SYNERGISTIC INTEGRATION OF DEMAND SIDE MANAGEMENT, RENEWABLE ENERGY SOURCES, BATTERY, AND HYDROGEN STORAGE IN HYBRID ENERGY SYSTEMS

By

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This thesis is dedicated to my children, who remind me every day of what truly matters. This thesis is dedicated to you, as a symbol of my commitment to our future and the world I hope to help shape for you

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ABSTRACT

In recent years, there has been a significant increase in the demand for hybrid energy systems (HES). This surge is attributed to a combination of factors, including the pursuit of sustainable and resilient future energy solutions. HES integrates various energy resources to achieve synchronized energy output. However, HES faces notable challenges due to escalating energy consumption, the expenses associated with utilizing multiple sources, and increased emissions from non-renewable energy resources. On the other hand, when utilizing renewable energy sources (RES), the management of distributed energy resources (DER) plays a crucial role in optimizing the practical objectives of the grid. This thesis employs optimization techniques, such as the shuffled frog leaping algorithm (SFLA), to manage DER and implement demand response programs (DSP). The aim is to optimize the economic, technical, and environmental aspects of a smart micro-grid (SMG). Furthermore, this thesis adopts a hybrid approach that combines well-established techniques, namely the Non-Dominated Sorting Genetic Algorithm II and Multi-Objective Particle Swarm Optimization (Hybrid-NSGA-II-MOPSO), aims to optimize operational costs, reduce pollution, and address the challenge of achieving a high penetration of RES while minimizing the energy gap between initial demand and consumption. For prediction of uncertain behavior of RES before integration with the grid, cumulative distribution function (CDF) and probability distribution function (PDF) are used. The DER included consists of wind, solar, micro-turbine, diesel generator, and utility grid. The demand side management (DSM) strategy is designed for three types of loads, sheddable loads, non-sheddable loads, and shiftable loads. To establish a bi-directional communication link between the grid and consumers, distribution grid operator (DGO) is employed. For validation, this model is is compared with different individual optimization techniques like SFLA, MOPSO and NSGA-II as well as different constraints are considered. The results obtained shows the superiority of proposed SFLA and Hybrid-NSGA-II-MOPSO algorithms in terms of avoiding pre-mature convergence which is a common challenge in optimization, and achieving global optimum for the proposed objectives.

LIST OF ABBREVIATION AND SYMBOLS USED

General Abbreviations

A3C	Asynchronous Advantage Actor-Critic
ABC-PSO	Artificial Bee Colony – Particle Swarm Optimization
BESS	Battery Energy Storage Systems
CDF	Cumulative Distribution Function
DER	Distributed Energy Resources
DG	Diesel Generators
DGO	Distribution Grid Operator
DOD	Depth of Discharge
DRP	Demand Response Programs
DS	Demand Shifting
DSM	Demand Side Management
EL	Electrolyzer
EMC	Energy Management Controller
ESS	Energy Storage Systems
EV	Electric Vehicle
FC	Fuel Cell
GIESB	Grid-Integrated Energy Storage Batteries
HES	Hybrid Energy Systems
HSS	Hydrogen Storage Systems
HTS	Hydrogen Storage Tanks

HYBRID-NSGA-II-MOPSO	Hybrid-Non-Dominated Sorting Genetic Algorithm II- Multi-Objective Particle Swarm Optimization
LP	Linear Programming
LS	Load Shifting
MILP	Mixed Integer Linear Programming
MIQCP	Mixed Integer Quadratic Constrained Programming
MOPSO	Objective Particle Swarm Optimization
MT	Micro Turbine
PAR	Peak to Average Ratio
PDF	Probability Distribution Function
PSO	Particle Swarm Optimization
PSOAIW	PSO Adaptive Inertia Weight
PSOCF	PSO With A Constriction Factor
PV	Photovoltaic
QTLBO	Quantum Teaching Learning-Based Optimization
RDS	Residential Demand Shifting
RE	Renewable Energy
RES	Renewable Energy Sources
SFLA	Shuffled Frog Leaping Algorithm
SMG	Smart Microgrids
SOC	State of Charge
TOU	Time-of-Use
UG	Utility Grid

WT	Wind Turbines

Parameters

A	Area covered by PV
$D_T(sc,t)$	Total demand
D_{unmet}	Unmet demand
Em_{DG}	Emission of diesel generator
$Em_{Gi}(h)$	Emission of generation unit
$Em_{Sj}(h)$	Emission of storage unit
Em_{UG}	Emission of utility grid
$EP_{Gi}(h)$, $EP_{Sj}(h)$	Price of energy offered
$EP_{grid}(h)$	Market price
G, S	Units of generation and storage
${G_H}^{EL}$	Hydrogen consumption
${G_H}^{FC}$	Hydrogen generation
h	hours
hyd	Hydrogen indices
MU, MD	Minimum up and minimum down time of DGs
O_{cost}	Operational cost
RU, RD	Ramp up and ramp down time of DGs
S	Rated speed of WT
sc	Probability of scenario
si	Solar irradiance
$SOC(t)_{batt}$	state of charge of battery

S_{ci}	Cut-in speed of WT
S_{co}	Cut-off speed of WT
${W_d}^{min}, {W_d}^{max}$	Maximum and minimum demand
W_{Cmax}	Maximum capacity of battery
W_{EL}	Total power of electrolyzer
W_{FC}	Total power of FC
W_{PV}	Total power of PV
$W_{grid}(h)$	Power exchange
$W_{in}(t)$	Power into the battery
$W_{out}(t)$	Power out of the battery
η_{EL}	Efficiency of electrolyzer
η_{FC}	Efficiency of FC
η_{PV}	PV efficiency
$\vartheta^{0n}, \vartheta^{0ff}$	On and off state of DGs

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CHAPTER 1 INTRODUCTION

1.1 Background

The demand of HES, which integrates both renewable energy sources (RES) and Non-RES , is one of the important topics these days due to several compelling factors. Additionally, HES contribute to environmental sustainability by incorporating renewables like solar and wind alongside backup non-RES, thus reducing carbon emissions while ensuring a stable power supply [1]. These systems enhance grid resilience through energy storage solutions, such as batteries, hydrogen storage systems (HSS), which stabilize grids and aid rapid recovery during outages [2]. Moreover, their cost efficiency, driven by optimized energy usage and incentives, makes them an attractive choice [3]. Finally, continuous technological advancements in RES and grid management further growing demand for these systems, promising a sustainable and resilient energy future [4] . HES with DSM strategy always need a communicational link through which information and data exchanges between the utility grid and the consumers.

RES plays a crucial role in enabling the transition towards a more environmentally sustainable and cleaner energy in the future. Given their uncertain nature, it is imperative to have backup energy sources in place when utilizing RES in smart microgrids (SMG). However, effectively managing DER is of paramount importance when incorporating RES, as this management contributes to optimizing the operational costs and pollution emissions of the grid [5]. Hence, it is essential to facilitate the DER optimal management and operation through proper planning for optimization of practical SMG objectives. In examining the energy management of DER in SMG, numerous methods and structures have been suggested, incorporating range of resources [6].

SMGs are advanced energy systems that integrate RES, storage system, and intelligent control technologies to efficiently generate, distribute, and manage electricity at the local level. These SMGs operate autonomously or in coordination with the larger grid, enhancing reliability, resilience, and sustainability of energy supply [7]. By leveraging digital communication and automation, SMGs optimize energy production and consumption, integrate diverse energy resources, and respond dynamically to fluctuations in demand and supply. This decentralized approach enables communities, campuses, or industrial facilities to enhance energy security, reduce carbon emissions, and achieve greater control over their power infrastructure. SMGs play a crucial role in modernizing the energy landscape and promoting a more flexible and resilient power grid [8]-[9]-[10]. The energy management of SMGs involves the management of both generation and demand sides [11]. It ensures the fulfillment of system constraints, aiming to achieve an economical, sustainable, and reliable operation of the SMGs [12]. The energy management of SMGs offers various advantages such as dispatch to energy savings, reactive power support, frequency regulation, reliability improvement, cost reduction, energy balance, reduced CO2 emissions, customer participation, and customer privacy etc. [13]- [14].

One of the primary challenges in HES pertains to the management and control of distributed generation [15]. The dynamic interaction amongst the RES and demand can lead to critical issues concerning power quality and system stability, which are not commonly encountered in conventional energy systems [16]. Consequently, it becomes imperative to efficiently regulate the energy flow within the HES to ensure a continuous and reliable power supply for the load demand [17]-[18]. Besides, to facilitate the transition towards a more sustainable and environmentally friendly energy future, the key role of renewable energy (RE) resources cannot be overstated [19]-[20]. Renewable energy technologies and alternative fuels are characterized by their ability to provide energy that is low in carbon emissions, clean, safe, reliable, and not subject to price fluctuations [21]. However, the intermittent nature of RES and the need for grid stability underscore the substantial challenges associated with large-scale energy storage[22].

1.2 Motivation

HES integrates various energy resources to achieve synchronized energy output. However, HES faces notable challenges due to the expenses associated with utilizing multiple sources, and increased emissions from non-RES, etc. [23]. On the other hand, when utilizing RES, the management of DER plays a crucial role in optimizing the practical objectives of the grid. Thus, to ensure sustainable, reliable, and cost-effective future energy solution, energy management of such systems is necessary, and it is considered as the primary motivation of this thesis.

1.3 Thesis objectives

The energy management of HES and DER is important to ensure cost-effective, reliable, and sustainable energy in the future. In order to tackle these problems, this work utilizes the shuffled frog leaping algorithm (SFLA) and a (Hybrid-NSGA-II-MOPSO) algorithm to optimize the following objective functions:

- Efficiently manage DER for optimal power allocation to minimize the operational cost and pollution emission, while considering the maximum usage of RES impact.
- Optimally engage consumers through demand response programs (DRP) and presenting its impact in terms of minimum operational cost and pollution emission.
- Integrate hydrogen and battery storage systems in HES for synchronized energy output.
- Planning strategies to address the challenges in HES, including rising energy consumption, escalating costs, and increasing emissions, involves identifying and implementing solutions to mitigate these issues.
- Develop a multi-objective optimization strategy that minimizes operational costs, reduces pollution, and maximizes renewable energy penetration.

1.4 Thesis methodologies and contributions

This work focuses on energy management of distribution grids incorporating DSM strategy, battery and HSS to optimize operational costs and reduce the pollution as minimization problems, while also addressing the challenges of achieving a high penetration of renewable energy resources, framed as a maximization problem. The third objective function is introduced through the implementation of the DSM strategy, aiming to minimize the energy gap between initial demand and consumption. This DSM strategy is designed around consumers with three types of loads, sheddable loads, non-sheddable loads, and shiftable loads. To establish a bi-directional communication link between the grid and consumers, a DGO is utilized. Additionally, the uncertain behavior of wind, solar, and load demand is modeled using probability distribution functions: Weibull for wind, PDF beta for solar, and Gaussian PDF for load demand. To tackle this complex tri-objective optimization problem, a (Hybrid-NSGA-II-MOPSO) algorithm is proposed. Simulation results demonstrate the effectiveness of the proposed model in optimizing the tri-objective problem while considering various constraints. The contributions of the proposed study are highlighted as follows:

- Management of DERs in SMG using SFLA technique, to tackle operational cost and emission problems.
- Integration of hydrogen and battery storage systems in hybrid energy system for synchronized energy output.
- Addressing challenges in hybrid energy systems, such as rising energy consumption, cost and emissions, and planning strategy for tackling these challenges.
- Development of a multi-objective optimization strategy for distribution grids that minimizes operational costs, reduces pollution, and maximizes renewable energy penetration.
- Introducing DSM strategy and a bi-directional communication system with consumers, coupled with a hybrid optimization approach, to tackle the complex tri-objective optimization problem effectively.

1.5 Thesis outline

The remaining sections of the work are organized as follows:

Chapter 2 – Literature Review.

This chapter provides the reader with a comprehensive literature review about the problems tackled, and techniques used for optimizing these problems, and flaws in the existing literature.

Chapter 3 – Proposed System Model

This chapter presents the system architecture in detail with uncertainty modeling of RES and constraints.

Chapter 4 – Proposed Optimization Techniques.

This chapter provides the detail overview of proposed optimization techniques that are used in this work. These techniques are (SFLA) and (Hybrid-NSGA-II-MOPSO).

Chapter 5 – Simulation tests, Results and Discussion.

This chapter provides detail overview of the simulation results, analysis, and discussion.

Chapter 6 – Conclusion and Future Work.

The last chapter presents the concluding remarks and the possible directions in which this work can be extended.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

The management of DERs in context of HESs modeling is an ongoing challenge for engineers, scientists, and researchers. In the last decade, different techniques are used by researchers to tackle the management of DERs in HESs systems. This chapter looks at the objectives tackled, approaches used, and scenario considered for optimization in HESs.

2.2 Integration of renewable energy sources

To facilitate the shift toward a more environmentally sustainable and cleaner energy future, RES plays a key role in ensuring the success of this transition. Renewables technologies are characterized by their low carbon emissions, cleanliness, safety, reliability [24]. Consequently, many researchers and scientists are dedicated to advancing energy systems that harness renewable and sustainable energy resources, such as geothermal, wind, and solar energy. Although, these energy sources present challenges in terms of storage and transportation [25]-[26]. This study [27] highlighted the intermittency of RES and the necessity for stabilization of grid, which underscores the challenge of implementing large-scale storage system. Since the supply of energy coming from RES unpredictable and inconsistent in nature, substantial quantities of energy storage systems (ESSs) are indispensable for effective management. ESSs are essential for transferring electricity production across various timeframes, including hourly, daily, and seasonal periods [28].

Battery energy storage systems (BESS) are playing a significant role in the integration of solar photovoltaic power generation into the grid while mitigating fluctuations. ESSs equipped with batteries have the capability to provide both active and reactive power, thereby enhancing system voltage and frequency. In addition to their primary focus on enhancing system stability, energy storage control systems can also be seamlessly integrated with energy markets, thereby promoting the cost-effectiveness of solar resources. A comprehensive review of BESS, including a historical overview and analysis of their role in renewable integration, can be found in[29] . Among various battery storage technologies, the most mature option presently available is the lead-acid battery [30]-[31]. Furthermore, [32] offers an in-depth sustainability analysis of a BESS when integrated with a hybrid renewable energy source in an island mode. In recent years, hydrogen integration into power systems considered by many researchers, encompassing various aspects, including production, storage, re-electrification, and safety concerns [33]. There is a multiple study available that uses RES such as solar and wind for hydrogen production holds great promise for the sustainable development of the world [34]. One potential method for storing renewable energy involves the utilization of a carrier gas, such as hydrogen, which can be stored, transported, and accessed as needed [35]-[36]. Energy storage technology facilitates the conversion of one medium into storable forms, enabling energy to be saved through multiple avenues and later converted back into electric power when required [37]. These energy storage technologies contribute for enhancing the security of energy, mitigating climate change, and augmenting the value of current and future energy systems [38]. HSS are gaining popularity as a relatively cost-effective means of storing renewable energy, with applications in transportation and trade.

2.3 Integration of energy storage systems

Over the past few years, the integration of storage systems into power grids has become a focal point of research efforts, particularly in conjunction with the utilization of renewable energy resources. This study is based on a comprehensive overview of three distinct storage systems, each playing a key role in addressing the challenges of renewable energy integration. These systems include the battery storage system, known for its flexibility and rapid response capabilities, the hydrogen storage system, which offers the potential for long duration and high-capacity of storing energy, and the hybrid-battery-hydrogen storage system, which combines the strengths of both technologies to create a versatile and robust solution.

