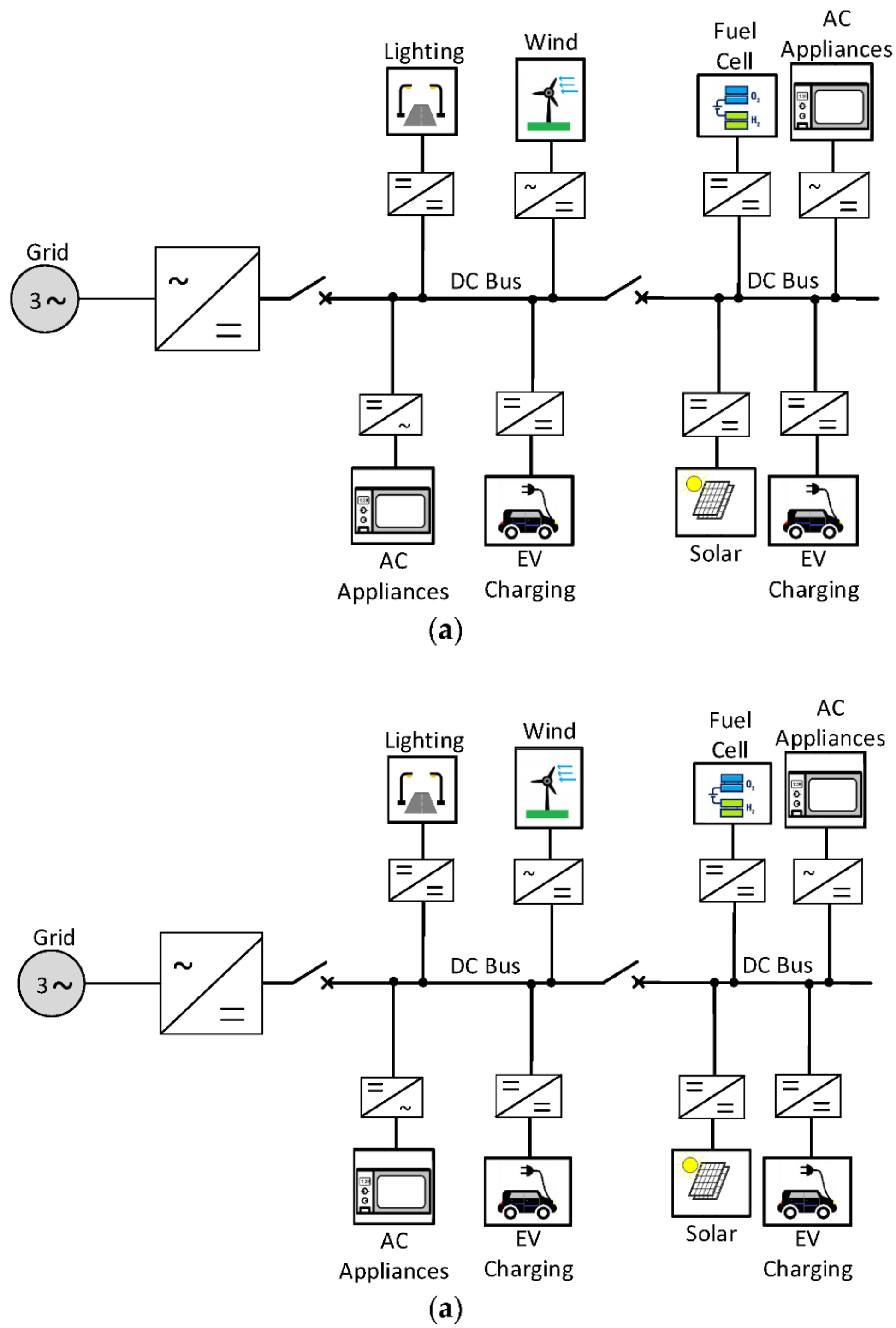


Figure 2-3: A schematic of typical example of the radial topology: (a) series configuration and (b) parallel configuration.

3. **Ring or Loop Topology**

In this topology, all generators, storage systems, and loads are connected to the same DC bus in a loop, allowing supply from two sides (Figure 2-4). This topology is more reliable compared to previous configurations, as it can operate in a single bus configuration in case of a fault in the DC bus. However, it is more complex.

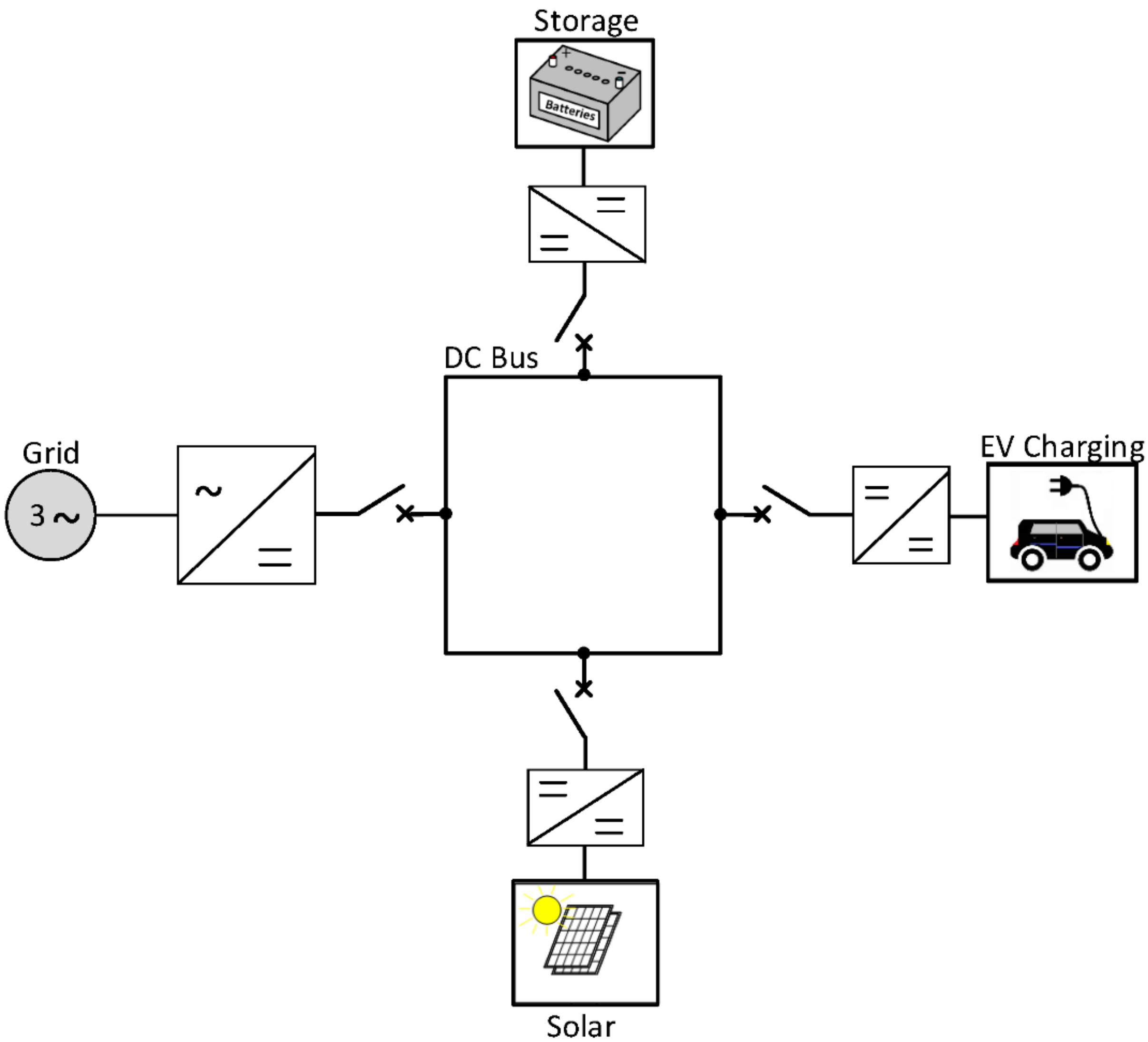


Figure 2-4: A schematic of typical example of the ring topology.

4. Mesh Topology

This topology integrates ring (or rings) with radial topologies, forming a mesh configuration (Figure 2-5). It is characterized by a complex structure that offers better reliability and flexibility compared to previous topologies.

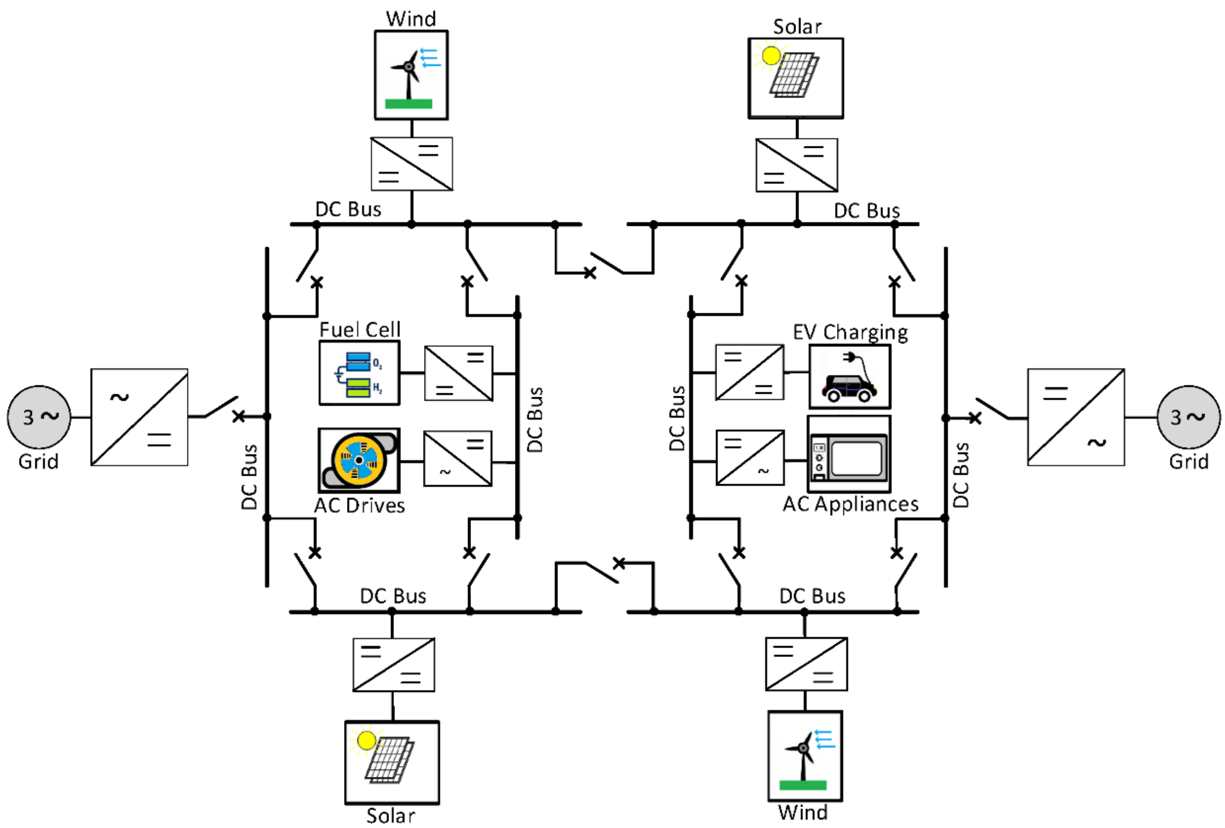


Figure 2-5: A schematic of typical example of the mesh topolog.

5. Interconnected Topology

Previous topologies typically feature a single connection to the AC main grid. To improve system reliability, it is possible to connect to alternative AC grids (two or more), resulting in an interconnected topology. Figure 2-6 shows an example where the DC microgrid is interconnected to two AC grid supplies.

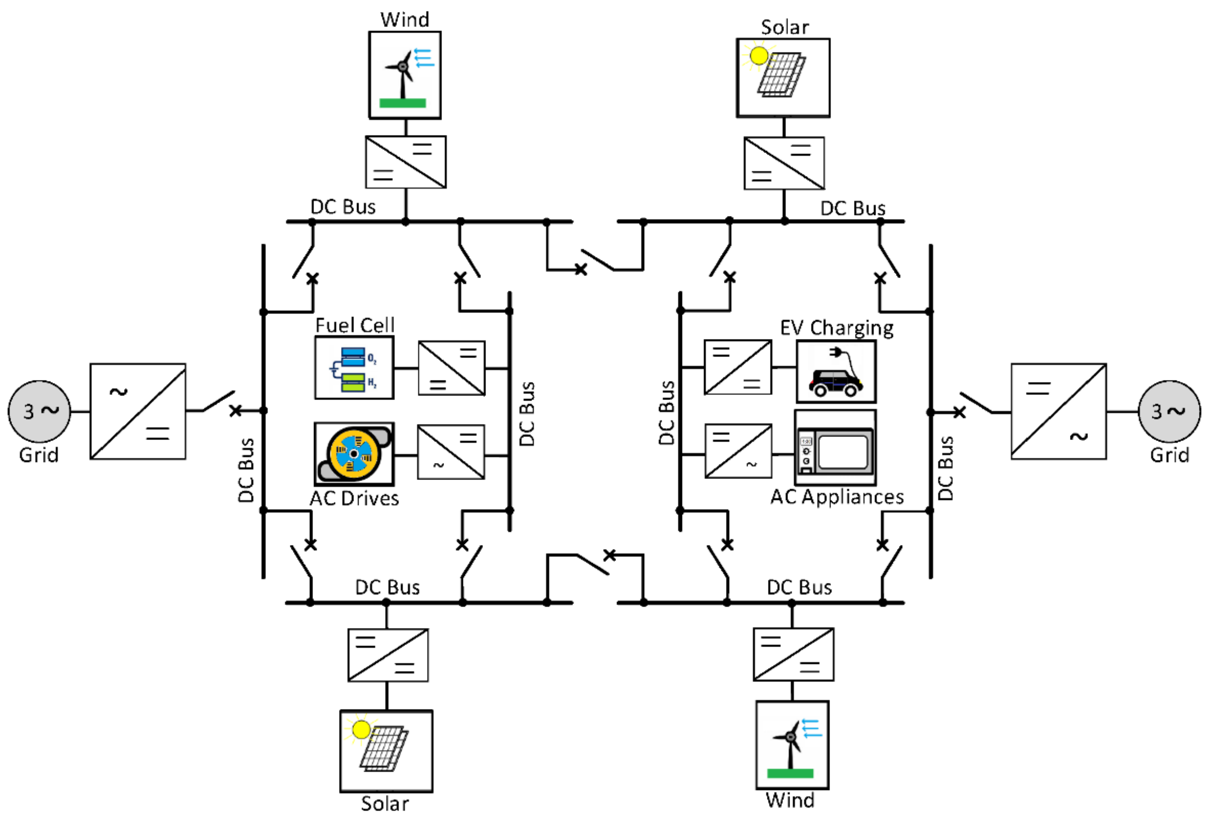


Figure 2-6: A schematic of typical example of the interconnected topology.

2-2-2 AC Microgrid

AC microgrids, which were initially considered the common meaning for all microgrids, have a significant advantage. Given that all network infrastructure for production, connection, and distribution worldwide is AC power networks, connecting this type of sub-network to the main grid and using the existing structure for power transmission is a significant advantage. An AC microgrid system connects internal distributed loads and low-pressure distributed energy sources like microturbines, wind turbines, solar cells, and energy storage devices. Among these, the presence of renewable energy sources like solar and wind is essential for reducing global warming and environmental issues [84]. Figure 2-7 shows a sample AC microgrid.

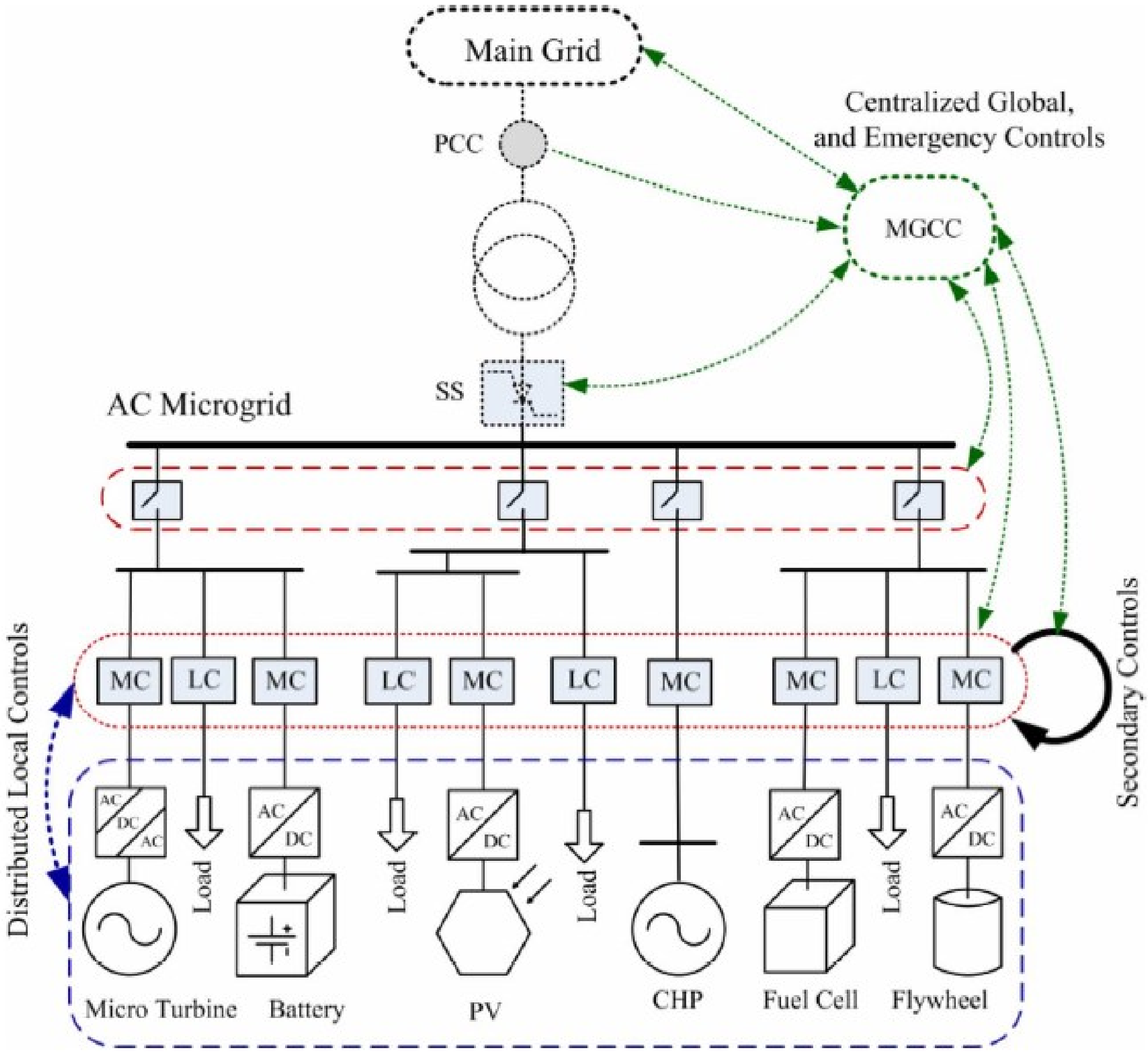


Figure 2-7: Sample AC microgrid with loads [84].

As mentioned, since a large portion of current power networks are AC, AC microgrids dominate and form the majority of power networks. Given this, the exclusive appearance of DC microgrids in the power network is expected in the near future. In many microgrids, electricity generation units with AC output power are directly connected to a bus and then connected to the main system for a sustainable building through power converters. Examples of DC units producing AC output power include biogas turbines, wave turbines, and tidal turbines.

These are usually either directly connected to the grid or may require AC/DC/AC converters to connect to LVAC networks. In this context, the LVAC network can be connected to the main grid through a power transformer. Additionally, AC loads are directly connected to the network, while DC loads require DC-AC power converters to connect to LVAC networks. In other words, DG units that produce DC power are connected to LVAC networks using DC/AC converters. One of the biggest challenges and complexities associated with AC microgrids is the complex control strategies for synchronization processes and system stability protection. Perhaps the general concept of a microgrid is an AC microgrid, a network where various sources, whether AC or DC, supply different AC loads. In this type of microgrid, DC sources provide a suitable and minimally distorted amount for AC loads using AC/DC converters and appropriate filters. The concept is that loads and micro-sources, whether AC or DC, and of course, all AC loads, operate as a single controllable system and often provide heat and power for local loads. These microgrids can be considered as a controlled cell of the power system, which, for example, should be able to act as a dispatchable load that can meet the needs of the transmission system in a fraction of a second. From the consumer's point of view, the microgrid should be able to meet the following needs:

- Increased local reliability
- Reduced feeder losses, local voltage supply
- Increased efficiency through the use of waste heat
- Voltage drop correction or provision of emergency power supply functions [84].

Micro-sources of particular interest for microgrids are units with power less than 100 kW with power electronics interfaces. These sources are located at customer sites, featuring low cost, low voltage, high reliability, and low greenhouse gas emissions. Power electronics and the required flexibility provide the microgrid concept. With proper control design and power electronics, the microgrid can meet consumer needs as well as network needs. The above features can be provided with a system architecture with the following three main components:

- Local micro-source control
- System optimizer
- Distributed protection

The distinguishing features of AC and DC microgrids are as follows:

- AC microgrids are more compatible with existing AC systems. However, synchronization methods must be followed before connection. In contrast, connecting a DC microgrid to AC systems is easier. DC microgrids are more compatible with the nature of today's loads, which are mostly DC (household appliances, lighting systems, and motor drives).
- Most renewable energy sources are DC, such as PV cells, fuel cells, and energy storage units. Protecting DC systems is more challenging due to the absence of zero current crossing, a self-extinguishing feature of fault current in AC systems. AC systems are associated with the skin effect of transmission lines. Given the above issues, hybrid AC/DC systems have emerged to take advantage of both networks. Additionally, losses will be significantly reduced with fewer power electronics conversion stages, and system reliability will be noticeably increased [85].

2-2-3 Hybrid AC/DC Microgrids

Various hybrid system structures have recently been used to connect AC and DC subsystems using a three-phase voltage source converter or back-to-back converters. Given the advantages of both AC and DC microgrids and the challenges ahead, hybrid AC/DC microgrids are recognized as an attractive idea with many unique features, and extensive research is being conducted to utilize and optimize this type of microgrid. In fact, this type of microgrid, as shown in Figure (2-8), is a combination of Westinghouse and Tesla's AC thoughts and Edison's DC arguments [86].

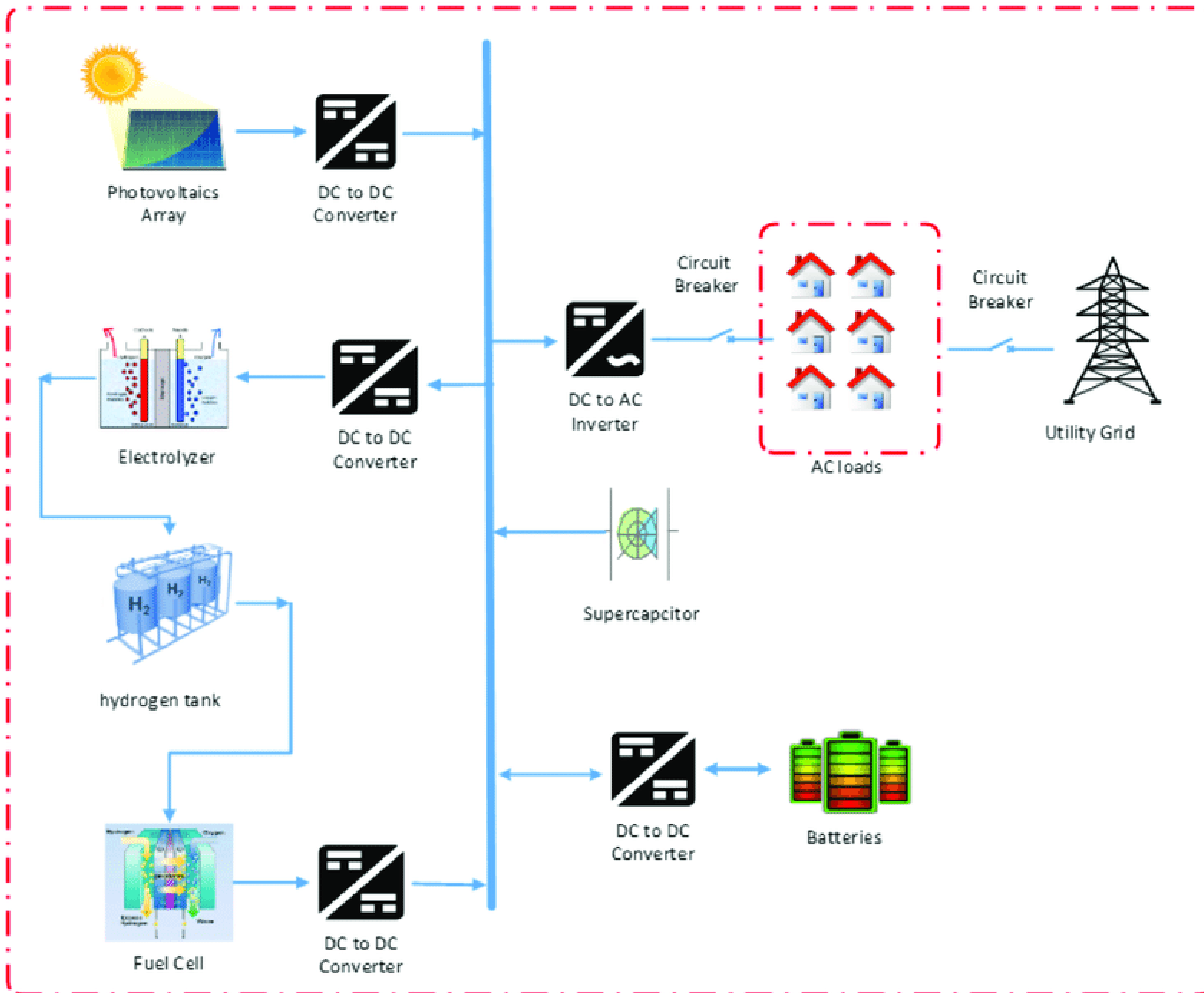


Figure 2-8: Sample hybrid microgrid [86]

The microgrid will be a good method for integrating primary micro-sources without any interruption. Power generation through micro-sources and renewable sources such as solar energy and wind farms will be a prominent move. Therefore, hybrid AC/DC microgrids are the best solution to reduce excessive AC-DC-AC conversions in an exclusive AC network. In this way, the AC network loads are connected to a separate AC network, and DC loads and sources are connected to each other [86]. Additionally, energy storage systems can be connected to either the AC or DC bus. Today, most renewable power conversion systems are connected to low voltage AC distribution systems as distributed generators and microgrids. Due to environmental issues caused by conventional fossil fuel power plants, the use of DC loads such as light-emitting diodes (LEDs) and electric vehicles is connected to AC power systems. When local renewable power sources are available, the use of high voltage lines over long distances is unnecessary.

Microgrids are presented to facilitate the connection of renewable energy sources to conventional AC systems. However, photovoltaic panels or fuel cells must be converted to AC using AC/DC inverters to connect to the AC grid. In the AC network, AC/DC and DC/DC converters are required for various household and office facilities to supply the required DC voltage. AC/DC/AC converters are usually used as drives to control the speed of AC motors in industrial plants. Recently, DC networks have been revived to develop and utilize DC renewable energy sources and the inherent advantage of DC loads in residential and industrial applications. The DC microgrid is presented to integrate various distributed generators. Multiple reverse conversions in DC or AC networks only add operational losses to the system and increase the complexity of office and household appliances. The smart grid concept is currently a dominant discussion in the power industry. The goal of the smart grid can be reliability, high-quality power for environmentally friendly digital communities, and a sustainable way. One of the most important characteristics of a smart grid is its complex structure, which can facilitate the connection of multiple AC and DC generation systems, energy storage options, and multiple AC and DC loads using optimal efficiency and operational productivity.

To meet these goals, power electronics technology plays a very important role in connecting various sources and loads to the grid and smartening it. Therefore, hybrid AC/DC microgrids have been introduced to reduce multiple reverse conversion processes in an exclusive AC or DC network and to facilitate the connection of renewable AC and DC sources and loads to the power grid [86].

Table 2-1: Comparison of different topologies for micro-grids

Topology	Properties	Advantages	Disadvantages
Single Bus	All generators, storage, and loads connect to a single DC bus.	Simple design, low maintenance, low cost.	Limited scalability and resilience.
Radial	Extension of the single bus with multiple DC buses in series or parallel configurations.	Allows different voltage levels, increased reliability over single bus topology.	Can experience instability in islanded mode.
Ring (Loop)	All components connect in a loop, allowing supply from two directions.	More reliable due to dual supply paths; can operate as a single bus during faults.	More complex design than single bus or radial.
Mesh	Combination of ring and radial topologies, forming a mesh network.	High reliability and flexibility; can handle complex networks.	High complexity and cost; challenging to implement and maintain.
Interconnected	Connects to multiple AC grids to enhance reliability.	Greater system reliability with multiple AC connections.	Increased complexity in control and synchronization across grids.
AC Microgrid	Comprises AC generation and loads, typically interfaced with the main AC grid.	Compatible with existing AC infrastructure; easier integration with main grid.	Complexity in control strategies, especially for synchronization

			and stability.
DC Microgrid	Uses DC generation and loads, suitable for modern DC appliances and renewable DC sources.	Reduces conversion losses, higher efficiency, suitable for DC loads and renewable sources	Protection and fault management are more challenging due to lack of current zero-crossing.
Hybrid AC/DC	Combines AC and DC subsystems using converters for both AC and DC loads.	Reduces conversions, efficiently integrates both AC and DC sources/loads; better suited for renewable energy systems.	Complex structure, high initial setup costs, and sophisticated control requirements for stability.

2-3 Microgrid Operating Modes

One of the most important requirements of a microgrid is the ability to operate in both grid-connected and islanded modes. This capability makes them suitable for providing emergency power to connected loads during an incident, thereby improving islanded power delivery. In grid-connected operation mode, distributed energy resources (DER) are connected to the main grid. In islanded or autonomous mode, local loads can be supplied without using the distribution network [87].

The two operating modes of the microgrid are explained below.

2-3-1 Grid-Connected Mode

In grid-connected mode, microgrids operate alongside the main utility grid, allowing for power exchange between the microgrid and the larger grid. This mode improves the reliability and stability of the power supply by offering additional support during peak demand and facilitating the integration of renewable energy sources. Grid-connected microgrids can also provide ancillary services, such as frequency regulation and voltage support, contributing to the overall stability of the power system. Advanced control strategies are crucial for managing the seamless transition between grid-connected and islanded modes, ensuring minimal disruption and maintaining power quality.

Recent studies have focused on developing robust control mechanisms to ensure the smooth operation of microgrids in grid-connected mode. These studies highlight the importance of coordinated control schemes that can manage the dynamic interactions between the microgrid and the main grid. For example, model predictive control and adaptive control techniques have been proposed to optimize power flow and enhance the resilience of the microgrid. Additionally, integrating energy storage systems is vital for balancing supply and demand, mitigating the intermittency of renewable energy sources, and providing backup power during grid outages [87].

2-3-2 Islanded Mode

If it is assumed that the distribution network is disconnected from the upstream grid for a long time and we want to operate the distribution network in islanded mode, any fault is likely to occur during network operation. According to IEEE 1547.4 standard [88], in the event of a fault in active networks, all energy sources and DGs must be disconnected from the circuit, and after the fault is cleared, energy sources and DGs are allowed to reconnect. Therefore, when a fault occurs in the network, the entire network shuts down for a while. To solve this problem, the microgrid structure has been proposed [89].

In islanded mode, load reduction/output is performed to maintain power balance. Critical loads are prioritized to receive high-quality power at all times, while remaining loads are subject to load shedding [90]. In islanded microgrids with typical loads (active or passive), frequency fluctuations are usually managed by droop control of active converters in grid-forming mode. The islanding capability of the microgrid allows for the supply of sensitive loads during main grid outages, increasing reliability for consumers within the microgrid [90].

The islanding process can be initiated by opening upstream switches at the substation that connect the main power grid and the microgrid. This change can occur due to any disturbance or intentional reasons. There is a difference between intentional and unintentional islanding.