2.3.1 Integration of the battery storage systems

Battery energy storage systems have undergone extensive testing and evaluation in recent years. This section provides a summary of the most recent research and developments in this field. This paper [39] explored integrating RES with the installation of a BESS in isolated power grids. The BESS is treated as a dispatchable generator and is integrated into the unit commitment and economic dispatch (UC+ED) platform. To minimize costs, the primary usage of the proposed energy system was to fulfill a portion of the spinning reserve requirements and secondarily to reduce the demand on thermal generators using available resources. This paper also presented BESS configurations that optimize economic feasibility and minimize RES curtailment. The findings suggested that this technology could yield profitability and significantly to reduce RES curtailment levels. This study [40] introduced a decentralized power management strategy aimed at mitigating the impact on grid voltages and enhancing the performance of grid-integrated energy storage batteries (GIESB) in conjunction with WTs and PVs. The aim of this strategy was to formulate three distinct clusters of the proposed objective functions for optimizing the discharging/charging cycles of GIESBs by employing a well-known technique called mixed integer linear programming (MILP). This study also considered the batteries depth of discharge (DOD) and state of charge (SOC), respectively. In order to minimize the cost of power charging for GIESBs, the first cluster was designed by leveraging time-of-use (TOU) tariffs. Moreover, to optimize the charging power of GIESBs, the second cluster was designed by considering per-unit generation from WTs and PVs. Finally, to minimize the discharging power of GIESBs, third cluster was designed based on consumption of residential loads (per-unit).

Besides, this study [41] presented an approach that combines the economic, technical design and power control of an off-grid hybrid-RES integrated with a hybrid energy storage system. This storage system includes batteries, such as lead-acid battery and lithium-ion, and a supercapacitor. Notably, it was investigated that the integration RES with hybrid energy storage systems is a unique contribution. First, authors utilized hybrid optimization of multiple energy resources (HOMER) software to assess the feasibility and optimize nine different configurations at a 1-minute resolution, determining the ideal component sizes. Subsequently, authors also developed MATLAB/Simulink models for the most promising design, implementing a dynamic rule-based strategy to study and analyze the dynamic response of the proposed system, monitoring of the DC-bus voltage, power balance, and load voltage control when faced with sudden changes in RES or load.

2.3.2 Integration of the hydrogen storage systems

Hybrid energy systems (HES) faces significant challenges such as increased in the consumption of energy, energy costs of operator used, and potential environmental repercussions stemming from heightened emissions resulting from the depletion of non-renewable energy resources, specifically fossil fuels. In this study [42] an energy management strategy was developed utilizing hydrogen storage system and DRP through the design of PLC unit. The performance of the proposed system was assessed through the comparison of different scenarios, including a demand response and hydrogen energy system. The objectives tackled in this study were to reduce peak energy demand, minimize system costs, and harness surplus power generation from the battery's charge rate. The application HSS within microgrids has the potential to enhance economic, environmental, and reliability metrics, offering a superior storage capacity compared to alternative technologies such as batteries. Building upon this concept, this paper [43] introduced a novel energy management strategy for microgrids (isolated) that considers hydrogen storage and demand response initiatives. The overall optimization framework is tackled through Constraint-and-Column Generation Algorithm. The resulting tool is tested on a standard isolated microgrid, affirming its suitability for industrial applications. Consequently, the impact of hydrogen storage and demand response initiatives is explored, leading to the conclusion that adaptable demand has a more significant influence on cost savings than hydrogen storage, resulting in a 6% reduction in total costs compared to the base scenario.

Furthermore, certain inherent issues are identified, such as the observation that flexible consumers are more frequently engaged when the hydrogen chain is operational, potentially leading to undesirable outcomes like response fatigue. One of the challenges faced by renewable energy sources is their unpredictable generation patterns. As a result, the incorporation of long-term storage systems such as HSS is imperative for integration of RES into power grids. By introducing such storage system, it is reasonable to assume that storing energy during off-peak hours and utilizing it during peak hours can enhance the overall efficiency of RES. Besides, assessing the economic viability of storage systems necessitates simulation over several years, with a minimum time step of 1 hour. Using averaged production and electricity tariff values would not provide a sufficiently accurate evaluation. To this end, a software-based simulation model and implemented model had been developed for determining the economic efficiency of a wind turbine with and without a hydrogen storage system was discussed in [44].

One possible approach for storing renewable energy involves employing a carrier gas, such as hydrogen, which possesses the qualities of being storable, transportable, and easily accessible [45]. The utilization of HSS is gaining prominence as a cost-effective means of storing renewable energy, including its application in transportation and trade [46]. Particularly, in research studies [47]-[48]-[49], HSS established a foundation for the realization of a hydrogen-based economy, characterized by a 100% reliance on renewable energy sources. The rationale for transitioning to a hydrogen-based economy is becoming increasingly compelling across various facets of the energy sectors, encompassing power generation and transportations [50]. The hydrogen-based economy holds promise as a mean to achieve a transition to a low-carbon energy system [51]. Besides, hydrogen has emerged as a viable energy storage solution for SMGs due to its high energy density and versatility. Hydrogen can be produced through electrolysis using excess electricity during low-demand periods. The hydrogen gas can then be stored and used for power generation when demand is high. Recent advancements in electrolyzer technology have improved the efficiency of hydrogen production, making it an attractive option for grid-scale energy storage [52]. One notable challenge with hydrogen integration is the cost of infrastructure and the issue of energy losses during the conversion process. Researchers are actively working on improving the efficiency and reducing the environmental impact of hydrogen production and storage systems [53]. Integration of hydrogen with smart grids is also seen as a way to balance the intermittent nature of RESs, enhancing grid stability. Batteries have been a fundamental component of smart grid systems for many years [54]. Lithium-ion batteries, in particular, have become the leading technology for energy storage due to their high energy density and reliability. Battery systems are known for their fast response time and the ability to store energy at various scales, from small residential installations to large utility-scale systems [55]. The combination of hydrogen and batteries as a hybrid energy storage solution has gained attention as a way to exploit the strengths of both technologies while mitigating their weaknesses. In a smart grid context, the hybrid approach can provide reliable and flexible energy storage solutions, especially in regions with intermittent renewable energy sources [56]. The integration of hydrogen and batteries has the potential to provide a continuous and stable energy supply, regardless of weather conditions or fluctuations in energy demand. Studies suggest that such systems can significantly increase the overall efficiency of the grid while reducing greenhouse gas emissions [57].

2.4 Optimization technique

Several models have been proposed for solving the environmental, economic and technical indices of HES as a single and multi-objective optimization problems [58]-[59]-[60]. In particular, the SMG problem consists of objective functions like operational cost, CO2 emissions and peak to average ratio (PAR) and this optimization problem was solved using max-min fuzzy technique [61]. By utilizing the DRP, results illustrate that the operational cost and CO2 emissions are minimized by 16% and 17%. This problem was solved as a bi and tri-objective optimization problem. Besides, an optimization model for operational cost reduction in integrated microgrid (MG) was solved using linear programming (LP) and heuristic approaches[62]. Results show that the LP approach saves up to approximately 3% to 5% excess energy of grid. In this study [63], optimization of energy flow in MG was performed using Quantum Teaching Learning-based optimization (QTLBO) technique. To address the DER uncertainty, four different scenarios were chosen based on seasonal variations. The results obtained indicated that the suggested model provides advantages for both market operators and consumers in terms of techno-economic benefits. The SMG's economical and technical problems are tackled using multi-objective genetic algorithm (MOGA). Authors used DSM strategy for scheduling and management of both the generation and demand side in terms of optimizing operational cost and emission as a bi-objective problem. Results revealed that the consumers active participation in the DSM strategy provide benefits to both the utility and customers [64]. The comparison between existing literature and proposed study is illustrated in Table 1. Besides, the limitations in the existing literature and the suggested solutions to fill those gaps are given as follows:

- Determining the most suitable unit sizing algorithm for HES is crucial. It should ensure the optimal utilization of power generated from RES without relying on the grid network.

Achieving the correct unit sizing for energy sources and storage is pivotal in determining the system's cost-effectiveness and reliability. Balancing the size of a hybrid power system to minimize/maximize multi-objective functions such as, operational cost, pollution emissions, energy gap, high penetration of renewable energy sources, while meeting targeted power supply availability remains a challenge[65] -[66]-[67]-[68].

- Managing a fully operational HES is a complex and expensive task. It demands effective supervision, coordination, management, and control of each subsystems using operators such as smart grid operator (SGO) for bi-directional communication between utility and consumers [69]. The control system plays a pivotal role in overseeing, coordinating, managing, and controlling the diverse tasks assigned to each subsystem to ensure the smooth operation and functionality of the entire system. Implementing proper supervision, management, and control across all subsystems and control systems can lead to increased operational efficiency [70]-[71]. Such a type of operator's involvement remains a challenge in context of energy management in distribution grids.
- Addressing DSM strategy and battery and hydrogen energy storage systems, hybrid model of battery and hydrogen storage system is essential. The unpredictability of load demand must be factored in when designing an appropriate energy storage system while using renewable energy sources. The integration of such storage systems is vital in HES, serving to provide continuous electricity supplementation during periods of renewable energy source unavailability. Implementation of such systems, specifically both batteries and hydrogen storage systems integration at the same time remain a challenge [72]-[73].

Table 1: Comparison of existing and proposed studies

References	Objectives	Techniques	Optimization problem	Limitations
[65]	Total cost	Constraint and Column Generation Algorithm	Single	Emissions and energy gap
[66]	Control performance	Genetic algorithm	Single	Ignored cost, emissions
[67]	Operational cost, stability	Asynchronous Advantage Actor-Critic (A3C) reinforcement learning algorithm	Multi (Bi)	Emissions
[68]	Capital and replacement cost	Mixed integer quadratic constrained programming (MIQCP)	Multi (Bi)	Emissions and energy balance ignored
[69]	Energy and demand gap	Improved harmony search and geographic information system (GIS) method	Single	Emissions
[70]	Levelized cost of energy	Particle swarm optimization (PSO) and ant colony optimization (ACO)	Single	Emissions
[71]	Cost	Artificial bee colony – Particle swarm optimization (ABC-PSO)	Single	Emissions ignored
[72]	Operational cost, economic analysis	PSO adaptive inertia weight (PSOAIW) and PSO with a constriction factor (PSOCF)	Multi (Bi)	Energy gap and Emissions
[73]	Cost of energy consumption	Mixed integer linear programing (MILP)	Single	Energy gap and emissions
This study	Operational cost, pollution emission, Energy gap, High penetration of RES	Hybrid-NSGA-II-MOPSO / SFLA	Multi (Tri)	-

2.5 Safety issues related to hydrogen and its justification

Using hydrogen as a storage system in distribution grids offers several advantages, such as long-term energy storage and the potential for clean energy production. However, it is important to consider safety issues associated with hydrogen, as it is a highly flammable and reactive gas. Here are some safety issues and justifications related to the use of hydrogen in the context of energy storage.[74], [75], [76]

2.5.1 Flammability

Safety Issue: Hydrogen is highly flammable and can form explosive mixtures with air in a wide concentration range (4-74% by volume).

Justification: Proper handling and storage procedures are essential to mitigate the risk of hydrogen leaks and potential ignition sources. Adequate ventilation, gas detection systems, and safety protocols must be in place to prevent and respond to fire hazards.

2.5.2 Leakage

Safety Issue: Hydrogen molecules are small and can permeate through materials, potentially leading to leakage.

Justification: Robust leak detection systems and well-designed storage and distribution infrastructure are crucial to minimize the risk of hydrogen leakage. Regular maintenance and inspections are essential to identify and address any potential leaks promptly.

2.5.3 Material Compatibility

Safety Issue: Hydrogen can cause embrittlement in certain materials, affecting the structural integrity of pipelines, storage tanks, and other components.

Justification: Selecting materials that are compatible with hydrogen and regularly inspecting and replacing components prone to embrittlement are necessary. Material standards and guidelines should be followed to ensure the integrity of the storage and distribution infrastructure.

2.5.4 Pressure

Safety Issue: Hydrogen is often stored and transported under high pressure, presenting risks of rupture or explosion.

Justification: Proper design, maintenance, and monitoring of pressure vessels are critical to prevent accidents related to overpressure. Safety relief devices and pressure regulation systems should be in place to control pressure within safe limits.

2.5.5 Hydrogen Combustion Characteristics

Safety Issue: Hydrogen flames are nearly invisible, making it challenging to detect a burning leak.

Justification: Advanced detection systems, such as flame detectors and gas sensors, are necessary to promptly identify and respond to hydrogen combustion incidents. Fire suppression systems and emergency response plans should be in place to mitigate the consequences of a fire.

2.5.6 Training and Awareness

Safety Issue: Lack of awareness and training among personnel working with hydrogen can lead to unsafe practices.

Justification: Comprehensive training programs for personnel involved in the handling, maintenance, and operation of hydrogen storage systems are crucial. Increasing awareness of hydrogen safety protocols and emergency response procedures is essential for preventing accidents and ensuring a quick and effective response in case of incidents.

2.5.7 Regulatory Compliance

Safety Issue: Failure to comply with relevant safety regulations and standards can increase the risk of accidents.

Justification: Adherence to local and international safety standards and regulations is necessary to ensure the safe design, installation, and operation of hydrogen storage and distribution systems. Regular audits and inspections can help verify compliance and identify areas for improvement.

While hydrogen holds promise as long-term energy storage solution, addressing safety issues is paramount to ensure the secure deployment and operation of hydrogen storage systems in distribution grids. Robust safety measures, advanced monitoring systems, and comprehensive training programs are essential components of a safe and reliable hydrogen infrastructure.

2.6 Summary

This chapter covers different literature review related renewables topics like the integration of RES, ESSs such as battery, and hydrogen with HESs and SMGs, followed by the review of different techniques used for energy management of distributed energy resources (DERs) in power systems.

CHAPTER 3 PROPOSED SYSTEM MODEL AND METHODOLOGY

3.1 Introduction

The system model of this thesis is divided into two components. The first model presents an accurate mathematical representation for energy management in SMG. This model aims to optimize two primary objectives: operational cost and CO2 emissions. Achieving this optimization is realized through the effective management of DER and the implementation of DRP, employing the SFLA.

In the second model, the focus shifts to addressing the tri-objective optimization problem within the distribution grid. This involves managing a high penetration of renewable energy sources and implementing a demand-side management strategy. The key objectives in this context include minimizing operational costs and pollution emissions, maximizing the integration of renewable energy resources, and reducing the energy gap between the initial demand and the optimal consumption value. To tackle this complex problem, a Hybrid-NSGA-II-MOPSO technique is employed, considering various constraints. Schematic diagrams illustrating the first and second models are presented in Figure 1 and Figure 2, respectively.

3.2 First model

This model presents an accurate mathematical representation for energy management in SMG to optimize two objectives, operational cost and CO2 emission by managing DER and employing DRP. The objectives formulation of this study is given as follows:

3.2.1 Objective functions formulation

3.2.1.1 Operating cost function

Optimizing the operational cost of SMG:

$$\min f1(Z) = \sum_{h=1}^{H} \left\{ \begin{array}{c} \sum_{i=1}^{G} S_{Gi}(h)W_{Gi}(h)EP_{Gi}(h) + SC_{Gi} \left| \begin{array}{c} S_i(h) - \\ S_i(h+1) \end{array} \right| - \cdots \\ \sum_{j=1}^{S} S_{Sj}(h)W_{Sj}(h)EP_{Sj}(h) + SC_{Sj} \left| \begin{array}{c} S_j(h) - \\ S_i(h-1) \end{array} \right| \cdots \\ -W_{grid}(h)EP_{grid}(h) \end{array} \right\} \qquad Eq(1)$$

Where h represents the time slot of the operation, G and S represent the units of generation and storage, $S_i(h)$ indicates the unit i at time slot h, $W_{Gi}(h)$ and $W_{Sj}(h)$ in (1) represent total output power for the unit i and storage j, $EP_{Gi}(h)$ and $EP_{Sj}(h)$ are the price of energy offered, SC_{Gi} and SC_{Gj} indicate the start and shut down cost, finally, $W_{grid}(h)$ and $EP_{grid}(h)$ represent the exchanging power with the market at time h.

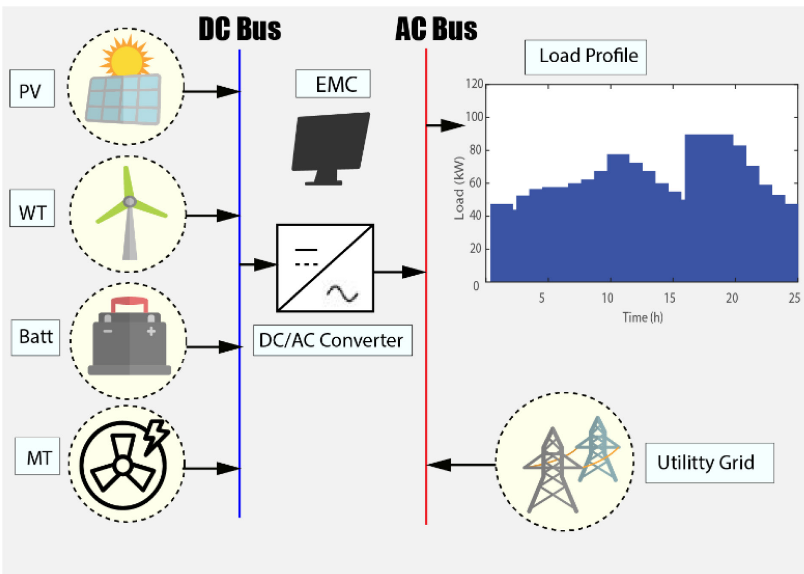

Figure 1: First Model: SMG schematic diagram

3.2.1.2 Pollution emission function

$$minf2(Z) = \sum_{h=1}^{H} Em^h$$

$$= \sum_{h=1}^{H} \left\{ \sum_{i=1}^{G} S_{Gi}(h) W_{Gi}(h) Em_{Gi}(h) + \sum_{j=1}^{S} S_{Sj}(h) W_{Sj}(h) Em_{Sj}(h) + W_{grid}(h) Em_{grid}(h) \right\} \qquad Eq(2)$$

Where $Em_{Gi}(h)$, $Em_{Sj}(h)$, $Em_{grid}(h)$ represents the emissions of generation, storage units and market.

3.2.2 Smart grid structure

The proposed SMG consist of DES (wind, solar, battery, micro turbine and utility), energy management controller (EMC), and consumers.

3.3 Second model

In this work, tri-objective optimization model of distribution grid is solved with high penetration of renewable energy sources and demand side management strategy and is considered as second model. The objective functions are operational cost and pollution emission, maximization of high penetration of renewable energy resources and minimization of energy gap between initial demand and optimal value of consumption. This model is optimized using hybrid MOPSO-NSGA-II technique considering multiple constraints. The proposed system schematic architecture is shown in Figure 2. The energy flow diagram of this system model is shown in Figure 3.

3.3.1 Smart grid overview and working mechanism

The proposed system consists of the following components: distributed energy resources (DERs), consumers, electric vehicle (EV) charging station, and the smart grid operator (SGO). Within the DER category, in this work, the energy resources, such as diesel generators (DGs), wind turbines (WTs), photovoltaic (PV) systems, batteries, and a Hydrogen storage system are used.. Consumers are further categorized into sheddable loads, non-sheddable loads and shiftable loads. Furthermore, technical constraints applicable to resources and the overall system are introduced. The resultant model is solved utilizing a Hybrid-MOPSO-NSGA-II approach, yielding a range of potential solutions (non-dominated solutions). Finally, decision-making mechanism is used to select the optimal solution from the set of solutions.

In times, when solar energy production diminishes, such as during nighttime hours, energy drawn from the battery storage system, hydrogen storage system, and the utility grid seamlessly takes over, ensuring uninterrupted electricity supply to households. Similarly, when wind energy is not available, the combined support of solar energy, battery storage, hydrogen storage, and the grid provide a reliable and stable source of power. Moreover, surplus energy generated from these RES can be efficiently directed towards charging electric vehicles at dedicated stations, thus promoting a sustainable and eco-friendly transportation system. This dynamic energy management approach not only optimizes energy utilization but also contributes significantly to reducing reliance on non-RES.

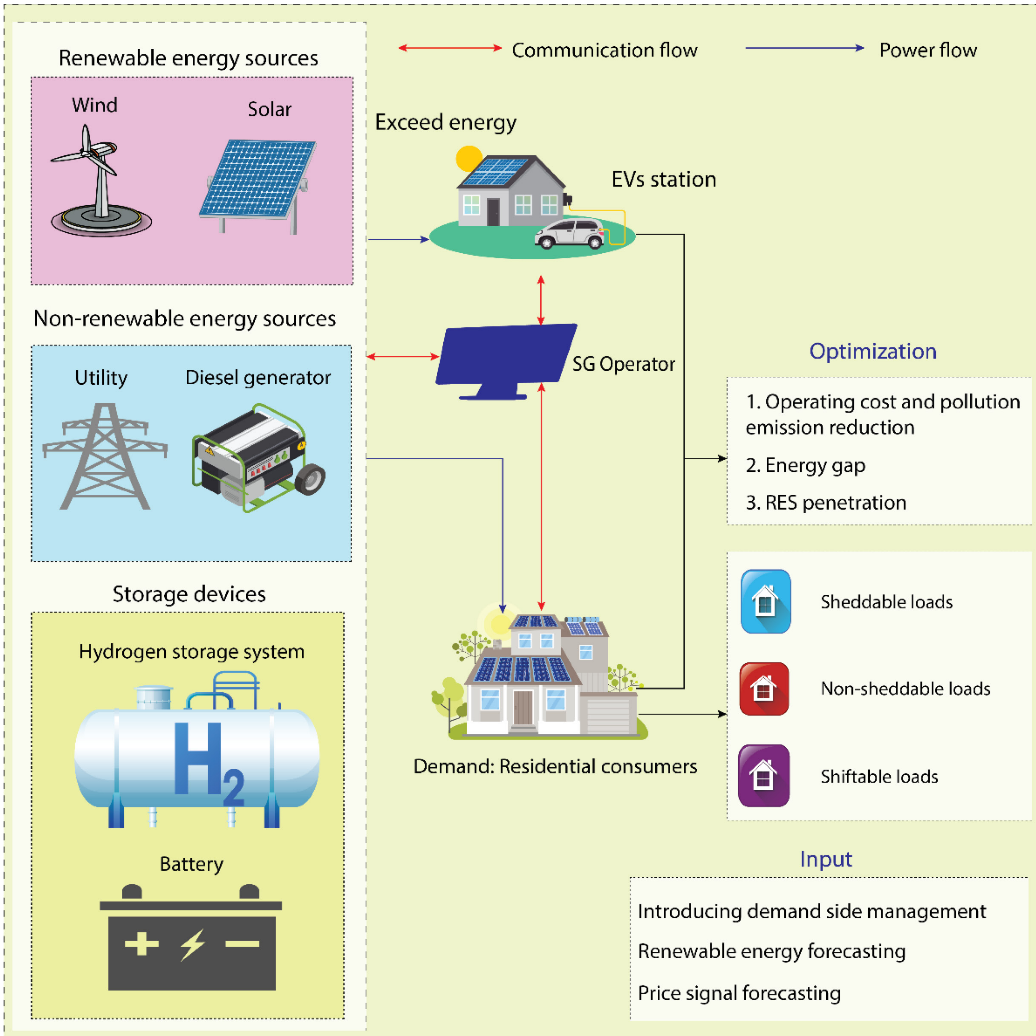

Figure 2: Second Model: SMG schematic diagram

3.3.2 Uncertain systems modeling

RES is uncertain and its prediction is necessary before integrating these sources with grids. PDF is used for modeling the uncertainty of wind and solar energy resources. The uncertain behavior of wind is modeled through PDF Weibull, PV is modeled through beta PDF and demand is modeled through Gaussian PDF, respectively.

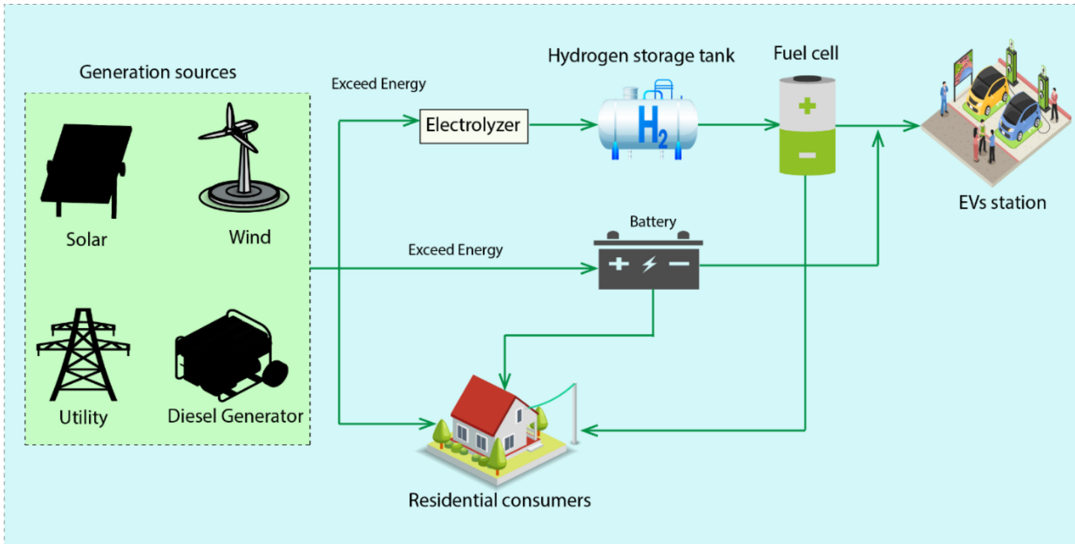

Figure 3: Energy flow diagram for second model

3.3.2.1 Wind system modeling

Wind energy source is uncertain in nature, PDF Weibull is used for modeling the intermittent behavior of wind speed [77]. The output power of wind turbine is shown in Equation 3.

$$W_{wt}(s) = \begin{cases} 0 & if\ S \leq S_{ci} \\ W_R \times \left(\dfrac{s - S_{ci}}{S_r - S_{ci}}\right) & if\ S_{ci} \leq s < S_r \\ W_R & if\ S_r \leq s < S_{CO} \\ 0 & if\ S_{co} \leq s \end{cases} \qquad Eq(3)$$

Where S_{ci}, S_{CO}, S_r, and s are the cut-in speed, the minimum wind speed at which the turbine starts to generate power, the cut-out speed, the maximum wind speed at which the turbine is designed to operate, the rated wind speed, and the speed at which the turbine generates its rated power.

3.3.2.2 Solar system modeling

In this study, PDF beta is used for modeling the intermittent behavior of solar irradiance [77]. The output power of solar energy is modeled in Equation 4 as follows:

$$W_{PV}(si) = \eta_{PV} \times A \times si \qquad Eq(4)$$

Where W_{PV} is PV power, si indicates solar irradiance, η_{PV} is PV efficiency, A area covered by PV.

3.3.2.3 Hydrogen storage system modeling

The Hydrogen Storage System (HSS) comprises several key components: An electrolyzer (EL), hydrogen storage tanks (HTS) and fuel cell (FC). This integrated system operates in a manner where, during the charging phase, the electrolyzer (EL) produces hydrogen molecules, which are subsequently stored in the hydrogen storage tanks (HTS). Conversely, during discharge, the stored hydrogen molecules in the HTS are converted by the fuel cell (FC) into electrical power. To describe this system mathematically, a comprehensive model is presented in Equation 5 and Equation 6. Specifically, the generation of hydrogen molecules by the EL is formulated in Equation 6 and the consumption of these hydrogen molecules to generate electrical power via the FC is determined using equation 5 [78].

$$G_H{}^{FC}(sc, t, hyd) = \frac{W_{FC}(sc, t, hyd)}{\eta_{FC}\ .H_L V_H} \quad \forall\ sc, t, hyd \qquad Eq(5)$$

$$G_H{}^{EL}(sc, t, hyd) = \frac{\eta_{EL}\ .W_{EL}(sc, t, hyd)}{H_L V_H} \quad \forall\ sc, t, hyd \qquad Eq(6)$$

Where sc, t, hyd represents the probability of scenario, time period, and hydrogen indices. $G_H{}^{FC}$ and $G_H{}^{EL}$ indicate the hydrogen generation and consumption in time slot t, $W_{FC}$and W_{EL}, represent the power of FC and EL, η_{FC} and η_{EL}, show the efficiency of FC and EL, and $H_L V_H$ represents lowering the hydrogen heating value, respectively.

The model also accounts for the limitations inherent in both the generation and consumption of hydrogen molecules by the EL and the fuel cell FC. These limitations are addressed through equations 7 and 8, respectively, ensuring a more accurate representation of the system's behavior.

$$G_H{}^{FC,min} \leq G_H{}^{FC}(sc, t, hyd) \leq G_H{}^{FC,max} \quad \forall\ sc, t, hyd \qquad Eq(7)$$

$$G_H{}^{EL,min} \leq G_H{}^{EL}(sc,t,hyd) \leq G_H{}^{EL,max} \quad \forall\, sc,t,hyd \qquad Eq(8)$$

3.3.2.4 Demand modeling

In this study, the uncertain nature of demand is modeled using Gaussian PDF. In order to predict the intermittent parameters such as wind speed, solar irradiance and demand, several scenarios are generated using Monte Carlo simulation. The occurrence probability of each scenario is modeled in Equation 9 as follows:

$$\rho_s = \rho_s{}^{WT} \times \rho_s{}^{PV} \times \rho_s{}^{L} \qquad Eq(9)$$

Where ρ_s, $\rho_s{}^{WT}$, $\rho_s{}^{PV}$, $\rho_s{}^{L}$ shows the probability of scenario s, probability of the WT in scenario s, and probability of the demand in scenario s, respectively.

3.3.3 Objective functions

3.3.3.1 First objective function (f1)

Operational cost and pollution emission of the proposed SG is considered as first objective function consisting of diesel generator, operational cost, degradation cost of battery, and operational cost of electrolyzer and fuel cell in hydrogen storage system, further, pollution emission of utility grid (UG) and DGs and modeled as equation 10.

$$\begin{aligned}\min f_1 = \sum_{sc=1}^{SC} \rho_{sc} \sum_{t=1}^{T} \Bigg[&\sum_{dg=1}^{DG} O_{cost}(sc,t,dg) \\ &+ \sum_{batt=1}^{BATT} O_{cost}{}^{charge}(sc,t,batt) + \sum_{batt=1}^{BATT} O_{cost}{}^{discharge}(sc,t,batt) \\ &+ \sum_{Hyd=1}^{HYD} O_{cost\,Hyd}(sc,t,hyd) + \sum_{d=1}^{D} Em_{DG}(t,d) + Em_{UG}(t) \Bigg] \qquad Eq(10)\end{aligned}$$

Where the first part in Equation 10 indicates the operational cost of DGs, the second and third parts represent the operational cost of charging and discharging of battery feeding the EVs station and demand, the fourth part shows the operational cost of hydrogen storage system which consist of electrolyzer and fuel cell costs, and the fifth part indicates the pollution emission associated with DGs and UG. In Equation 10, ρ_{sc}, represents the probability of each scenario in the system model which on weather patterns, demand patterns and reliability of the grid, and O_{cost}, ${O_{cost}}^{charge}$, ${O_{cost}}^{discharge}$, Em_{DG}, Em_{UG} indicate the operational cost, and cost of charging and discharging, emission of DGs and UG, respectively.