Intentional islanding refers to a managed and controlled transition operation, while unintentional islanding refers to unwanted islanding due to a fault in the power grid. In islanded microgrid operations, the fault current level is low due to the absence of the main grid. Additionally, inverter-based distributed generation sources, such as distributed sources based on synchronous machines, cannot inject significant current during faults. Furthermore, due to the presence of distributed generation sources, the fault current direction in microgrids is bidirectional. This issue is more pronounced in microgrids with ring configurations [91].

If the unbalanced power within the microgrid is smaller than the available control capacity, transitioning to islanded operation is possible. This capacity includes feedback control of locally controlled DER units, sufficiently robust energy storage for rapid response, and controllable microgrid loads that can quickly disconnect from the main grid. Therefore, the transition is very easy due to the rapid communication between components and the management system [92].

Voltage source inverters (VSIs) are commonly used to connect distributed generation sources to the microgrid. These converters are very popular among industries and power companies due to their high flexibility in providing controlled and high-quality power to loads. This type of inverter can have either voltage control or current control. In voltage control mode, it generates a voltage with the desired amplitude and frequency, suitable for islanded operation conditions. In current control mode, the converter's output current follows its reference current, but the output voltage and frequency range are not controlled and are determined by the grid.

Based on the points mentioned in this section, it can be concluded that one of the fundamental problems facing microgrid designers is the stable islanding of microgrids to avoid issues for consumers. Consequently, one of the important issues in this area is the control of distributed generation sources in islanded microgrids so that they can control the system's frequency and voltage and properly distribute the existing loads. In other words, the microgrid must be able to quickly manage frequency and power changes in the network. As a result, one of the main challenges of integrating renewable energy storage sources is the need for more flexible and coordinated frequency control mechanisms based on energy storage technologies to address voltage fluctuation issues in the microgrid, instead of using costly diesel sources for faster recovery and maintaining frequency and voltage stability.

2-4 Sustainable Energy Management in Microgrids

To properly operate a network that includes more than two distributed generation units, especially in off-grid mode, power management strategy and energy management strategy are needed. Figure (2-9) shows the information flow and functions used in PMS/EMS for a microgrid.

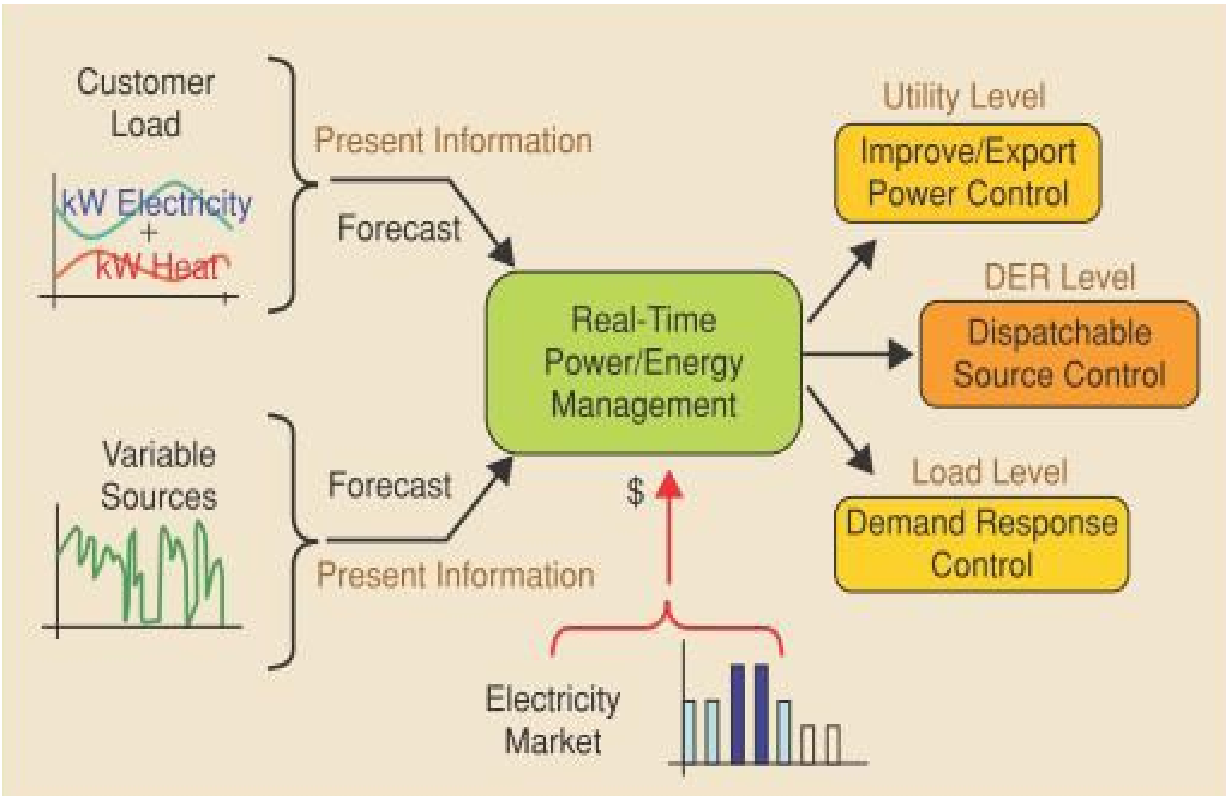


Figure 2-9: Information flow and functions used in real-time PMS/EMS in a microgrid [92]

In the figure, the real-time power-energy management block receives information about the predicted and real-time data of load, generation, and market, and based on this received information, sends appropriate control signals for load dispatch and load level determination [93].

The control structure in the microgrid is divided into two main categories: centralized and decentralized. Each of these control structures includes three hierarchical levels:

1. Distribution Network Operator (DNO), which can be accompanied by a Market Operator (MO).

2. Microgrid Central Controller (MGCC), which is also the microgrid operator.
3. Local Controllers (LC), which are related to each of the distributed generation units or loads.

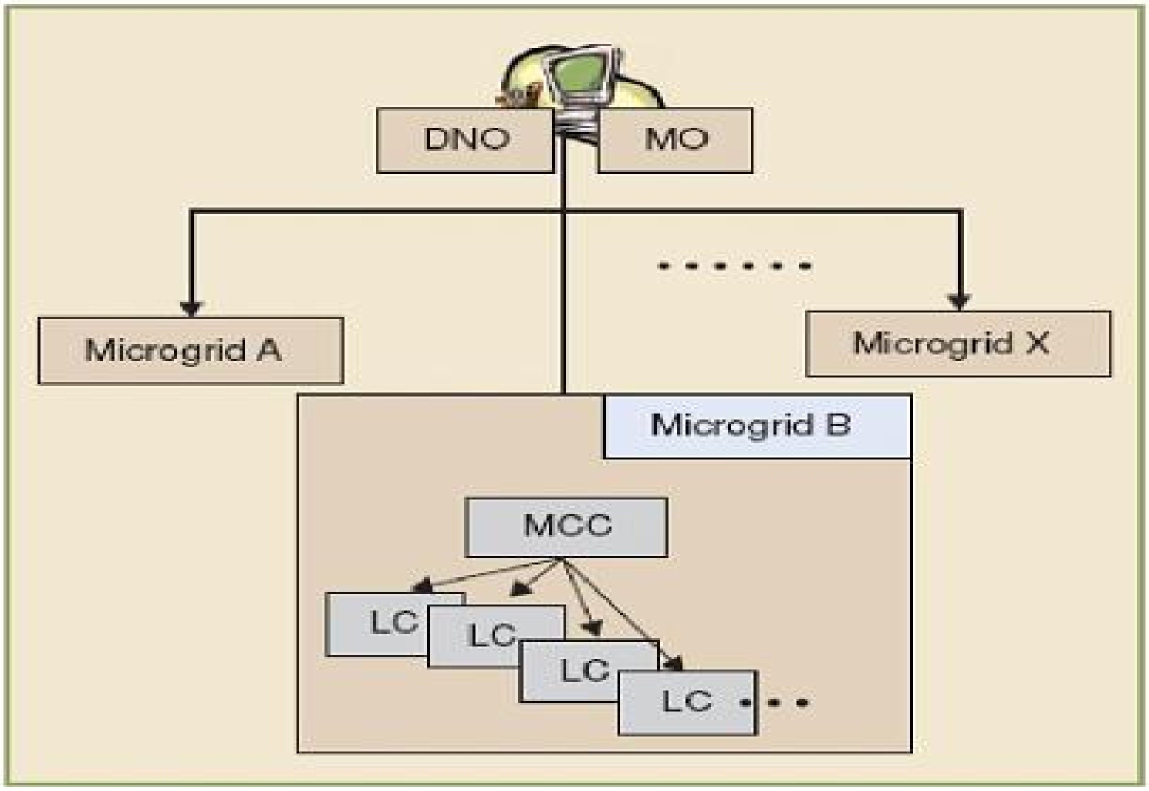


Figure 2-10: Management and control structure in microgrids[93]

The distribution company operator is at the highest control level, overseeing an area with more than one microgrid. Additionally, one (or more) market operator(s) for each specific area handle market-related tasks. The distribution company operator and market operator are not part of the microgrid but are dependent on the main grid. The microgrid central controller, or the microgrid operator, is the main interface between the microgrid, the distribution company operator, and the market operator. The microgrid central controller has various tasks, from maximizing the microgrid's value to coordinating between local controllers. Local controllers, which are at the lowest control level, control the distributed generation units and controllable loads in the microgrid. Depending on the control structure, each local controller may have a certain level of intelligence [93].

2-4-1 Control Methods for Microgrid Energy Sources

In recent years, the analysis and design of large-scale systems, such as power systems with many renewable energy generators, have attracted the attention of many researchers. Uncertainty in the output of renewable energies causes frequency deviations in the entire power system. To achieve a reliable supply-demand system, advanced design and control methods are needed to stabilize power voltage in these systems [94]. Recent advances in computer network technology have enabled DER-equipped systems to operate spatially distributed. For example, in power system control, a system operator manages distributed power plants with distributed measurement units to meet the demands of several consumers. In line with the systematic control of such networked systems, decentralized and distributed control techniques have been studied over the past half-century.

Recently, researchers' efforts have focused on designing suitable controllers for DER-equipped systems and extending these controllers to more general cases. The following sections review some control methods for these networks.

Decentralized Control

Decentralized control in microgrids involves each distributed energy resource (DER) operating autonomously using local data, without the need for a central controller. This method improves the reliability and scalability of microgrids by enabling the easy addition of new units with minimal changes. A significant benefit of decentralized control is its capacity to maintain system stability and performance even if communication links fail. Techniques like droop control, model predictive control, and adaptive control are frequently used to manage power sharing and voltage regulation in decentralized microgrids. These methods ensure that each DER can adapt to changes in load and generation, thereby maintaining the overall stability of the microgrid.

Recent research has shown the effectiveness of decentralized control in both AC and DC microgrids. For example, a decentralized control strategy using optimal control techniques has been found to enhance the dynamic performance and stability of DC microgrids with composite loads. Additionally, decentralized control schemes for inverter-interfaced microgrids have been developed, employing model predictive control to manage interconnection couplings and improve system robustness. These developments underscore the potential of decentralized control to tackle the challenges of integrating renewable energy sources and varying load demands, ensuring reliable and efficient microgrid operation. Figure 2-7 shows an example of decentralized control, including the system's inputs and outputs. Controllers are implemented in a decentralized manner, as shown in Figure 2-11 (a). The entire controlled system is represented by a repetitive feedback system in which structured subsystems are also connected to a base system. This issue is shown in Figure 2-11 (b). In practice, not only implementation but also controller design must be decentralized so that each controller is designed independently of the others. The most important point in designing decentralized controllers is achieving stability and proper performance in the entire controlled system [95].

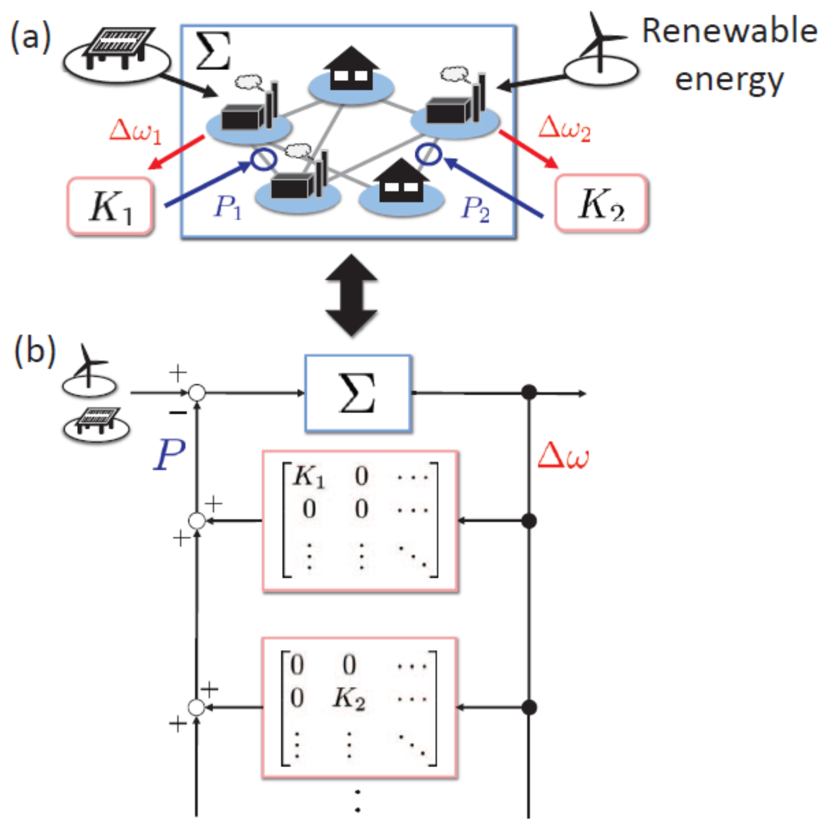


Figure 2-11: Schematic of decentralized control of a power system comprising many renewable energy generators.

The passivity theory has helped develop decentralized control schemes for systems with DER sources. Based on this theory, it has been proven that designing feedback controllers for linear and nonlinear systems is beneficial. Such controllers have been used in many applications, such as robotics and energy systems. Various efforts have also been made to develop robust and adaptive controllers based on passivity. Additionally, many passivity-based control schemes have been designed in continuous time. However, it is well known that the passivity properties of continuous-time systems are lost under discretization due to energy leakage from zero-order hold. Therefore, various methods, such as using small sampling intervals where passivity is preserved under discretization, have been developed.

A passivity-based control system design approach, or more generally, dissipativity, relates to the modular design of networked systems. This approach has the advantage that the input-output behavior of the entire networked system can be analyzed using only the subsystems, which are associated with compatible energy supply rates. However, analysis based on supply rates is only valid when an acceptable supply rate for the common variable, i.e., the stacked vector, disturbance and interaction inputs, and the common variable evaluation and interaction outputs, is found.

Decentralized control in power systems with DER sources has advantages, including flexibility in the system structure, as each subsystem has a separate controller. With structural changes in part of the system, the controller for that part is updated according to the new structure, eliminating the need to redesign a central controller, which is very challenging in power systems with DER sources.

Other advantages of decentralized control include fault tolerance, fewer computations, and no need for information from the entire system. As described, each local controller uses local signals and a small amount of information from other subsystems to issue commands.

Many industrial systems are still controlled by decentralized architecture, where the control variable (input u) and the controlled variable (output y) are grouped into separate sets. These sets are combined to form non-overlapping pairs for which local regulators are designed to operate completely independently. These local regulators can be single-input-single-output (SISO) or multivariable, depending on the chosen input and output sets. An example of a decentralized control structure is shown in Figure (2-12), where the controlled system consists of two subsystems S1 and S2, with state variables and input and output variables (x1, u1, y1) and (x2, u2, y2), respectively, and the relationship between these subsystems is shown by the effects of two state variables [95].

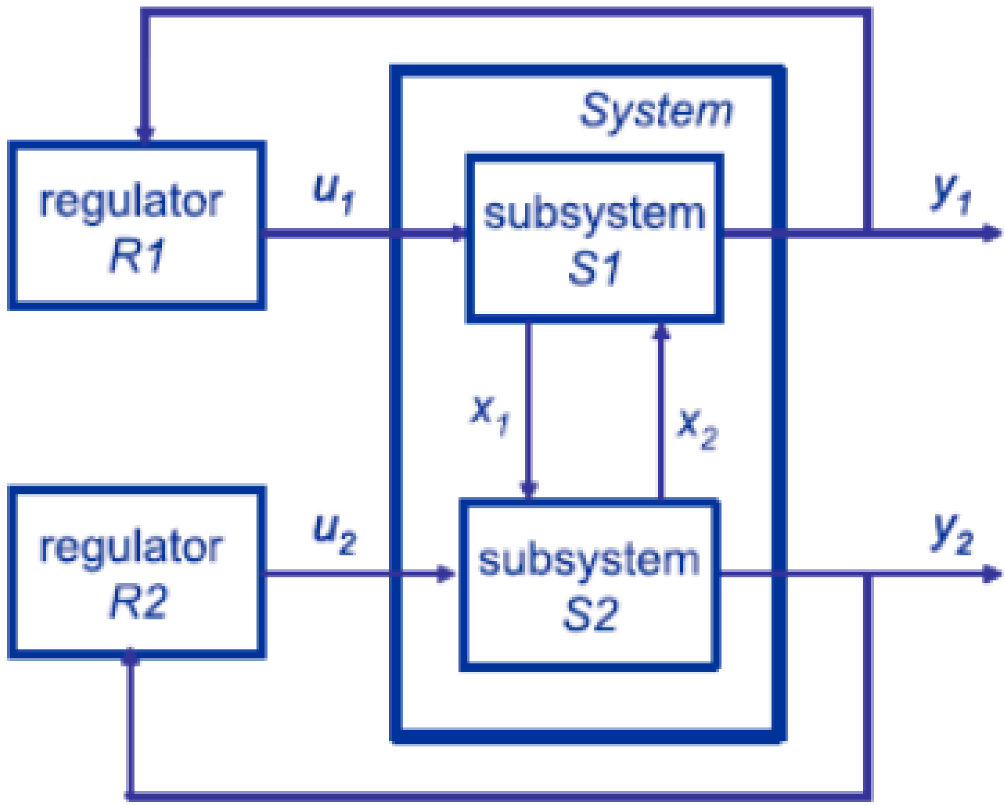


Figure 2-12: Decentralized control structure for a two-input two-output system.

When the decentralized regulatory structure is specified, and the internal interactions between the inputs and outputs of different pairs are weak, designing local regulators (R1 and R2 in Figure (2-12)) is straightforward. These internal interactions can be direct (input coupling) or created by the mutual effects of the internal states of the controlled subsystems, as shown in Figure (2-12). Conversely, it should be noted that strong internal interactions can prevent decentralized control from achieving stability or proper performance.

As stated in [96], which examines various structures from the perspective of communication networks, more than two decades have passed since the application of this structure in power systems, at a time when communication networks did not allow for extensive information exchange.

Centralized Control

In contrast to decentralized control, centralized control schemes are usually used to coordinate the control actions of the entire system, assuming that comprehensive information from the entire system is available. Centralized control means that information from the entire system is sent to a single center, where all control components are located, and that part is responsible for performing all computations, estimations, and generating control inputs for the entire system.

There are important reasons for replacing centralized control structures with other structures, which are highlighted below. As the above definition indicates, centralized control is usually not feasible for geographically distributed power systems, and implementing this control structure for such systems is very challenging for technical and economic reasons. Sending information from the entire system to a single control unit and providing high computational power is practically impossible and costly.

Additionally, designing centralized controllers is highly dependent on the system structure, and these controllers cannot handle structural changes in the systems and perform their functions optimally. Furthermore, the system may consist of separate and independent subsystems with unique control tools. Therefore, the best way to control such systems is to use local computing and control resources. As mentioned, power systems usually consist of many interconnected and interrelated subsystems, and therefore, control by a centralized control structure can be very challenging due to the inherent computational complexity required, resistance and reliability issues, and communication bandwidth limitations. Moreover, when central control in a centralized structure is lost, the entire system goes out of control, and control accuracy is not guaranteed when control components are lost. In some cases, comprehensive system information is not available to the central controller [97, 98].

For all these reasons, many decentralized control structures have been developed and applied to systems over the past forty years. Instead of designing a general and comprehensive centralized control scheme, decentralized control designs separate controllers for each subsystem. Subsystem controllers only need local signals and a small amount of information from other subsystems. Among the proposed structures, fully decentralized structures, distributed control systems with information exchange between local controllers, and hierarchical or tiered structures are of particular importance.

It should be noted that centralized control has the best performance in terms of functionality because fewer constraints are applied to the system. Therefore, simulation results in papers usually aim to bring the performance of distributed and decentralized control closer to that of centralized control.

Hierarchical Control

A point that emerges after decomposing a power system with DER sources into smaller subsystems is the interconnection and interaction between these subsystems. Each of these subsystems, which interact internally with other subsystems through their inputs or states, are "neighboring subsystems." If the interconnection and interaction between subsystems are strong and cannot be ignored, decentralized control will not provide effective performance. Thus, the presence of a coordinator that provides the necessary information to each local controller is helpful.

The hierarchical control scheme includes primary and secondary controllers. The secondary control level is a central controller that first receives the instantaneous output currents of all DG units via a low-bandwidth communication link (LBC). Then, the secondary control level calculates the instantaneous circulating currents corresponding to the main components and dominant harmonics and sends them to the primary controllers of all DG units to achieve accurate reactive power and harmonic current sharing and reduce circulating currents between units.

Hierarchical control is a key approach for managing microgrids, which are localized power systems capable of functioning autonomously or alongside the main grid. This control framework is structured into three tiers: primary, secondary, and tertiary. The primary tier ensures voltage and frequency stability through local controllers. The secondary tier corrects any voltage and frequency deviations resulting from primary control actions. The tertiary tier optimizes the microgrid's overall operation, including power flow and economic dispatch, to achieve efficient and cost-effective energy management. Recent research underscores the success of hierarchical control in both AC and DC microgrids. For example, a hybrid microgrid model that includes both AC and DC subgrids has been created, showcasing the adaptability of hierarchical control strategies. These studies highlight the significance of incorporating advanced control techniques, such as model predictive control and machine learning, to improve the performance and reliability of microgrids. By utilizing these advanced methods, hierarchical control can effectively manage the challenges associated with the variability of renewable energy sources and the dynamic nature of load demands [98].

Figure 2-13 shows the application of the hierarchical control scheme for a three-phase islanded microgrid where N three-phase DG units with inverter interfaces are connected to the PCC bus through LCL filters and feeder impedances ZF. It is worth noting that as long as they operate in parallel, the LCL filter is generally preferred over multiple VSI LC filters. Note that for DG units with voltage control, the capacitor voltage control filter inductances on the network side are considered part of the feeder impedances. Additionally, as shown in Figure 2-7, the microgrid system includes both linear and nonlinear loads, which are considered jointly at the AC bus (PCC) and locally at the DG output terminals. For each DG unit, the required power is supplied by power generators and/or energy storage systems. In the microgrid system, it is assumed that the DC links of the DG units are controlled and maintained separately.

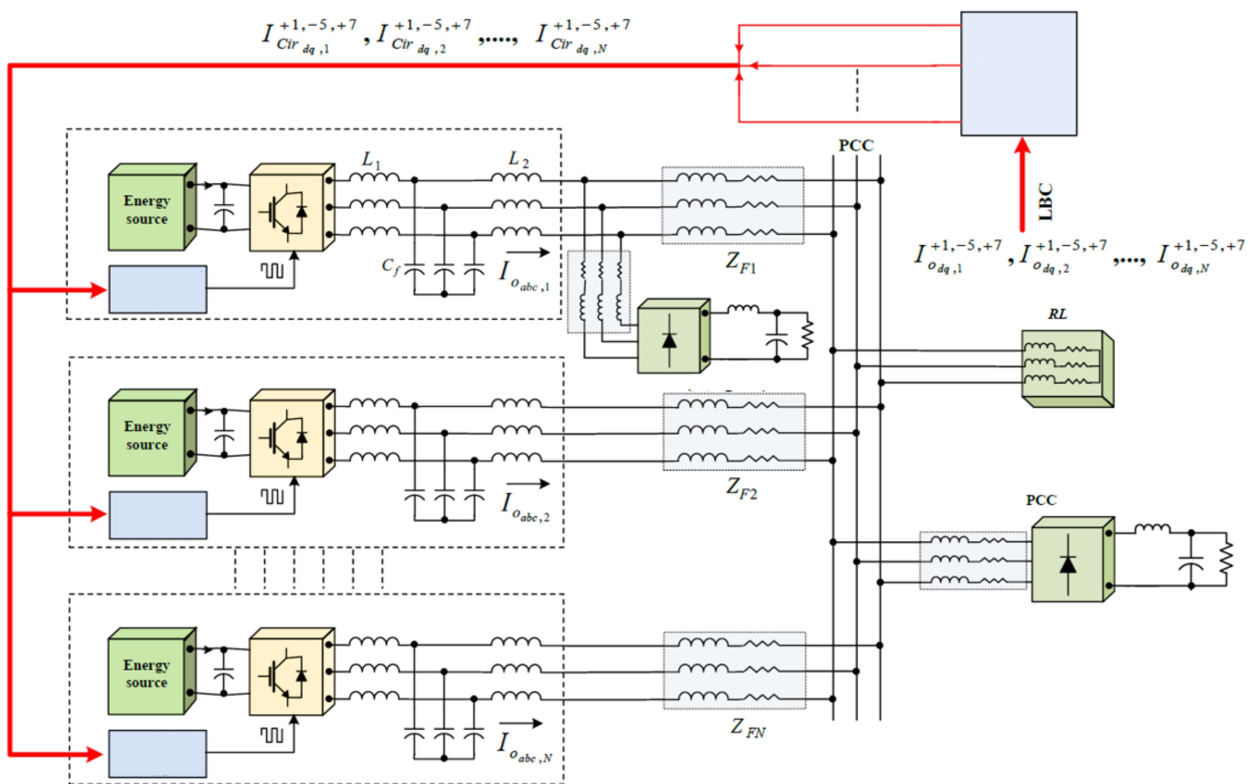


Figure 2-13: Example of a hierarchical control scheme on a microgrid [98].

Distributed Control

With the advent of new communication structures, the architecture and control structures also change. Hierarchical communication networks with physical subsystems at the lower layer and coordinators at the upper layer are replaced by distributed control structures. This structure will utilize graph theory, where the communication configuration is described by a directed graph, with each node representing physical subsystems along with their corresponding control units, and each edge representing a communication link. The most important issue is finding a communication topology for a given objective.

Distributed control systems (DCS) have three main features. The first is the distribution of various control functions in relatively small sets of subsystems that are semi-automatic and interconnected through a high-speed communication bus. Some of these functions include data acquisition, data presentation, process control, process monitoring, information reporting, and data storage and retrieval. The second feature of the distributed control system is the automation of the production process by integrating advanced control strategies, and the third feature is organizing everything as a system. DCS organizes the entire control structure as a single automation system, where different subsystems are unified through an appropriate command structure and information flow. These features of DCS can be shown in its architecture, as illustrated in the diagram below. The main elements formed in DCS include the engineering workstation, operator station or HMI, process control unit or local control unit, smart devices, and the communication system.

In the distributed control structure, local controllers decide for themselves which controllers to send information to and from which controllers to receive the required information, eliminating the need for a coordinating unit. In the distributed control structure, as shown in the example in Figure (2-14), it is assumed that some information is exchanged between local regulators (R1 and R2), so each regulator or controller has some information about the behavior and actions of other controllers. Figure (2-14) shows a simple system where controllers R1 and R2 are designed to control subsystems S1 and S2, respectively [99].

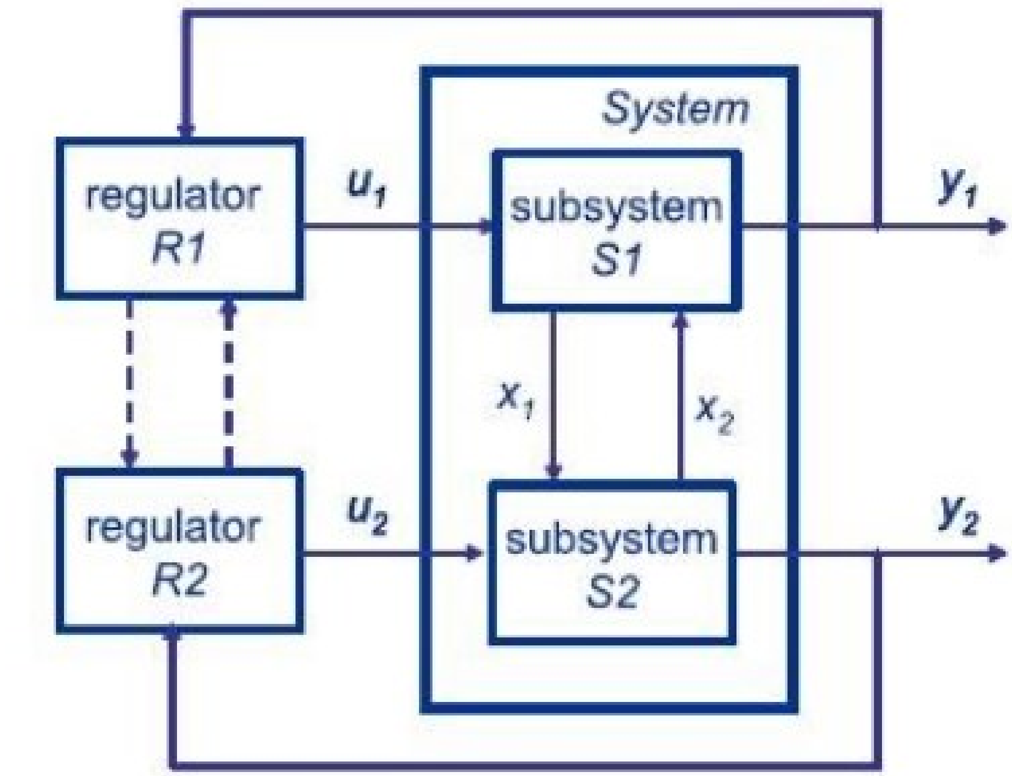


Figure 2-14: Distributed control structure for a two-Input two-output system.

In geographically distributed systems like transportation and power networks, which include hundreds or thousands of nodes, collecting all sensor information in one place for control is not feasible. In this case, distributed methods are needed that rely only on locally available information or information sent from nearby nodes, where some communication between nearby nodes is allowed. To understand the distributed control system, consider a system where a base system is involved by gradually connecting several subsystems step by step (Figure 2-15). Then, multiple subsystems are implemented in a decentralized manner in a base system. Additionally, the implementation continues as a modular connection. For practical reasons, not only the implementation but also the design process must be modular. This type of design is called distributed design, where each subsystem is designed independently of the others, except for brief specifications. Despite the difficulty of modular design, achieving stability and proper control performance for the entire control system is also essential [99].

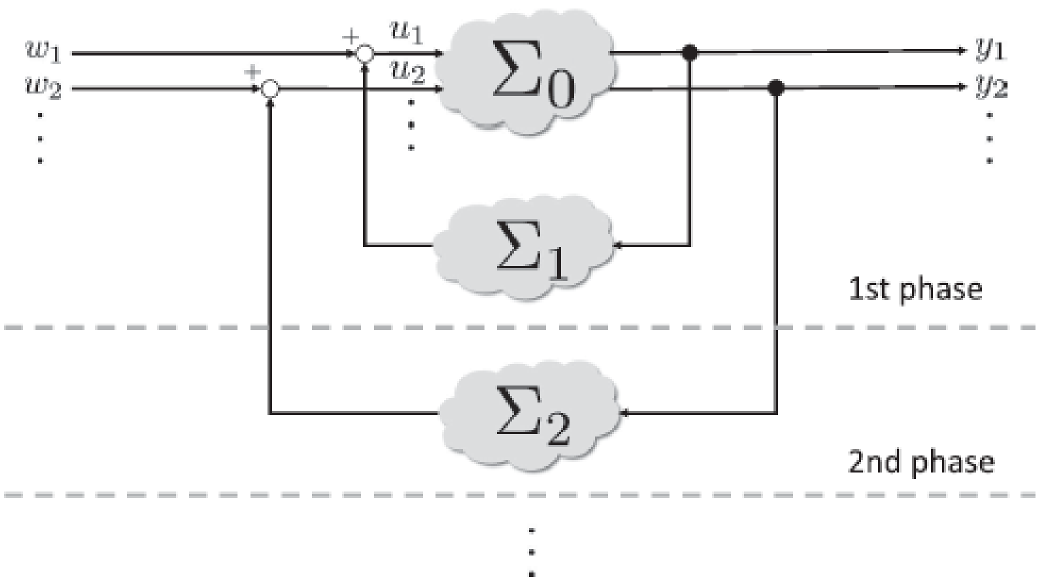


Figure 2-15: Evolution of a base system Σ0 with gradual connection of several subsystems

Robust control is an efficient method for designing distributed controllers. Within this framework, the networked system to be controlled is considered an interconnected system consisting of the desired subsystem and its environment, comprising other unknown subsystems with their interactions. Robust controllers are defined as controllers that can ensure the internal stability of the networked system for any environment, as long as the initial stability of the controlled networked system is maintained. By designing a robust controller as a sub-controller, each sub-controller can also implement its control policy independently of other controllers. All robust controllers can be specified through the Euler parameter with a linear constraint on the Euler parameter. Unfortunately, since controlling bounded parameters analytically is difficult, the general combination of the most robust controller cannot be done simply. Figure 2-16 shows a schematic of a robust control. Accordingly, Σ2 in Figure 2-12 can be considered a networked system consisting of sub-controllers and existing subsystems, as its dimensions and structure have no limitations. Generally, the assumption that a complete system model is available for networked systems is unrealistic. Additionally, simultaneous design of all sub-controllers is generally difficult for controlling networked systems equipped with DER. Even if Σ2 is considered model uncertainty, it is usually assumed to be normative in robust control. The robust control problem, searching for a controller that ensures the stability of the closed-loop system for all possible Σ2, so that the pre-existing system Σ is stable, differs from typical robust control issues [100].