3.3.3.2 Second objective function (f2)

Load consumption management is one of the most important parameters of power systems, specifically, when using renewable energy resources. In this work, the mathematical model of load consumption management is proposed and modelled in equation 11, 12 and 13. The energy gap between the initial demand and its optimal value is minimized in Equation 11, the system initial demand is modeled in Equation 12 and the power consumption optimal value is modeled in Equation 13 as follows:

$$\min f2 = \sum_{sc=1}^{SC} \rho_{sc} \sum_{t=1}^{T} \left| W_{original}(sc,t) - W_{optiml} \right| \qquad Eq(11)$$

Where $W_{original}(sc,t)$, W_{optiml}, and ρ_{sc} in Equation 11 indicate the original power, optimal value of power and probability of scenarios, respectively.

$$\begin{aligned} W_{original}(sc,t) \\ &= D_T(sc,t) + W_{EL}(sc,t,hyd) + W_{wind}(sc,t) + W_{pv}(sc,t) + W_{batt}(sc,t,batt) \\ &- D_{unmet}(sc,t) \;\; \forall \;\; sc,t,hyd,batt \qquad Eq(12) \end{aligned}$$

Where $D_T(sc,t)$, $W_{EL}(sc,t,hyd)$, $W_{wind}(sc,t)$, $W_{pv}(sc,t)$, $W_{batt}(sc,t,batt)$, and $D_{unmet}(sc,t)$ in Equation 12 represent, total demand, power of electrolyzer, power of wind, power generated by PV, power of battery and unmet demand in time slot t, respectively.

$$W_{optiml} = \frac{\sum_{t \in T} W_{original}(sc,t)}{T} \quad \forall\, sc, t \qquad Eq(13)$$

3.3.3.3 Third objective function (f3)

The substantial integration of renewable energy resources to meet demand significantly affects the operational costs of the system. Consequently, this factor is considered as the third objective function of the proposed system model. Utilizing renewable energy resources to meet demand clearly results in a cost-effective system response. This function is characterized by the total energy produced by the wind turbine (WT) and photovoltaic (PV) systems divided by the overall energy demand of the system during the operational time and as modeled in Equation 14 as follows:

$$\max f3 = \sum_{sc=1}^{SC} \rho_{sc} \sum_{t=1}^{T} \left[\frac{\sum_{wt=1}^{WT} W_{wt}(sc,t,wt) + \sum_{pv=1}^{PV} W_{pv}(sc,t,pv)}{D_T(sc,t)} \right] \qquad Eq(14)$$

Where $W_{wt}(sc,t,wt)$, $W_{pv}(sc,t,pv)$, $D_T(sc,t)$, and ρ_{sc} indicate the power generated by wind, PV, total demand required and probability of scenarios in time slot t, respectively.

3.4 Demand side management strategy and classification of loads

The demand side management strategy in this study is based on load shifting (LS). The responsive consumers participate in this strategy according to the status of the grid, which results in benefiting both the consumers and utility during the operational time.

3.4.1 Demand shifting modeling

The Demand Shifting (DS) strategy serves the purpose of redistributing energy consumption from peak hours to off-peak hours, ultimately smoothing out the demand profile. This strategy aims to alleviate the strain on the energy grid during peak periods and promote more efficient resource utilization. the model for the DS strategy is presented through equations (15) and (16). Equation 15 outlines the calculation of the demand for the Residential Demand Shifting RDS system during each time step. This calculation considers the shifted demand from time t to time t1 within a specific scenario (Sc). Essentially, it determines how the energy demand is shifted from its original peak time to a more favorable off-peak time.

$$D_{LS}(sc,t) = \sum_{t1}\sum_{ls=1}^{LS} D_{LS}(sc,t1,t) - \sum_{ls=1}^{LS} D_{LS}(sc,t1,t) \qquad \forall\, sc, ls, t \qquad Eq(15)$$

Where sc, ls, t represents the probability of scenario, load shifting in time slot t to t1, and time period t, besides, D_{LS} shows the demand.In order to manage and control the extent of participation of the RDS system in this strategy, equation 16 is introduced. This equation sets limits on the degree to which the RDS system can actively engage in the demand-shifting process. It establishes boundaries to ensure that the strategy operates within predefined constraints, aligning with overall system goals and requirements.

$$0 \le \sum_{t1}\sum_{ls=1}^{LS} D_{LS}(sc,t1,t) \le r \times \sum_{ls=1}^{LS} D_{LS}(sc,t) \qquad \forall\, sc, ls, t \qquad Eq(16)$$

In Equation 16, sc, ls, t represents the probability of scenario, load shifting in time slot t to t1, and time period t, besides, D_{LS} shows the demand.

3.4.2 Classification of loads

In this study, the loads are divided into three categories, sheddable, non-sheddable and shiftable loads and are explained as follows [79]:

3.4.2.1 Sheddable loads

Sheddable loads refer to those loads that, during various times of the day, can be switched off by consumers or electricity distribution companies without causing any disruptions to the daily lives, well-being, or security of individuals in their homes[78]. This approach offers benefits to both customers and power companies. This work exclusively focuses on sheddable loads in residential settings. We have also categorized sheddable loads specifically for the residential houses. In this context, we have gathered data on the average power consumption associated with sheddable loads in household appliances.

3.4.2.2 Non-Sheddable loads

Non-sheddable loads encompass those appliances and devices that consumers cannot switch off at any specific time throughout the day (24 hours). These include items such as refrigerators, coolers, aquariums, cell phones, TVs, toasters, blenders, electric samovars, coffee makers, microwaves, electric mixers, and extractor hoods. It is important to note that electricity distribution companies do not have the authority to interrupt the power supply to these loads. Instead, they must ensure a consistent and uninterrupted energy supply with the desired quality for consumers.

3.4.2.3 Shiftable loads

Shiftable loads refer to those loads that must be consumed over the course of a 24-hour day, but do not have a specific time allocated for their use. These loads play a crucial role in optimizing customer pricing strategies. The total load of these appliances is communicated to the electricity distribution company, which is responsible for distributing them evenly throughout the day.

3.5 Constraints modeling

The objective functions which are defined as minimization of operational cost and pollution emission in generation side, minimization of energy gap between initial demand and optimal value of consumption in demand side and maximization of the renewable energy sources penetration are optimized regarding several constraints such as technical constraints of diesel generator and power balance constraints and are modeled by Equations 17 to 22 in the following subsections.

3.5.1 Power balance constraints

The system's power balance constraint, which is applicable to every time step and scenario, is mathematically represented by Equation 17 [80]. This equation effectively ensures that the total power generation from various sources within the system, including DGs, PV systems, WTs and the power generated by FC, is equal to the sum of the overall energy demand of the system. This energy demand comprises the power required for charging EVs station, the energy consumed by EL minus the unmet demand.

$$\begin{aligned}\sum_{d=1}^{D} W_d(sc,t) + \sum_{pv=1}^{PV} W_{pv}(sc,t) \\ &+ \sum_{wt=1}^{WT} W_{wt}(sc,t) \\ &+ \sum_{hyd=1}^{HYD} W_{fc}(sc,t) \\ &= D_{eq}(sc,t) \\ &+ \sum_{lg}^{LG} {W_{EVs}}^{charge}(sc,t) \\ &+ \sum_{hyd=1}^{HYD} W_{EL}(sc,t) - D_{unmet}(sc,t)\ \ \forall\ \ sc,t \qquad Eq(17)\end{aligned}$$

Where $W_{pv}, W_{wt}, W_{fc}, W_{EVs}, W_{EL}, D_d, D_{unmet}$ indicates the power of PV, WT, FC, EVs, EL, total demand and unmet demand, respectively. Besides, sc, t represents the probability of scenario and total time period. Equation 17 serves as a critical constraint in the system's operation. It guarantees that the generation and consumption of power are in equilibrium, ensuring that all energy demands are met while accounting for the contributions of different power sources and the fluctuating needs of the system over various time steps and under various scenarios. This balance is fundamental for the reliable and efficient functioning of the system, promoting sustainability by integrating renewable energy sources like PV systems, WT, and minimizing the unmet demand, thereby enhancing overall system stability and resilience.

3.5.2 Technical DGs constraints

The technical limitations imposed on DGs are represented by Equations 18 through 22. Both the minimum and maximum operational boundaries of DGs are captured by Equation 18. Furthermore, the minimum uptime and downtime requirements for DGs are mathematically described by Equations 19 and 20. Finally, the constraints on the rate of ramp-up and ramp-down for DGs are depicted using Equations 21 and 22 respectively.

$$W_d{}^{min} \leq W_d(sc,t) \leq W_d{}^{max} \qquad \forall \quad sc,t,d \qquad Eq(18)$$

$$\vartheta^{0n}(sc,t,d) + \sum_{\tau=t+1}^{\min(T,t-1+MU)} \vartheta^{0ff}(sc,\tau,d) \leq 1 \quad \forall \ sc,t,d \qquad Eq(19)$$

$$\vartheta^{0ff}(sc,t,d) + \sum_{\tau=t+1}^{\min(T,t-1+MD)} \vartheta^{0n}(sc,\tau,d) \leq 1 \quad \forall \ sc,t,d \qquad Eq(20)$$

$$W_d(sc,t,d) - W_d(sc,t-1,d) \leq RU \quad \forall \quad sc,t,d \qquad Eq(21)$$

$$W_d(sc,t-1,d) - W_d(sc,t,d) \leq RD \quad \forall \quad sc,t,d \qquad Eq(22)$$

Where RU, RD, MU, MD, ϑ^{0ff}, and ϑ^{0n} in above Equations represent, ramp-up, ramp-down time of DGs, minimum-up and minimum-down time of DGs and binary variables of DGs. Its operation takes place using on=1 and off=0. Besides, $W_d{}^{min}$, $W_d{}^{max}$, W_d, represents the minimum, maximum and total demand [81].

3.5.3 Battery constraints

To enhance the balance between energy generation and demand, a commonly employed approach is to incorporate an energy storage system (ESS), such as a battery, HSS, etc. into the grid. The State of Charge (SOC) signifies the dynamic balance between the charging and discharging of energy within the battery. In this framework, battery efficiently storing electrical energy during surplus generation periods and discharging it during peak demand hours. This approach not only optimizes the grid's performance but also enhances energy utilization, and integration of RES with proposed grid. The SOC of the battery at time 't' is mathematically described by the following equation[77]:

$$SOC(t)_{batt} = SOC(t-1)_{batt} + W_{\frac{charge}{discharge}}(t) \qquad Eq(23)$$

$$0 \le W_{\frac{charge}{discharge}}(t) \le W_{Cmax}(t) \qquad Eq(24)$$

Where $SOC(t)_{batt}$ and $SOC(t-1)_{batt}$ in equation indicates the amount of charging in current and previous hours, $W_{\frac{charge}{discharge}}(t)$ represents the amount of charging and discharging of battery at peak hours, and $W_{Cmax}(t)$ shows maximum battery capacity.

While using battery storage system, the energy balance is a key component. To ensure energy balance, the power flow into the battery must be equal to the power flow out as shown in Equations 25 and 26 as follows:

$$W_{in}(t) = W_{out}(t) \qquad Eq(25)$$

$$W_{in}(t) - W_{out}(t) = 0 \qquad Eq(26)$$

Where $W_{in}(t)$, $W_{out}(t)$ represents the power into the battery and power out from the battery, respectively.

3.6 Summary

This chapter provides detailed mathematical representation and explanation of proposed system model. The proposed techniques for both models will be discussed in detail in next chapter.

CHAPTER 4 OPTIMIZATION TECHNIQUES

4.1 Introduction

This chapter of the thesis provides a detailed discussion of the optimization techniques, which consist of existing and proposed techniques. The existing techniques includes particle swarm optimization (PSO), multi-objective particle swarm optimization (MOPSO), genetic algorithm (GA), non-dominated sorting genetic algorithm (NSGA), and non-dominated sorting genetic algorithm-II (NSGA-II). Besides the proposed techniques are shuffled frog leaping algorithm (SFLA) and hybrid of Non-Dominated Sorting Genetic Algorithm II and Multi-Objective Particle Swarm Optimization (hybrid-NSGA-II-MOPSO).The shuffled frog leaping algorithm (SFLA) is used to manage DER and implement demand response programs (DSP). The aim is to optimize the economic, technical, and environmental aspects of a smart micro-grid (SMG). Furthermore, this thesis adopts a hybrid approach that combines well-established techniques, namely the Non-Dominated Sorting Genetic Algorithm II and Multi-Objective Particle Swarm Optimization (Hybrid-NSGA-II-MOPSO), aims to optimize operational costs, reduce pollution, and address the challenge of achieving a high penetration of RES while minimizing the energy gap between initial demand and consumption. The detailed discussion of SFLA and hybrid-MOPSO-NSGA-II algorithms is as follows:

4.2 Shuffled frog leaping algorithm

SFLA draws inspiration from a collective of frogs seeking sustenance through two primary actions: shuffling and leaping. The specificities of these behaviors involve the frogs jumping to locate a position with a greater abundance of food than their current one, followed by the shuffling of information. This technique considers the frog's population and each represents an outcome to the associated problem. There is one important terminology named "memeplex" which indicates the groups consists of population of frogs. Each group in the memeplex searches locally and then shuffles information [82]. The position of frog's changes using Equations 27 and 28. Where p_{worst} and p_{best} represent the positions of worst and best frog in the current memeplex, p'_{worst} indicate the new position of the worst frog, C shows the permissible degree of positional change of frog, and k is a random value between 0 and 1.

$$p'_{worst} = p_{worst} + C \qquad Eq(27)$$

$$C = k(p_{best} - p_{worst}) \qquad Eq(28)$$

Algorithm 1: Pseudo code for SFLA

Input: Number of iterations, population size, fitness values, objective functions.

Output: Optimization of objective functions

Initialization: Initialize variables.

for $h = 1$ *to* h_{max} **do**

    Calculating each frog fitness value

    for each memeplex **do**

        for $k = 1$ *to* k_{max} **do**

            Determining the worst and best frog in the given memeplex (f_{best}, f_{worst}).

            Calculating the position of the candidate (p') by using Equation (3) and (4) for finding the f_{worst} in the given memeplex.

                if p' is better than the worst frog's position.

                Taking p' is a new position.

                else

                calculating the position of the candidate in the given memeplex.

                    if p' is better than the worst frog's position

                    Taking p' is a new position.

                    else

                    Moving the f_{worst} to random position.

                    end if

                end if

            end for

end for

Shuffle frogs

end for

Frog with best position is an optimal solution.

In this work, the distributed energy sources management at the generation side and employing DRP at the demand side is performed for optimizing the operational cost and CO2 emission of SMG using SFLA. The proposed objective functions are in conflict and not proportionate with each other, thus this algorithm yields number of solutions instead of single optimal solution which leads to optimize the objective functions simultaneously [83], [84], [85]. In this work, the operational cost and CO2 emission are considered as a multi-objective optimization problem by managing the DER and employing DRP. Both the objective functions are minimization problem and subjected to constraints, the formulation of this problem is given as follows:

$$\min F(Z) = [f_1(Z), f_2(Z)]^T$$

Subject to:

$$k_i(Z) < 0 \qquad i = 1.2 \dots \dots M_{ueq}$$

$$l_i(Z) = 0 \qquad i = 1.2 \dots \dots M_{eq} \qquad Eq(29)$$

Where F represents a vector encompassing the objective functions, while Z is a vector containing the optimization variables. The inequality and equality constraints of this problem are represented by $k_i(Z)$ and $l_i(Z)$, while M indicates the number of objective functions which is considered as two objective functions in this work. Algorithm 1 outlines the implementation procedure of SFLA and the concept diagram of the proposed SFLA is shown in Figure 4.

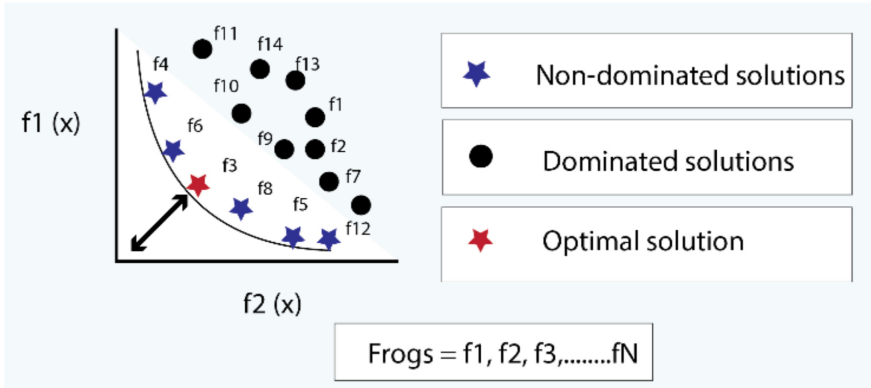

Figure 4: SFLA conceptual diagram

4.3 Particle swarm optimization (PSO)

Particle Swarm Optimization (PSO) is a nature-inspired optimization algorithm that is based on the social behavior of birds and fish. The underlying idea is to simulate the social behavior of a group of individuals, called particles, in order to find optimal solutions in a search space. In PSO, each particle represents a potential solution to the optimization problem. The position of a particle in the search space corresponds to a possible solution, and the quality of that solution is evaluated using an objective function. The particles move through the search space, adjusting their positions based on their own experience and the experience of their neighbors. The algorithm is initialized with a population of particles, each assigned a random position and velocity in the search space. As the algorithm iterates, particles adjust their positions and velocities according to the following principles. [80]

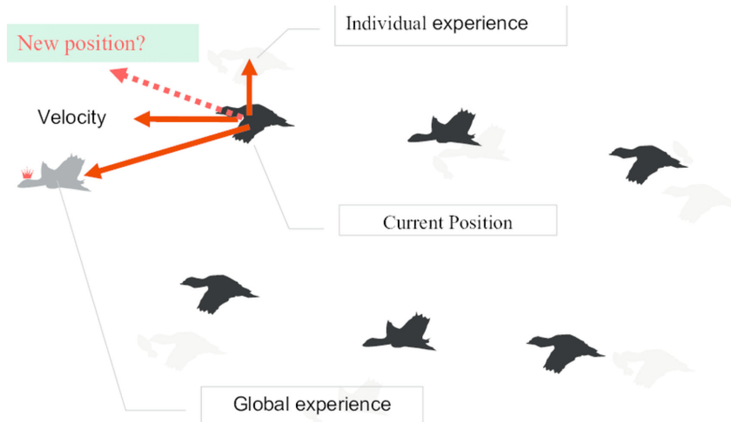

Figure 5:PSO algorithm concept (birds flock), position and velocity of particles

Individual Best ($\boldsymbol{P_{best}}$): Each particle remembers its own best-known position in the search space. If the current position is better than the remembered best, the particle updates its P_{best}.

Global Best ($\boldsymbol{G_{best}}$): Among all the P_{best} positions, the one with the best fitness value is considered the global best. Particles adjust their velocities to move towards the G_{best} position.

Velocity Update: The velocity of each particle is updated based on its current velocity, the difference between its current position and P_{best}, and the difference between its current position and G_{best}. This velocity update equation guides the particles towards promising regions in the search space.

The process continues iteratively, and the algorithm converges towards optimal or near-optimal solutions.

4.3.1 Mathematical Modeling of PSO

Let's represent the position of a particle in the search space as $X_i = (x_{i1}, x_{i1}, x_{i1}, \dots \dots \dots x_{in})$, where i is the particle index and n is the dimensionality of the search space. The velocity of the particle is represented as $V_i = (v_{i1}, v_{i1}, v_{i1}, \dots \dots \dots v_{in})$.

The velocity update equation for each dimension j is given by:

$$vij(t+1) = w \cdot vij(t) + c1 \cdot r1 \cdot (P_{Best}ij - xij(t)) + c2 \cdot r2 \cdot (G_{best}j - xij(t)) \qquad Eq(30)$$

Where w is the inertia weight, controlling the impact of the previous velocity on the current velocity, c1 and c2 are acceleration coefficients, r1 and r2 are random numbers between 0 and 1, $P_{Best}ij$ is the best-known position of particle i in dimension j and $G_{best}j$ is the best-known global position in dimension j respectively.

The position update equation for each dimension j is given by:

$$xij(t+1) = xij(t) + vij(t+1) \qquad Eq(30)$$

These equations are applied for each dimension of each particle in the swarm during each iteration of the algorithm. The process continues until a termination condition is met, such as reaching a maximum number of iterations or achieving a satisfactory solution.

This mathematical representation captures the core dynamics of the PSO algorithm, where particles explore the search space, remember their own best positions, and adjust their velocities to converge towards promising solutions. This algorithm can be used for optimizing single objectives in SMG and distribution grids, to optimize multi-objectives in SMG and smart distribution grids, multi-objective particle swarm optimization can be used. The details of MOPSO is given as follows:

4.4 Multi-Objective Particle Swarm Optimization (MOPSO)

MOPSO is a powerful optimization algorithm inspired by the social behavior of bird flocks. It is particularly effective in solving complex optimization problems involving multiple conflicting objectives. In the context of SMG and smart distribution grids, MOPSO plays a crucial role in optimizing various parameters to enhance the overall performance, efficiency, and reliability of the grid system. MOPSO builds upon the principles of PSO. In PSO, a population of potential solutions, called particles, moves through the solution space. Each particle adjusts its position based on its own experience and the experiences of its neighbors. This cooperative behavior allows the swarm to explore and exploit the search space efficiently. Traditional optimization methods often focus on a single objective, but real-world problems, especially in smart grids, involve multiple conflicting goals. MOPSO addresses this by simultaneously optimizing multiple objectives, creating a trade-off frontier known as the Pareto front. [86]Let's consider a smart microgrid and smart distribution grid scenario where various conflicting objectives need optimization. Suppose we have 'n' objectives to minimize (or maximize) denoted by:

$$f1(x), f2(x), \ldots, fn(x) \qquad Eq(32)$$

where x represents the solution vector. Each particle in the swarm is represented as a solution vector:

$$xi = [xi1, xi2, \ldots, xid] \qquad Eq(33)$$

where d is the dimension of the search space. Besides, the velocity (vij) and position (xij) of each particle are updated iteratively using equations 32 and 33.

4.4.1 Applications of MOPSO in context of SMG and smart distribution grids

In the context of smart grids, MOPSO can be applied to optimize various objectives, such as optimizing the operation and control of distributed energy resources to minimize the overall cost, ensuring a reliable power supply by optimizing the allocation and scheduling of resources, reducing carbon emissions and promoting the use of RESs, and distributing the load efficiently among different components of the grid. MOPSO enables the simultaneous consideration of these conflicting objectives, providing a set of solutions on the Pareto front that represents the trade-offs between different goals. [87]

MOPSO is a versatile optimization algorithm that proves beneficial in the complex and dynamic environment of SMGs and smart distribution grids. By addressing multiple conflicting objectives simultaneously, it aids in achieving a balance between economic, environmental, and reliability considerations, ultimately contributing to the efficient and sustainable operation of modern grid systems.

4.5 Genetic algorithm (GA)

GA is an optimization algorithm inspired by the process of natural selection. Developed to solve complex optimization and search problems, GA draw their inspiration from the principles of evolution, with the aim of finding high-quality solutions within large and often nonlinear solution spaces. This algorithm belongs to the broader category of evolutionary algorithms and have been widely applied in various fields, including engineering and artificial intelligence. GA is the representation of potential solutions as individuals in a population. Each individual, often represented as a string of parameters or a chromosome, corresponds to a candidate solution to the optimization problem at hand. The algorithm begins by initializing a population of these individuals randomly or through some heuristics. The quality of each solution is assessed using a user-defined objective function, which evaluates how well the solution satisfies the optimization criteria.

The evolutionary process unfolds through a series of iterative steps, mimicking the mechanisms of natural selection. During each iteration, known as a generation, individuals are selected from the current population to serve as parents for the creation of the next generation. The selection process is typically biased towards individuals with higher fitness, i.e., those that perform better according to the objective function. This reflects the survival-of-the-fittest principle, allowing the algorithm to focus on promising regions of the solution space. Reproduction occurs through genetic operators, primarily crossover and mutation. Crossover involves combining genetic material from two parent individuals to create offspring. This is analogous to genetic recombination in nature, where traits are inherited from both parents. Mutation introduces small random changes in an individual's genetic material, adding diversity to the population and preventing premature convergence to suboptimal solutions. [88]

The offspring constitute the new generation, and the cycle of selection, crossover, and mutation continues. Over successive generations, the population tends to evolve towards better solutions, guided by the iterative interplay of selection pressures and genetic operators. The termination criterion, such as a maximum number of generations or the achievement of a satisfactory solution, determines when the algorithm concludes its search. One of the strengths of genetic algorithms lies in their ability to explore large and complex solution spaces effectively.

Their stochastic nature allows for a broad exploration of the search space, making them particularly useful when dealing with nonlinear, multi-modal, or ill-defined optimization problems. Despite their versatility, the success of genetic algorithms depends on appropriately tuning parameters, selecting suitable genetic operators, and designing an effective fitness function tailored to the specific optimization task at hand.

4.5.1 Mathematical modeling of GA

Mathematical modeling of GAs involves expressing the key components and processes of the algorithm in a formal mathematical framework. Let's denote the following terms to facilitate the mathematical representation.

$\boldsymbol{P_i}$: Population at generation i, where each individual is represented as x_i.

$\boldsymbol{f(x_i)}$: Objective function evaluating the fitness of an individual x_i.

$\boldsymbol{P_{i^*}}$: The selected subset of individuals from P_i based on their fitness.

$\boldsymbol{C_i}$: Crossover operator applied to P_{i^*} to produce offspring.

$\boldsymbol{M_i}$: Mutation operator applied to the offspring.

$\boldsymbol{P_{i+1}}$: New population formed by combining P_{i^*} and M_i.

The mathematical modeling of the GA can be expressed through the following equations:

1. **Initialization**

$$P_0 = x_1, x_2, x_3, \dots \dots \dots \dots ., x_n \qquad Eq(34)$$

2. **Selection**

The selection operator chooses individuals from P_i based on their fitness. Common methods include roulette wheel selection, tournament selection, or rank-based selection.

$$P_{i^*} = \text{Selection Operator } (P_i, f) \qquad Eq(35)$$

3. **Crossover**

$$C_i = \text{Crossover operator } (P_{i^*}) \qquad Eq(36)$$

The crossover operator combines pairs of individuals from P_{i^*} to create offspring. This can be expressed as:

$$\text{Crossover operator } (x_i, x_j) = \begin{cases} (x'_i, x'_j) & \text{with probability } \rho_c \\ (x_i, x_j) & \text{Otherwise} \end{cases} \qquad Eq(37)$$

4. **Mutation**

$$M_i = Mutation\ operator\ (C_i) \qquad Eq(38)$$

The mutation operator introduces small random changes to the offspring. It can be defined as:

$$Mutation\ operator\ (x'_i) = \begin{cases} (x''_i) & \text{with probability } \rho_c \\ (x'_i) & \text{Otherwise} \end{cases} \qquad Eq(39)$$

Where x''_i is the mutated version of x'_i, and ρ_c is the probability of mutation.

5. **New population**

The new population P_{i+1} is formed by combining the selected individuals P_{i^*} and the mutated offspring M_i.

6. **Termination**

The algorithm terminates after a predefined number of generations or when a satisfactory solution is found. This mathematical model provides a high-level overview of the GA process, incorporating selection, crossover, mutation, and the formation of new populations. The specific details of the selection, crossover, and mutation operators will depend on the problem at hand and the design choices made during the algorithm's implementation.

4.6 Non-dominated sorting genetic algorithm (NSGA)

Non-dominated Sorting Genetic Algorithm (NSGA) is a multi-objective optimization algorithm that leverages genetic algorithms to efficiently search for solutions in a complex, multi-dimensional objective space. NSGA addresses optimization problems with multiple conflicting objectives, where finding a single optimal solution may not be feasible due to the trade-offs among different objectives. The fundamental concept of NSGA lies in the evolution of a population of potential solutions, commonly referred to as individuals or chromosomes. These individuals are encoded representations of candidate solutions, and the algorithm aims to explore and refine this population to identify a set of solutions that are non-dominated, meaning no other solution in the population is better in all objectives simultaneously.

One key element of NSGA is the sorting of individuals into different fronts based on their non-dominated status. The sorting process involves ranking individuals according to their dominance relationships, creating a hierarchy of fronts where individuals in the first front are non-dominated by any other, those in the second front are dominated only by individuals in the first front, and so on. This non-dominated sorting ensures that the algorithm maintains a diverse set of solutions that cover the Pareto front, representing the trade-offs between conflicting objectives. To drive the evolution of the population, NSGA employs genetic operators such as crossover and mutation. Crossover combines the genetic information of two parent solutions to generate new offspring, while mutation introduces small changes to the genetic code of an individual. These operators allow the algorithm to explore the solution space efficiently, adapting and refining the population over successive generations.

NSGA further enhances its ability to explore diverse solutions by introducing a concept known as crowding distance. Crowding distance measures the density of solutions in the objective space, promoting the selection of solutions that contribute to the diversity of the Pareto front. This diversity is crucial for capturing a representative set of trade-off solutions, providing decision-makers with a range of choices based on their preferences for different objectives.

4.7 Non-dominated sorting genetic algorithm (NSGA-II)

NSGA-II is a multi-objective optimization algorithm that has found applications in various fields, including smart microgrids and smart distribution grids. It is particularly valuable in scenarios where multiple conflicting objectives need to be optimized simultaneously. In the context of smart grids, NSGA-II can be employed to address challenges related to energy management, system reliability, and cost-effectiveness. Smart microgrids and distribution grids involve complex systems with diverse objectives, such as minimizing energy costs, maximizing renewable energy integration, and enhancing system resilience. NSGA-II excels in handling such multi-objective optimization problems by efficiently exploring the trade-offs between conflicting objectives. [89]

NSGA-II is capable of handling multiple conflicting objectives. In smart grids, these objectives could include minimizing power losses, maximizing the use of renewable energy sources, and ensuring grid stability [90]. NSGA-II allows the formulation of an objective function that reflects these diverse goals. NSGA-II employs Pareto dominance to compare and rank solutions. A solution is considered better than another if it performs at least as well in all objectives and outperforms in at least one. This enables the algorithm to generate a set of solutions representing the trade-offs between conflicting objectives, known as the Pareto front. Smart microgrids and distribution grids often require diverse solutions that cater to different operational scenarios. NSGA-II incorporates mechanisms to maintain diversity in the population, preventing the algorithm from converging prematurely to a specific solution. This is crucial for adapting to dynamic changes in the grid environment.

NSGA-II is known for its ability to adapt to dynamic environments. In the context of smart grids, where energy demand and availability of renewable resources can vary, NSGA-II can continuously evolve solutions to optimize system performance under changing conditions. Smart grids may have constraints related to system reliability, equipment limitations, and regulatory requirements. NSGA-II can be extended to handle these constraints effectively, ensuring that the generated solutions are not only Pareto-optimal but also feasible within the given constraints. NSGA-II can be integrated into decision support systems for smart grids, providing valuable insights to grid operators and planners. The Pareto front generated by NSGA-II serves as a decision-making tool, offering a range of optimal solutions for stakeholders to choose from based on their preferences and priorities. [91]

4.8 Hybrid-MOPSO-NSGA-II algorithm

Particle swarm optimization (PSO) algorithm [80]is highly efficient and well-known technique for solving single-objective optimization problems which was extended to multi-objective particle swarm optimization (MOPSO) for solving multi-objective problems [92]. The MOPSO extended version include Pareto dominance into the conventional PSO technique which uses leader that guides other particles in the search space, stores record of the trad-off/non-dominated solutions in external repository.

By exploring the features of the two algorithms discussed earlier, in this study, we proposed a hybrid MOPSO-NSGA-II algorithm for solving non-linear and complex problem of proposed SG in highly challenging search space. The purpose of the proposed hybrid technique is to enhance the overall search mechanism of the hybrid algorithm. It achieves this by combining NSGA II and MOPSO, which utilize distinct approaches to explore and exploit the search space. This combination helps to avoid the problem of solutions getting stuck in local optima by striking a balance between exploration and exploitation within the hybrid algorithm. In order to prevent premature convergence and obtain a well-distributed Pareto optimal solution, the entire population is divided into two halves based on the ranking generated by non-domination fronts. The first half of the population is improved using the NSGA II algorithm, while the other half is treated as swarm particles and optimized using MOPSO to guide them towards the best possible solutions. The detailed explanation of both algorithms is discussed in [92], [93].