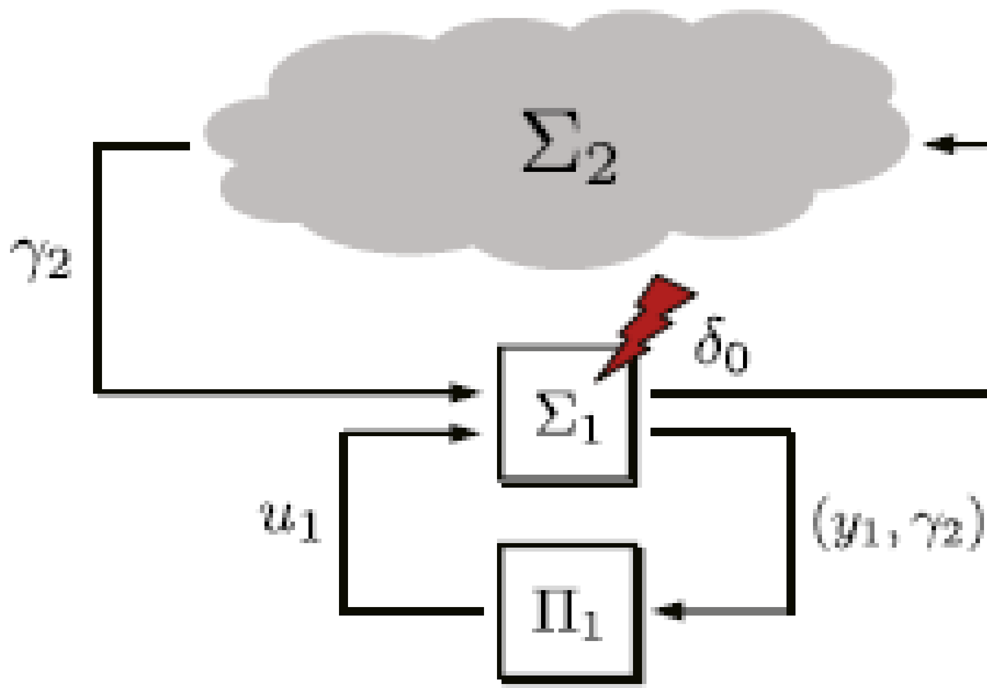


Figure 2-16: Schematic of signal flow in robust control [100].

Table 2-2: Comparison of different methods for energy management in micro-grids

Method	Properties	Advantages	Disadvantages
Decentralized	Each distributed energy resource (DER) operates autonomously using local data, without a central controller.	- High reliability and scalability - Fault tolerance - Adaptable to structural changes - Limited computational needs	- Limited by local information - Can struggle with system-wide coordination and interaction when communication links fail
Centralized	A single control unit	- Optimal performance with	- High dependency

	receives all system information, performs computations, and sends control signals to the entire system.	complete information - Effective for unified control	on central unit - Prone to total control loss in failures - Challenging in geographically dispersed setups
Hierarchical	Three-tier structure: primary, secondary, and tertiary controls to manage voltage, frequency, and optimize overall microgrid operations.	- Efficient management of localized issues - Maintains stability across subsystems - Adaptable to hybrid AC/DC setups	- Complexity in setup - Higher communication requirements - Limited flexibility in dynamic systems
Distributed	Control functions are spread across subsystems that communicate through a high-speed bus, often using graph theory for communication topologies.	- Reduces central dependency - Allows local autonomy with some inter-subsystem communication	- Can be complex to design - Dependent on reliable local and peer communications
Robust Control	Controllers designed to maintain system stability under uncertainties, with sub-controllers operating independently of one another.	- High resilience to system disturbances - Maintains stability despite uncertainties	- Difficult to design modularly - Performance may vary with large uncertainties

In summary, Chapter 2 has highlighted the critical role of sustainable energy management within microgrids and the diverse configurations and operational modes they offer. Microgrids stand out for their potential to improve energy reliability, reduce emissions, and support renewable energy integration, especially as distributed energy resources become more widespread. However, as this chapter has outlined, effective energy management in microgrids requires sophisticated control strategies to handle the variability in supply and demand while balancing environmental and economic goals. The insights from this chapter lay the foundation for the development of a multi-stage optimization framework, as presented in subsequent chapters, to address the complex challenges of microgrid management within active distribution systems.

Chapter 3: Electric Vehicles and Flexible Loads

3-1 Electric Vehicles

In the past decade, air pollution has been recognized as the most significant environmental risk to health, causing the deaths of 7 million people annually [101]. Globally, 40% of premature deaths each year are attributed to prolonged exposure to polluted air. With increasing population in developed societies and rapid economic growth, air pollution has become a major pollutant, forcing governments to adopt effective measures to combat it. Human and developmental activities such as construction, production, and transportation, although primarily aimed at increasing efficiency and modernizing global communities, have led to increased pollution worldwide. These activities produce large amounts of waste and greenhouse gases, leading to ozone layer depletion, global warming, and increased diseases and deaths due to pollution exposure. However, the occurrence, distribution, and significance of dust production largely depend on meteorological and ground conditions at the time and place of activity [102].

Transportation systems include various modes of transport (e.g., buses and cars) and facilities related to boarding or alighting (e.g., stations). Exposure to air pollutants in these systems is very high. For example, the concentration of particulate matter (PM2.5) in transportation models is reported to be about 10-40% higher than ambient PM2.5 concentrations in some cities like Delhi, India [85]. Therefore, to combat global climate change moving towards sustainability, mobility is one of the most comprehensive approaches. Thus, decarbonizing the transportation sector using electric vehicles (EVs) is currently a safe and efficient solution for the environment. EVs include hybrid EVs (HEVs), plug-in hybrid EVs (PHEVs), and battery electric vehicles (BEVs). The widespread adoption of electric vehicles is possible with technological improvements and government support. However, the potential of EVs to save greenhouse gas (GHG) emissions is debatable when the power required to charge EVs is supplied from traditional fossil fuel sources [102].

On the other hand, the shortage of fossil fuels and air pollution has increasingly concerned people, leading to more criticism of fossil fuel consumption in combustion engines. Electric vehicles are a suitable alternative to combustion engines to address these issues. These vehicles do not rely on gasoline or liquid gas as fuel but only use electricity stored in the vehicle's battery as a kinetic energy source. Additionally, the rising gasoline prices have increased the motivation to use electric vehicles. Consequently, the automotive industry is undergoing a global transformation. Current steps to improve efficiency and reduce energy demand must be taken much deeper and developed to meet the conditions of the Sustainable Development Scenario (SDS). Globally, transportation-related GHG emissions increased by 0.6% in 2018 compared to the previous decade, reaching 1.6%. As mentioned, the transportation sector significantly contributes to CO2 emissions from fuel combustion (i.e., 24% of CO2 emissions are from transportation). Vehicles such as personal cars, buses, trucks, and heavy vehicles account for nearly three-quarters of transportation-related CO2 emissions [103].

In recent years, the use of electric vehicles as an effective solution to reduce fossil fuel consumption in transportation has been widely welcomed by people and governments worldwide. Consequently, the number of electric vehicles is increasing significantly; according to reports from the International Energy Agency in 2016, the number of electric vehicles worldwide exceeded 1,000,000 in 2015 [104].

Electric vehicles have minimal emissions and play a significant role in reducing pollutant gases. Given the limited fossil fuels, using electric vehicles significantly reduces fossil fuel consumption. Additionally, electric vehicles are more efficient than diesel and gasoline vehicles. In diesel and gasoline vehicles, 75% of energy is wasted as heat and friction, and only 25% of energy is converted to wheel drive power. In contrast, only 20% of energy is wasted in electric vehicles. Since the number of parts used in electric vehicles is less than in conventional vehicles and they generate less heat, electric vehicles have lower maintenance costs than conventional vehicles. Additionally, in some countries, governments offer incentives such as tax and duty reductions for purchasing electric vehicles and providing facilities for their purchase.

Another advantage of electric vehicles is that they can be charged from electricity generated by multiple sources. These sources include wind, solar, nuclear, hydro, and biofuels. Using these sources can reduce dependence on oil and gasoline, resulting in fewer fuel imports and lower imported fuel costs. The use of these vehicles in the transportation industry (public, goods, etc.) is increasing, and many studies have been conducted on designing and optimizing the performance of these vehicles. The main limitation of using electric vehicles is their low battery energy compared to fossil fuel vehicles, long recharge times, and limited refueling (charging) stations. Since refueling these vehicles requires unique equipment and, unlike other vehicles (such as gasoline and diesel), they have limited refueling stations, the limitation of charging stations for these vehicles must also be considered. Another limitation of these vehicles is that their energy consumption depends on the vehicle's load, which imposes limitations in the real world. However, due to their positive impact on reducing air pollution, the design and creation of refueling stations are increasing. It is worth noting that reducing fuel consumption leads to lower service costs and, consequently, customer satisfaction [104].

3-1-1 History of Electric Vehicles

Regarding the history of electric vehicles, it can be said that hybrid and electric vehicles experienced a golden age around the 1920s, with approximately 34,000 units produced in the United States, roughly the same as the production of these vehicles in 2002 in the same country. If a reason can be found for these golden years, it can be attributed to humanity's limited knowledge of oil resources worldwide. It can be said that demand for vehicles was very high at that time, while the discovery of new oil resources did not match the demand for new vehicles, leading companies to produce electric vehicles. After that, research and studies related to these vehicles stopped due to the discovery of vast oil resources worldwide, and automakers focused more on producing fossil fuel vehicles [105].

Before the emergence of global warming, no one thought of producing electric vehicles on an industrial scale. The benefits of these vehicles include their environmental friendliness and simpler drive systems compared to their fossil counterparts. Additionally, the high efficiency of these vehicles should be considered, with electric vehicles having an efficiency of about 90%, while fossil fuel vehicles have an efficiency of about 30% to 35%, meaning fossil fuel vehicles have much higher energy losses than electric vehicles. From an energy consumption perspective, electric vehicles have higher efficiency, which is why they have attracted so much attention from automakers. As we know, one of the optimal energy management solutions is using electric vehicles. Electric vehicles have electric motors, and in these vehicles, the battery provides the electric energy for the vehicle. It can be said that electric vehicles are a new achievement in the automotive and transportation industry. Driving them is very cost-effective.

Electric vehicles also have disadvantages that make their use challenging. Some of the main disadvantages of these vehicles are:

- Inability to charge batteries in all conditions
- Dependence on fossil fuel-consuming engines [106]

Batteries play a crucial role in electric vehicles because a significant concern for electric vehicle owners is the fear of battery depletion on the road. Therefore, battery manufacturers pay extra attention to the construction of electric vehicle batteries. There is always extensive collaboration between automakers and battery manufacturers in various countries. Considering the stated conditions, one of the goals in battery manufacturing is the cost of producing electrical power. Currently, this cost is about \$500 to \$600 per kilowatt-hour, which should decrease to \$450 per kilowatt-hour by 2020.

International agencies have provided significant support for electric vehicles to manage energy consumption, resulting in a curved trend in the sales and use of these vehicles compared to others. The following curves illustrate the importance and necessity of using electric vehicles in the future and compare their sales.

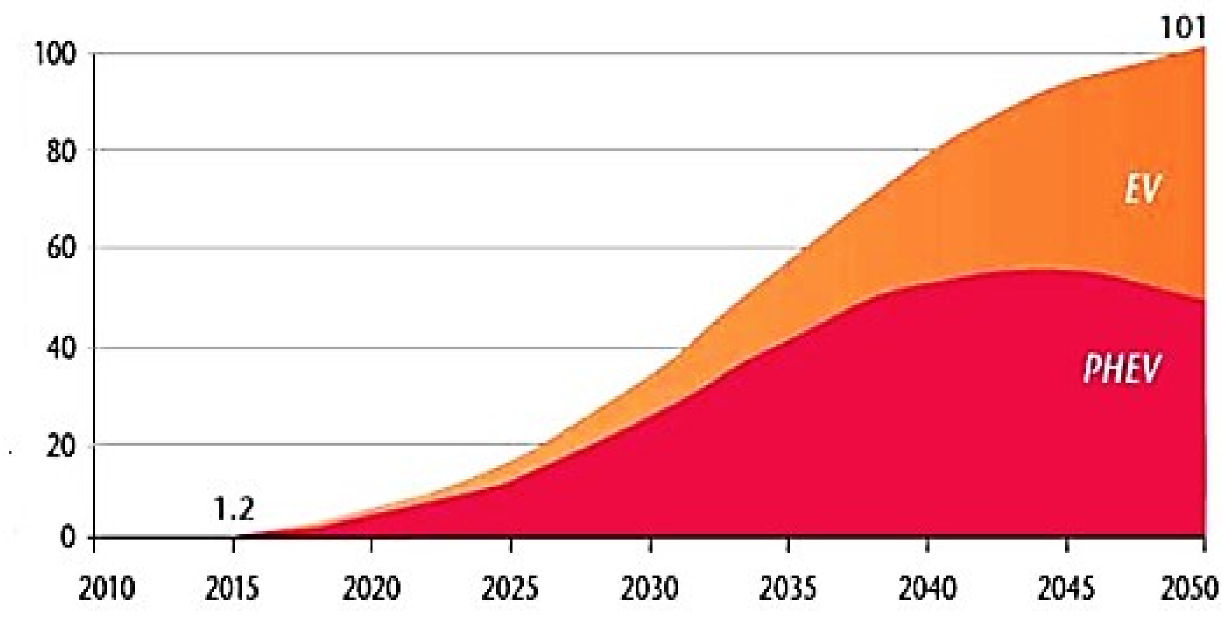


Figure 3-1: Projected sales of electric vehicles until 2050 [106].

Various countries have included the use of electric vehicles in their plans and are leveraging this technology to optimize energy management. Next, we will examine the impact of electric vehicles on distribution networks.

3-1-2 The Role of Electric Vehicles in Distribution Networks

Energy loss and reducing energy consumption have become significant concerns for operators and energy consumers. With the increasing demand for electricity and decreasing available resources, optimizing its use and reducing losses in the power grid is crucial. Studies show that about 13% of the generated power is lost as ohmic losses at various transmission and distribution levels. Various methods are used to optimize distribution systems, primarily aiming to reduce system losses. Capacitor placement and reconfiguration are the main and common methods in this field. The high penetration of grid-connected vehicles in the transportation sector significantly reduces air pollution and transportation costs, especially in large cities. The main characteristic of these vehicles is the use of batteries as a source to supply all or part of the propulsion power.

In general, using electric vehicles in the distribution network to charge their batteries creates negative effects on the transmission and distribution network. The impact of electric vehicle penetration on the distribution network varies, affecting charging patterns, charging speed, charging characteristics, power losses in the distribution network, driving patterns, demand response strategies to reduce load, driving distance, battery size, and tariffs. Researchers are pursuing solutions to these issues and programs to mitigate these effects. The widespread use of electric vehicles with new technology positively impacts the economy and the environment, as these vehicles significantly reduce air pollution and improve environmental conditions [107].

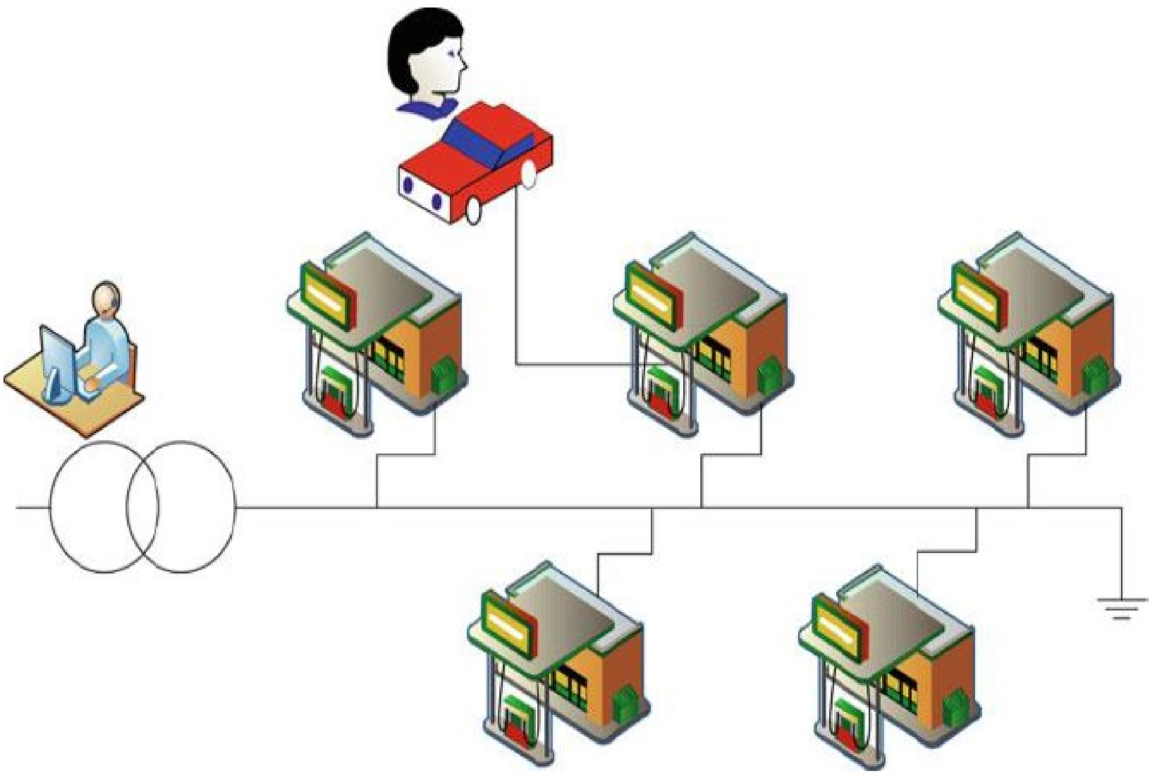


Figure 3-2: Distribution network with electric vehicle charging stations.

3-1-3 Equivalent Circuit Analysis with an Electric Vehicle

The need for electric vehicle charging is inevitable and must be considered. A vehicle fleet includes an n×m set of electric vehicles based on VSC (Vehicle Stability Control) systems connected to a distribution network bus through a charging center transformer. Electric vehicles in the parking lot participate in the exchange of active and reactive power with the distribution system. While active power charging depends on the battery's state of charge, the amount of reactive power produced by the vehicle depends on the VSC's reactive power limits and the specified voltage at the voltage control bus. Since a dispersed vehicle fleet may include dozens of vehicles, it is more effective to replace a vehicle fleet with a single vehicle model for load flow analysis. The figure below shows a simplified diagram of a charging center.

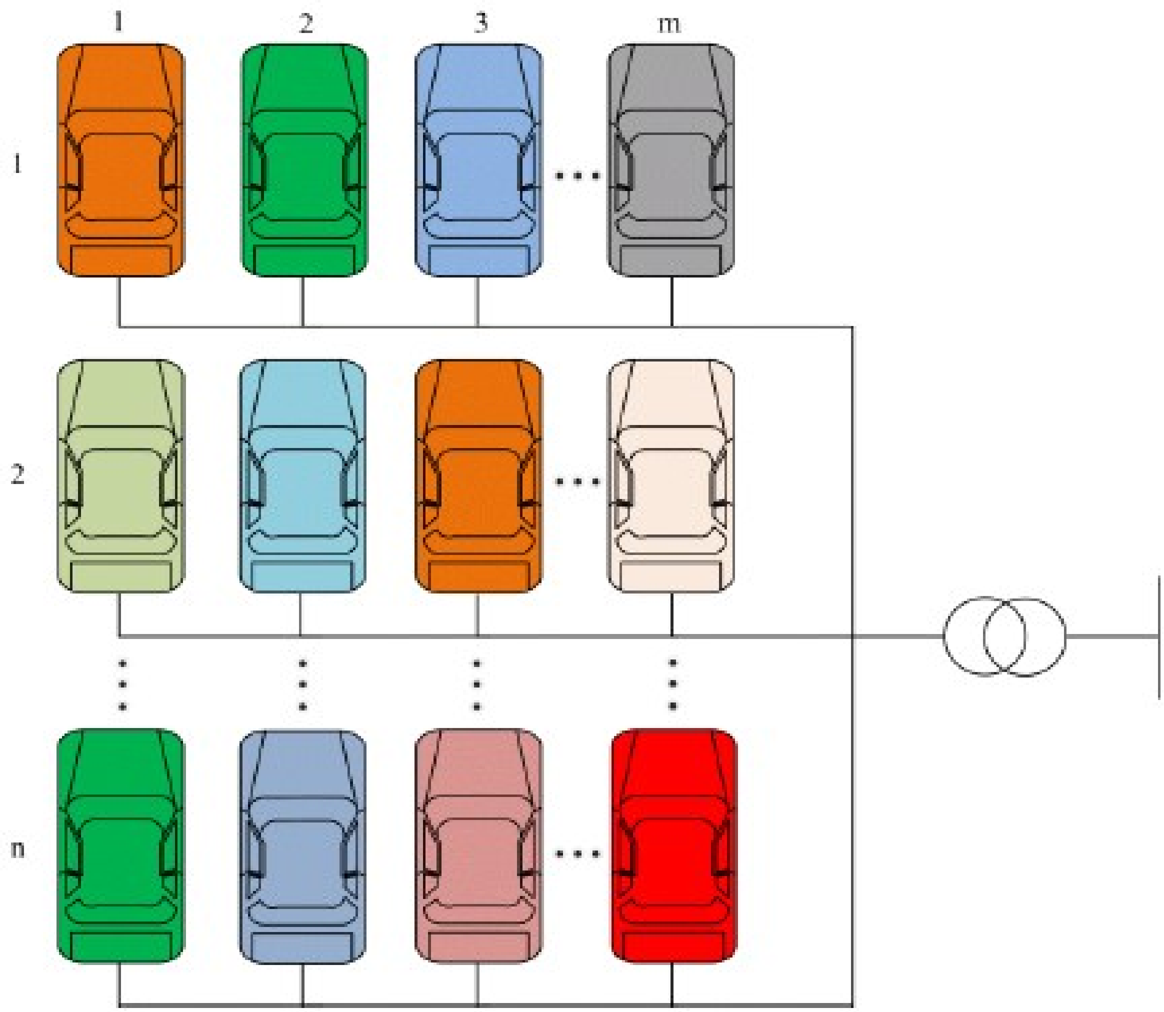


Figure 3-3: Representation of an n×m vehicle fleet during charging.

In the above figure, the distribution system and the charging center transformer are shown with abbreviations, and the operation of the charging support system can be observed and evaluated [108].

3-1-4 Effects of EVs charging

The deployment of a large number of electric vehicles in the electric grid demands additional power from the distribution network, and this increase in demand will bring many negative effects on the distribution network. These effects may vary depending on the level of penetration of electric vehicles, charging patterns, charging locations, driving patterns of vehicles, driving distance, charging modes, charging start times, battery SOC during charging tariffs, etc. The effects of electric vehicles on the distribution network can be divided into two categories: positive and negative effects. The positive effects are actually the benefits of using vehicle-to-grid (V2G) technology, but the negative effects of electric vehicles on the grid include voltage instability, increased peak demand, power quality problems, increased losses and equipment overload, especially transformers, which will be briefly explained below.

Regarding voltage instability, electric vehicles have non-linear load characteristics and take a large amount of electrical power from the network in a short period of time to charge their batteries. In other words, the amount of electric energy consumption by an electric vehicle cannot be accurately predicted. And for this reason, these vehicles have different load characteristics from other traditional loads in the network, such as industrial and residential loads, etc. Therefore, the effect of electric vehicles on the stability of the network voltage should be considered in an appropriate and related manner.

Regarding the increase in peak demand due to uncoordinated charging and controlled charging, it can be mentioned that the deployment of electric vehicles on a large scale in the electric network will lead to an increase in peak demand. Several studies have been conducted to investigate the effect of electric vehicle charging on the peak load of the network. For example, reference [109] has shown that inconsistent charging of electric vehicles with a penetration level of 30% will increase peak demand by 53%. However, the reference [110] states that even the normal charging of an electric vehicle in normal conditions will increase the demand peak and for this reason, the concept of smart charging should be used. In terms of power quality problems, it can be stated that the mass penetration of electric vehicles in the distribution network can affect the quality of power supply. Because if there is a large accumulation of electric vehicles in the network, the charging demand may reach high levels. Unbalance and voltage deviation occur only in multi-phase systems due to the presence of non-uniform loads in the distribution lines. Shahnia et al. [111] analyzed the sensitivity of voltage imbalance by considering the locations and levels of charging and discharging of electric vehicles in a weak pressure distribution network show that electric vehicles have a small effect at the beginning of the weak pressure feeder and a major effect at its end.

They proved at the penetration level of 34% of electric vehicles, the voltage imbalance index exceeds its allowed value in weak voltage networks, i.e. 2%. In addition, single-phase electric vehicle charging will also cause an imbalance of phases due to the non-uniform distribution of the load in the three-phase system. Regarding the voltage drop, studies show that up to 10% penetration level for controlled charging and 60% penetration level for uncontrolled charging of these vehicles in the distribution network can perform optimally without any negative effect on its voltage [112].

In explaining the losses and the effects of coordinated and uncoordinated charging, it can be mentioned that one of the negative effects of mass penetration of electric vehicles in the distribution network is the increase in network losses. The conducted studies show that the penetration level of electric vehicles, charging mode, charging level (charging start time) as well as the use of uncoordinated and unplanned charging methods can cause adverse effects on the voltage profile and losses of the distribution network. On the other hand, using a coordinated and pre-planned charging strategy and using uniformly distributed charging methods to charge electric vehicles near production sources can minimize network losses. Also, the increase of electric vehicles in the distribution network increases the load on transformers, for this reason it is necessary to choose the appropriate capacity of transformers, optimal planning for the network and use of load management strategy to reduce the negative effects of electric vehicles [113].

Environmental effects of electric vehicles

The use of electric vehicles, even with the assumption that the electric energy consumed by them is produced only by using fossil fuels in the thermal power plant and there is no other renewable production unit, it can still be environmentally and economically more suitable than internal combustion vehicles such as gasoline vehicles, because the production of mechanical energy in internal combustion engines takes place with a much lower efficiency than the production of electric energy in power plants. Also, when fossil fuels are consumed centrally in power plants and the electrical energy produced by them is delivered to electric vehicles, the management of pollutant emissions is much easier than when fossil fuels are consumed by individual vehicles with internal combustion engines [114].

Economic effects of electric vehicles

From the point of view of electric vehicle owners, the fuel and operation costs of electric vehicles are lower than vehicles with internal combustion engines, because electric engines are more efficient compared to internal combustion engines. The efficiency of an internal combustion vehicle is usually around 15-18%, while the efficiency of an electric vehicle is reported to be approximately 60-70%. In addition, V2G technology also provides the opportunity for the owners of electric vehicles to earn money through the exchange of energy stored in the battery with the network. From the point of view of the power supply network, the presence of electric vehicles in the distribution network increases the losses and costs of the entire system, however, the use of appropriate charging methods can significantly minimize the negative effects. For example, the use of controlled charging can reduce the costs and peak demand of the system by more than 50% compared to uncontrolled charging [115].

3-1-5 Electric Vehicle Charging

Electric vehicle (EV) charging is the process of replenishing the energy stored in an electric vehicle's battery by connecting it to an electric power source. This charging process is essential for the operation of electric vehicles, as they rely solely on electricity as their energy source. Here are some key aspects of electric vehicle charging:

1. **Charging Levels:**

    1) Level 1 Charging: This is the slowest and simplest form of charging. It uses a standard 120-volt household outlet and is typically used for overnight charging at home. It provides a charging rate of about 2 to 5 miles of range per hour of charging.
    2) Level 2 Charging: Level 2 chargers operate at 240 volts and are commonly found in residential garages, workplace charging stations, and public charging stations. They can provide a much faster charging rate, typically offering 10 to 30 miles of range per hour of charging.
    3) Level 3 Charging (DC Fast Charging): Also known as fast charging or rapid charging, Level 3 chargers use high-voltage direct current (DC) and can charge an EV much faster than Level 1 or 2 chargers. They are often found along highways and major routes, and can provide up to 100 miles of range in as little as 20-30 minutes.

2. **Charging Connectors:**

   Different regions and manufacturers may use different types of connectors for EV charging. Common connectors include the SAE J1772 for Level 2 charging in North America, CCS (Combined Charging System) for DC fast charging, and CHAdeMO for DC fast charging, primarily used by some Japanese automakers.

In the problem of electric vehicle routing, it is necessary to pay attention to the importance of battery charging stations. First, the warehouse should be equipped to charge vehicle batteries. So that the batteries of the vehicles in the warehouse are fully charged at night and start their journey with a fully charged battery. This action reduces charging costs. Secondly, in addition to the warehouse, public charging stations should also be installed at the desired geographical level. Among the most important limitations that distinguish the electric vehicle routing model from other vehicle routing models is the limitation of calculating the battery charge level at each node.

Fast Charging Stations and Their Location

With the growth of electric vehicles, access to the charging system of these vehicles becomes an emerging and important issue. The very large batteries of these vehicles have a length of about 1.7 meters and have a range between 5 and 30 kilowatt-hours. Accordingly, electric vehicles are considered a very large load for the electric network. Charging these vehicles with usual methods requires a lot of time. So that residential chargers spend about 14 hours to charge an electric vehicle with normal batteries [115], due to the limited capacity of home meters, we cannot quickly charge an electric vehicle with a normal battery capacity because the current consumption is much more than the capacity of the home meter.

Therefore, fast charging should be proposed in the form of public charging stations. On the other hand, connecting these vehicles to the grid during peak times will increase the current of the distribution transformers beyond their nominal limits. This issue will reduce the expected life of a transformer and other network components. For the growth of electric vehicles, fast charging stations in cities are an important need, so that in addition to supplying energy to vehicles, it can bring peace of mind to citizens with electric vehicles. In these stations, vehicles are charged in about 10 to 15 minutes and reach 80 to 100% of the final charge, which is a relatively suitable time for electric vehicle owners [116].

Electric vehicle fast charging station can have one to several charging units like fossil fuel stations. Due to the high consumption of fast charging stations, these stations should be connected and fed to the medium pressure distribution network and substations. Therefore, the closer the charging station is to the distribution substation, in addition to reducing the connection cost, the losses in the network are also reduced. The most important issue in the construction of an electric vehicle fast charging station is to determine the right place to build and operate the station. The issue of locating the charging station can be examined from several perspectives. Since fast charging stations connect transportation and electrical networks, the location and size of this station has a significant impact not only on the driving behavior of vehicles, but also on the performance of these networks. Therefore, the location of the fast charging station should be done considering the presence of both networks. From the point of view of the electricity company, the best place to build a fast charging station is a place where the least losses occur in the distribution network and the least development in the distribution network in terms of adding a line, dedicated feeder or transformer, and on the other hand, the charging station can be easily connected to the network. From the point of view of the owner of the station, a place should be chosen where the costs are the lowest. Costs such as the price of land, the cost of connecting to the network, the cost of charging and maintenance units. Therefore, the station should be built in a place where there is the highest density of EVs. Generally, fast charging stations have a small or large number of charging units (capacity) according to the density of electric vehicles. It is clear that it is not logical to consider economic benefits alone to solve the problem in question, therefore, the main goal is to determine the optimal location and size of charging stations with the help of various optimization methods in such a way that both the total cost is minimized and the security of the power system is ensured. In order to achieve the desired goals, various methods have been used to solve the problem of locating fast charging stations, some of which will be presented below.

Types of Location Models of Charging Stations

1) Location based on burgers

In the location model of the charging station based on nodal demand, the current passing through the nodes is considered and it is assumed that the charging of electric vehicles that can be connected to the grid (PEV) occurs on some geographical nodes of the target planning area and the charging stations are located to meet the demand. However, this method only considers the geographical straight-line distance between the charging nodes, while the limitations of the density of the transportation network are ignored [117].

2) Location based on traffic flow

In this planning model based on traffic simulation, it is used to estimate PEV charging requirements. Simulations are often based on data from real-world trips. Obtaining such data can be expensive for some areas. Considering the mobile behavior of rechargeable electric vehicles, some researchers proposed planning methods based on traffic flow. In this method, source and destination traffic flows are used to estimate charging demand which includes FCLM and FRLM. In the FCLM model, it is basically a flow-based route coverage maximization problem, which locates the p number of charging equipment to maximize the amount of routes covered by a charging station anywhere along the flow path (Berman, et al., 1992). The FRLM model, which is a modified FCLM model, is called the fuel-flow location model. Fuel-flow location locates a given number of stations in order to maximize route-based demands that can be refueled. The main difference between FRLM and FCLM is that in FCLM a flow is covered if at least one charging station is located anywhere along the flow path. But in FRLM, depending on the distance of the route and the maximum driving range that the vehicles have (assumed coverage area), a combination of two or more charging stations may be required to refuel and cover the flow so that the vehicle does not run out of fuel.[1]

[1] Flow capturing location model

3-1-6 Wireless Charging of Electric Vehicles

The wireless charging system is a more advanced generation of charging stations for electric vehicles. By completing the charging capacity of electric vehicles, you can only travel up to a certain distance and after that the vehicle must be connected to the electricity again. Therefore, it is clear that electric vehicle charging stations are installed in different places, just like gas pumps and gas pumps, and it may result in loss of time, both during charging and waiting in line, as well as energy loss. In other words, using the above-mentioned charging stations on the one hand limits us to time and place, and on the other hand, we cannot continue on our way until charging time, so the idea of wireless charging arose from these problems.

In order to build wireless charging stations for electric vehicles, different ideas were studied, each of which was complementary to the previous ideas. For example, one of the ideas was the use of transmitter and receiver wires. In such a way that the receiver wires were embedded in the vehicle and one or more large transmitter wires were installed on the side or under the roads. This approach required high investment costs. Therefore, the researchers came to the conclusion to modify the wires of the transmitter and receiver. This means that the wires of the same size should be used in the transmitter and receiver. With the difference that the transmitter coil in the station can expand and control the field under its radius based on the reactance reflected from the receiver coil, thus the power losses will be greatly reduced and the destructive effects of the magnetic fields will also be reduced. In other words, when the electric vehicle approaches one of the wireless charging stations, the transmitter system will notice and increase its output power by 400%. When the vehicle is moving away, the transmitter waves gradually decrease. Therefore, not only it will not be dangerous for people's health, but less electrical power will be wasted [118].

A typical EV wireless charging system is shown in the figure below, which includes several steps to charge an EV wirelessly [119]. First, the AC electric power is converted into a DC power supply by modifying the power factor by an AC to DC converter.

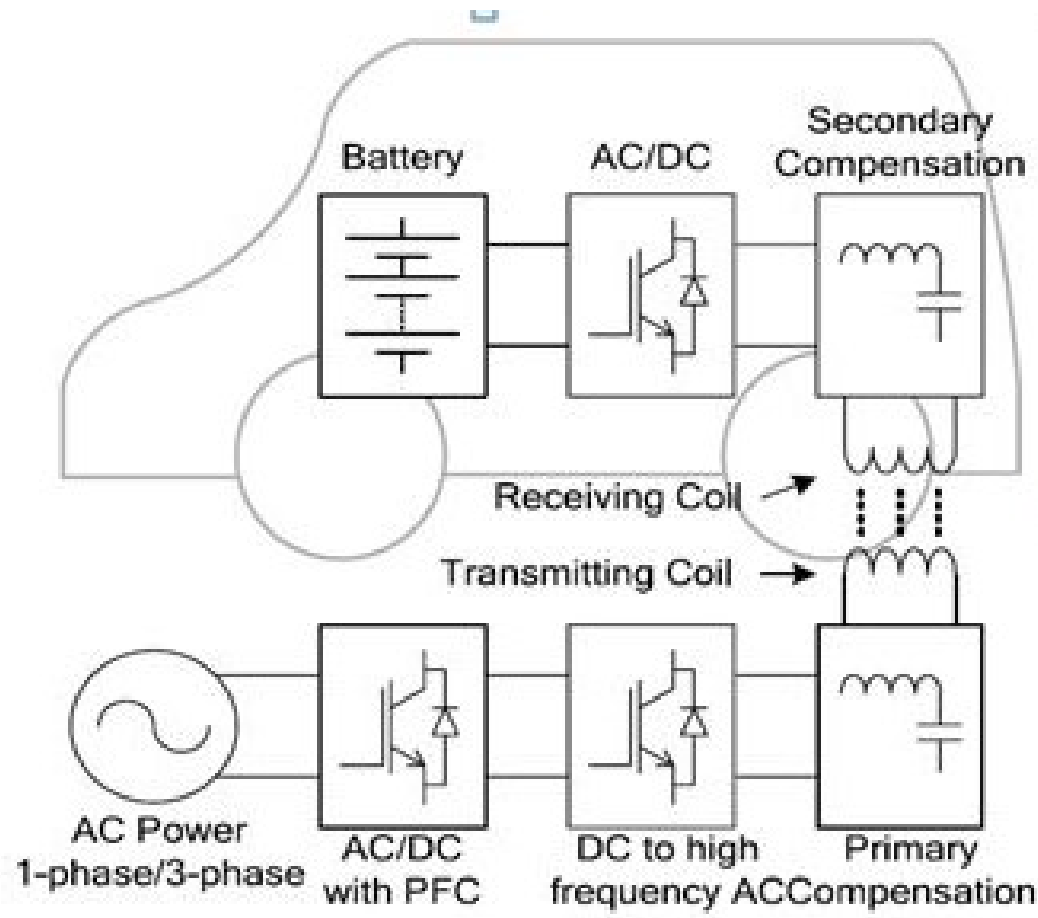


Figure 3-4: A conventional EV wireless charging system [119].

Then, the DC power is converted to a high frequency signal to drive the transmission signal through a compensating network. Due to the insulation failure of the primary winding for added safety and protection, a high frequency isolation transformer may be placed between the DC-AC inverter and the primary winding. The high frequency current in the transmitter coil creates an alternating magnetic field that causes AC voltage in the receiver coil. By resonating the secondary compensator network, the transmitted power and efficiency are significantly improved. Finally, the AC power is rectified to charge the battery [120].

As a result, wireless power transmission has many components including: rectifier, power factor corrector, inverter, network compensator on the transmitter side, magnetic coupler (transmitter and receiver coil), network compensator on the receiver side and rectifier for DC chargers, an additional DC-DC converter on the transmitter side.

Various topologies have been presented in this field that define the connection method as series-series, series-parallel or vice versa and parallel-parallel [120]. Of course, it can also be considered as a compound, which includes SPS and PSP [121]. On the other hand, the compensation operation has been done so far based on the use of a coil, which can be done using only one capacitor or a combination of both with different LCL or LCC topologies. In the LCL converter, one or two LC network compensators are used on the sides. The advantage of LCL at the resonance frequency is that the current on the primary side can be independent of the load condition, and in other words, it can act as an independent current source. The LCC design requires an additional coil, which is usually an additional capacitor in series with the coil to reduce the size and cost of the additional coil, which is called the LCC model. Using LCC, a zero switch current can achieve the highest efficiency by adjusting the network compensator parameters. Therefore, when LCC is confirmed on the secondary side, the reactive power of the secondary side can somehow compensate and the distortion current may be reduced [122]. Figures 3-5 and 3-6 show the general LCL and LCC topology, respectively.

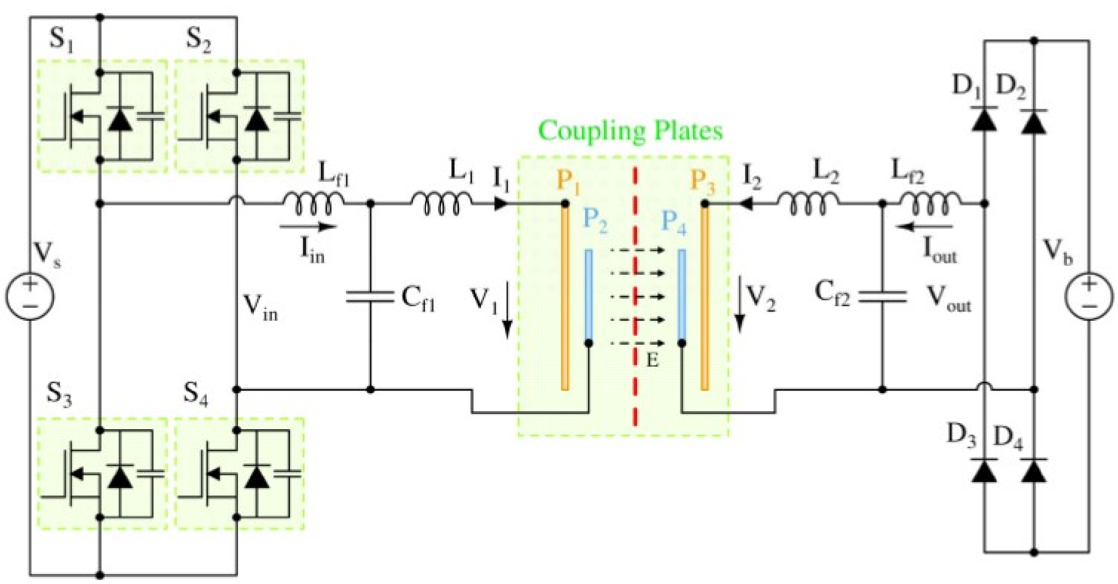


Figure 3-5: LCL compensated topology integrated circuit [122].

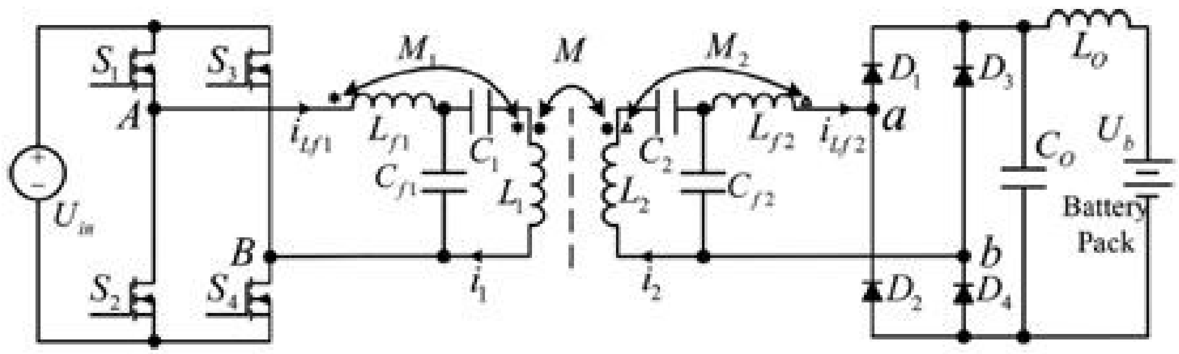


Figure 3-6: LCC compensated topology integrated circuit [122].

Static Electric Vehicle Charging (SEVC)

One of the problems of electric vehicles is their maximum range, which is closely related to battery and charger technology. Fast charging, wireless charging and vehicle charging while moving are some of the proposed solutions. Recently, a new wireless charging system has been introduced that has high capabilities. Currently, the charging of electric vehicles that exist in the home environment and other places is generally done by a special relationship. Most of today's electric vehicles need a physical connection wire to fill the charge level of their batteries. However, in some areas, you can use wireless charging services for electric vehicles, but these devices can only charge the electric vehicle battery with a power of 3.3 kW. This amount of power is enough to charge electric vehicles during the night, but the main solution that can solve this big problem is the possibility of charging electric vehicles on public roads wirelessly and quickly. Fortunately, the results of recent research in this direction also show that this category of work will be offered in the near future. The figure (2-2) shows a local wireless charging station [123].

Figure 3-7: Static wireless charging station

Dynamic Electric Vehicle Charging (DEVC)

Paying attention to the current trend, there is no doubt that the future belongs to electric vehicles. Although these vehicles have many advantages, they also face disadvantages that have been mentioned before, among which the following can be mentioned.

- Limited travel distance
- Few charging stations
- Relatively long time to recharge the batteries

One of the ways to solve all three problems is called DEVC, and if implemented, it will provide the possibility of infinite distance travel for electric vehicles. This technology, which stands for dynamic electric charging of the vehicle. Using wireless charging technology, it can continuously feed the moving vehicle. The well-known company Qualcomm, which is known mostly for its mobile chipsets, has been researching a similar technology and has shown some of its findings. This American company, in cooperation with the French company Vedcom, designed a 100-meter test track in the city of Versailles to test its DEVC system there. In the figure below, the vehicle can be seen moving on the wireless charging station on the route.

Figure 3-8: A vehicle moving on a wireless charging station

3-2 Demand Response

Demand response is one of the new developments in the DSM (Demand-Side Management) field, meaning consumer participation in improving energy consumption patterns. Demand response is generally defined as the participation of small consumers in the electricity market, facing real-time market prices, and responding to them. This participation occurs in response to prices that change momentarily. Additionally, incentive payments designed during times when wholesale market prices are high or when system reliability is at risk can motivate consumers to change their consumption. Therefore, the overall goal of implementing demand response programs is to achieve two important characteristics: network reliability and price reduction.

According to the definition provided by the DOE in February 2006: Demand response is the change in electricity consumption by consumers from their normal consumption patterns in response to changes in electricity prices or in response to incentive payments designed to reduce electricity consumption (during times when electricity prices are high or system reliability is at risk) [123].

The overall goal of demand response is to reduce electricity consumption during critical hours. Critical hours are times when wholesale market prices are very high, or the system's reserve level is low due to unexpected events such as transmission line and generator outages or severe weather conditions.

Two factors can lead to the acceptance of demand response by consumers: changes in electricity prices at the retail level, reflecting the variable nature of real electricity prices, or the implementation of an incentive program to encourage customers to reduce their consumption during critical hours. This incentive cost is separate from the regular price paid for electricity. This incentive can be a payment to the consumer for reducing load, a penalty for not reducing load, or both. Demand response is essentially a change in load consumption behavior in response to a stimulus. Demand response can result from rescheduling the production of an industrial consumer, readjusting the heating system of a commercial consumer, or direct control by the utility company over a residential consumer's water heater. Additionally, demand response can involve replacing electricity supplied by the power system with internal generation (using a backup generator for a few hours during peak load).

3-2-1 Importance of Demand Response:

Today, load forecasting curves indicate a growing demand for electrical energy, which requires significant investments to meet this consumption. It is evident that in such conditions, demand response can greatly help solve this issue. Generally, the importance of demand response becomes clear when we realize the numerous financial and practical benefits it provides to consumers and even the network itself, such as reducing outages, lowering production costs, smoothing the load curve, stabilizing market prices, and more. In general, electrical power systems have three important characteristics, which include [124]:

1. Electrical energy cannot be widely stored at the power system level. Therefore, the available generation capacity at all times must be equal to or greater than the total load of the system's consumers. At certain times during the year, the system's consumption increases significantly, and without considering demand response, the required generation capacity to supply power and reserve for these hours will increase.
2. The installation cost of power plants is very high and time-consuming. However, by implementing demand response programs, consumption during peak hours by consumers

willing to reduce their usage decreases, thereby avoiding additional costs for creating generation capacity for a short period.

3. Electricity prices vary significantly at different times of the day due to changes in the system's load requirements during different periods and hours, as well as changes in available generation and transmission line capacity (due to unexpected events). During peak hours, more expensive units must be used to supply power, increasing market prices. Despite the variable market prices, consumers always pay a fixed cost (retail market price), which is the average cost of production, transmission, and distribution. This disconnect between the actual electricity price and the cost paid by consumers leads to improper resource use. Since consumers are unaware of the actual electricity prices at different times, they lack the motivation to align themselves with energy suppliers. Therefore, fixed electricity prices result in high consumption during peak hours (when the actual electricity price is higher than the average) and lower consumption during off-peak hours (when the actual electricity price is lower than the average). Consequently, electricity prices increase during peak hours due to the use of expensive generators for consumer power needs.

Given the points mentioned above, using demand response seems necessary. For example, by implementing demand response programs, the construction of new power plants can be delayed, electricity production costs can be saved, and a balance between production and consumption can be maintained at all times.

Additionally, demand response can increase system reliability. In this program, loads can reduce some of their consumption to address system or local capacity constraints. During emergencies or when the system's reserve level is low, the utility company must ration consumer power to prevent continuous outages and maintain system integrity. However, providing load reduction services by consumers reduces the losses caused by unwanted power outages. Voluntary consumer participation in balancing production and consumption during emergencies is more cost-effective and appropriate than mandatory cuts.

Moreover, real electricity prices can be used to address limited system capacity issues. Consumers will respond to high electricity prices during peak hours by reducing their consumption. Consequently, applying wholesale market price changes to loads will reduce their consumption during peak hours, lowering market prices during these hours and freeing up some system capacity (when the power system faces a shortage).

Additionally, during peak hours, production companies may increase their proposed energy production costs to achieve higher profits (when most generators must be in operation to produce electricity), further increasing market prices. In such conditions, demand response can reduce this market power exerted by production companies and help stabilize prices. During peak hours, instead of using expensive generation resources, the capacity offered by loads willing to reduce their consumption can be used, thereby controlling electricity prices.

3-2-2 Types of Demand Response:

Demand response can be broadly categorized based on how consumers participate in changing their electricity consumption patterns:

1. Price-Based Demand Response (PBDR)
2. Incentive-Based Demand Response (IBDR)

Each of the above categories is further divided into several subgroups. It should be noted that some articles use the term "time-based demand response" instead of price-based demand response [124, 125]. Additionally, some articles categorize demand response into various groups, including system and market-related programs, economic and emergency programs, or sustainability and economic-based programs [126]:

Price-Based Demand Response:

Most electricity consumers are unaware of prices that change momentarily and treat electricity as a commodity offered at a fixed rate. Therefore, they have no incentive to change their electricity consumption patterns in response to these prices. Economists believe that applying real electricity prices to consumers will increase efficiency. Price-based demand response programs create this incentive for end consumers, encouraging them to change their electricity consumption patterns. The use of these demand response programs has recently received special attention. If electricity price information is provided to consumers, they can control their consumption, reducing it when prices are high (and vice versa), thereby reducing their costs. This change in electricity consumption patterns in response to prices is entirely voluntary and carried out by end consumers.

In price-based demand response programs, no payments are made by utility companies to consumers for their participation. Consumers voluntarily adjust their consumption based on market prices, managing their costs. Price-based demand response includes time-of-use tariffs, critical peak pricing, and real-time pricing. It should be noted that some articles expand this classification to include critical peak day pricing and critical day pricing .

Typically, demand response is implemented through an internal decision-making process by the consumer, and all actions to adjust consumption are voluntary.

1. Real-Time Pricing (RTP)

As the name suggests, these programs use real-time prices as a signal for consumers to change their consumption. These hourly price changes reflect price fluctuations in the wholesale market, representing the actual production costs for all hours of the day. These programs provide a direct link between the retail and wholesale markets, and consumers are usually informed of the real-time market price a day or an hour in advance, adjusting their consumption accordingly. Generally, implementing RTP programs requires advanced metering equipment to provide consumers with hourly price information and measure their hourly consumption [127]. The RTP model improves market conditions by providing the necessary incentives for loads, preventing market power, stabilizing variable market prices, and enhancing system reliability. Additionally, RTP can reduce or shift peak loads like other demand response methods [128].

It is clear that this method and other demand response methods are not applicable for loads that cannot flexibly adjust their consumption. The RTP method is most useful for large consumers, as dealing with real-time wholesale market prices is practically challenging for residential consumers.

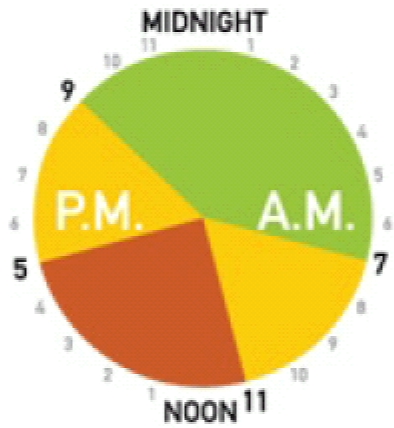
Time-of-Use (TOU) Programs

This program is one of the most common demand response programs among residential consumers. This method encourages customers to improve their electricity consumption patterns (using electricity during off-peak hours and reducing consumption during peak hours) by varying prices at different times. As mentioned earlier, the appropriate way to encourage customers to reduce their consumption is to inform them of the real electricity prices in the market and charge them accordingly. However, market electricity prices change rapidly, and if these prices are applied as electricity tariffs to customers, the price changes would be instantaneous. It is clear that most customers do not have the time or equipment to respond to these instantaneous changes. Therefore, using several time intervals throughout the day to apply different electricity tariffs to these consumers seems more logical [129].

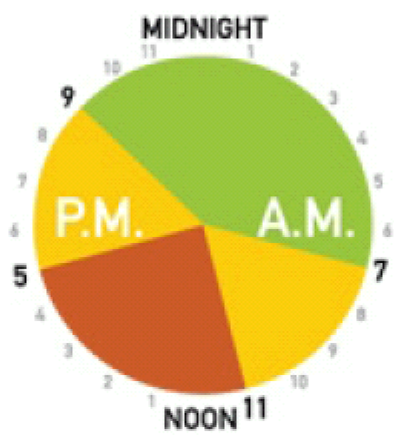
In the TOU method, electricity tariffs are set as different prices for various time intervals within a day. These tariffs are usually considered as the average cost of production and transmission of power in each time interval. TOU tariffs typically change from one time interval to another within a day or from season to season and are usually predetermined for several months or years. In this method, energy prices are typically calculated and charged in three states: peak, mid-peak, and off-peak, based on the different energy prices in each state. These tariffs can also be calculated for different hours of each day, different days of the week, or different times of the year. In other words, these tariffs can be daily or seasonal. These tariffs are widely used by large industrial and commercial consumers and require measuring devices capable of recording consumption in different time intervals (where electricity prices vary) [130]. The time intervals and electricity prices in each interval in these programs vary among different utility companies based on their daily, seasonal, and yearly peak loads. In other words, the goal of the TOU program is to create an incentive for consumers to shift their consumption from peak hours to off-peak hours, thereby reducing their costs [131].

Experience shows that using these tariffs in the residential sector results in a smoother consumption load curve. As an example of this type of tariff, Figure 3-6 shows the different tariffs set in Canada. In these figures, the 24-hour period of each day is divided into three categories: peak, mid-peak, and off-peak, depending on the season and whether the day is a working day or a holiday. As seen, in the first half of the year, there is one peak load corresponding to the hot hours of the day. However, in the second half of the year, there are two peaks during the day. This is because the days are shorter in this period, with the first peak in the morning and the second peak at noon. On weekends and holidays, due to the closure of commercial and industrial centers, electricity consumption is low, and as shown in Figure 3-6, these days are considered off-peak days. For the three considered intervals (peak, mid-peak, and off-peak), different electricity tariffs are specified. The electricity prices during peak hours are 9.9 cents/kWh, mid-peak hours are 8.1 cents/kWh, and off-peak hours are 5.1 cents/kWh.

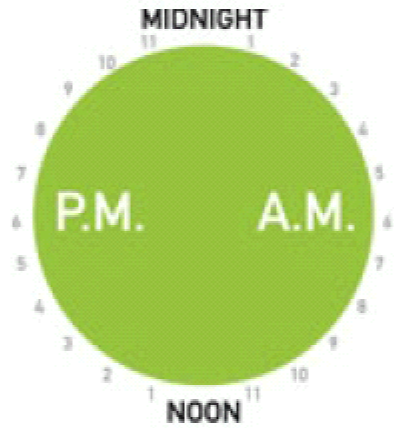
For example, according to Figure 3-9, residential consumers can run their dishwasher at 9 PM (since this time is considered off-peak). Additionally, since weekends and holidays are considered off-peak days (due to the closure of commercial and industrial centers), using the washing machine can be postponed to these days.



a- First Half of the Year (May 1 - October 31)



b- Second Half of the Year (November 1 – April 30)



c- Weekends and Other Holidays

Highest Price (Peak Hours)

Medium Price (Mid-Peak Hours)

Lowest Price (Off-Peak Hours)

Figure 3-9: Example of TOU tariffs in Canada [131].

In addition to the mentioned advantages, TOU also has disadvantages. One issue with this program is that TOU has a static nature and does not differentiate between different days of a season (it sets fixed rates for consumers on days within a season), which may lead to a mismatch between actual peak hours and the hours specified as peak in the tariff [132].

For example, on July 7, the temperature may be very high (e.g., 40 degrees) during certain hours (e.g., 10 to 11 AM), increasing the use of cooling devices and potentially turning these hours into peak hours (while in the specified tariff, these hours are considered mid-peak). In contrast, on August 7 (the following month), during the same hours, the temperature may be cooler (e.g., 20 degrees), reducing the need for cooling devices.

For instance, on July 5, 2003, in the PJM market, a comparison was made between the implementation of RTP and TOU programs, and the air conditioning consumption was calculated. The results are shown in Table 3-1:

Table 3-1: Comparison of costs in different programs

Program Type	Cost
Fixed Rate	1928
TOU	1716
RTP	1317

As seen in Table 3-1, costs vary between programs. If a consumer uses the TOU program to reduce their consumption, their cost is 11% lower than using fixed rates. On the other hand, using the RTP program reduces system costs by 33% compared to fixed rates and 22% compared to the TOU program.

Critical Peak Pricing (CPP)

As previously mentioned, some loads cannot implement the RTP method. It was also observed that the TOU method applies price fluctuations in the form of several general tariffs to the loads. To meet the need to reduce consumption during critical hours of the year, when electricity consumption is very high (e.g., extreme heat) and system reliability is at risk (due to an unexpected event) or wholesale market prices are very high, critical peak pricing seems to be a suitable solution. The CPP tariff is essentially an additional tariff applied to fixed or TOU pricing during critical hours.

This method has fewer economic benefits compared to RTP due to predetermined prices. However, this feature makes it attractive because, unlike RTP, it does not face the risk of sudden severe price changes. Although this program is part of price-based demand response programs, it is also categorized under reliability-based programs because it can be used when the system is at risk. Empirical evidence shows that these programs can significantly reduce loads during critical hours. For example, in California, using the CPP tariff resulted in a 41% reduction in loads from their normal consumption (without the CPP tariff) during a 2-hour period due to extreme heat. It is worth noting that without end-user control, this reduction was 13% over a 5-hour period [133].

Generally, CPP programs can be divided into four categories:

- **Fixed Period CPP**: In this program, the time and duration of price increases (during critical hours) are predetermined, but the days when critical peaks occur are not specified. The maximum number of days usually called during the year is also predetermined, and the occurrence of the event is notified to consumers on the same day.
- **Variable Period CPP**: In this program, the time, duration, and day of price increases are not predetermined and are notified to consumers on the same day. This program is usually used in devices that automatically respond to critical peak prices (such as telecommunication thermostats).
- **Variable Peak Pricing CPP**: In this program, the energy price during off-peak and mid-peak periods for a month or more is predetermined. The price during peak hours is determined based on the average price of the same day. This method has the advantage of creating a direct link between retail and wholesale market prices.
- **CPP with Critical Peak Rebate**: In this program, the consumer pays a fixed rate for electricity consumption and receives a rebate if they reduce their consumption during critical peak periods.

Extreme Day Critical Peak Pricing (ED-CPP)

These tariffs are a type of CPP that considers higher prices for the entire critical day compared to regular days, and for hours of the day when electricity consumption reaches its peak, prices are significantly higher than other hours of the same day.

Extreme Day Pricing (EDP)

This program is similar to CPP in having high prices during critical hours. However, the difference is that CPP only includes limited hours, while EDP covers the entire critical day. These prices are unspecified until the critical day. Generally, price-based demand response programs cannot be immediately implemented for all consumers. In other words, conventional and traditional metering devices and billing systems are not suitable for such programs, and consumers cannot make daily and hourly decisions. Therefore, strengthening incentive-based demand response programs until price-based demand response programs develop can significantly help increase system efficiency and reliability.

Incentive-Based Demand Response Programs

Incentive-based demand response programs create an incentive for consumers to reduce their consumption. Unlike the first group of programs, these do not deal with price signals but generally provide a suitable tool for load control in emergency conditions for utility companies and network operators to maintain system reliability and manage costs. These programs offer incentives for voluntary consumer participation in load reduction. These incentives are unrelated to electricity prices and may be in the form of discounts on subsequent bills, pre-arranged payments, or measured reduced load. Some of these programs impose penalties on consumers who commit to reducing load but fail to do so at the scheduled time [134].

In general, incentive-based demand response includes Direct Load Control (DLC), Interruptible/Curtailable Load (I/C), Demand Bidding Programs (DBP), Emergency Demand Response Programs (EDRP), Capacity Market Programs (CMP), and Ancillary Services Market Programs (ASMP).

3-2-3 Benefits of Demand Response

Demand response provides numerous financial and practical benefits to consumers and even the network itself. The benefits of demand response are examined from the perspectives of consumers and the network.

Benefits of Demand Response from the Consumer's Perspective

Consumers participate in demand response to achieve economic benefits and prevent outages (helping to maintain power supply continuity). However, the main reason for consumer participation is generally to achieve financial and economic benefits. They usually contribute implicitly to improving network reliability. Therefore, these benefits can be categorized into financial benefits and reliability benefits.

Financial Benefits

The increase in fuel and electricity prices in recent years has created additional motivation for consumers to adjust their consumption. Consumers can reduce their costs by shifting their consumption to cheaper hours. Additionally, incentive payments given to consumers to keep their load ready for curtailment (or curtail it when necessary) can provide significant financial benefits.

Reliability Benefits

Consumers, by responding to high prices, unintentionally improve network reliability and compensate for production shortages during peak hours (high-price hours), reducing outages and ensuring continuous power supply.

Benefits of Demand Response from the Market and Network Perspective

Demand response, through its impact on market operations, system reliability, and social welfare, creates network benefits that most or all consumers will benefit from. The main driver for implementing demand response programs is these benefits. These benefits can be divided into short-term and long-term impacts on the market and system reliability.

Short-Term Market Impacts

As previously mentioned, economists believe that optimal economic efficiency is achieved when the real price of a commodity is applied to its consumers. On the other hand, if the real price of electricity is applied to consumers, during peak hours when electricity prices are high, consumers will reduce or shift their consumption to other hours. This reduces the real-time market price. In electricity markets, part of the energy is traded in the form of long-term contracts. With the reduction in real-time market prices due to demand response, electricity prices in long-term contracts also decrease. This is because the risk of consumers facing high prices in real-time markets (if needed) is reduced, and if production companies are unwilling to sell electricity at lower prices in long-term contracts, consumers will prefer to procure their required electricity from the real-time market. Therefore, demand response programs generally reduce electricity prices in the electricity market, benefiting all electricity consumers (both participants in demand response programs and others). In California, a 2.5% reduction in electricity consumption reduced real-time market prices by 24%, and a 5% reduction in consumption caused prices to drop to 50% of their initial value in 2000 and 2001.

Long-Term Market Impacts

By implementing demand response programs, system peaks are reduced, reducing the need for building new power plants and expanding distribution systems.

Critical Peak Pricing (CPP)

As previously mentioned, some loads cannot implement the RTP method. It was also observed that the TOU method applies price fluctuations in the form of several general tariffs to the loads. To meet the need to reduce consumption during critical hours of the year, when electricity consumption is very high (e.g., extreme heat) and system reliability is at risk (due to an unexpected event) or wholesale market prices are very high, critical peak pricing seems to be a suitable solution. The CPP tariff is essentially an additional tariff applied to fixed or TOU pricing during critical hours.

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In general, incentive-based demand response includes Direct Load Control (DLC), Interruptible/Curtailable Load (I/C), Demand Bidding Programs (DBP), Emergency Demand Response Programs (EDRP), Capacity Market Programs (CMP), and Ancillary Services Market Programs (ASMP).