MOPSO is a metaheuristic algorithm designed for tackling optimization problems with multiple conflicting objectives. Taking inspiration from the social behaviors observed in birds, MOPSO operates with a population of particles navigating the solution space. Each particle represents a potential solution, and their movements are influenced by personal best and global best solutions. The primary goal of using this algorithm is to identify a set of solutions forming the Pareto front. On other hand, NSGA-II is a powerful optimization algorithm designed for multi-objective optimization problems. Inspired by genetic algorithms, NSGA-II introduces a novel non-dominated sorting and crowding distance mechanism to maintain a diverse set of solutions. The algorithm begins with an initial population and employs genetic operators like crossover and mutation to generate offspring. The solutions are then ranked based on non-domination, creating Pareto fronts. The crowding distance mechanism ensures the spread of solutions in the Pareto fronts, promoting diversity. Through successive generations, NSGA-II efficiently evolves a population of solutions that represents a well-distributed set along the Pareto front, providing decision-makers with a range of trade-off options for multiple conflicting objective.

In real-world optimization problems, many problems entail the simultaneous optimization of multiple objective functions. These objectives are often non-proportional and can be in conflict with each other. Consequently, the optimization process yields a set of solutions instead of a single optimal solution since it is not feasible to find a single solution that can optimize all objectives simultaneously.

$$\left\{\begin{matrix} Min\ f1, f2\ and\ Max\ f3 \\ subject\ to \\ constraints \end{matrix}\right\} \qquad Eq(40)$$

In this work MOPSO-NSGA-II algorithm is applied in the following steps

Step 1: Specify the SG problem parameters,

- Total demand of proposed power system
- Decision variables upper bound
- Decision variables lower bound
- Total number of decision variables

Step 2: Specify the MOPSO parameters,

- Size of the repository
- Coefficients c1 and c2
- Inertial weight W

- Selection of leader

Step 3: Specify the NSGA-II parameters,

- Maximum iteration
- Size of the population
- Crossover
- Mutation

Step 4: Evaluation of the proposed SG objective functions f1, f2 and f3,

- Calculate the objective functions
- Provide the calculated objective functions to the algorithm

Step 5: Perform non-dominating sorting

Step 6: Start MOPSO for exploration

Step 7: Start NSGA-II exploitation

Step 8: Apply decision making mechanism

Step 9: Stop when conditions met

The flowchart of proposed Hybrid-NSGA-II-MOPSO method is shown in Figure 5.

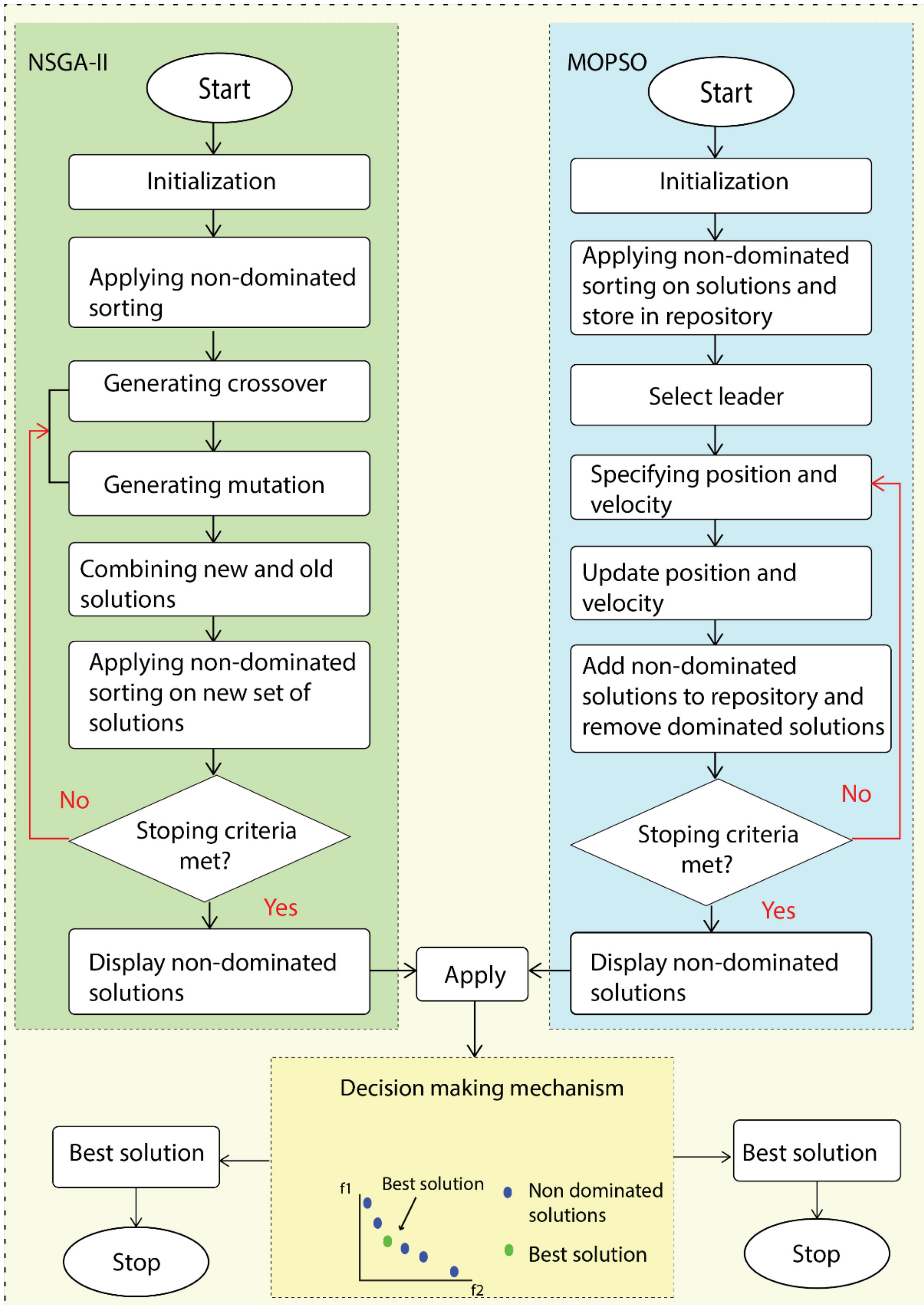

Figure 5: Hybrid MOPSO-NSGA-II Algorithm flow chart

The Hybrid-NSGA-II-M0PSO algorithm exhibits several advantages. One notable advantage is its ability to strike a balance between exploration and exploitation. NSGA-II, with its non-dominated sorting and crowding distance mechanism, promotes diversity within the Pareto front, preventing premature convergence. On the other hand, M0PSO excels in global exploration by leveraging particle swarm optimization principles, allowing for effective exploitation of promising regions in the solution space. This synergy results in an algorithm that not only converges faster but also maintains a diverse set of high-quality solutions. Additionally, the hybrid approach enhances robustness, as it can adapt to the problem's characteristics and demands, making it well-suited for addressing the complexities inherent in real-world optimization scenarios. The Hybrid-NSGA-II-M0PSO algorithm thus stands out as a powerful and versatile optimization tool, capable of delivering superior performance across a wide range of multi-objective optimization challenges.

4.9 Summary

This chapter provides detailed overview and explanation of proposed optimization algorithms, its general explanation, implementation steps and advantages.

CHAPTER 5 RESULTS, ANALYSIS AND DISCUSSION

5.1 Introduction

This chapter of thesis provides the results, analysis, and discussion for both models. The first model aims to optimize two primary objective functions: operational cost and CO2 emissions. Achieving this optimization is realized through the effective management of DER and the implementation of DRP, employing the SFLA. However, the second model presents the results that focus on addressing the tri-objective optimization problem within the distribution grid. This involves managing a high penetration of renewable energy sources and implementing a demand-side management strategy. The key objectives in this context include minimizing operational costs and pollution emissions, maximizing the integration of renewable energy resources, and reducing the energy gap between the initial demand and the optimal consumption value. To tackle this complex problem, a modified hybrid Multi-Objective Particle Swarm Optimization (MOPSO) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) technique is employed, considering various constraints. The detailed discussion of the results for both models are discussed in detail as follows:

5.2 First model results

This model is implemented based on three different scenarios: 1) Basic grid operation, 2) Operation with maximum usage of renewable energy resources, 3) Operation with maximum usage of renewable energy resources and demand response programs. The load profile of proposed SMG is shown in Figure 6.

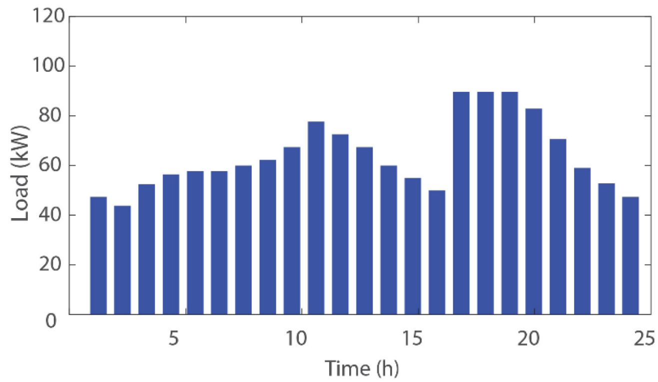

Figure 6: SMG load profile

The DER emissions coefficients are shown in Table 1. Besides, the battery considered in the proposed study has capacity of 40 kWh.

5.2.1 Case 1: Basic grid operation

In this case, the grid operation is executed with a focus on the objective functions that represent the operational costs and CO2 emissions. The simulation results for this scenario are illustrated in Figure 7. As depicted in figure, the operational cost at the optimal point stands at 251.9 estimated cost (Ect- E-chain network), while the pollution emission registers at 452.4 kg. The operational cost and pollution emission are high due to reliance on the utility grid for the energy supplied in this particular case.

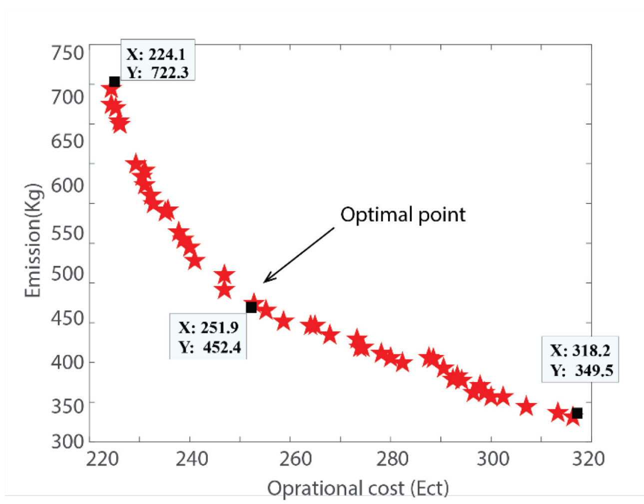

Figure 7: Pareto criterion distribution for case 1 using SFLA

5.2.2 Case 2: Operation with maximum usage of renewable energy resources

In this case, the primary emphasis is on maximizing the use of RES to optimize operational costs and reduce CO2 emissions in the SMG through the implementation of the SFLA. The simulation results for this scenario are depicted in Figure 8 illustrating that the operational cost at the optimal point is 297.5 Ect, and the pollution emission is 419.1 kg. Through maximum usage of RES, the outcomes indicated that, in comparison to Case 1, operational costs have increased while CO2 emissions have decreased.

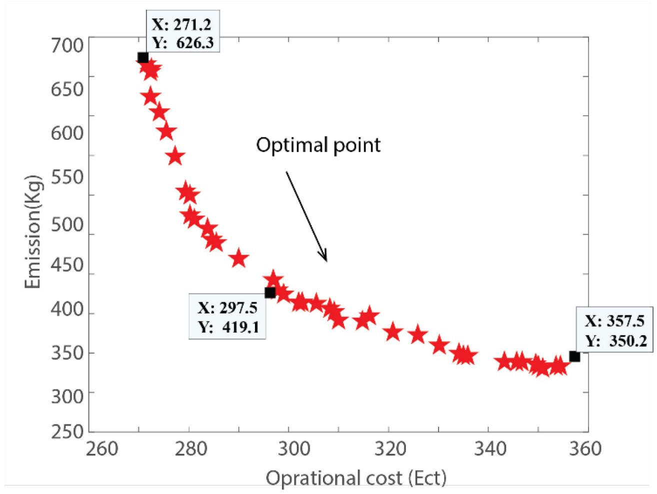

Figure 8:Pareto criterion distribution for case 2 using SFLA

Table 2: Distributed energy resources emissions coefficients

Sources	CO2 kg/MWh
Wind Turbine	0.00
Photovoltaic	0.00
Battery	9.80
Grid	960
Micro Turbine	710

Table 3: Optimal power allocation (kw) using SFLA

Hrs	WT-1	WT-2	WT-3	PV-1	PV-2	MT-1	MT-2	Battery	Utility
1	1.645	2.545	1.543	0.00	0.00	8.841	9.966	6.546	12.05
2	1.645	4.321	3.232	0.00	0.00	7.674	11.654	-16.622	28.42
3	1.593	1.453	0.936	0.00	0.00	7.784	12.545	-11.541	30.31
4	1.595	2.353	4.215	0.00	0.00	5.776	10.457	-12.342	28.56
5	1.598	0.253	0.124	0.00	0.00	8.564	6.346	15.560	27.08
6	0.824	4.543	6.424	0.00	0.00	8.564	9.543	6.898	22.56
7	0.632	2.653	4.211	0.00	0.00	5.453	5.231	11.560	29.88
8	0.632	1.640	1.420	0.21	0.24	24.676	8.121	13.885	10.50
9	1.351	1.542	1.145	3.32	2.43	30.665	5.321	31.677	-17.19
10	3.699	2.321	1.213	8.14	2.72	31.654	11.132	28.810	-19.24
11	8.180	4.032	3.422	4.04	5.40	31.654	25.321	31.553	-29.31
12	11.815	8.432	7.443	5.22	4.32	31.654	10.840	29.901	-31.45
13	3.045	1.231	1.036	10.07	6.43	28.332	8.542	28.021	-19.98
14	2.561	3.433	2.540	8.22	7.32	28.440	11.554	28.025	-31.53
15	1.330	1.054	1.221	7.51	2.341	31.552	3.541	28.030	-19.66
16	1.432	1.054	1.041	6.67	2.05	20.560	2.542	31.910	-14.58
17	1.688	1.242	3.242	6.67	8.54	28.401	23.541	31.055	-6.05
18	0.381	2.412	6.332	0.00	0.00	19.750	29.929	13.034	25.76
19	0.293	0.541	0.432	0.00	0.00	23.800	27.322	15.660	21.31
20	0.980	0.924	0.532	0.00	0.00	25.504	22.321	22.070	11.54
21	0.998	0.908	0.402	0.00	0.00	28.667	22.532	27.430	-14.59
22	1.242	1.542	1.904	0.00	0.00	20.041	16.212	25.010	-8.67
23	0.401	0.341	0.612	0.00	0.00	8.901	16.312	-7.906	29.60
24	0.560	0.432	0.320	0.00	0.00	27.886	12.532	-7.881	7.54

Table 4: Operational cost and emissions in case i, ii and iii

Cases	Operational cost (Ect)	Emissions (kg)
1	251.9	452.4
2	297.5	419.1
3	218.5	374.2

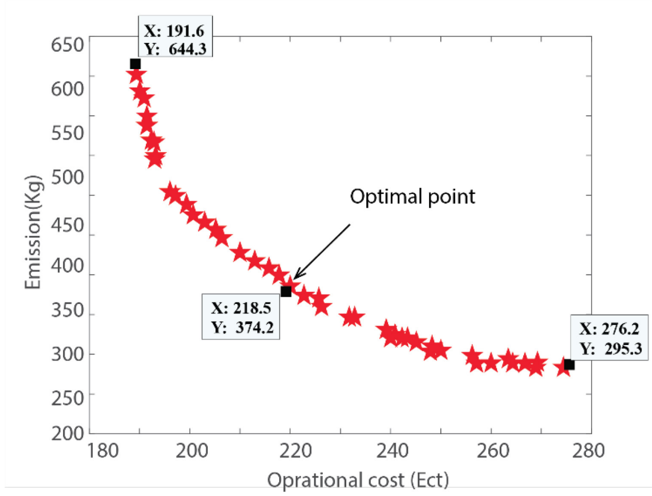

Figure 9: Pareto criterion distribution for case 3 using SFLA

5.2.3 Case 3: Operation with maximum usage of renewable energy resources and demand response programs

In this case, the maximum RES is utilized with the implementation of DRP to optimize operational costs and CO2 emissions in SMG using SFLA. The simulation results obtained in this case are shown in Figure 9, indicating that the operational cost at the optimal point is 218.5 Ect, and pollution emissions are 374.2 kg, which outperforms both cases discussed earlier in terms of minimizing both objectives. Case 3 highlights the impact of DRP in the proposed scenario. The optimal power allocation in this case is shown in Table 3. The operational cost and CO2 emissions obtained in all three cases are shown in Table 4.