In conclusion, Chapter 3 has explored the critical role of electric vehicles (EVs) and demand response as flexible resources within modern power distribution networks. EVs introduce unique challenges and opportunities due to their energy demands, while demand response offers a pathway to balance these new loads with existing resources. Together, these elements enhance grid resilience and adaptability, though they require careful integration into existing infrastructure. This chapter has highlighted the potential for EVs and demand response programs to support grid stability, lower emissions, and improve overall energy management. The insights gained here set the stage for developing optimized control strategies in subsequent chapters, aiming to achieve a sustainable, cost-effective, and reliable energy system.

Chapter 4: Epsilon Constraint Method (Multi-Objective)

4-1 Optimization Problems

The goal of optimization is to find the best acceptable solution considering the constraints and requirements of the problem. For a problem, there may be various solutions, and to compare them and select the optimal solution, a function called the objective function is defined. The choice of this function depends on the nature of the problem. For example, travel time or cost are common objectives in optimizing transportation networks. Selecting an appropriate objective function is one of the most critical steps in optimization. Sometimes, multiple objectives are considered simultaneously in optimization; such optimization problems are called multi-objective problems. The simplest way to handle these problems is to form a new objective function as a linear combination of the main objective functions, where the impact of each function is determined by its assigned weight. Each optimization problem has several independent variables called design variables, represented by an n-dimensional vector X. The goal of optimization is to determine the design variables such that the objective function is minimized or maximized. Different optimization problems are divided into the following two categories:

a) **Unconstrained Optimization Problems**: In these problems, the goal is to maximize or minimize the objective function without any constraints on the design variables.

b) **Constrained Optimization Problems**: Optimization in most practical problems is performed considering constraints related to the behavior and performance of a system, known as behavioral constraints, and constraints in the physics and geometry of the problem, known as geometric or side constraints.

4-1-1 Optimization Process

The necessary steps to solve an optimization problem are as follows:

1. **Formulating the Problem**: In this step, a decision-making problem is defined along with its general structure. This general structure may not be very precise but describes the overall situation of the problem, including input and output factors and the objectives of

the problem. Clarifying and structuring the problem can be complex for many optimization problems.

2. **Modeling the Problem**: In this step, a general mathematical model for the problem is constructed. Modeling may use similar models from the literature. This step breaks down the problem into one or more optimization models.
3. **Optimizing the Problem**: After modeling, the problem-solving process generates a good solution for the problem, which may be optimal or near-optimal. It is important to note that the obtained solution is for the designed model, not the real problem. During formulation and modeling, changes may occur in the real problem, and the new problem may differ significantly from the real problem.
4. **Implementing the Solution**: The obtained solution is reviewed by the decision-maker and, if acceptable, is used. If the solution is not acceptable, the model or optimization algorithm must be developed, and the optimization process repeated [137].

4-2 Multi-Objective Optimization Methods

Multi-objective optimization methods are used in many branches of science and engineering when it is necessary to balance (trade-off) between two or more conflicting objectives to reach optimal decisions in a system. Undoubtedly, in many engineering applications, process and system designers make decisions based on conflicting objectives. For example, in car design, engineers aim to design a car with maximum performance while simultaneously seeking to design a car with minimal emissions and fuel consumption.

In such cases, where more than one objective function needs to be considered, multi-objective optimization methods must be examined. The most important feature of such methods is that by using multi-objective optimization models, more than one candidate solution (a possible solution for the problem) is provided to system designers and engineers. Each of these solutions represents a balance between different objective functions. Even for a simple multi-objective optimization problem, the likelihood of finding an optimal solution that simultaneously optimizes all defined objective functions is very low. In many cases, the defined objective functions in multi-objective optimization are conflicting. In such cases, it is said that Pareto optimal solutions exist for a multi-objective optimization problem. Theoretically, there may be infinite Pareto optimal solutions for a multi-objective optimization problem.

4-2-1 Basic Concepts in Multi-Objective Optimization

The concept of scalar (numerical) optimality in single-objective optimization problems does not directly apply to multi-objective optimization. To understand the concept of optimality in multi-objective optimization problems, the concept of Pareto optimality must first be explained. In this section, concepts such as design space and criterion space (objective space) will be explained using the first example.

Criterion Space and Design Space in Multi-Objective Optimization Problems

In the first example, the design space of a multi-objective optimization problem was shown. Then, the set of feasible solutions (set SS) was defined, the contours of the objective functions were drawn, and finally, the Pareto optimal set (set SpSp) of this multi-objective optimization problem was identified in the design space.

Another possible method for solving multi-objective optimization problems is using the criterion space. Alternatively, a multi-objective optimization problem can be represented in a space called the criterion space, where the axes are represented by the objective functions. For example, the figure below shows the multi-objective optimization problem of the first example in the design space.

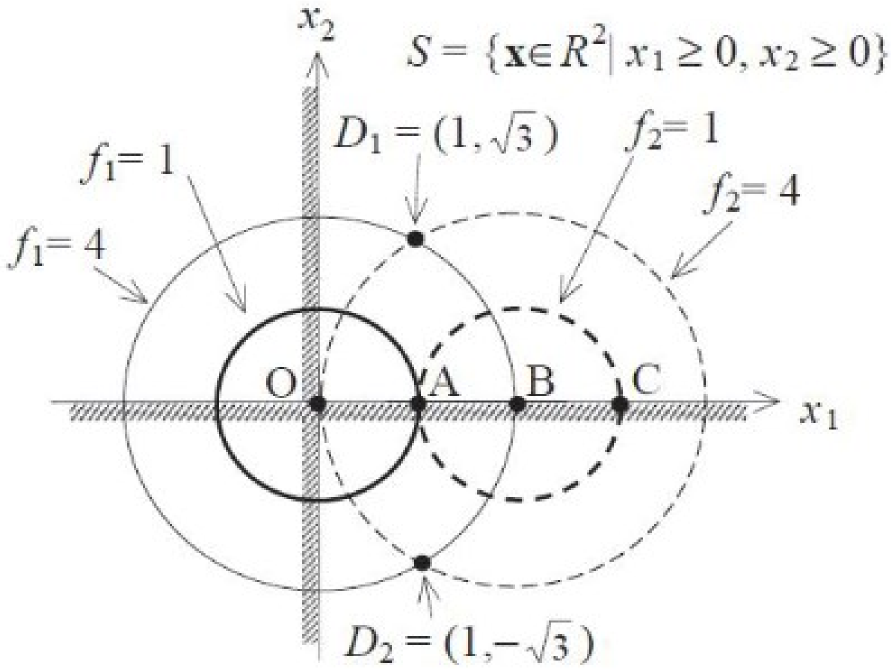


Figure 4-1: Design space in a multi-objective optimization problem [137].

Figure 4-2 shows the multi-objective optimization problem of the first example in the criterion space or the f1-f2 plane. As shown in the figure below, the axes of this space are represented by the objective functions.

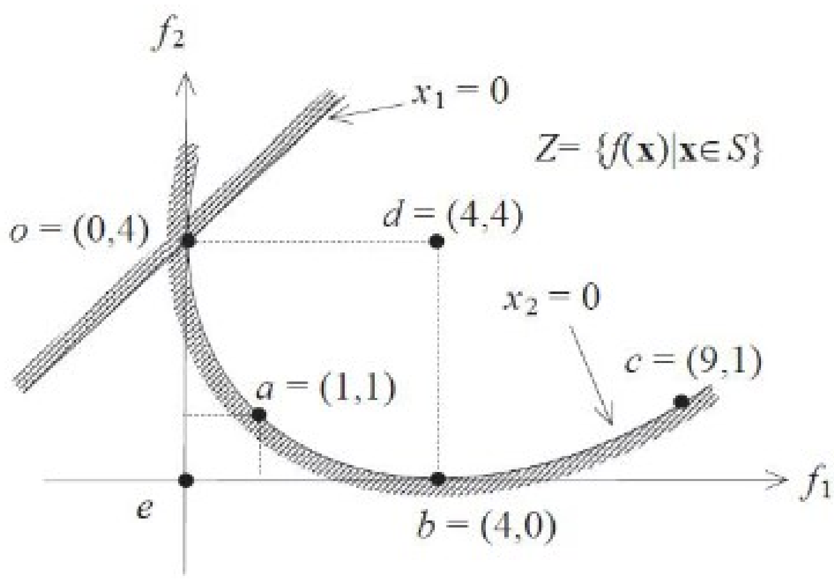


Figure 4-2: Criterion space (Objective Space) in a multi-objective optimization problem [137]

4-3 Epsilon Constraint Algorithm (ε-constraint)

Various techniques exist for solving multi-objective problems, one of which is the epsilon constraint method. This method was first proposed by Laumanns et al. (2006). It is used to create the Pareto front of solutions (set of solutions P) for a bi-objective problem. This method solves single-objective problems iteratively by selecting one objective function as the sole objective (f2) and setting the other objective function (f1) as a constraint, known as the epsilon constraint. In this method, one of the objective functions is considered the main objective, and the other objective functions are applied as constraints to the problem. Various developments have been made to the epsilon constraint method to make it more efficient, such as the extended epsilon constraint method mentioned in Mavrotas' paper. The steps of the extended epsilon constraint method are as follows [138]:

- **Step One**: Select one of the objective functions as the main objective function.
- **Step Two**: Solve the problem each time considering one of the objective functions, and obtain the optimal value for each objective function.
- **Step Three**: Using the lexicographic method, determine the best and worst values for each objective function. The best value of the first objective function is equal to its optimal value when the problem is optimized considering the objective function individually. Then, optimize the second objective function with the constraint that the first objective function remains at its optimal value to determine the worst value of the second objective function. This process continues until all objective functions are optimized, thus determining the range for each objective function.

$$[f_i^{\max}, f_i^{\min}] \tag{4-1}$$

$$r_i = f_i^{\max} - f_i^{\min} \tag{4-2}$$

- **Step Four**: Divide the range between the two optimal values of the secondary objective functions into a predetermined number of intervals (qi), and obtain a table of values for the epsilons.

$$k = 0,1,\ldots,q_i \; \varepsilon_i^k = f_i^{\max} - \frac{r_i}{q_i} * k \tag{4-3}$$

- **Step Five**: Solve the problem with the main objective function each time considering each epsilon value. The constraints related to the secondary objective functions are converted into equality constraints using appropriate surplus or shortage variables. By considering a delta coefficient between 10^{-3} and 10^{-6} for these surplus or shortage variables, the problem is solved, and efficient solutions are generated. The new problem is defined as follows:

$$\begin{aligned} &(s_2 + s_3 + \ldots + s_p)\} \\ &f_2(x) = \varepsilon_2 + s_2 \\ &f_3(x) = \varepsilon_3 + s_3 \\ &\vdots \\ &f_p(x) = \varepsilon_p + s_p \\ &x \in X \\ &s_i \in R^+ \end{aligned} \tag{4-4}$$

- **Step Six**: Finally, report the found Pareto solutions.

In conclusion, Chapter 4 has provided an in-depth analysis of the epsilon constraint method and its application to multi-objective optimization problems. This approach has been highlighted as a robust tool for addressing complex trade-offs between conflicting objectives, such as cost and environmental impact, in energy management systems. By converting secondary objectives into constraints, the epsilon constraint method enables the creation of a Pareto front, which facilitates the identification of optimal solutions for various objectives. The insights gained here are foundational for the development of a coordinated scheduling framework in subsequent chapters, where the integration of multiple objectives within networked microgrids is further explored. This serves as a critical step towards achieving efficient, resilient, and environmentally sustainable energy systems.

Chapter 5: Coordinated Scheduling of Networked Microgrids in Active Distribution Systems Considering the Economic and Environmental Impact of Electric Vehicles and Flexible Loads.

5-1 Introduction

The increasing penetration of renewable energy sources and the widespread adoption of electric vehicles (EVs) have ushered in a new era of challenges and opportunities for modern power systems. Traditional power grids, designed for centralized, predictable generation, are increasingly inadequate for managing the decentralized and variable nature of renewable energy. This shift has led to the emergence of microgrids—localized energy systems that can operate independently or in conjunction with the main grid—as a vital component of future energy infrastructure. Microgrids not only enhance the reliability and resilience of power supply but also facilitate the integration of renewable energy and advanced technologies, such as EVs and hydrogen refueling stations.

However, the successful operation of microgrids, particularly within active distribution systems, requires sophisticated management strategies that can optimize the use of diverse energy resources while balancing economic and environmental objectives. The coordinated scheduling of networked microgrids presents a complex optimization problem, involving multiple, often conflicting, goals such as minimizing operational costs, reducing greenhouse gas (GHG) emissions, and ensuring reliable power delivery. This complexity is further compounded by the need to account for the dynamic behavior of flexible loads and the variable availability of renewable energy resources.

Chapter 5 of this thesis addresses these challenges by introducing a comprehensive framework for the coordinated scheduling of networked microgrids. The framework is designed to optimize the operation of microgrids within an active distribution system, considering the economic and environmental impacts of integrating EVs and flexible loads. The chapter begins by outlining the methodological approach used to tackle the scheduling problem, which involves a multi-stage optimization process. This process is grounded in the principles of stochastic programming, allowing for the accommodation of uncertainties related to renewable energy generation and load demands.

One of the key innovations of the proposed framework is its ability to simultaneously manage the distribution of power among multiple microgrids, taking into account the interactions between EV charging stations, hydrogen refueling stations, and other flexible loads. The framework leverages advanced optimization techniques, including the epsilon constraint method, to navigate the trade-offs between different objectives. By systematically exploring these trade-offs, the framework provides a robust tool for decision-makers to optimize microgrid operations in a way that aligns with both economic and environmental goals.

The chapter also delves into the practical implementation of the framework, detailing the algorithms and software tools used to solve the optimization problem. The GUROBI solver within the GAMS software environment plays a central role in this process, enabling the efficient computation of optimal schedules under various scenarios. The integration of these tools ensures that the proposed framework is not only theoretically sound but also practically applicable to real-world energy systems.

To validate the effectiveness of the coordinated scheduling framework, Chapter 5 presents a series of simulation studies based on a representative active distribution system. These studies demonstrate the ability of the framework to achieve significant reductions in both operating costs and GHG emissions, while maintaining or enhancing the reliability of power supply. The results highlight the potential of the proposed approach to contribute to the broader goals of sustainability and energy security, particularly in the context of the ongoing transition to a low-carbon energy future.

In conclusion, Chapter 5 sets the stage for a detailed exploration of the coordinated scheduling framework, offering insights into how networked microgrids can be effectively managed within active distribution systems. The chapter not only addresses the technical challenges associated with microgrid optimization but also considers the broader implications for energy policy and planning. By providing a comprehensive and practical solution to the scheduling problem, this chapter contributes to the development of more resilient, efficient, and sustainable energy systems.

5-2 Service Area Detection

This paper utilizes Graph Theory to incorporate scheduling constraints for establishing the range of microgrids. Binary variables are used to indicate the activation of each line or network bus. The constraints for determining the network graph are presented in Equations (1)-(3). Equation (1) specifies the requirement for each bus to be owned by only one microgrid. Furthermore, Equation (2) highlights that for a microgrid to possess other buses, the main bus with master generator must be active.

$$\sum_{k} I_{n,k}^{Bus} \leq 1 \tag{1}$$

$$I_{n,k}^{Bus} \leq I_{m,k}^{Bus} \qquad m \in \{\Omega_{DG}\} \tag{2}$$

In Equation (3), the relationship between three binary variables is associated with each line and its ending nodes. It is known that the operation of each line is feasible only if the two buses at the beginning and end of that line are part of the same microgrid. Hence, if the two buses at the beginning and end do not belong to any of the microgrids, it is possible to utilize the line. Additionally, to enable the scheduling for buses that are not currently planned, i.e., buses without any faults or interruptions, the logical operator has been employed. As this equation involves the product of two binary numbers, it can be linearized using auxiliary variables. A detailed explanation of how to linearize this equation can be found in [139].

$$I_{l,k}^{Line} \leq I_{n,k}^{Bus} \square\, I_{m,k}^{Bus} = I_{n,k}^{Bus} I_{m,k}^{Bus} + \left(1 - I_{n,k}^{Bus}\right)\left(1 - I_{m,k}^{Bus}\right) \tag{3}$$

To ensure the radiality of the formed graph, Equations (4)-(6) express the constraint related to the connection between the buses of each microgrid. Equation (4) sets one of the binary variables of power transfer ($I_{n,m,k}^{Line} / I_{m,n,k}^{Line}$) based on the direction of power transfer in active lines. Equation (5) indicates that each bus can receive power only from one of its neighboring nodes. Moreover, Equation (6) states that the base node in each microgrid, which is equal to the main bus, must not receive power from any other node.

$$I_{n,m,k}^{Line} + I_{m,n,k}^{Line} = I_{l,k}^{Line} \tag{4}$$

$$\sum_{m} I_{m,n,k}^{Line} \leq 1 \tag{5}$$

$$\sum_{m} I_{m,n\in\Omega_{DG},k}^{Line} = 0 \tag{6}$$

5-2-1 Flexible Loads

Equation (7) calculates the amount of load supplied to each bus based on the binary variables of the graph. In this equation, $\tilde{P}_{i,t,s}^{Load}$ represent the predicted amount of load for active and reactive power, respectively, in each scenario.

$$P_{n,t,s}^{Load} = \sum_{k} I_{n,k}^{Bus} \tilde{P}_{i,t,s}^{Load} - P_{n,t,s}^{Flex} \tag{7}$$

Equation (7), $P_{n,t,s}^{Flex}$ shows the amount of flexible load. Equations (8) express how this variable is calculated and its range is determined in Equation (9). The method of applying load control in the resiliency section is a stepwise function. So, loads at any point can change a percentage of their load in a certain number of blocks. Equation (10) states that only one of the load change blocks can be selected in the given hour and scenario. It is worth noting that there is a non-linear term in Equation (8) caused by the multiplication of two binary variables. The process of linearizing this multiplication using an auxiliary variable is illustrated in Equations (11)-(14).

$$P_{n,t,s}^{Flex} = \sum_{k} I_{n,k}^{Bus} \sum_{b} \left(I_{b,n,t,s}^{Block} P_{b,n}^{LC} \right) \tag{8}$$

$$P_{b,n}^{LC} \in \left(P_{b,n}^{LC,Min}, P_{b,n}^{LC,Max} \right) \tag{9}$$

$$\sum_{b} I_{b,n,t,s}^{Block} \leq 1 \tag{10}$$

$$I_{b,n,k,t,s}^{Bus.Block} \triangleq I_{n,k}^{Bus} I_{b,n,t,s}^{Block} \tag{11}$$

$$I_{b,n,k,t,s}^{Bus.Block} \leq I_{n,k}^{Bus} \tag{12}$$

$$I_{b,n,k,t,s}^{Bus.Block} \leq I_{b,n,t,s}^{Block} \tag{13}$$

$$I_{b,n,k,t,s}^{Bus.Block} \geq I_{n,k}^{Bus} + I_{b,n,t,s}^{Block} - 1 \tag{14}$$

5-2-2 Distributed Resources

Equation (16) defines the limits on the utilization of power plants within each microgrid based on the binary variable of bus ownership. This equation provides a crucial constraint for ensuring that the power plants operate within the allowed limits, as determined by their capacity and the demand of the microgrid they are serving.

$$P_g^{DG,Min}\sum_n\sum_k I_{n,k}^{Bus} \le P_{g,t,s}^{DG} \le P_g^{DG,Max}\sum_n\sum_k I_{n,k}^{Bus} \tag{16}$$

$$C_{g,t,s}^{DG} = a_g I_{g,t,s}^{DG} + b_g P_{g,t,s}^{DG} + c_g\left(P_{g,t,s}^{DG}\right)^2 \tag{17}$$

Taking into account the presence of renewable resources in the main grid, Equations (18) and (19) enable the calculation of the wind and solar energy generation, respectively, based on the wind speed and sun irradiance.

$$P_{w,t,s}^{Wind} = \begin{cases} 0 & v_{w,t,s} \le v_{ci}, v_{w,t,s} \ge v_{co} \\ p_w^r \dfrac{v_{w,t,s} - v_{ci}}{v_r - v_{ci}} & v_{ci} \le v_{w,t,s} \le v_r \\ p_w^r & v_r \le v_{w,t,s} \le v_{co} \end{cases} \tag{18}$$

$$P_{pv,t,s}^{PV} = \eta^{PV}\frac{G_{t,s}^{PV}}{G^{STC}} p_{pv}^r \tag{19}$$

5-2-3 EV Parking and Hydrogen Refueling Stations

Equation (20) specifies the allowable range of energy levels that can be charged in the battery of the storage system. To update the energy level in the system, Equation (21) is utilized. Equations (22) and (23) present the maximum allowable charging and discharging power, respectively. It is important to maintain the initial energy level at the end of the planning period, as expressed in Equation (24). To avoid simultaneous charging and discharging, Equation (25) is employed [140].

$$E_e^{Min} \le E_{e,t,s} \le E_e^{Max} \tag{20}$$

$$E_{e,t,s} = E_{e,t-1,s} + \left(\eta^{Ch} P_{e,t,s}^{Ch} - \frac{P_{e,t,s}^{Dch}}{\eta^{Dch}}\right)\Delta t \tag{21}$$

$$0 \le P_{e,t,s}^{Ch} \le P_e^{Ch,Max} I_{e,t,s}^{Ch} \tag{22}$$

$$0 \le P_{e,t,s}^{Dch} \le P_e^{Dch,Max} I_{e,t,s}^{Dch} \tag{23}$$

$$E_{e,t=0,s} = E_{e,t=24,s} = E_e^{Initial} \tag{24}$$

$$I_{e,t,s}^{Ch} + I_{e,t,s}^{Dch} \le 1 \tag{25}$$

Which in (21), $E_{e,t,s}$ represents the energy stored in the energy storage system (such as a battery or hydrogen storage) associated with entity eee at time ttt during scenario sss. It indicates the state of charge at a given time step. $E_{e,t-1,s}$ is the energy stored in the system at the previous time step, illustrating how the state of charge accumulates or depletes over time. η is the overall efficiency factor accounting for system losses not directly related to charging or discharging. It modifies the net change in storage to account for inefficiencies such as thermal losses or other systemic inefficiencies. η^{Ch} is charging efficiency, which represents the efficiency of converting electric power into stored energy during the charging process. This factor accounts for losses such as heat generation during the charging process. $P_{e,t,s}^{Ch}$ is power input to the storage system, indicating the rate at which energy is being stored during the charging process at time t for scenario s. $P_{e,t,s}^{Dch}$ is power output from the storage system, representing the rate at which energy is discharged from storage to be used by the grid or other applications at time t for scenario s. η^{Dch} is discharging efficiency, which reflects the efficiency of converting stored energy back into electrical energy. This factor similarly accounts for losses incurred during the energy discharge process. Δt is time step increment, representing the duration of each simulation interval within which power flows into or out of the storage system are calculated.

In Equations (25) to (29), the same set of equations are presented for utilizing the electric vehicle batteries. Equation (30) specifies that the battery's charge level upon entering the parking lot should be the same as its initial value (initial value randomly selected between 30% and 40%). In addition, Equation (31) indicates that the battery of EVs should be charged to a certain level (E_{ev}^{Final}) before leaving the parking lot. Equations (32) and (33) are used to prevent simultaneous charging and discharging of the car battery and to ensure that the car is in the parking lot during charging or discharging.

$$E_{ev}^{Min} \le E_{ev,t,s} \le E_{ev}^{Max} \tag{26}$$

$$E_{ev,t,s} = E_{ev,t-1,s} + \left(\eta^{Ch} P_{ev,t,s}^{Ch} - \frac{P_{ev,t,s}^{Dch}}{\eta^{Dch}} \right) \Delta t \tag{27}$$

$$0 \le P_{ev,t,s}^{Ch} \le P_{ev}^{Ch,Max} I_{ev,t,s}^{Ch} \tag{28}$$

$$0 \le P_{ev,t,s}^{Dch} \le P_{ev}^{Dch,Max} I_{ev,t,s}^{Dch} \tag{29}$$

$$E_{ev,t=T^a,s} = E_{ev}^{Initial} \tag{30}$$

$$E_{ev,t=T^d,s} = E_{ev}^{Final} \tag{31}$$

$$I_{ev,t,s}^{Ch} + I_{ev,t,s}^{Dch} \le 1 \qquad t \in [T^a, T^d] \tag{32}$$

$$I_{ev,t,s}^{Ch} + I_{ev,t,s}^{Dch} = 1 \qquad t \notin (T^a, T^d) \tag{33}$$

Hydrogen refueling stations operate through a set of equations (34)-(39), constituting a structured framework to effectively manage hydrogen supply for Fuel Cell Vehicles (FCVs) while aiming to minimize daily operational costs. Equation (34) within this operational structure serves to compute the quantity of hydrogen produced by these small-scale P2H units. Meanwhile, constraint (35) puts a cap on the electrolyzer's power consumption, ensuring operational efficiency within set limits. The dynamics of hydrogen storage are managed through Eq. (36), where the current hour's hydrogen tank level is calculated by considering its previous level, injection, and extraction rates. Specific parameters such as hydrogen constants, internal tank temperatures, tank capacity, and the molar mass of hydrogen play crucial roles within these computations. Constraints (37) and (38) work to restrict the hydrogen levels during station operations within predefined thresholds, ensuring safe and efficient storage practices. Furthermore, Eq. (39) outlines the possibility of redirecting surplus power generated by solar panels to either the electrolyzer for hydrogen production or selling it back to the grid.

$$H_{s,t}^{El} = \frac{\eta^{El} P_{s,t}^{El}}{LHV^{H2}} \tag{34}$$

$$P_{\mathrm{s}}^{El,Min} \le P_{s,t}^{El} \le P_{s}^{El,Max} \tag{35}$$

$$E_{s,t}^{H} = E_{s,t-1}^{H} + \frac{R^H T^H}{U_s^H M^H} \left(H_{s,t}^{El} - \sum_{fcv} H2_{fcv,t}^{Ch} \right) \tag{36}$$

$$E_{s,t=24}^{H} = E_{s,t=0}^{H} = E_{s,t}^{H,Initial} \tag{37}$$

$$E_{s}^{H2,Min} \le E_{s,t}^{H2} \le E_{s}^{H2,Max} \tag{38}$$

$$\sum_{pv} P_{pv,t}^{Solar} = P_{s,t}^{El} + P_{s,t}^{Sell} \tag{39}$$

5-2-4 Power Balance

The balance of active load in microgrids is described in Equation (40). To determine the correct load distribution method, Equation (41) is utilized to calculate the passing power of the lines. It is important to note that load spreading was used at the first level to solve the problem. Lastly, Equation (42) models the limit of power that can pass through the lines.

$$\sum_{g} P_{g,t,s}^{DG} + \sum_{e} \left(P_{e,t,s}^{Dis} - P_{e,t,s}^{Ch} \right) + \sum_{w} P_{w,t,s}^{Wind} + \sum_{pv} P_{pv,t,s}^{PV} = P_{n,t,s}^{Load} \tag{40}$$

$$\frac{\theta_{n,t,s} - \theta_{m,t,s}}{x_l} - \sum_{k} \left(1 - I_{l,k}^{Line} \right) M \le P_{l,t,s}^{Line} \le \frac{\theta_{n,t,s} - \theta_{m,t,s}}{x_l} + \sum_{k} \left(1 - I_{l,k}^{Line} \right) M \tag{41}$$

$$-P_{l,t,s}^{Line,Max} B_{l,k} \le P_{l,t,s}^{Line} \le P_{l,t,s}^{Line,Max} B_{l,k} \tag{42}$$

5-3 Energy Management

Assuming that some parts of the network remain operational without interruption or that certain microgrids can communicate with the main grid, power exchange with the main grid is modeled in Equations (43) to (47). Power exchange limitations are included in both directions, as shown in Equations (43). The non-simultaneous nature of purchasing and selling is also considered and modeled in Equation (47).

$$-P_{k}^{Grid,Max} \le P_{k,t,s}^{Grid} \le P_{k}^{Grid,Max} \tag{43}$$

$$P_{k,t,s}^{Grid} = P_{k,t,s}^{Grid,Buy} - P_{k,t,s}^{Grid,Sell} \tag{44}$$

$$0 \le P_{k,t,s}^{Grid,Sell} \le P_{k}^{Grid,Max} \times I_{k,t,s}^{Sell} \tag{45}$$

$$0 \le P_{k,t,s}^{Grid,Buy} \le P_{k}^{Grid,Max} \times I_{k,t,s}^{Buy} \tag{46}$$

$$I_{k,t,s}^{Sell} + I_{k,t,s}^{Buy} \le 1 \tag{47}$$

5-3-1 Distributed Resources

The operational behavior of controllable resources is demonstrated in Equations (48)-(55). Specifically, Equations (48)-(50) account for the gas turbine capacity in each microgrid, subject to unit commitment constraints. To minimize abrupt changes in power output over consecutive hours, Equations (51) and (52) are introduced. Moreover, the startup and shutdown costs are factored into the model, and represented by Equations (53) and (54), respectively. The overall operation cost of gas turbines is then computed using Equation (55).

$$P_{g,k}^{DG,Min} = \sum_{k} \left(P_{g}^{DG,Min} I_{n,k}^{Bus} \right) \tag{48}$$

$$P_{g,k}^{DG,Max} = \sum_{k} \left(P_{g}^{DG,Max} I_{n,k}^{Bus} \right) \tag{49}$$

$$P_{g,k}^{DG,Min} I_{g,t,s}^{DG} \le P_{g,t,s}^{DG} \le PD_{g,k}^{G,Max} I_{g,t,s}^{DG} \tag{50}$$

$$P_{g,t,s}^{DG} - P_{g,t-1,s}^{DG} \le P_{g}^{RU} + P_{g,k}^{DG,Min} I_{g,t,s}^{SU} \tag{51}$$

$$P_{g,t-1,s}^{DG} - P_{g,t,s}^{DG} \le P_{g}^{RD} + P_{g,k}^{DG,Min} I_{g,t,s}^{SD} \tag{52}$$

$$I_{g,t,s}^{SU} - I_{g,t,s}^{SD} = I_{g,t,s}^{DG} - I_{g,t-1,s}^{DG} \tag{53}$$

$$I_{g,t,s}^{SU} + I_{g,t,s}^{SD} \le 1 \tag{54}$$

$$C_{g,t,s}^{DG} = a_g I_{g,t,s}^{DG} + b_g P_{g,t,s}^{DG} + c_g \left(P_{g,t,s}^{DG} \right)^2 + C_k^{SU} I_{g,t,s}^{SU} + C_k^{SD} I_{g,t,s}^{SD} \tag{55}$$

Power Flow

Equations (56) and (57) represent the power balance equation and the operation of transmission lines, respectively. To solve the power flow problem, a linearized model from [140] is utilized, and the power flow equations are provided in (58) to (60). The relationship between the power flowing through the lines and the state variable of the lines ($B_{l,k}$) is expressed in equations (61) and (62). Additionally, voltage magnitude and angle limits are presented in equations (63) and (64), respectively [141].

$$P_{k,t,s}^{Grid}\Big|_{n=pcc} + \sum_{g \in \Omega_{n,k}^{g}} P_{g,t,s}^{DG} + \sum_{e \in \Omega_{n,k}^{e}} \left(P_{e,t,s}^{Dis} - P_{e,t,s}^{Ch} \right) + \sum_{w \in \Omega_{n,k}^{w}} P_{w,t,s}^{Wind} = P_{n,t,s}^{Load} + \sum_{l \in \Omega_{n,k}^{l}} P_{l,t,s}^{Flow} \tag{56}$$

$$P_{k,t,s}^{Grid}\Big|_{n=pcc} + \sum_{g \in \Omega_{n,k}^{g}} Q_{g,t,s}^{DG} = Q_{n,t,s}^{Load} + \sum_{l \in \Omega_{n,k}^{l}} Q_{l,t,s}^{Flow} \tag{57}$$

$$k_l^1 = \frac{r_l}{r_l^2 + x_l^2}, \quad k_l^2 = \frac{x_l}{r_l^2 + x_l^2} \tag{58}$$

$$P_{l,t,s}^{Line} = k_l^1 \left(V_{n,t,s} - V_{m,t,s} \right) + k_l^2 \left(\theta_{n,t,s} - \theta_{m,t,s} \right) \tag{59}$$

$$Q_{l,t,s}^{Line} = k_l^1 \left(\theta_{m,t,s} - \theta_{n,t,s} \right) + k_l^2 \left(V_{n,t,s} - V_{m,t,s} \right) \tag{60}$$

$$-P_{l,t,s}^{Line,Max}\sum_{k}B_{l,k}\le P_{l,t,s}^{Line}\le P_{l,t,s}^{Line,Max}\sum_{k}B_{l,k} \tag{61}$$

$$-Q_{l,t,s}^{Line,Max}\sum_{k}B_{l,k}\le Q_{l,t,s}^{Line}\le Q_{l,t,s}^{Line,Max}\sum_{k}B_{l,k} \tag{62}$$

$$V_{n}^{Min}\le V_{n,t,s}\le V_{n}^{Max} \tag{63}$$

$$\theta^{Min}\le \theta_{n,t,s}\le \theta^{Max} \tag{64}$$

5-4 Objective Function of First Stage

Equation (65) represents the objective function used to determine the range of microgrids in the first stage, to supply the maximum load possible under special conditions such as faults or attacks [142]. In this equation, $\gamma_{n,t}$ the coefficient of load priority $P_{n,t,s}^{Load}$ denotes the load supplied at each bus and ρ_s represents the probability of occurrence for each scenario. The function takes into account the importance of each load, and the amount of load supplied is determined accordingly. The final range of microgrids is determined to maximize the supply of highly important loads.

$$\max \mathrm{Z}_1=\sum_{s}\rho_s\left(\sum_{t}\sum_{n}(\gamma_{n,t}P_{n,t,s}^{Load})\right) \tag{65}$$

5-5 Objective Function of Second Stage

In the second stage, the energy management problem is solved by considering two objective functions: cost and emission. These functions are presented in Eqs. (66) and (67), respectively [143,144]:

$$\min Z_2=\sum_{s}\rho_s\left(\begin{array}{l}\sum_{t}\sum_{g}C_{g,t,s}^{DG}+\sum_{t}\sum_{k}\left(\pi_t^{Grid}P_{k,t,s}^{Grid}\right)+\sum_{t}\sum_{n}\left(\pi^{ENS}P_{n,t,s}^{Flex}\right)\\+\sum_{t}\sum_{e}\pi^{EES}\left(P_{e,t,s}^{Ch}+P_{e,t,s}^{Dis}\right)+\sum_{t}\sum_{ev}\pi^{EV}\left(P_{ev,t,s}^{Ch}+P_{ev,t,s}^{Dis}\right)\end{array}\right) \tag{66}$$

$$\min Z_3=\sum_{s}\rho_s\sum_{t}\sum_{g}\left(\alpha_g I_{g,t,s}^{DG}+\beta_g P_{g,t,s}^{DG}+\mu_g P_{g,t,s}^{DG\,2}\right) \tag{67}$$

Equation (66) consists of four main terms, which include the cost of power plants, the cost of load control, the cost of power exchange with the main grid, and the cost of storage systems. The power plant cost in this study includes the fuel cost function as well as startup and shutdown costs.

Multi-objective Modeling

The ε-constraint method is a commonly used technique in multi-objective optimization where one objective function is prioritized over the others. In this method, the main objective function is formulated as the optimization objective, while the other objective functions are introduced as constraints [145]. This approach allows the decision-maker to balance trade-offs between multiple objectives by adjusting the constraint values. The equations used in the ε-constraint method for energy management systems can be expressed as follows:

$$\Phi_1 = Z_2, \Phi_2 = Z_3 \tag{68}$$

$$OF = \min(\Phi_1) \tag{69}$$

$$\begin{cases} \Phi_2 \le \varepsilon \\ \text{Equal \& Unequal Equations} \end{cases} \tag{70}$$

The objective is to minimize the total cost subject to an emission constraint (70), which is set to a value ε. This approach allows for the optimization of the energy management system to balance the economic efficiency and environmental impact of the system. By adjusting the value of ε, the decision-maker can find a solution that satisfies the emission constraint while minimizing the total cost of the system.

5-6 Methodology

In this paper, a stochastic two-step method for configuring and managing microgrids in distribution networks is proposed. The first stage involves determining the operating range of each microgrid by considering its disconnection from the main grid. The structure and protection characteristics of the grid are used to form microgrids, with the main goal of supplying the highest possible load using existing power plants. Once the microgrids are formed, information on the equipment in each microgrid is determined, including the number of covered buses, controllable resources, and EV/FCV parking. In the second stage, energy management for each microgrid is performed independently, and the operation of the equipment is determined. In this stage, the microgrid is not in emergency mode and can exchange power with the main grid. Therefore, each microgrid plans to minimize cost and pollution based on its load. The demand side management (DSM) is used in the form of flexible loads and smart charging to increase the flexibility of the system in the second stage. Figure 5-1 illustrates the steps of the proposed model.

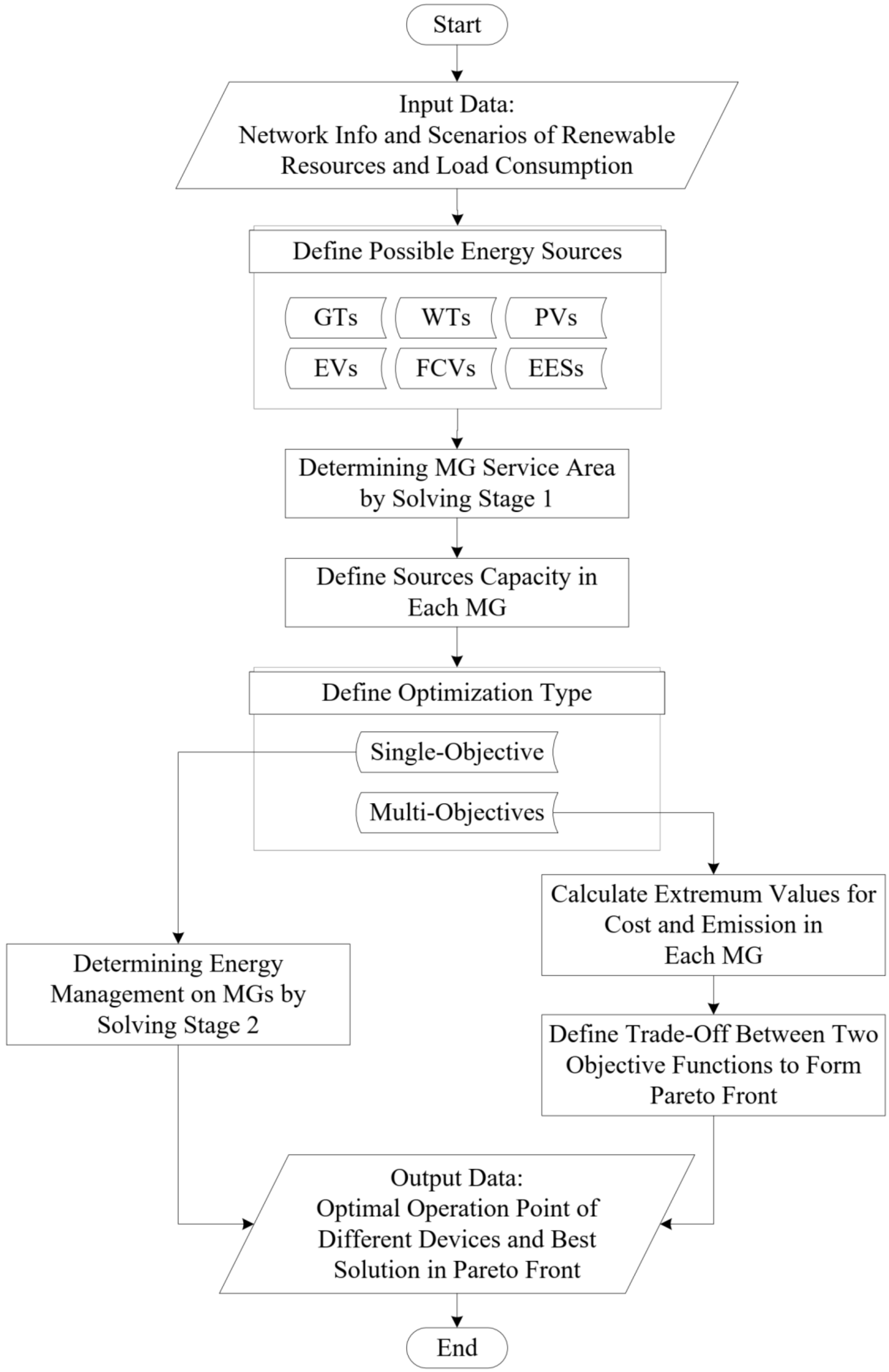


Figure 5-1: Flowchart of the proposed model

5-7 Results

5-7-1 Test Network

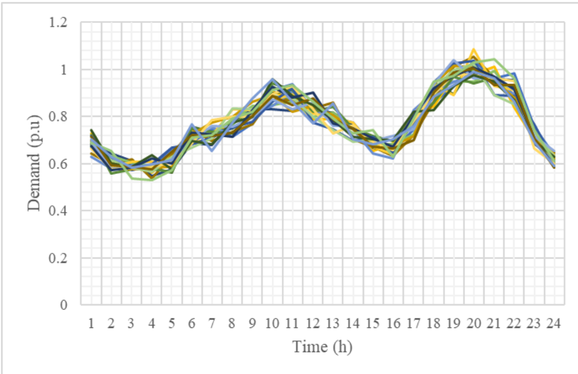
In this paper, a test network consisting of a modified IEEE118-bus distribution network is utilized, which comprises 3 feeders, 118 buses, 3 circuit breakers, 31 switches, and 9 tie lines [146]. The network has an active and reactive power demand of 22.71 MW and 17.04 MVAR, respectively. The information regarding the location and capacity of distributed generation units, wind turbines, and energy storage systems can be found in Table 1. It is noteworthy that out of 14 existing DG units, only 7 of them can act as master units, resulting in a maximum of 7 microgrids that can be formed. Table (5-1) illustrates the technical specifications of all system components used in this study. Additionally, to enhance the flexibility of the system, the total load of each bus is divided into five equal blocks, which can be managed through demand response programs. It is important to note that the storage systems are assumed to be located adjacent to the renewable sources, and their capacity is set to be equal to 30% of the capacity of the corresponding renewable source. This configuration allows for the efficient integration of renewable sources with the storage systems, enabling them to store excess energy and supply it during periods of low production.

Table 5-1: Specification of the distributed generations

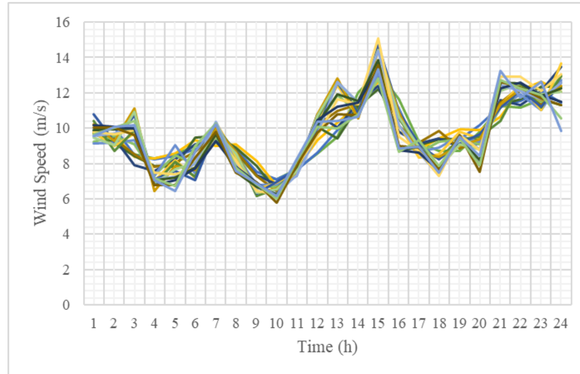
Gen No.	Location	Active Power Limits (kW)		Reactive Power Limits (kVAR)		Cost Function Coefficients ($-$/kW-$/kW^2)			Type
1	7	0	200	150	-150	0.02	0.34	0	Thermal
2	11	0	150	0	0	0	0	0	PV
3	14	0	500	0	0	0	0	0	Wind
4	17	0	800	600	-600	0.04	0.31	0	Thermal
5	20	0	200	0	0	0	0	0	PV
6	24	0	1000	800	-800	0.04	0.32	0	Thermal
7	27	0	450	0	0	0	0	0	Wind
8	30	0	100	0	0	0	0	0	PV
9	33	0	300	200	-200	0.04	0.31	0	Thermal
10	42	0	550	0	0	0	0	0	Wind
11	43	0	300	200	-200	0	0.32	0	Thermal
12	51	0	9000	800	-800	0.032	0.33	0	Thermal
13	53	0	400	0	0	0	0	0	Wind

14	59	0	12000	1000	-1000	0.04	0.31	0	Thermal
15	62	0	150	0	0	0	0	0	PV
16	67	0	1000	800	-800	0.04	0.31	0	Thermal
17	69	0	250	0	0	0	0	0	PV
18	74	0	450	0	0	0	0	0	Wind
19	75	0	150	0	0	0	0	0	PV
20	76	0	1100	800	-800	0.04	0.32	0	Thermal
21	79	0	200	0	0	0	0	0	PV
22	84	0	500	0	0	0	0	0	Wind
23	88	0	200	100	-100	0	0.31	0	Thermal
24	88	0	400	0	0	0	0	0	Wind
25	96	0	400	0	0	0	0	0	Wind
26	98	0	150	0	0	0	0	0	PV
27	99	0	450	0	0	0	0	0	Wind
28	101	0	100	0	0	0	0	0	PV
29	103	0	500	300	-300	0.04	0.32	0	Thermal
30	107	0	1500	1200	-1200	0	0.33	0	Thermal
31	110	0	150	0	0	0	0	0	PV
32	112	0	500	0	0	0	0	0	Wind
33	113	0	300	150	-150	0.04	0.31	0	Thermal
34	117	0	300	150	-150	0	0.33	0	Thermal

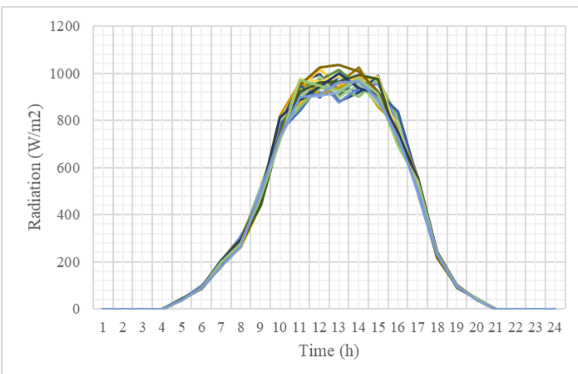
Uncertainties related to the amount of energy consumption and the generation from renewable wind and solar sources have been taken into account and are considered with a scenario-based model. To cover the uncertainties, 20 scenarios have been considered for each of the three variables [147]. Figure 5-2 illustrates the hourly curves for different scenarios, which have been used to evaluate the proposed method's performance under various conditions. Also, the preferred charging pattern for EV parking is presented in Figure 5-2.



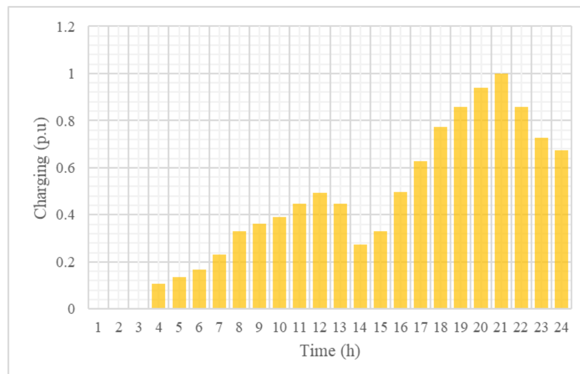
a) Load



b) wind speed



c) Sun irradiance



d) Charging pattern

Figure 5-2: Hourly curve of different scenarios and charging pattern

5-7-2 Simulation

This paper presents the implementation of the proposed model on the IEEE118-Bus system through four selected cases, as outlined in Table 5-2. The first and second cases analyze the impact of EV parking on the service area, while the third and fourth cases examine the benefits of using the multi-objective model. Through these cases, this study aims to provide a comprehensive understanding of the proposed model's effectiveness in addressing the challenges of EV integration in power systems.

Table 5-2: Information on case studies

Case No.	Stage 1		Stage 2			
			DERs	EV Parking	Objectives	
	DERs	**EV Parking**			**Cost**	**Emission**
1	✓	×	-	-	-	-
2	✓	✓	-	-	-	-
3	✓	✓	✓	✓	✓	×
4	✓	✓	✓	✓	✓	✓

In the study conducted on the IEEE118-bus distribution network, the incident considered is hurricane. This situation causes several nodes and network lines to be disrupted, leading to a part of the system entering an islanded condition depending on the performance of the protection system. With the proposed model, it is possible to supply the load with minimal lost load during this situation. The simulation process involves the formation of microgrids that can be implemented in different scenarios to achieve the highest level of resiliency.

Figure 5-3 presents the specifications of the network under investigation, highlighting the automatic network switches in green. The Tie-lines are depicted in red and marked with a dotted line. It is worth noting that all Tie-lines in this network have automatic switches. The identified error in the network pertains to the disconnection of the two main feeders, feeder 1 (between bus 1 and 2) and feeder 2 (between bus 1 and 63).

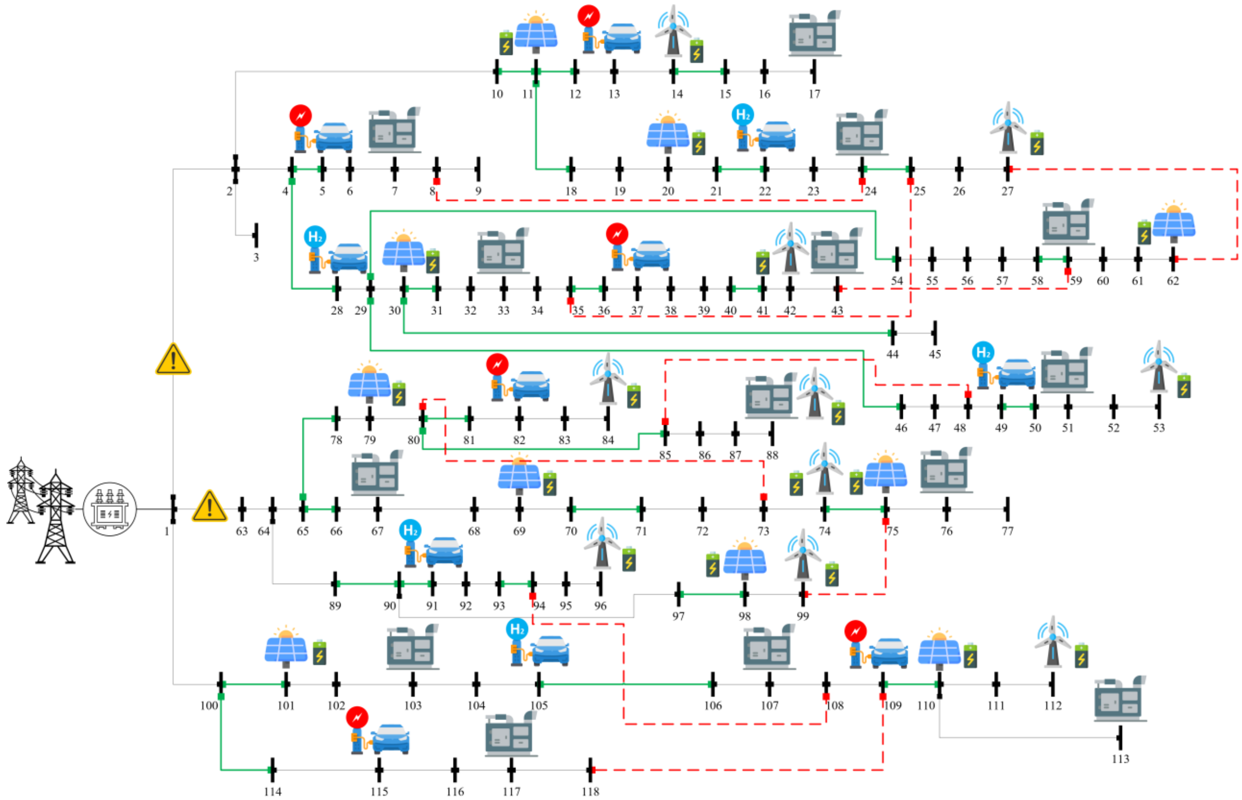


Figure 5-3: Modified IEEE 118-bus test system

5-7-3 Results of the First Stage in Cases 1 and 2

The impact of hurricanes on the IEEE118-bus distribution network was analyzed in this study. As a result of this incident, several nodes and network lines were disrupted, causing a part of the system to enter an islanded condition depending on the performance of the protection system. The proposed model was implemented to supply the load with the least amount of lost load. In the simulation process, microgrids were formed, which can be implemented in different scenarios and have the highest level of resiliency.

As depicted in Figure 5-3, two feeders (1 and 2) were disconnected from the main grid. Meanwhile, feeder 3 remained unaffected and worked without fault. Two microgrids were formed in the faulty area, and 61 out of 87 faulty buses were recovered. The structure of the microgrids are presented in Figure 5 with purple and blue color, respectively. The active power provided in this case was 7956.162 kW. The details of the formed microgrids are listed in Table 5-3.

Table 5-3. Specifications of the established microgrids in case 1

MG No.	Recovered Buses	Thermal Capacity (kW)	Wind Capacity (kW)	PV Capacity (kW)	Load Info		
					Toral (kW)	Supplied (kW)	Recovery (%)
MG 1	44	1500	2300	600	7405.084	5267.211	71.129
MG 2	17	1000	900	750	4036.703	2688.951	66.612

Table 5-3 reveals that the percentage of load recovery in microgrid 1 and microgrid 2 is 71.129% and 66.612%, respectively, taking into account the amount of load control. The higher percentage of load recovery in microgrid 1 is due to the larger capacity of the wind energy and storage systems in this microgrid.

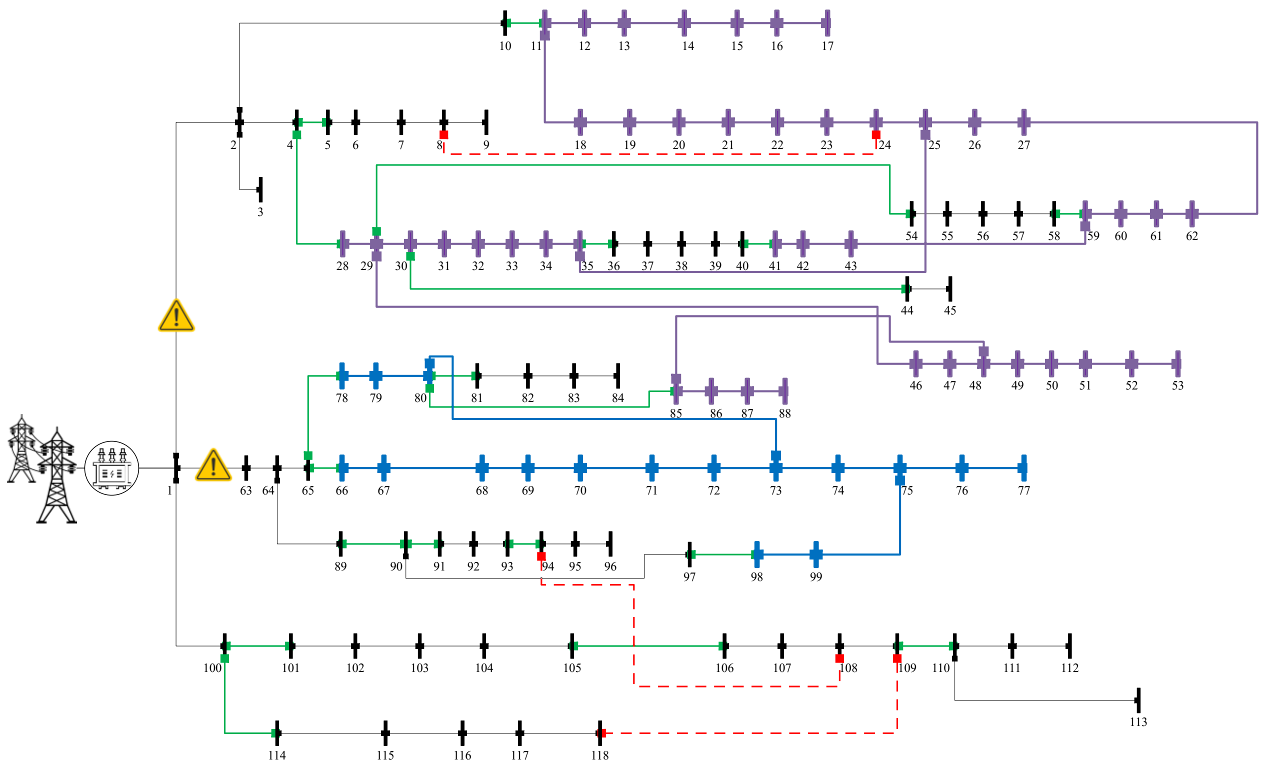
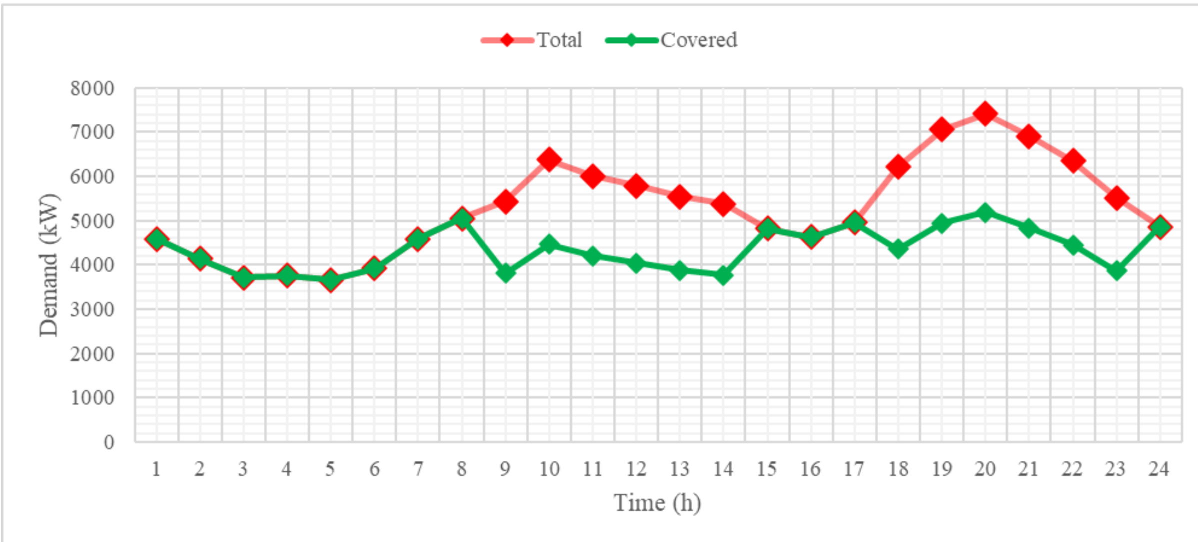
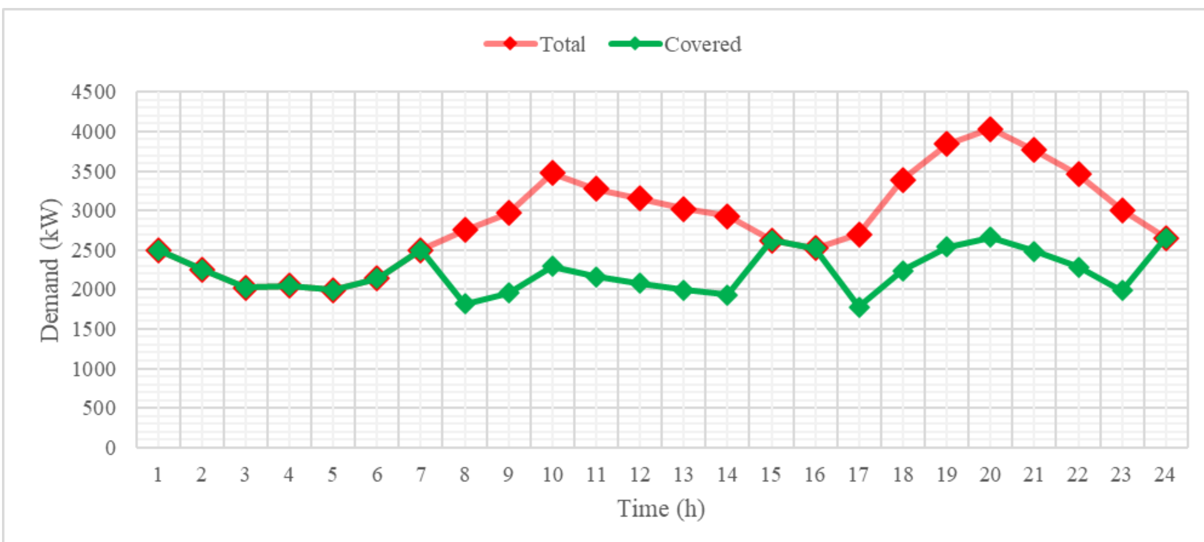


Figure 5-4: The range of formed microgrids in case 1

Figure 5-5 illustrates the impact of flexible loads on the demand profile before and after its application in two specific buses within each microgrid. The figure highlights the effectiveness of flexible loads in reducing the peak value and flattening the demand profile, which helps to ensure a more stable and efficient operation of the microgrids. Also, the use of flexible loads allows a greater range of network buses to be covered and electrified.



a) MG 1



b) MG 2

Figure 5-5: The amount of use of load control at network buses in case 1

Figure 5-6 demonstrates the impact of electric car parking on the coverage range of microgrids in the second mode. The coverage range expands due to the presence of EV parking. The underlying reason for this expansion is the potential for smart charging of electric vehicles, which can lead to a reduction in the peak load of the network. Consequently, the service area can be extended while still maintaining the desired recovery percentage.

Table 5-4 showcases the numerical outcomes of the second case. As evidenced by the table, the amount of load recovery in two microgrids has notably improved, with an increase of 2.105% and 1.7%, respectively. Furthermore, each microgrid has expanded its coverage area by adding 12 more load points. Based on the findings, it can be inferred that adjusting the charging pattern and location of EVs can significantly enhance the network's utility conditions during emergency scenarios.

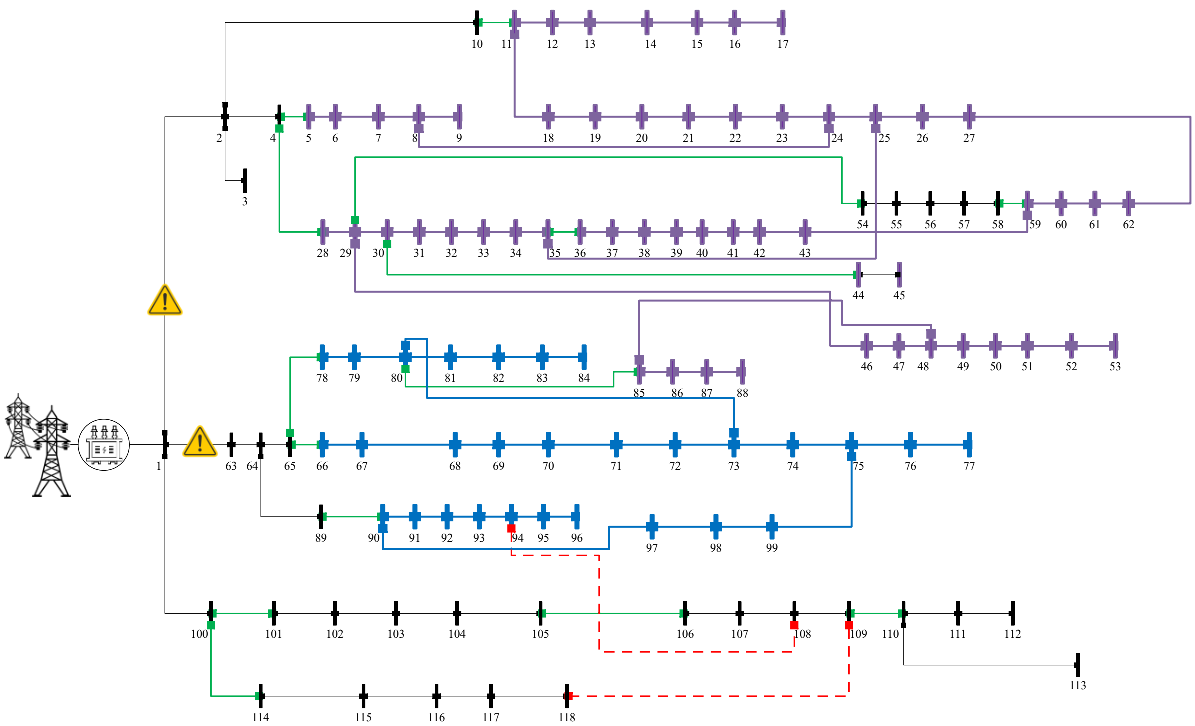


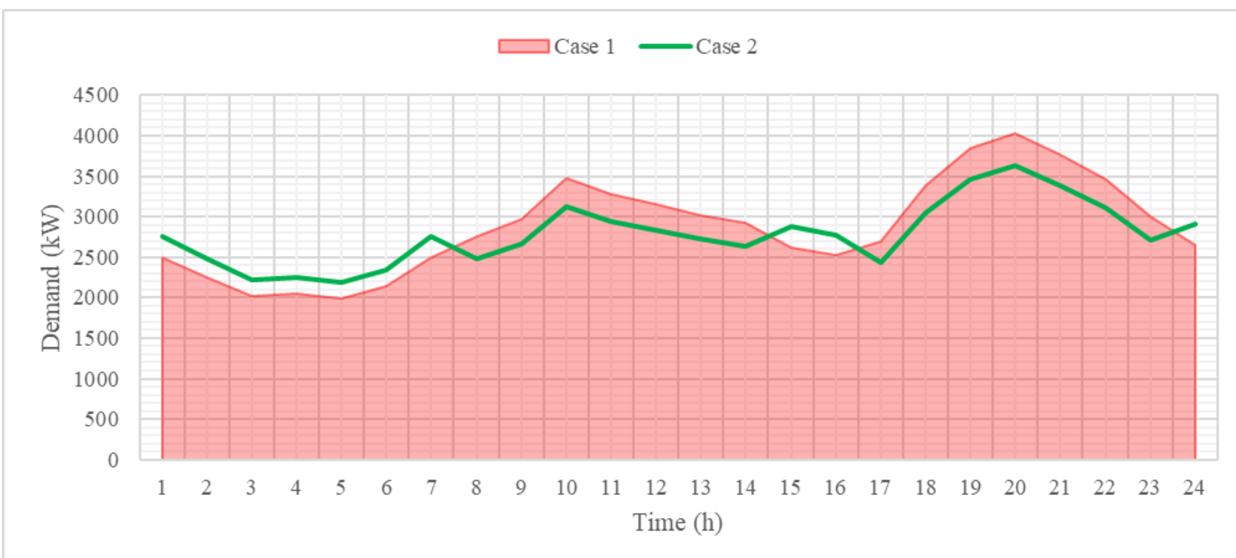
Figure 5-6: The range of formed microgrids in case 2

Table 5-4: Specifications of the established microgrids in case 2

MG No.	Recovered Buses	Thermal Capacity (kW)	Wind Capacity (kW)	PV Capacity (kW)	Load Info		
					Toral (kW)	Supplied (kW)	Recovery (%)
MG 1	56	1700	2300	600	9385.198	6779.304	73.234
MG 2	29	1000	1800	750	6073.148	4087.957	68.312

Figure 5-7 illustrates the differences in the consumption pattern of electric cars between the first and second states. In the first mode, the charging pattern of electric cars is set to default, and each car begins charging upon entering the parking lot according to the schedule outlined in Figure 5-2. By contrast, in the second mode, modifications are made to the charging curve. The results demonstrate that these modifications have smoothed out the load curve of the entire microgrid.

a) MG 1



b) MG 2

Figure 5-7: Demand profile of microgrids in cases 1 and 2

5-7-4 Results of the Second Stage in Cases 3 and 4

After determining the configuration of each microgrid and the equipment within its range in the first stage, this subsequent phase presents the outcomes of solving the energy management problem. It is important to note that all the results obtained in this stage are based on the findings from case 2.