5.3 Second model results

In this model, Hybrid-NSGA-II-MOPSO model is employed to smart distribution grid for optimization of tri-objective function considering DSM strategy and residential consumers with sheddable, non-sheddable and shiftable loads. The hourly wind speed for the proposed study is shown in Figure 10, Figure 11 illustrates the hourly solar irradiance, Figure 6 provides insights into the status of hydrogen storage and Figure 12 represents the pressure levels within stored hydrogen. The state of charge (SOC) of the battery is depicted in Figure 13. Fuel cell and PEM electrolyzer design and operating parameters are given in Table 5 and Table 6, respectively.

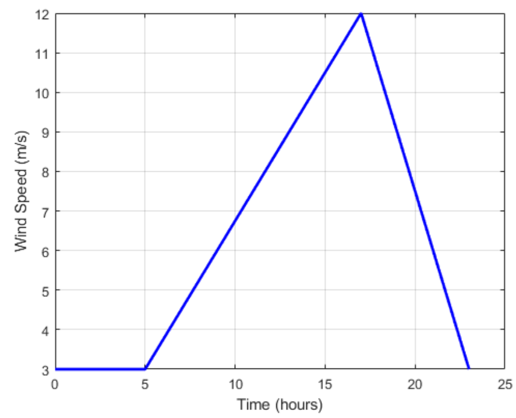

Figure 10:Wind speed

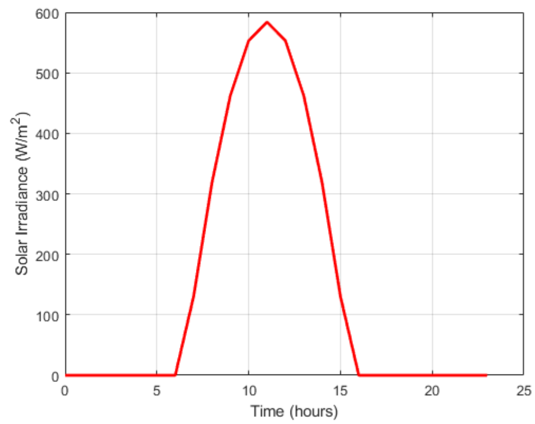

Figure 11: Solar irradiance

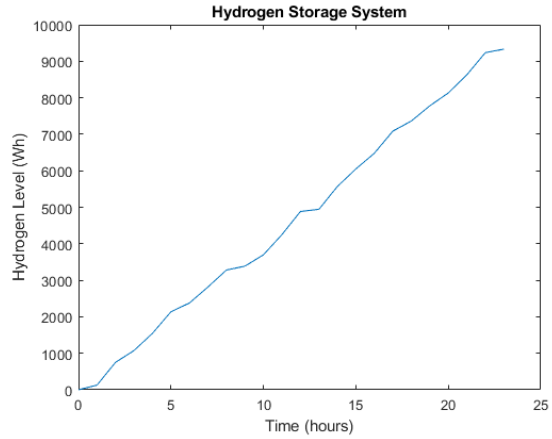

Figure 12: Hydrogen storage status

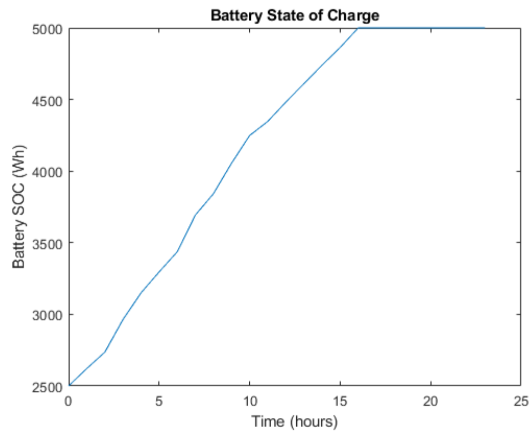

Figure 13: Battery SOC

Table 5: Fuel cell design and operating parameters

Parameter	Value
Current density	1100 A/m^2
Area of cell	0.1 m^2
Heat rate of fuel cell	1518 W
Fuel cell operating pressure	100 kPa
Fuel cell operating temperature	80°C

Table 6: PEM electrolyzer design and operating parameters

Parameter	Value
Cathode activation energy	18000 j/mol
Anode activation energy	76,000 j/mol
Temperature	80℃
Thickness of membrane	0.1 mm

In order to demonstrate the proposed model's efficiency, the simulation of this model is planned and implemented in four different scenarios.

1) Scenario 1: Optimize the first objective function.
2) Scenario 2: Optimize the first and second objective functions.
3) Scenario 3: Optimize the first and third objective functions.

4) Scenario 4: Tri-objective simultaneous optimization

For the comparison purpose, first we implement a basic grid operation, we have seen that the utility grid operational cost and pollution emission was 60% and 85% of the overall operational cost and pollution emission. This implies that the operational cost and pollution emission of utility grid is high, therefore, by utilizing the maximum utilization of RES with DSM strategy, using hydrogen storage system to store electricity and used that in peak hours may results in minimizing the operational cost and pollution emission. Therefore, by implementing these four distinct modes, the proposed model's efficiency is thoroughly evaluated, and its performance is quantified. The four modes are explained in detail as follows:

5.3.1 Case 1: First objective (operational cost and pollution emission optimization)

In this mode of simulation, the utilization of RES with implementation of DSM strategy is performed, the primary focus lies in the optimization of operational costs and pollution emission objective functions of the proposed grid. The goal is to strike a balance between minimizing operational cost and reducing environmental impact. To achieve this, the simulation employs a Hybrid-NSGA-II-MOPSO technique, which serves as an effective tool for obtaining the Pareto set solutions or non-dominated solutions. The selection process is facilitated through a robust decision-making mechanism, designed to provide guidance when choosing the ideal solution. Among the array of Pareto set solutions, the 15th solution is picked as best/optimal solution, as depicted in Figure 14. Results show that the operational cost is reduced by 12% and pollution emission is reduced by 7% as compared with basic operation mode using Hybrid-NSGA-II-MOPSO technique.

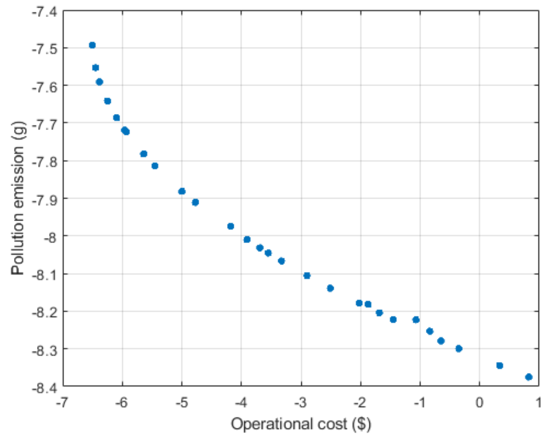

Figure 14: First objective: Operational cost and pollution emission optimization using Hybrid-NSGA-II-MOPSO

5.3.2 Case 2: First and second objective optimization

The second mode extends the optimization scope to both the first and second objectives of the model, by utilizing both RES with DSM in the system. By simultaneously targeting two key objectives, this mode evaluates the model's capacity to handle multiple optimization criteria. In this mode of simulation, operational cost, pollution emission and minimizing energy gap is optimized, the Pareto set solution/non-dominated solutions are obtained using the proposed Hybrid-NSGA-II-MOPSO technique and decision-making mechanism is used for picking best/optimal solution in the search space. Results illustrate, among the Pareto set solutions, 20th solution is picked as optimal solution as shown in Figure 15. Results show that the operational cost and pollution emission is reduced by 11% and 5% and energy gap is minimized by 13% as compared to basic operational mode using Hybrid-NSGA-II-MOPSO technique.

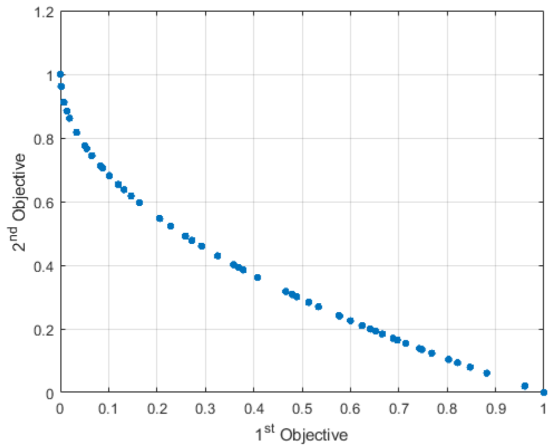

Figure 15: First and second objective optimization using Hybrid-NSGA-II-MOPSO

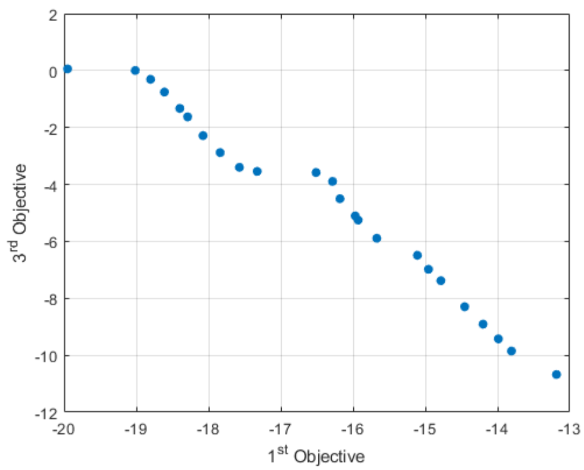

Figure 16: First and third objective optimization using Hybrid-NSGA-II-MOPSO

5.3.3 Case 3: First and third objective optimization

Similar to the previous mode, this mode introduces different sets of objectives. It concentrates on optimizing the first and third objectives of the model, emphasizing the significance of these specific objectives. This mode helps to assess whether the model can adapt to diverse optimization requirements and excel in situations where objectives differ from the previous cases. In this mode of simulation, the first objective, reducing operational cost and pollution emission (minimization problem) and maximizing penetration of renewable energy sources (maximization problem) is optimized, the Pareto set solution/non-dominated solutions are obtained using the proposed

Hybrid-NSGA-II-MOPSO technique and decision-making mechanism is used for picking best/optimal solution in the search space as shown in Figure 16. Considering minimization problem, results indicate that the operational cost and pollution emission is reduced by 10% and 7% as compared with basic operational mode, on other hand, penetration of renewable energy is maximized by 15%.

5.3.4 Case 4: First, second and third (tri-objective) simultaneous optimization

The final mode pushes the boundaries further by considering a tri-objective optimization scenario. In this mode, all three objectives are simultaneously optimized, mirroring complex real-world situations where multiple, often conflicting, objectives need to be addressed. This mode evaluates the model's versatility and its ability to navigate intricate trade-offs among objectives. Besides, the proposed tri-objective complex model is solved considering three different case studies as follows:

a) Case study 1: Basic operation
b) Case study 2: Operation with DSM and Battery
c) Case study 3: Operation with DSM considering both battery and hydrogen

The involvement of DSM strategy and different sources in each case study is shown in Table 7. The study introduces a novel and intricate tri-objective complex model, which is tackled using the Hybrid-NSGA-II-MOPSO optimization approach across three distinct case studies. The first scenario, denoted as the "basic operation," serves as the fundamental benchmark, characterizing the system's performance without any additional features. In the second case, referred to as "operation with DSM and battery," the DSM strategies and battery storage are introduced, reflecting a more dynamic and flexible energy management framework. The third and most advanced scenario, "operation with DSM considering both battery and hydrogen," showcases the convergence of DSM with both battery and hydrogen storage solutions, representing a cutting-edge approach to energy optimization. The proposed case studies and their outcomes are explained in detail as follows:

Table 7: Different case studies for tri-objective optimization using Hybrid-NSGA-II-MOPSO

Case studies	Sources	Involvement	DSM Strategy
Basic operation	Wind	✓	×
	Solar	✓	
	Battery	✓	
	Hydrogen	×	
	Utility	✓	
	Diesel generator	✓	
Operation with DSM and Battery	Wind	✓	✓
	Solar	✓	
	Battery	✓	
	Hydrogen	×	
	Utility	✓	
	Diesel generator	×	
Operation with DSM considering both battery and hydrogen	Wind	✓	✓
	Solar	✓	
	Battery	✓	
	Hydrogen	✓	
	Utility	✓	
	Diesel generator	×	

5.3.4.1 Case study 1: Basic operation

This operational case study represents the standard operational framework without the integration of advanced energy storage system or strategies, providing a baseline for comparison. The results in case study 1 revealed high operational costs and emissions, underscoring the necessity for more efficient and sustainable energy management practices by utilizing high penetration of RES, implementing DSM strategy and minimizing the energy gap. In case study 1, considering the tri-objective optimization, the utility grid operational cost and pollution emission is 65% and 73% of the overall operational cost and pollution emission. This implies that the operational cost and pollution emission of utility grid is high, therefore, by utilizing the maximum utilization of RES with DSM strategy, using hydrogen storage system to store electricity and used that in peak hours may results in minimizing the operational cost and pollution emission. The Pareto set solution obtained through Hybrid-NSGA-II-MOPSO and best/optimal solution obtained through decision making mechanism in case study 1 is shown in Figure 17.

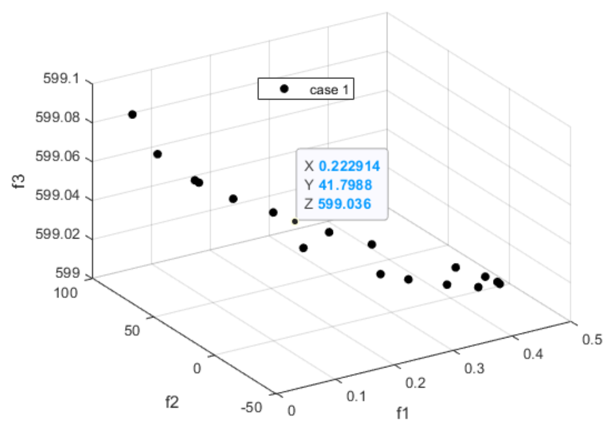

Figure 17: Basic operation using Hybrid-NSGA-II-MOPSO

5.3.4.2 Case study 2: Operation with DSM and Battery

The "operation with DSM and battery" case study introduces two key elements to enhance energy management. DSM strategy is employed to regulate energy consumption patterns and mitigate peak loads, while battery storage systems are integrated to store excess energy and release it when demand is high. This combination enhances the system's flexibility and resilience, reducing the reliance on the grid during peak periods. This case study showcased substantial improvements, with a 4.1% reduction in operational cost, a 9% decrease in pollution emissions, and a 12.5% reduction in the energy gap using Hybrid-NSGA-II-MOPSO method. These findings emphasize the effectiveness of integrating DSM and battery storage in achieving cost savings and environmental benefits. Moreover, the penetration of renewable energy sources is increased by 7%, reflecting a positive shift towards cleaner and more sustainable power sources. The Pareto set solution obtained through Hybrid-NSGA-II-MOPSO and best/optimal solution obtained through decision making mechanism in case study 2 is shown in Figure 19.