Single-Objective (Case 3)

In case 3, scheduling was performed to minimize the overall cost of the system. The total cost of the system under this scenario amounts to 51266.274 $, with an estimated emission of 46377.314 kg. Figure 5-8 displays the hourly power exchange diagram with the main grid.

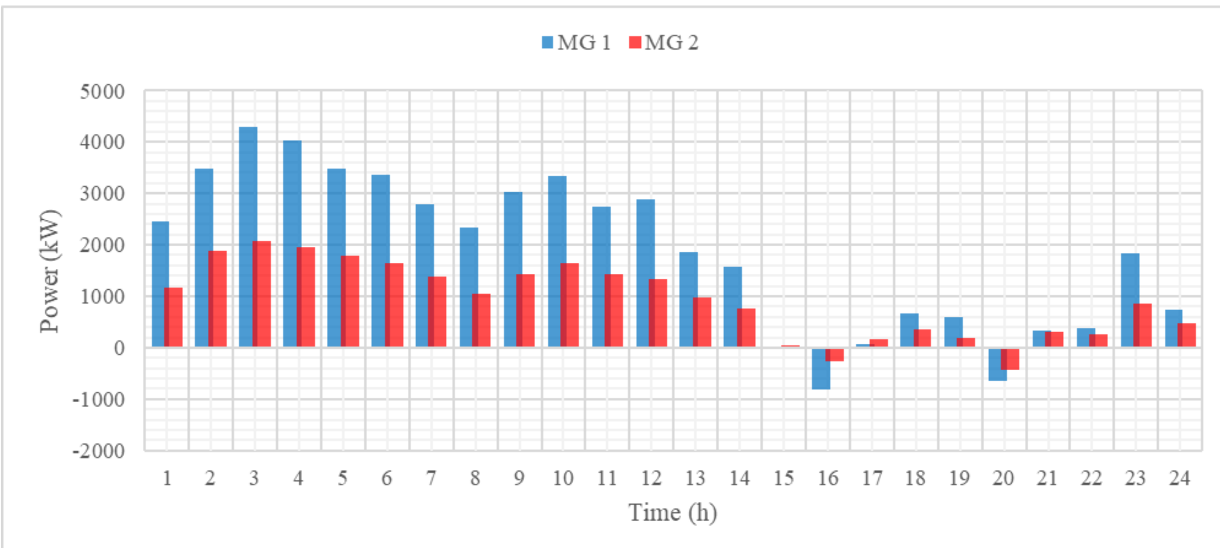
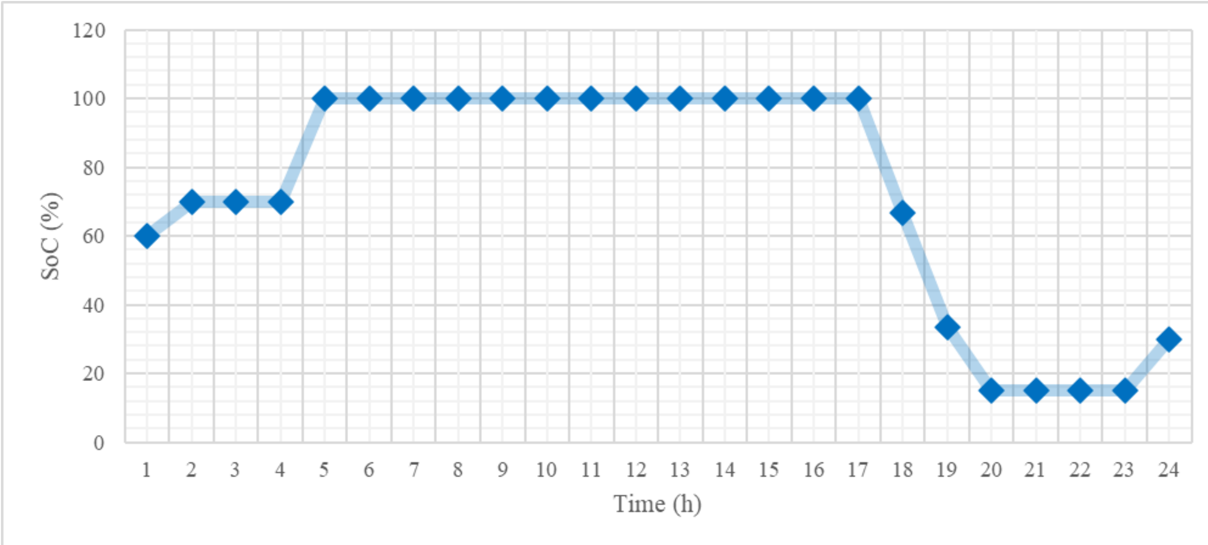
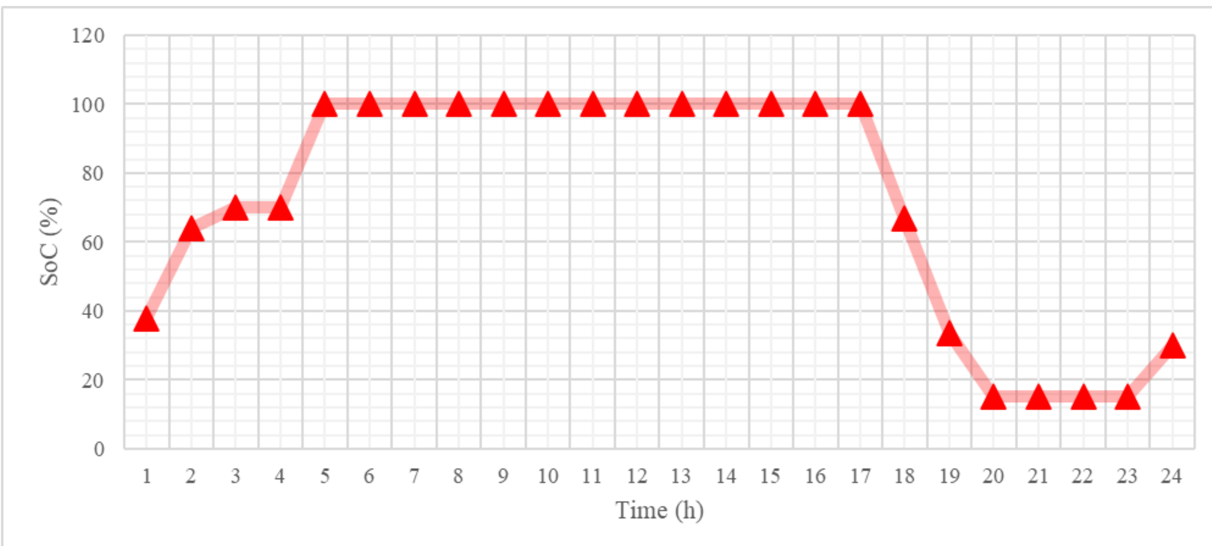


Figure 5-8: Hourly exchange of power with the main grid in case 3

Figure 5-8 indicates that the amount of energy purchased during the early hours of the day was higher than during peak hours. This is attributable to the charging of EVs and EESs during off-peak hours, which is economically advantageous due to the lower electricity prices. Figure 5-9 illustrates the state of charge (SoC) of EESs for each microgrid.



a) MG 1



b) MG 2

Figure 5-9: SoC of storage systems in microgrids in case 3

To examine the influence of flexible loads and smart charging as a demand response program (DRP) on the operating costs of each microgrid, Table 5-5 presents the results of the problem solution with and without load control. The findings reveal a substantial decrease in operating costs in the presence of the load control program. As shown in Table 5-5, implementing load control has not only lowered the costs of energy production and purchase but has also increased the revenue from selling energy to the primary grid. The operating costs without load control were calculated to be 53833.518 $.

Table 5-5: Impact of load control on energy management

Without Load Control				
MG No.	**Generation ($)**	**Power Exchange ($)**		**Total ($)**
		Buy	**Sell**	
MG 1	21381.911	15240.372	54.172	36676.455
MG 2	9630.392	7526.671	0	17157.063
With Load Control				
MG No.	**Generation ($)**	**Power Exchange ($)**		**Total ($)**
		Buy	**Sell**	
MG 1	20097.113	14121.975	696.551	34915.639
MG 2	9046.048	7012.834	291.753	16350.635

Multi-Objective (Case 4)

Table 5-7 presents the results of the multi-objective model that used the ε-constraint method. To form the Pareto front and identify the best solution, we used the fuzzy satisfaction method. The optimal solution is highlighted in bold in Table 5-6. Notably, the multi-objective model yielded a higher operating cost compared to the single-objective model. This is because the multi-objective model included modeling emissions as a separate objective function to reduce emissions. The optimal points for the ε-constraint method are 52309.464 $ and 23590.434 kg for cost and emission, respectively. The optimal points and the Pareto front curve for the two solution methods are depicted in Figure 5-10. As shown in the figure, while the total cost increased by 2.034% in the multi-objective model, the emission decreased by 49.133%.

Table 5-6: Numerical results of case 4

Iteration No.	Cost ($)	Emission (kg)	Cost Membership Value (p.u)	Emission Membership Value (p.u)	Min Membership Value (p.u)
1	57704.931	2385.546	0	1	0
2	55756.193	7686.759	0.289	0.951	0.289
3	54417.052	12987.971	0.436	0.823	0.436
4	53317.883	18289.182	0.557	0.742	0.557
5	**52309.464**	**23590.434**	**0.668**	**0.623**	**0.623**
6	51372.562	28891.616	0.772	0.512	0.512
7	50579.723	34192.872	0.858	0.438	0.438
8	49995.647	39494.803	0.922	0.345	0.345
9	49597.078	44795.264	0.965	0.278	0.278
10	49361.189	50096.464	0.991	0.123	0.123
11	49282.517	55397.672	1	0	0

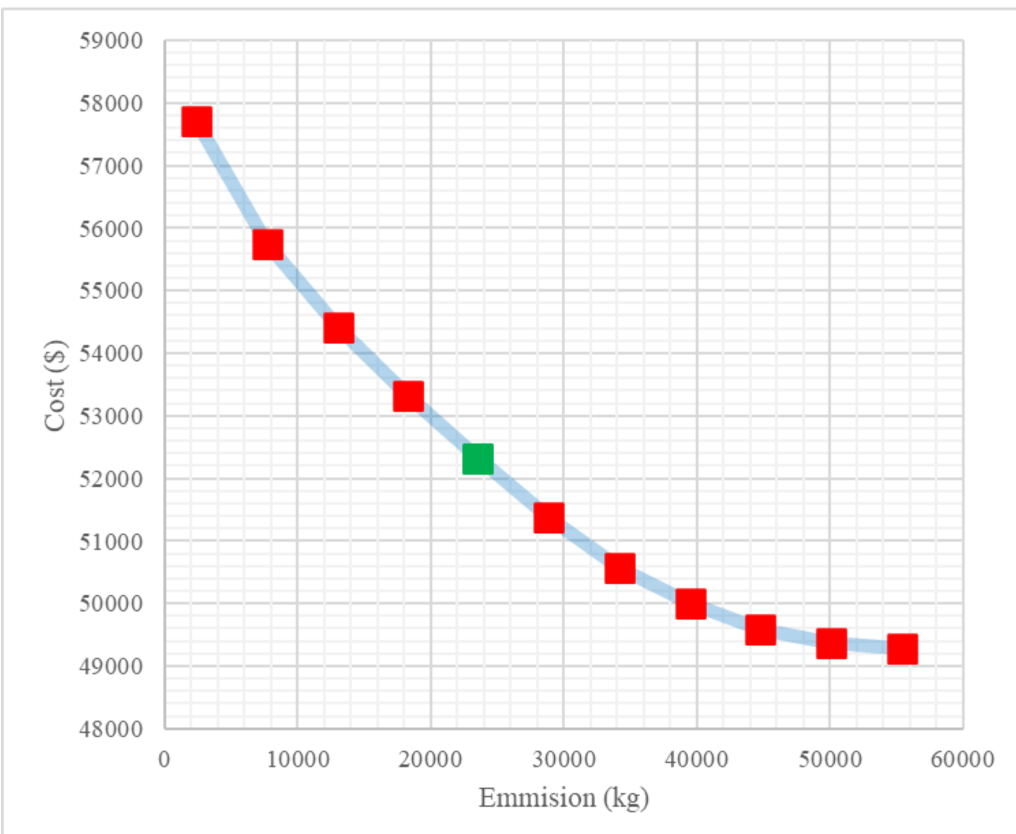


Figure 5-10:. Cost-emission pareto front in case 4

In summary, Chapter 5 has introduced a comprehensive framework for the coordinated scheduling of networked microgrids, addressing both economic and environmental challenges in modern power distribution systems. Through simulations on a representative test network, the proposed model demonstrated substantial reductions in operational costs and greenhouse gas emissions, validating the effectiveness of this multi-objective approach. By integrating flexible loads, electric vehicles, and hydrogen refueling stations, this framework not only enhances grid resilience but also aligns with sustainable energy goals. These findings lay the groundwork for future chapters, where further refinements and applications of this model will be explored, contributing to the broader goal of developing adaptable, efficient, and low-carbon energy systems.

Chapter 6: Conclusion and Future Works

6-1 Conclusion

In this thesis, a comprehensive framework for the coordinated scheduling of networked microgrids in active distribution systems has been developed, with a particular focus on the integration of electric vehicles (EVs), hydrogen refueling stations, and flexible loads. The research directly addresses several of the critical challenges facing modern power systems, particularly those associated with the increasing penetration of renewable energy sources and the growing demand for EV infrastructure. The widespread adoption of renewable energy has introduced variability and unpredictability into power generation, while the rise of electric vehicles has created new patterns of energy consumption. These developments are reshaping the structure and operation of traditional power systems, pushing the need for innovative solutions that can adapt to this new energy landscape.

By employing a two-stage stochastic programming approach, this thesis provides a robust and flexible solution for optimizing microgrid operations. This framework effectively balances economic and environmental objectives, addressing the inherent challenges that arise from the integration of intermittent renewable energy and the fluctuating demand patterns introduced by EVs. The first stage of the framework focuses on delineating service areas for microgrids, ensuring that the design takes into account security constraints, especially during emergency conditions. The second stage optimizes energy management by integrating renewable resources, EV charging stations, hydrogen refueling stations, and flexible loads.

One of the key aspects of this research is the development of a multi-objective optimization model that manages the complexities of microgrid operations. The model not only accommodates the integration of renewable energy sources, EV and fuel cell vehicle (FCV) charging stations, but also includes flexible loads to optimize the overall energy distribution within the network. The complexity of modern microgrids lies in the need to manage multiple, and often conflicting, objectives: minimizing operational costs while ensuring system reliability, maximizing the use of renewable resources, and reducing greenhouse gas (GHG) emissions. The multi-objective optimization model developed in this research offers a structured and practical approach to navigating these challenges.

The simulation results clearly demonstrate the efficacy of the proposed framework, showcasing significant reductions in both operational costs and emissions. Specifically, the incorporation of flexible loads and smart charging strategies for EVs and FCVs has resulted in a reduction in operating costs by approximately 4.77%, while emissions have decreased by an impressive 49.13%. These outcomes underscore the potential for substantial cost savings and environmental benefits through strategic energy management practices within microgrids. The ability to balance economic and environmental objectives makes this framework particularly relevant for power system operators who must comply with both budgetary constraints and environmental regulations.

The successful application of the GUROBI solver within the GAMS software environment validates the practicality and effectiveness of the model. This solver enables the efficient handling of complex optimization problems, ensuring that the framework can be scaled to manage large networks of interconnected microgrids. The flexibility and robustness of the model make it adaptable to different grid configurations, renewable energy penetration levels, and geographic contexts, making it applicable to a wide range of real-world scenarios.

A significant focus of this thesis has been the consideration of emergency scenarios, such as grid outages or natural disasters, which can compromise the stability of power systems. By delineating the service areas of microgrids and incorporating security constraints, the framework ensures that critical loads can be prioritized, and microgrids can continue to function independently if disconnected from the main grid. This aspect of the research highlights the importance of resilience in microgrid design. As climate change leads to more frequent and severe weather events, the ability to maintain power supply during emergencies is becoming increasingly vital.

The findings of this thesis have far-reaching implications for the future of energy systems, especially in the context of the growing integration of renewable energy sources and the widespread adoption of electric vehicles. The research demonstrates that well-designed microgrids, equipped with advanced energy management systems, can significantly enhance the resilience, reliability, and sustainability of power distribution networks. By optimizing the use of renewable energy sources and flexible loads, microgrids can reduce reliance on fossil fuel-based power generation, lower operational costs, and minimize carbon emissions. These outcomes align with global efforts to transition to cleaner, more efficient energy systems, particularly in light of the urgent need to address climate change and meet international sustainability goals.

The integration of hydrogen refueling stations and EV charging infrastructure into microgrid operations introduces new opportunities for energy storage and distribution. Hydrogen refueling stations, for example, offer a promising solution for storing excess renewable energy in the form of hydrogen, which can then be converted back into electricity when needed or used as a clean fuel source. This capability enhances the flexibility of the grid, allowing for more effective management of supply and demand fluctuations. The potential for hydrogen to act as both an energy carrier and storage medium makes it a key player in the future of sustainable energy systems. Additionally, the widespread adoption of EVs creates both challenges and opportunities for grid management. The increased demand for electricity to charge EVs can strain the grid, particularly during peak hours. However, EVs also represent a distributed energy resource, with the potential to provide power back to the grid during periods of high demand through vehicle-to-grid (V2G) technology.

Moreover, the potential for microgrids to contribute to energy security is strongly emphasized in this research. In regions prone to grid instability, natural disasters, or geopolitical tensions, microgrids provide a level of energy autonomy that can mitigate the impacts of large-scale outages. By allowing communities, businesses, and critical infrastructure to maintain power independently of the central grid, microgrids enhance the resilience of power systems. This capability is particularly valuable in remote or underserved regions, where access to reliable electricity is often limited.

While this thesis lays a strong foundation for optimizing microgrid operations, several areas merit further exploration. One promising avenue for future research is the integration of advanced energy storage technologies, such as solid-state batteries and supercapacitors. These technologies offer improved energy density, faster response times, and longer lifespans compared to traditional battery systems, making them ideal for use in microgrids. The incorporation of such storage technologies could further enhance the efficiency, reliability, and flexibility of microgrids, particularly in managing the variability of renewable energy sources.

Incorporating machine learning and artificial intelligence (AI) into the energy management framework could also greatly improve predictive capabilities, resource allocation, and decision-making processes in real-time. AI-driven energy management systems have the potential to optimize the operation of microgrids by learning from past data, predicting future energy consumption patterns, and dynamically adjusting energy distribution strategies. These capabilities would make microgrids more adaptive to changing conditions, whether they be fluctuations in renewable energy generation or sudden increases in demand. Additionally, AI could improve the resilience of microgrids by enabling faster and more accurate responses to unforeseen events, such as equipment failures or grid disruptions.

Additionally, testing the scalability and adaptability of the proposed framework in diverse geographic regions and grid configurations would provide valuable insights into the practical challenges of real-world implementation. Different regions have varying renewable energy potentials, grid infrastructure, and regulatory environments, all of which can impact the performance of microgrids. Conducting pilot projects in a variety of settings would help refine the model and ensure its broader applicability. Furthermore, engaging with local stakeholders, such as utilities, governments, and community groups, would provide a more holistic understanding of the social, economic, and environmental benefits of microgrids.

In conclusion, this thesis makes a significant contribution to the field of sustainable energy management by offering a comprehensive framework for the coordinated scheduling of networked microgrids. The findings highlight the potential of microgrids to improve system reliability, reduce operational costs, and lower emissions, making them an essential component of future power distribution networks. By addressing both economic and environmental objectives, this research offers a pathway toward more resilient and sustainable energy systems, capable of meeting the demands of an evolving energy landscape. The integration of advanced energy storage technologies, flexible loads, and smart EV charging strategies will be critical in shaping the future of microgrid operations. As the energy sector continues to transition toward a more decentralized and renewable-driven model, the contributions of this thesis provide valuable insights and practical solutions for optimizing the operation of microgrids in active distribution systems.

6-2 Research Contribution

This thesis makes several significant contributions to the field of sustainable energy management, particularly in the context of networked microgrids within active distribution systems. The research introduces a novel framework for the coordinated scheduling of microgrids, integrating electric vehicle (EV) charging stations, hydrogen refueling stations, and flexible loads. This integration is critical for addressing the dual challenges of economic efficiency and environmental sustainability in modern power systems.

One of the primary contributions of this work is the development of a two-stage stochastic programming model that effectively manages the uncertainties inherent in renewable energy sources and variable load demands. By incorporating these uncertainties into the decision-making process, the framework ensures more robust and reliable microgrid operations, which are essential for maintaining grid stability and resilience under varying conditions.

The research also advances the field by demonstrating the practical benefits of integrating smart charging strategies for EVs and fuel cell vehicles (FCVs). The results show a substantial reduction in operational costs and greenhouse gas emissions, highlighting the potential of these technologies to contribute to broader sustainability goals. The implementation of a multi-objective optimization approach, solved using the GUROBI solver within the GAMS software environment, further underscores the practical applicability of the proposed framework.

Additionally, this thesis provides a detailed analysis of the role of hydrogen refueling stations in microgrid operations, a relatively underexplored area in current research. By emphasizing the importance of these stations for energy storage and distribution, the research contributes to the understanding of how hydrogen can be leveraged to enhance microgrid performance and support the transition to a low-carbon energy system.

Furthermore, the framework's focus on ensuring microgrid reliability during emergency conditions by carefully delineating service areas adds a valuable dimension to the design of resilient energy systems. This aspect of the research addresses critical security concerns and offers practical solutions for maintaining power supply continuity in the face of disruptions.

Overall, the contributions of this thesis lie in its comprehensive approach to optimizing microgrid operations, its innovative integration of emerging technologies, and its practical solutions for enhancing both economic and environmental outcomes in active distribution systems. These contributions provide a foundation for future research and development in sustainable energy systems, offering insights that are both theoretically significant and practically applicable.

6-3 Future Work

The research presented in this thesis has developed a comprehensive multi-stage framework for the coordinated scheduling of networked microgrids in active distribution systems, with a particular focus on the economic and environmental impacts of electric vehicles (EVs) and flexible loads. While the proposed framework offers significant advancements in optimizing microgrid operations, several areas remain open for further investigation and development. The following directions outline potential future work that could extend and enhance the findings of this study.

1. **Integration of Advanced Energy Storage Technologies**

While this thesis has primarily focused on the role of hydrogen refueling stations and EVs, future research could explore the integration of advanced energy storage technologies, such as solid-state batteries, supercapacitors, and flywheels, into microgrid operations. These technologies have the potential to provide faster response times, higher energy densities, and longer lifespans compared to conventional batteries. Investigating the combined effects of these storage solutions on microgrid stability, cost-effectiveness, and environmental impact could yield valuable insights into the design of next-generation energy management systems.

2. **Incorporation of Machine Learning and Artificial Intelligence**

As the complexity of energy management systems increases, incorporating machine learning (ML) and artificial intelligence (AI) techniques could significantly enhance the performance and adaptability of microgrids. Future research could focus on developing AI-driven algorithms for real-time demand forecasting, predictive maintenance of microgrid components, and dynamic optimization of energy flows. These techniques could also be applied to improve the decision-making process in stochastic programming, enabling more accurate predictions and robust management strategies under uncertain conditions.

3. **Development of a Comprehensive Grid Interaction Model**

While the current framework addresses the coordination of microgrids within a distribution system, future work could extend this model to include a more comprehensive interaction with the main grid. This would involve developing strategies for bi-directional energy exchanges, demand response coordination, and ancillary service provision, such as frequency and voltage regulation, to the main grid. Additionally, the impact of high penetration levels of distributed energy resources (DERs) and microgrids on grid stability and resilience could be further explored.

4. **Exploration of Multi-Energy Systems Integration**

The integration of multi-energy systems, such as electric, thermal, and gas networks, presents an exciting avenue for future research. Future studies could explore how microgrids can be designed to optimize the use of multiple energy carriers, enhancing overall system efficiency and reducing carbon footprints. The development of coordinated control strategies that consider the interdependencies between different energy systems could lead to more resilient and sustainable energy infrastructures.

5. **Real-World Implementation and Pilot Projects**

While the simulation results presented in this thesis demonstrate the potential benefits of the proposed framework, real-world implementation and validation through pilot projects would be an essential next step. Future research could focus on collaborating with industry partners and utilities to deploy the framework in actual microgrid installations. These pilot projects could provide valuable feedback on the practical challenges and opportunities of implementing the proposed strategies, leading to refinements and improvements in the framework.

6. **Economic and Policy Analysis**

Future research could also delve deeper into the economic and policy implications of widespread microgrid adoption. This includes analyzing the economic feasibility of microgrid investments under various market conditions, exploring business models for microgrid operators, and examining the regulatory frameworks that could support or hinder the deployment of microgrids. Additionally, assessing the societal impacts, such as job creation and energy equity, could provide a broader understanding of the benefits and challenges associated with microgrid integration.

7. **Enhanced Environmental Impact Assessment**

While this thesis has quantified the reduction in greenhouse gas emissions due to the integration of EVs and flexible loads, future work could expand this assessment to include a more detailed lifecycle analysis of the environmental impacts of microgrid components. This would involve evaluating the entire supply chain, from material extraction and manufacturing to end-of-life disposal, to provide a more comprehensive understanding of the environmental benefits and trade-offs of microgrid technologies.

8. **Scalability and Adaptability of the Framework**

Finally, future research could explore the scalability and adaptability of the proposed framework to different geographic regions and grid configurations. This includes testing the framework in regions with varying levels of renewable energy penetration, different regulatory environments, and diverse socio-economic conditions. Such studies could help identify the necessary adaptations to ensure the framework's effectiveness in a wide range of settings, ultimately contributing to the broader adoption of microgrid solutions globally.

References

[1] J. Li, R. Xiong, Q. Yang, F. Liang, M. Zhang, and W. Yuan, "Design/test of a hybrid energy storage system for primary frequency control using a dynamic droop method in an isolated microgrid power system," Applied Energy, vol. 201, pp. 257-269, 2017.

[2] Q. Wang, F. Li, B. Sun, and Y. Huo, "Summary of research on stability of independent microgrid based on high permeability distributed generation," in IOP Conference Series: Earth and Environmental Science, vol. 440, no. 3, p. 032125, February 2020.

[3] L. Y. Lu, H. J. Liu, H. Zhu, and C. C. Chu, "Intrusion detection in distributed frequency control of isolated microgrids," IEEE Transactions on Smart Grid, vol. 10, no. 6, pp. 6502-6515, 2019.

[4] C. Zhang, W. Gao, S. Guo, Y. Li, and T. Yang, "Opportunistic maintenance for wind turbines considering imperfect, reliability-based maintenance," Renewable Energy, vol. 103, pp. 606-612, 2017.

[5] B. Fitzgerald, S. Sarkar, and A. Staino, "Improved reliability of wind turbine towers with active tuned mass dampers (ATMDs)," Journal of Sound and Vibration, vol. 419, pp. 103-122, 2018.

[6] K. Jalilpoor, A. Oshnoei, B. Mohammadi-Ivatloo, and A. Anvari-Moghaddam, “Network hardening and optimal placement of microgrids to improve transmission system resilience: A two-stage linear program,” Reliab. Eng. Syst. Saf., vol. 224, p. 108536, 2022.

[7] Y. Huang, G. Li, C. Chen, Y. Bian, T. Qian, and Z. Bie, “Resilient Distribution Networks by Microgrid Formation Using Deep Reinforcement Learning,” IEEE Trans. Smart Grid, vol. 13, no. 6, pp. 4918–4930, 2022.

[8] A. Younesi, H. Shayeghi, Z. Wang, P. Siano, A. Mehrizi-Sani, and A. Safari, "Trends in modern power systems resilience: State-of-the-art review," Renew. Sustain. Energy Rev., vol. 162, p. 112397, 2022.

[9] C. Alcarruz, J. D. Mina-Casaran, and A. Navarro-Espinosa, “From passive network to PV urban community microgrids: Finding the optimal size and upgrading cost,” Energy Sustain. Dev., vol. 70, pp. 387–402, 2022.

[10] K. Jalilpoor, S. Nikkhah, M. S. Sepasian, and M. G. Aliabadi, “Application of precautionary and corrective energy management strategies in improving networked microgrids resilience: A two-stage linear programming,” Electr. Power Syst. Res., vol. 204, p. 107704, 2022.

[11] Y. Ding, T. Lu, Z. Wang, H. Wu, and X. Lu, “A full time scale resilience improvement strategy of distribution network under extreme weather,” Energy Reports, vol. 8, pp. 1019–1025, 2022.

[12] Q. Shi, W. Liu, B. Zeng, H. Hui, and F. Li, “Enhancing distribution system resilience against extreme weather events: Concept review, algorithm summary, and future vision,” Int. J. Electr. Power Energy Syst., vol. 138, p. 107860, 2022.

[13] G. Kandaperumal, S. Majumder, and A. K. Srivastava, "Chapter Seven - Microgrids as a resilience resource in the electric distribution grid," in R. C. Bansal, M. Mishra, and Y. R. B. T.-E. P. S. R. Sood, Eds., Academic Press, pp. 181–212, 2022.

[14] D. Quiroga, E. Sauma, and D. Pozo, "Power system expansion planning under global and local emission mitigation policies," Applied Energy, vol. 239, pp. 1250-1264, 2019.

[15] Y. Zhu, C. Zhu, C. Song, Y. Li, X. Chen, and B. Yong, "Improvement of reliability and wind power generation based on wind turbine real-time condition assessment," International Journal of Electrical Power & Energy Systems, vol. 113, pp. 344-354, 2019.

[16] M. Mahdavi, L. H. Macedo, and R. Romero, "Transmission and Generation Expansion Planning Considering System Reliability and Line Maintenance," in Electrical Engineering (ICEE), Iranian Conference on, pp. 1005-1010, May 2018, IEEE.

[17] M. A. Mohamed, H. M. Abdullah, M. A. El-Meligy, M. Sharaf, A. T. Soliman, and A. Hajjiah, "A novel fuzzy cloud stochastic framework for energy management of renewable microgrids based on maximum deployment of electric vehicles," International Journal of Electrical Power & Energy Systems, vol. 129, p. 106845, 2021.

[18] S. D. Saldarriaga-Zuluaga, J. M. Lopez-Lezama, and N. Munoz-Galeano, "Optimal coordination of over-current relays in microgrids considering multiple characteristic curves," Alexandria Engineering Journal, vol. 60, no. 2, pp. 2093-2113, 2021.

[19] C. Reiz and J. B. Leite, "Optimal coordination of protection devices in distribution networks with distributed energy resources and microgrids," IEEE Access, vol. 10, pp. 99584-99594, 2022.

[20] K. Utkarsh and F. Ding, "Self-Organizing Map-Based Resilience Quantification and Resilient Control of Distribution Systems Under Extreme Events," IEEE Trans. Smart Grid, vol. 13, no. 3, pp. 1923-1937, 2022.

[21] S. N. Jahromi, E. Hajipour, and M. Ehsan, “Optimal Resilience-Oriented Microgrid Formation Considering Failure Probability of Distribution Feeders,” Electr. Power Syst. Res., vol. 209, p. 108012, 2022.

[22] D. Fan, Y. Ren, Q. Feng, Y. Liu, Z. Wang, and J. Lin, “Restoration of smart grids: Current status, challenges, and opportunities,” Renew. Sustain. Energy Rev., vol. 143, p. 110909, 2021.

[23] A. Nawaz, M. Zhou, J. Wu, and C. Long, “A comprehensive review on energy management, demand response, and coordination schemes utilization in multi-microgrids network,” Appl. Energy, vol. 323, p. 119596, 2022.

[24] R. Nourollahi, P. Salyani, K. Zare, and B. Mohammadi-Ivatloo, “Resiliency-oriented optimal scheduling of microgrids in the presence of demand response programs using a hybrid stochastic-robust optimization approach,” Int. J. Electr. Power Energy Syst., vol. 128, p. 106723, 2021.

[25] H. Xiao, W. Pei, L. Wu, L. Ma, T. Ma, and W. Hua, “A novel deep learning based probabilistic power flow method for Multi-Microgrids distribution system with incomplete network information,” Appl. Energy, vol. 335, p. 120716, 2023.

[26] R. S. Kumar, L. P. Raghav, D. K. Raju, and A. R. Singh, “Intelligent demand side management for optimal energy scheduling of grid connected microgrids,” Appl. Energy, vol. 285, p. 116435, 2021.

[27] A. Mehrbakhsh, S. Javadi, M. H. Aliabadi, and H. Radmanesh, “A robust optimization framework for scheduling of active distribution networks considering DER units and demand response program,” Sustain. Energy, Grids Networks, vol. 31, p. 100708, 2022.

[28] G. Jimenez-Estevez, A. Navarro-Espinosa, R. Palma-Behnke, L. Lanuzza, and N. Velazquez, "Achieving Resilience at Distribution Level: Learning from Isolated Community Microgrids," IEEE Power and Energy Mag., vol. 15, no. 3, pp. 64-73, 2017.

[29] P. Bajpai, S. Chanda, and A. K. Srivastava, "A Novel Metric to Quantify and Enable Resilient Distribution System Using Graph Theory and Choquet Integral," IEEE Trans. Smart Grid, vol. 9, no. 4, pp. 2918-2929, 2018.

[30] E. Craparo, M. Karatas, and D. I. Singham, "A robust optimization approach to hybrid microgrid operation using ensemble weather forecasts," Applied Energy, vol. 201, pp. 135-147, 2017.

[31] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, "Enhancing Power System Resilience Through Hierarchical Outage Management in Multi-Microgrids," IEEE Trans. Smart Grid, vol. 7, no. 6, pp. 2869-2879, 2016.

[32] H. Haddadian and R. Noroozian, "Multi-microgrids approach for design and operation of future distribution networks based on novel technical indices," Applied Energy, vol. 185, pp. 650-663, 2017.

[33] N. Nikmehr, S. Najafi-Ravadanegh, and A. Khodaei, "Probabilistic optimal scheduling of networked microgrids considering time-based demand response programs under uncertainty," Applied Energy, vol. 198, pp. 267-279, 2017.

[34] M. Mazidi, H. Monsef, and P. Siano, "Robust day-ahead scheduling of smart distribution networks considering demand response programs," Applied Energy, vol. 178, pp. 929-942, 2016.

[35] A. Kumar, N. K. Meena, A. R. Singh, Y. Deng, X. He, R. C. Bansal, and P. Kumar, "Strategic integration of battery energy storage systems with the provision of distributed ancillary services in active distribution systems," Applied Energy, vol. 253, p. 113503, 2019.

[36] A. Alzahrani, H. Alharthi, and M. Khalid, "Minimization of Power Losses through Optimal Battery Placement in a Distributed Network with High Penetration of Photovoltaics," Energies, vol. 13, no. 1, p. 140, 2020.

[37] P. Lata and S. Vadhera, "Reliability Improvement of Radial Distribution System by Optimal Placement and Sizing of Energy Storage System using TLBO," Journal of Energy Storage, vol. 30, p. 101492, 2020.

[38] M. Enayati, G. Derakhshan, and S. M. Hakimi, "Optimal energy scheduling of storage-based residential energy hub considering smart participation of demand side," J. Energy Storage, vol. 49, p. 104062, 2022.

[39] A. S. Kahnamouei and S. Lotfifard, "Enhancing Resilience of Distribution Networks by Coordinating Microgrids and Demand Response Programs in Service Restoration," IEEE Syst. J., vol. 16, no. 2, pp. 3048-3059, 2022.

[40] A. Azarhooshang, D. Sedighizadeh, and M. Sedighizadeh, "Two-stage stochastic operation considering day-ahead and real-time scheduling of microgrids with high renewable energy sources and electric vehicles based on multi-layer energy management system," Electr. Power Syst. Res., vol. 201, p. 107527, 2021.

[41] B. Zhou, D. Xu, C. Li, C. Y. Chung, Y. Cao, K. W. Chan, and Q. Wu, "Optimal Scheduling of Biogas–Solar–Wind Renewable Portfolio for Multicarrier Energy Supplies," IEEE Trans. Power Syst., vol. 33, no. 6, pp. 6229-6239, 2018.

[42] H. Chamandoust, G. Derakhshan, S. M. Hakimi, and S. Bahramara, "Tri-objective scheduling of residential smart electrical distribution grids with optimal joint of responsive loads with renewable energy sources," J. Energy Storage, vol. 27, p. 101112, 2020.

[43] K. Hamedi, S. Sadeghi, S. Esfandi, M. Azimian, and H. Golmohamadi, "Eco-Emission Analysis of Multi-Carrier Microgrid Integrated with Compressed Air and Power-to-Gas Energy Storage Technologies," Sustainability, vol. 13, no. 9. 2021.

[44] K. Ullah, Q. Jiang, G. Geng, S. Rahim, and R. A. Khan, "Optimal Power Sharing in Microgrids Using the Artificial Bee Colony Algorithm," Energies, vol. 15, no. 3. 2022.

[45] X. Dou, J. Wang, Z. Wang, T. Ding, and S. Wang, "A decentralized multi-energy resources aggregation strategy based on bi-level interactive transactions of virtual energy plant," Int. J. Electr. Power Energy Syst., vol. 124, p. 106356, 2021.

[46] R. M. Chabanloo, M. G. Maleki, S. M. M. Agah, and E. M. Habashi, "Comprehensive coordination of radial distribution network protection in the presence of synchronous

distributed generation using fault current limiter," International Journal of Electrical Power & Energy Systems, vol. 99, pp. 214-224, 2018.

[47] A. M. Hariri, H. Hashemi-Dezaki, and M. A. Hejazi, "A novel generalized analytical reliability assessment method of smart grids including renewable and non-renewable distributed generations and plug-in hybrid electric vehicles," Reliability Engineering & System Safety, vol. 196, p. 106746, 2020.

[48] M. W. Altaf, M. T. Arif, S. Saha, S. N. Islam, M. E. Haque, and A. M. T. Oo, "Renewable Energy Integration challenge on Power System Protection and its Mitigation for Reliable Operation," in IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society, pp. 1917-1922, October 2020.

[49] N. L. Mo, Z. H. Guan, D. X. Zhang, X. M. Cheng, Z. W. Liu, and T. Li, "Data-driven based optimal distributed frequency control for islanded AC microgrids," International Journal of Electrical Power & Energy Systems, vol. 119, p. 105904, 2020.

[50] M. Li, N. M. Hamawandy, F. Wahid, H. Rjoub, and Z. Bao, "Renewable energy resources investment and green finance: Evidence from China," Resources Policy, vol. 74, p. 102402, 2021.

[51] M. Farangi, E. A. Soleimani, M. Zahedifar, O. Amiri, and J. Poursafar, "The environmental and economic analysis of grid-connected photovoltaic power systems with silicon solar panels, in accord with the new energy policy in Iran," Energy, vol. 202, p. 117771, 2020.

[52] A. Khosravi, V. Olkkonen, A. Farsaei, and S. Syri, "Replacing hard coal with wind and nuclear power in Finland-impacts on electricity and district heating markets," Energy, vol. 203, p. 117884, 2020.

[53] X. Yao, B. Yi, Y. Yu, Y. Fan, and L. Zhu, "Economic analysis of grid integration of variable solar and wind power with conventional power system," Applied Energy, vol. 264, p. 114706, 2020.

[54] I. A. Nassar and M. M. Abdella, "Impact of replacing thermal power plants by renewable energy on the power system," Thermal Science and Engineering Progress, vol. 5, pp. 506-515, 2018.

[55] N. Holjevac, T. Baskarad, J. Dakovi, M. Krpan, M. Zidar, and I. Kuzle, "Challenges of High Renewable Energy Sources Integration in Power Systems—The Case of Croatia," Energies, 2021.

[56] S. Duman, M. Akbel, and H. Tolga Kahraman, "Development of the Multi-Objective Adaptive Guided Differential Evolution and optimization of the MO-ACOPF for wind/PV/tidal energy sources," Applied Soft Computing, vol. 112, p. 107814, 2021.

[57] Yi He, Su Guo, J. Zhou, J. Ye, J. Huan, K. Zheng, and Xinru Du, "Multi-objective planning-operation co-optimization of renewable energy system with hybrid energy storages," Renewable Energy, vol. 184, pp. 776-790, 2022.

[58] A. Maleki, M. Gholipour Khajeh, and M. Ameri, "Optimal sizing of a grid independent hybrid renewable energy system incorporating resource uncertainty, and load uncertainty," Electrical Power and Energy Systems, vol. 83, pp. 514-524, 2016.

[59] A. Abbassi, R. Abbassi, M. Dami, and M. Jemli, "Multi-objective genetic algorithm based sizing optimization of a stand-alone wind/PV power supply system with enhanced battery/supercapacitor hybrid energy storage," Energy, vol. 163, pp. 351-363, 2018.

[60] D. Mazzeo, O. Giusepp, B. Cristin, and M. Congedo, "Energy reliability-constrained method for the multi-objective optimization of a photovoltaic-wind hybrid system with battery storage," Energy, vol. 156, pp. 688-708, 2018.

[61] N. Ghorbani, A. Kasaeian, A. Toopshekan, L. Bahrami, and A. Magham, "Optimizing a hybrid wind-PV-battery system using GA-PSO and MOPSO for reducing cost and increasing reliability," Energy, vol. 154, pp. 581-591, 2018.

[62] S. Barakat, H. Ibrahim, and Adel A. Elbaset, "Multi-objective optimization of grid-connected PV-wind hybrid system considering reliability, cost, and environmental aspects," Sustainable Cities and Society, vol. 60, p. 102178, 2020.

[63] Y. Arya, "A new optimized fuzzy FOPI-FOPD controller for automatic generation control of electric power systems," Journal of the Franklin Institute, vol. 356, no. 11, pp. 5611-5629, 2019.

[64] M. M. Eissa, A. A. Ali, K. M. Abdel-Latif, and A. F. Al-Kady, "A frequency control technique based on decision tree concept by managing thermostatically controllable loads at smart grids," International Journal of Electrical Power & Energy Systems, vol. 108, pp. 40-51, 2019.

[65] V. F. Pires, A. Pires, and A. Cordeiro, "DC microgrids: benefits, architectures, perspectives and challenges," Energies, vol. 16, no. 3, p. 1217, 2023.

[66] I. Muñoz-Benavente, A. D. Hansen, E. Gómez-Lázaro, T. García-Sánchez, A. Fernández-Guillamón, and Á. Molina-García, "Impact of combined demand-response and wind power plant participation in frequency control for multi-area power systems," Energies, vol. 12, no. 9, p. 1687, 2019.

[67] M. Tostado-Véliz, A. A. Ghadimi, M. R. Miveh, D. Sánchez-Lozano, A. Escamez, and F. Jurado, "A Novel Stochastic Mixed-Integer-Linear-Logical Programming Model for Optimal Coordination of Hybrid Storage Systems in Isolated Microgrids Considering Demand Response," Batteries, vol. 8, no. 11, p. 198, 2022.

[68] T. Surinkaew and I. Ngamroo, "Coordinated robust control of DFIG wind turbine and PSS for stabilization of power oscillations considering system uncertainties," IEEE Transactions on Sustainable Energy, vol. 5, no. 3, pp. 823-833, 2014.

[69] Q. Wang, F. Li, B. Sun, and Y. Huo, "Summary of research on stability of independent microgrid based on high permeability distributed generation," in IOP Conference Series: Earth and Environmental Science, vol. 440, no. 3, p. 032125, 2020.

[70] M. Shamshiri, C. K. Gan, and C. W. Tan, "A review of recent development in smart grid and micro-grid laboratories," in 2012 IEEE International Power Engineering and Optimization Conference, Melaka, Malaysia, pp. 367-372, 2012.

[71] H. Bevrani, F. Habibi, P. Babahajyani, M. Watanabe, and Y. Mitani, "Intelligent frequency control in an AC microgrid: Online PSO-based fuzzy tuning approach," IEEE Transactions on Smart Grid, vol. 3, no. 4, pp. 1935-1944, 2012.

[72] E. N. Sosnina, A. V. Shalukho, I. A. Lipuzhin, A. Y. Kechkin, and A. A. Voroshilov, "Optimization of virtual power plant topology with distributed generation sources," in 2018 International Conference and Utility Exhibition on Green Energy for Sustainable Development (ICUE), pp. 1-7, October 2018.

[73] E. Buraimoh and I. E. Davidson, "Modeling and Analysis of Standalone Inverter-Based Microgrid with Grid-Supporting Voltage-Source Control under Changing Load," in 2020 IEEE PES/IAS PowerAfrica, pp. 1-5, August 2020.

[74] Z. Lv, Y. Zhang, M. Yu, Y. Xia, and W. Wei, "Decentralised coordinated energy management for hybrid AC/DC microgrid by using fuzzy control strategy," IET Renewable Power Generation, vol. 14, no. 14, pp. 2649-2656, 2020.

[75] T. Ahmad and D. Zhang, "Renewable energy integration/techno-economic feasibility analysis, cost/benefit impact on islanded and grid-connected operations: A case study," Renewable Energy, vol. 180, pp. 83-108, 2021.

[76] "IEEE Guide for Design, Operation, and Integration of Distributed Resource Island Systems with Electric Power Systems," IEEE, 2011.

[77] Z. Wang, & J. Wang, "Self-healing resilient distribution systems based on sectionalization into microgrids," IEEE Transactions on Power Systems, vol. 30, no. 6, pp. 3139-3149, 2015.

[78] B. J. Brearley, & R. R. Prabu, "A review on issues and approaches for microgrid protection," Renewable and Sustainable Energy Reviews, vol. 67, pp. 988-997, 2017.

[79] J. Guo, T. Chen, B. Chaudhuri, & S. Y. R. Hui, "Stability of isolated microgrids with renewable generation and smart loads," IEEE Transactions on Sustainable Energy, vol. 11, no. 4, pp. 2845-2854, 2020.

[80] A. A. Memon, & K. Kauhaniemi, "Real-time hardware-in-the-loop testing of IEC 61850 GOOSE-based logically selective adaptive protection of AC microgrid," IEEE Access, vol. 9, pp. 154612-154639, 2021.

[81] O. Hafez and K. Bhattacharya, “Optimal planning and design of a renewable energy based supply system for microgrids,” Renew. Energy, vol. 45, pp. 7–15, Sep. 2012.

[82] H. V. Haghi, S. M. Hakimi, and S. M. M. Tafreshi, “Optimal Sizing of a Hybrid Power System Considering Wind Power Uncertainty Using PSO-Embedded Stochastic Simulation,” pp. 722–727, 2010.

[83] M. Chung, K. L. Huang, J. L. Avelino, L. Tayo, C. Lin, M. H. Tsai, & S. T. Huang, "Toxic assessment of heavily traffic-related fine particulate matter using an in-vivo Wild-type Caenorhabditis elegans model," Aerosol and Air Quality Research, vol. 20, no. 9, pp. 1974-1986, 2020.

[84] S. A. Sarpong, R. F. Donkoh, J. K. S. Konnuba, C. Ohene-Agyei, & Y. Lee, "Analysis of PM2.5, PM10, and total suspended particle exposure in the Tema metropolitan area of Ghana," Atmosphere, vol. 12, no. 6, p. 700, 2021.

[85] Z. J.Andersen, M. Pedersen, G. Weinmayr, M. Stafoggia, C. Galassi, J. T. Jørgensen, & O. Raaschou-Nielsen, "Long-term exposure to ambient air pollution and incidence of brain tumor: the European Study of Cohorts for Air Pollution Effects (ESCAPE)," Neuro-oncology, vol. 20, no. 3, pp. 420-432, 2018.

[86] A. Ghosh, "Possibilities and challenges for the inclusion of the electric vehicle (EV) to reduce the carbon footprint in the transport sector: A review," Energies, vol. 13, no. 10, p. 2602, 2020.

[87] K. A. Mamun, F. R. Islam, R. Haque, A. A. Chand, K. A. Prasad, K. K. Goundar, "Systematic Modeling and Analysis of On-Board Vehicle Integrated Novel Hybrid Renewable Energy System with Storage for Electric Vehicles," Sustainability, vol. 14, no. 5, p. 2538, 2022.

[88] R. Zhang, X. Cheng, and L. Yang, “Stable matching based cooperative V2V charging mechanism for electric vehicles,” in 2017 IEEE 86th Vehicular Technology Conference (VTC-Fall), pp. 1-5, September 2017.

[89] C. Jin, J. Tang, and P. Ghosh, “Optimizing electric vehicle charging with energy storage in the electricity market,” IEEE Transactions on Smart Grid, vol. 4, no. 1, pp. 311-320, 2013.

[90] J. H. Wong, T. Sutikno, N. R. N. Idris, and M. Anwari, “A parallel energy-sharing control strategy for fuel cell hybrid vehicle,” TELKOMNIKA (Telecommunication Computing Electronics and Control), vol. 9, no. 2, pp. 357-364, 2011.

[91] R. Liu, L. Dow, and E. Liu, “A survey of PEV impacts on electric utilities,” in Innovative Smart Grid Technologies (ISGT), IEEE PES, pp. 8-1, 2011.

[92] L. Ramesh, S. P. Chowdhury, S. Chowdhury, A. A. Natarajan, and C. T. Gaunt, “Minimization of power loss in distribution networks by different techniques,” Int. J. Electr. Electron. Eng., vol. 3, pp. 521–527, 2019.

[93] M. H. Albadi and E. F. El-Saadany, “A summary of demand response in electricity markets,” Electric Power Syst. Res., vol. 78, no. 11, pp. 1989–1996, 2018.

[94] J. Li, R. Xiong, Q. Yang, F. Liang, M. Zhang, and W. Yuan, “Design/test of a hybrid energy storage system for primary frequency control using a dynamic droop method in an isolated microgrid power system,” Appl. Energy, vol. 201, pp. 257–269, 2017.

[95] H. A. Aalami, M. P. Moghaddam, and G. R. Yousefi, “Demand response modeling considering interruptible/curtailable loads and capacity market programs,” Appl. Energy, vol. 87, no. 1, pp. 243–250, 2010.

[96] M. Joung and J. Kim, “Assessing demand response and smart metering impacts on long-term electricity market prices and system reliability,” Appl. Energy, vol. 101, pp. 441–448, 2013.

[97] M. Lee et al., “Assessment of demand response and advanced metering,” Federal Energy Regulatory Commission, Tech. Rep., 2013.

[98] E. J. Edward and P. Policy, “Assessment of Customer Response to Real Time Pricing”, New Jersey: Edward J, Bloustein School of Planning and Public Policy, Rutgers University, 2005.

[99] K. Herter, "Residential implementation of critical-peak pricing of electricity," Energy Policy, vol. 35, no. 4, pp. 2121-2130, 2007.

[100] D. Duan, J. Liu, H. Niu, and J. Wu, "A risk-evasion TOU pricing method for distribution utility in deregulated market environment," in Power System Technology, 2004. PowerCon 2004. 2004 International Conference on, vol. 1, pp. 527-531, Nov. 2004.

[101] H. A. Aalami, M. P. Moghaddam, and G. R. Yousefi, "Demand response modeling considering interruptible/curtailable loads and capacity market programs," Applied Energy, vol. 87, no. 1, pp. 243-250, 2020.

[102] K. Herter, P. McAuliffe, and A. Rosenfeld, "An exploratory analysis of California residential customer response to critical peak pricing of electricity," Energy, vol. 32, no. 1, pp. 25-34, 2007.

[103] P. S. Deshwal and K. Deb, "Design of an optimal Hindi keyboard for convenient and efficient use," Indian Institute of Technology, Kanpur, Tech. Rep., 2003.

[104] C. Burkart, P. C. Nolz, and W. J. Gutjahr, "Modelling beneficiaries' choice in disaster relief logistics," Annals of Operations Research, vol. 256, pp. 41-61, 2017.

[105] S. Shahzad, M. A. Abbasi, H. Ali, M. Iqbal, R. Munir, and H. Kilic, "Possibilities, challenges, and future opportunities of microgrids: A review," Sustainability, vol. 15, no. 8, p. 6366, 2023.

[106] Y. Shan, L. Ma, and X. Yu, "Hierarchical control and economic optimization of microgrids considering the randomness of power generation and load demand," Energies, vol. 16, no. 14, p. 5503, 2023.

[107] Z. Wang and R. Paranjape, "An evaluation of electric vehicle penetration under demand response in a multi-agent based simulation," in 2014 IEEE Electrical Power and Energy Conference, 2014, pp. 220-225.

[108] S. W. Hadley, "Impact of plug-in hybrid vehicles on the electric grid," ORNL Report, vol. 640, 2006.

[109] F. Shahnia, A. Ghosh, G. Ledwich, and F. Zare, "Voltage unbalance sensitivity analysis of plug-in electric vehicles in distribution networks," in AUPEC 2011, pp. 1-6, 2011.

[110] M. S. ElNozahy and M. M. Salama, "A comprehensive study of the impacts of PHEVs on residential distribution networks," IEEE Trans. Sustainable Energy, vol. 5, no. 1, pp. 332-342, Jan. 2013.

[111] X. Zhang, X. Bai, and J. Shang, "Is subsidized electric vehicles adoption sustainable: Consumers’ perceptions and motivation toward incentive policies, environmental benefits, and risks," J. Cleaner Prod., vol. 192, pp. 71-79, Nov. 2018.

[112] O. Berman, R. C. Larson, and N. Fouska, "Optimal location of discretionary service facilities," *Transp. Sci.*, vol. 26, no. 3, pp. 201-211, Aug. 1992.

[113] M. Kuby and S. Lim, "The flow-refueling location problem for alternative-fuel vehicles," Socio-Econ. Plann. Sci., vol. 39, no. 2, pp. 125-145, Jun. 2005.

[114] N. Rastegarfar, B. Kashanizadeh, M. Vakilian, and S. A. Barband, "Optimal placement of fast charging station in a typical microgrid in Iran," in Proc. 2013 10th Int. Conf. European Energy Market (EEM*)*, May 2013, pp. 1-7.

[115] L. Jia, Z. Hu, W. Liang, W. Lang, and Y. Song, "A novel approach for urban electric vehicle charging facility planning considering combination of slow and fast charging," in Proc. 2014 Int. Conf. Power System Technology, Oct. 2014, pp. 3354-3360.

[116] O. Veneri, C. Capasso, L. Ferraro, and A. Del Pizzo, "Performance analysis on a power architecture for EV ultra-fast charging stations," in Proc. 2013 Int. Conf. Clean Electrical Power (ICCEP), June 2013, pp. 183-188.

[117] Y.-B. Kooh and N. H. Vaidya, "Location-aided routing (LAR) in mobile ad hoc networks," Wireless Networks, pp. 307-321, 2018.

[118] C. Li, T. Ding, X. Liu, and C. Huang, "An electric vehicle routing optimization model with hybrid plug-in and wireless charging systems," IEEE Access, vol. 6, pp. 27569-27578, 2018.

[119] R. Zhang, X. Cheng, and L. Yang, "Stable matching based cooperative V2V charging mechanism for electric vehicles," in 2017 IEEE 86th Vehicular Technology Conference (VTC-Fall), pp. 1-5, 2017.

[120] C. S. Wang, G. A. Covic, and O. H. Stielau, "Power transfer capability and bifurcation phenomena of loosely coupled inductive power transfer systems," IEEE Transactions on Industrial Electronics, vol. 51, no. 1, pp. 148-157, Feb. 2004.

[121] J. L. Villa, J. Sallan, J. F. S. Osorio, and A. Llombart, "High-misalignment tolerant compensation topology for ICPT systems," IEEE Transactions on Industrial Electronics, vol. 59, no. 2, pp. 945-951, Feb. 2012.

[122] S. D. Manshadi, M. E. Khodayar, K. Abdelghany, and H. Üster, "Wireless charging of electric vehicles in electricity and transportation networks," IEEE Transactions on Smart Grid, vol. 9, no. 5, pp. 4503-4512, Sep. 2017.

[123] R. R. Shukla, M. M. Garg, and A. K. Panda, "Driving grid stability: Integrating electric vehicles and energy storage devices for efficient load frequency control in isolated hybrid microgrids," Journal of Energy Storage, vol. 89, pp. 111654, 2024.

[124] A. Mohamed, E. M. Wazeer, S. M. El Masry, A. A. Ghany, and M. A. Mosa, "A novel scheme of load frequency control for a multi-microgrids power system utilizing electric vehicles and supercapacitors," Journal of Energy Storage, vol. 89, pp. 111799, 2024.

[125] M. A. Aslam, S. A. R. Kashif, M. M. Gulzar, M. Alqahtani, and M. Khalid, "A novel multi-level dynamic decomposition based coordinated control of electric vehicles in multimicrogrids," Sustainability, vol. 15, no. 16, pp. 12648, 2023.

[126] H. Pan, X. Feng, F. Li, and J. Yang, "Energy coordinated control of DC microgrid integrated incorporating PV, energy storage and EV charging," Applied Energy, vol. 342, 121155, 2023.

[127] N. Mohammed, A. Lashab, M. Ciobotaru, and J. M. Guerrero, "Accurate Reactive Power Sharing Strategy for Droop-based Islanded AC Microgrids," IEEE Transactions on Industrial Electronics, 2022.

[128] A. Alzahrani, H. Alharthi, and M. Khalid, "Minimization of Power Losses through Optimal Battery Placement in a Distributed Network with High Penetration of Photovoltaics," Energies, vol. 13, no. 1, p. 140, 2019.

[129] A. S. Mary Antony, J. Sumithra, K. Rayudu, G. Dhanalakshmi, R. Agilesh Saravanan, A. Kavitha, and K. V. Malini, "Dynamic and Model Predictive Controllers for Frequency Regulation of an Isolated Microgrid with Electrical Vehicles and the ESS Integration," Electric Power Components and Systems, vol. 52, no. 3, pp. 426-444, 2024.

[130] B. Singh, A. Slowik, S. K. Bishnoi, and M. Sharma, "Frequency Regulation Strategy of Two-Area Microgrid System with Electric Vehicle Support Using Novel Fuzzy-Based Dual-Stage Controller and Modified Dragonfly Algorithm," Energies, vol. 16, no. 8, p. 3407, 2023.

[131] H. S. Salama, G. Magdy, A. Bakeer, and I. Vokony, "Adaptive Coordination Control Strategy of Renewable Energy Sources, Hydrogen Production Unit, and Fuel Cell for Frequency Regulation of a Hybrid Distributed Power System," Protection and Control of Modern Power Systems, vol. 7, no. 3, pp. 1-18, 2022.

[132] S. Kaur, T. Kaur, and R. Khanna, "Frequency Control in Microgrids Based on Fuzzy Coordinated Electric Vehicle Charging Station," in Smart Grids and Microgrids: Technology Evolution, pp. 127-145, 2022.

[133] W. Li, M. Zhang, and Y. Deng, "Consensus-based Distributed Secondary Frequency Control Method for AC Microgrid Using ADRC Technique," Energies, vol. 15, no. 9, p. 3184, 2022.

[134] X. Wan, X. Ding, H. Hu, and Y. Yu, "An Enhanced Second-Order-Consensus-Based Distributed Secondary Frequency Controller of Virtual Synchronous Generators for Isolated AC Microgrids," Energy Reports, vol. 7, pp. 5228-5238, 2021.

[135] M. Eydi and R. Ghazi, "A Novel Communication-Less Control Method to Improve DC Microgrid Performance Based on AC Signal Injection," International Journal of Electrical Power & Energy Systems, vol. 123, 106309, 2020.

[136] M. Z. Khan, C. Mu, S. Habib, W. Alhosaini, and E. M. Ahmed, "An Enhanced Distributed Voltage Regulation Scheme for Radial Feeder in Islanded Microgrid," Energies, vol. 14, no. 19, 6092, 2021.

[137] P. Khemmook, K. Prompinit, and T. Surinkaew, "Control of a Microgrid Using Robust Data-Driven-Based Controllers of Distributed Electric Vehicles," Electric Power Systems Research, vol. 213, 108681, 2022.

[138] M. A. Baherifard, R. Kazemzadeh, A. S. Yazdankhah, and M. Marzband, "Intelligent Charging Planning for Electric Vehicle Commercial Parking Lots and Its Impact on Distribution Network's Imbalance Indices," Sustainable Energy, Grids and Networks, vol. 30, 100620, 2022.

[139] Y.-P. Xu, R.-H. Liu, L.-Y. Tang, H. Wu, and C. She, “Risk-averse multi-objective optimization of multi-energy microgrids integrated with power-to-hydrogen technology, electric vehicles and data center under a hybrid robust-stochastic technique,” Sustain. Cities Soc., vol. 79, p. 103699, 2022.

[140] C. Gu, Y. Zhang, J. Wang, and Q. Li, “Joint planning of electrical storage and gas storage in power-gas distribution network considering high-penetration electric vehicle and gas vehicle,” Appl. Energy, vol. 301, p. 117447, 2017.

[141] T. Hai, A. K. Alazzawi, J. Mohamad Zain, and H. Oikawa, “A stochastic optimal scheduling of distributed energy resources with electric vehicles based on microgrid considering electricity price,” Sustain. Energy Technol. Assessments, vol. 55, p. 102879, 2023.

[142] M. Nozarian, A. Fereidunian, and A. Hajizadeh, “An operationally induced approach to reliability-oriented ACOPF-constrained planning of interconnected multicarrier energy hubs: An MILP formulation,” Sustain. Energy Technol. Assessments, vol. 57, p. 103196, 2023.

[143] M. Sheikh, J. Aghaei, A. Letafat, M. Rajabdorri, T. Niknam, M. Shafie-Khah, and J. P. S. Catalão, "Security-constrained unit commitment problem with transmission switching reliability and dynamic thermal line rating," IEEE Systems Journal, vol. 13, no. 4, pp. 3933-3943, 2019.

[144] M. A. Hannan, “ANN-Based Binary Backtracking Search Algorithm for VPP Optimal Scheduling and Cost-Effective Evaluation,” IEEE Trans. Ind. Appl., vol. 57, no. 6, pp. 5603–5613, 2021.

[145] B. Liu, “Optimal scheduling of combined cooling, heating, and power system-based microgrid coupled with carbon capture storage system,” J. Energy Storage, vol. 61, p. 106746, 2023.

[146] S. A. Mansouri, E. Nematbakhsh, A. Ahmarinejad, A. R. Jordehi, M. S. Javadi, and M. Marzband, “A hierarchical scheduling framework for resilience enhancement of decentralized renewable-based microgrids considering proactive actions and mobile units,” Renew. Sustain. Energy Rev., vol. 168, p. 112854, 2022.

[147] M. Yang, Y. Cui, and J. Wang, "Multi-Objective optimal scheduling of island microgrids considering the uncertainty of renewable energy output," Int. J. Electr. Power Energy Syst., vol. 144, p. 108619, 2023.