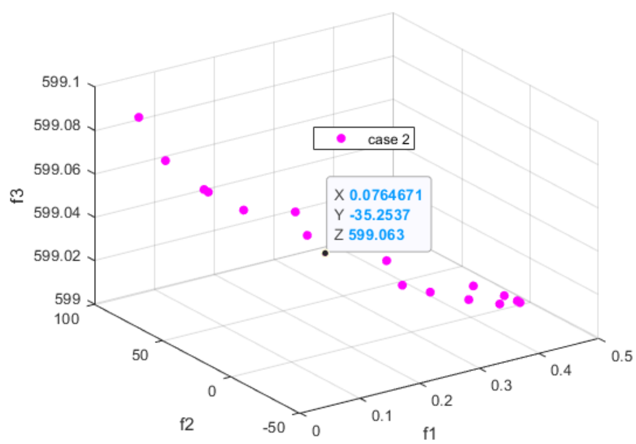

Figure 18: Operation with DSM and Battery using Hybrid-NSGA-II-MOPSO

5.3.4.3 Case study 3: Operation with DSM considering both battery and hydrogen

The most advanced scenario, "operation with DSM considering both battery and hydrogen," takes energy management to a cutting-edge level. It combines DSM strategy with the utilization of both battery and hydrogen storage solutions. This multifaceted approach optimizes energy usage by leveraging the benefits of two storage technologies, offering a dynamic and sustainable energy management strategy that is forward-looking and environmentally conscious. In this case study, the results exhibited even more remarkable outcomes. Operational cost was reduced by 5.4%, pollution emissions dropped by 13%, and the energy gap decreased by 14.5% using Hybrid-NSGA-II-MOPSO method. Notably, the integration of hydrogen storage further improved the system's performance. Moreover, the penetration of renewable energy sources increased significantly by 15%, illustrating a substantial commitment to sustainable energy solutions. These findings underscore the immense potential of combining advanced storage technologies and demand-side management strategies for optimizing energy systems, simultaneously reducing costs, emissions, and energy shortfalls while maximizing the adoption of renewable energy sources. The Pareto set solution obtained through Hybrid-NSGA-II-MOPSO and best/optimal solution obtained through decision making mechanism in case study 3 is shown in Figure 20.

Table 8: Diesel generator technical and economic data

Parameters	$P_{min}(MW)$	$P_{max}(MW)$	RU (MW)	RD (MW)	MU (h)	MD(h)
DG-1	0	1	0.06	0.01	5	3
DG-2	0	1.2	0.08	0.02	8	1
DG-3	0	0.85	0.03	0.01	10	1

Table 9: Battery parameters

Parameter	Value
${P^{max}}_{Batt-charge}$	1.125 MW
${P^{max}}_{Batt-discharge}$	1.125 MW
SOC^{min}	10%
SOC^{max}	100%
η_{charge}	90%
$\eta_{discharge}$	95%

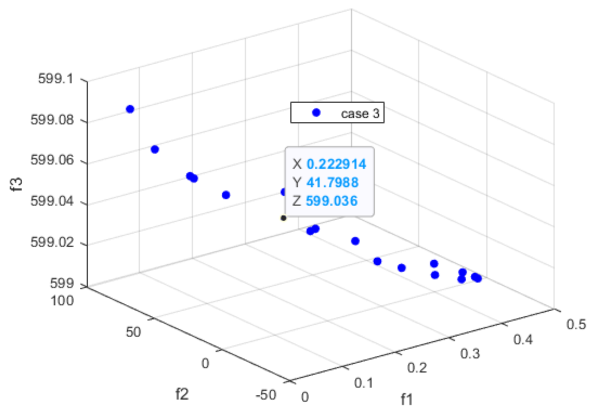

Figure 19: Operation with DSM considering both battery and hydrogen using Hybrid-NSGA-II-MOPSO

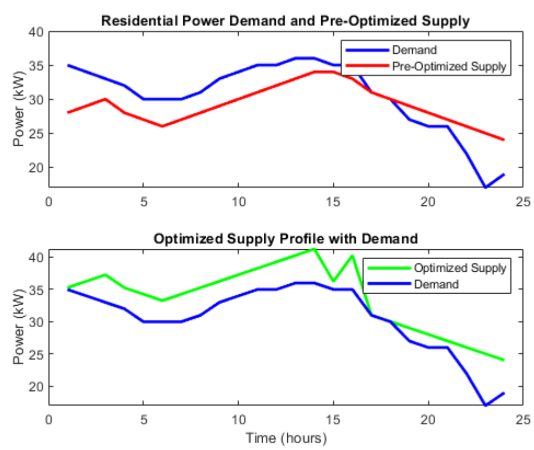

Figure 20: Comparison between pre-optimized and optimized power supplies

The comparison between the pre-optimized and optimized energy supply is shown in Figure 21, revealing a transformation in the system's performance. Prior to optimization, the system's energy supply fell short of meeting the prevailing demand, resulting in a noticeable deficit that affected the operation of the energy infrastructure. However, the transition to an optimized supply scenario yielded remarkable results. Following the implementation of proposed DSM strategy, battery and hydrogen storage systems, the energy supply was not only brought in line with the demand but, in fact, surpassed it. The surplus power generated is used to feed electric vehicle (EV) charging stations with the additional energy it required. This enhancement in supply not only eradicated the previous energy shortfall but also contributed to the sustainability goals of the system by facilitating the electrification of transportation through the EV station. The optimization, thus, is not only rectified a critical supply-demand imbalance but also harnessed excess power to promote the growth of eco-friendly technologies and services. The final demand and supply of the proposed system model considering third case study is shown in Figure 22.

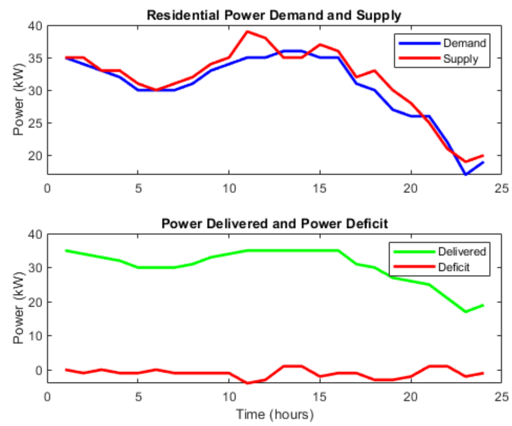

Figure 21: Demand and supply in final case study

Table 10: Comparison between case studies considering the proposed objective functions

Case studies	Operational cost reduction	Pollution emission reduction	Penetration of RES	Energy gap reduction
Bi-objectives				
Case 1	12%	7%	-	-
Case 2	11%	5%	-	13%
Case 3	10%	7%	15%	-
Tri-objectives				
Case 1	-	-	-	-
Case 2	4.1%	9%	7%	12.1%
Case 3	3.4%	13%	15%	14.5%

5.4 Summary

This chapter provides details of simulation results for two proposed models. The first model presents simulation test for energy management in SMG considering management of DERs using SFLA algorithm. The second model utilizes a modified Hybrid-NSGA-II-MOPSO model to smart distribution grid for optimization of tri-objective function considering DSM strategy.

CHAPTER 6 CONCLUSION

This chapter of the thesis presents the concluding remarks of the proposed work, challenges, and future directions.

This thesis work exploring two distinct models, the primary focus of the first model lies in addressing the challenges of operational cost reduction and pollution emission mitigation within SMG. By integrating DRP, this model fosters active consumer participation, which is beneficial for both consumers and utility providers. The optimization process for the first model is executed through the innovative SFLA algorithm. Considering the second model, this work extended to tackle tri-objective optimization energy management problem within distribution grids. This model optimizes operational cost, pollution emission, the substantial integration of renewable energy resources, and the minimization of the energy gap. Enabling consumer involvement through DSM strategies and incorporating three types of loads. The second model employs the hybrid-NSGA-II-MOPSO algorithm to solve this complex tri-objective optimization problem.

The significance of the proposed models in this thesis work playing a key role in advancing the integration of renewables within the energy landscape. The first model addressing operational cost and pollution emissions in smart microgrids, introduces a paradigm shift by incorporating DRPs. This approach not only optimizes operational efficiency but also fosters a symbiotic relationship between consumers and utilities. By actively engaging consumers in the energy management process, the model paves the way for seamless integration of RESs, thereby enhancing the overall sustainability of the microgrid. Besides, by encouraging consumers to engage in load-shifting and demand-response activities, the model promotes a flexible grid that can seamlessly accommodate the intermittent nature of renewable energy sources which results in improving the renewables integration with SMG and smart distribution networks.

First model successfully addresses the economic and environmental challenges of the SMG through a multi-objective approach, employing DER management and DRP integration using the SFLA technique. The simulation results are evaluated across three distinct cases and validate the effectiveness of the proposed model in various dimensions. In Case 1, where the energy supply heavily relies on the utility grid, both operational costs and pollution emissions were observed to be high. In Case 2, despite elevated operational costs, a notable reduction in CO_2 emissions was achieved through maximizing the utilization of RES. Lastly, in Case 3, by strategically implementing DRP and optimizing RES usage, the proposed model demonstrated a significant reduction in both operational costs and CO2 emissions compared to Case 1 and Case 2. This underscores the efficacy of the SFLA-based approach in achieving a balanced and sustainable solution for the economic and environmental concerns within the SMG context.

Based on the results obtained from the first model it is found that the model can be improved by adding more objective functions and adding hydrogen which is a long storage system. Besides, this work employing a hybrid optimization technique which combining the strengths of two different algorithms: In second model, a tri-objective optimization problem concerning energy management within distribution grids through the analysis of three distinct case studies is addressed. In the first case, basic operation of distribution grid is performed, the operational cost and pollution emissions is investigated high due to the absence of demand side management strategy and storage system. In the second case, the operational cost and pollution emission are decreased by 4.1% and 9%, and the energy gap narrowed by 12.5%, highlighting the benefits of demand side management strategy and battery storage system. Moreover, the penetration of renewable energy sources in the second case is increased by 7%, indicating a substantial shift towards more sustainable power generation. In the final case of study, DSM strategy, and both battery and hydrogen storage systems are used, the reduction in operational costs is investigated as 5.4% as compared to case 2, a 14.5% reduction in pollution emissions, a substantial 13.5% decrease in the energy gap, and the penetration of RES increased significantly by 15%. The introduction of hydrogen storage system in third case study further enhanced system performance, emphasizing the commitment to more sustainable energy solutions.

6.2 Link between proposed work and practical applications

This work involves the simultaneous optimization of smart micro grid and distribution grid objective functions, such as, operational cost, pollution emission, energy gap minimization, and high penetration of renewable energy sources using SFLA and hybrid-NSGA-II-MOPSO algorithms. This work has direct and significant implications for practical applications in the field of energy management and smart grid systems. Here are some links between our work and practical applications[94], [95]:

6.2.1 Renewable energy integration

Link: This optimization approach aims to achieve high penetration of renewable energy sources (wind and solar) in the micro grid.

Practical application: This is crucial for real-world applications as it addresses the challenge of integrating variable and intermittent renewable sources into the energy mix, optimizing their contribution to overall energy generation.

6.2.2 Operational cost reduction

Link: Optimization of operational costs is one of our objectives, indicating a focus on efficient resource utilization.

Practical application: Reducing operational costs is a key goal for practical implementation, as it directly impacts the economic viability of smart micro grids and distribution grids, which encourages sustainable energy practices.

6.2.3 Pollution emission minimization

Link: Another objective involves minimizing pollution emissions, reflecting a commitment to environmentally friendly energy solutions.

Practical application: This aligns with the global push towards cleaner energy and sustainability. Practical applications include meeting environmental regulations and reducing the carbon footprint associated with energy generation.

6.2.4 Energy Gap Minimization

Link: This work also addresses the minimization of energy gaps, indicating a focus on maintaining a stable and reliable power supply.

Practical application: In real-world scenarios, minimizing energy gaps is crucial for ensuring a consistent and reliable power supply, which is vital for industries, residences, and critical infrastructure.

6.2.5 Integration of Multiple Energy Sources

Link: This optimization considers a mix of energy sources, including wind, solar, battery storage system, hydrogen storage system, diesel generator, and the utility grid.

Practical application: The ability to integrate diverse energy sources is essential for building resilient and adaptable smart micro grids and distribution grids. Practical applications involve achieving energy independence, reducing reliance on non-renewable sources, and enhancing grid reliability.

6.2.6 Constraints handling

Link: our work incorporates various constraints such as power balance, generation bounds, battery constraints, and diesel generator constraints, etc.

Practical application: Real-world energy systems are subject to numerous operational constraints. Your approach addresses these constraints, making the optimization results more applicable and feasible for practical implementation.

6.2.7 Managing distributed energy resources in smart micro-grid

Link: Managing distributed energy resources (DERs) within a smart micro-grid is a critical aspect of modern energy systems. The proposed DERs include various decentralized and often renewable sources, energy storage systems, demand response technologies, and other distributed components. our focus on optimizing smart micro grids, including the management of DERs, aligns with the broader goals of enhancing grid efficiency, reliability, and sustainability.

Practical application: Real-world smart grids need to effectively incorporate DERs to maximize their benefits. This includes optimizing the use of RES, managing energy storage efficiently, and coordinating demand response actions.

6.2.8 Demand Response and Load Management

Link: The proposed smart micro-grid optimization involves demand response strategies, which are integral to managing DERs and overall grid performance.

Practical application: Effective demand response, facilitated by the management of DERs, enables utilities to balance supply and demand, reduce peak loads, and enhance overall grid stability. This is particularly important for optimizing energy consumption patterns.

This work contributes directly to the development of practical solutions for optimizing the operation of smart micro grids and smart distribution grids, making them more efficient, sustainable, and adaptable to real-world constraints and challenges in the energy sector.

6.3 Challenges

Following are challenges associated with energy management of power systems using renewable and non-renewable energy resources.

6.3.1 Intermittency and Variability

One of the primary challenges with renewable energy sources, such as solar and wind, is their intermittent and variable nature. The generation of power depends on weather conditions, time of day, and seasonal changes, making it difficult to predict and manage the energy supply consistently within a grid.

6.3.2 Grid Stability and Reliability

Integrating a high percentage of renewable energy into the smart grid can pose challenges to grid stability and reliability. Fluctuations in energy production may lead to voltage and frequency variations, potentially causing disruptions in the power supply. Developing effective energy storage solutions becomes crucial to address this issue.

6.3.3 Energy Storage Technologies

Although energy storage is a key solution to manage the intermittent nature of renewable energy, the development and implementation of cost-effective and efficient energy storage technologies remain a challenge. Current storage solutions often have limitations in terms of capacity, lifespan, and environmental impact.

6.3.4 Conflicting Objectives

Energy management in power systems often involves conflicting objectives, such as minimizing costs, maximizing reliability, and reducing environmental impacts. Balancing these objectives requires careful consideration and trade-offs, and finding a Pareto-optimal solution that satisfies multiple conflicting goals can be challenging.

6.3.5 Computational Complexity

Multi-objective optimization algorithms can be computationally intensive, especially for large-scale power systems with numerous variables and constraints. This complexity may result in longer computation times, limiting the practical applicability of these algorithms in real-time energy management scenarios.

6.3.6 Communication and Coordination

In multi-objective optimization, decisions often need to be made collaboratively. Coordinating actions and ensuring effective communication among different entities in the power system, such as generators, grid operators, and consumers, is essential for achieving optimal results.

6.4 Future directions

In future, this work will be extended in diverse direction. We will use artificial intelligence-based techniques to optimize the following objectives in micro-grids and distribution grids:

- To perform an accurate techno-economic analysis of proposed distribution grids and micro-grids.

To optimize and control the power flow in smart micro-grids and distribution grids.

- To optimize the capital, operating costs and environmental pollution problems.
- Peer to peer micro grids constraint will be add to the objective functions.

Besides, we will implement more DSM strategies such as flexible load scheduling, load curtailment, time of use, incentive programs, etc. To involve different types of consumers to improve the efficiency of energy systems.

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