DISTRIBUTED GENERATION PLANNING IN DISTRIBUTION SYSTEM

A Thesis Submitted in Partial Fulfillment of the Requirements for the Award of the Degree of

DOCTOR OF PHILOSOPHY

Submitted by

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DECALARATION

I hereby affirm that the research work presented in the thesis titled "Distributed Generation Planning in Distribution Systems," submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Electrical Engineering at Delhi Technological University, Delhi, is entirely original and conducted under the guidance of Prof. Narendra Kumar II and Prof. Uma Nangia. This thesis has not been previously submitted for any other academic degree.

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CERTIFICATE

I hereby certify, based on the candidate's declaration, that the work presented in this thesis titled "Distributed Generation Planning in Distribution System," submitted to the Department of Electrical Engineering, Delhi Technological University, Delhi, in partial fulfillment of the requirements for the award of the degree of Doctor of Philosophy, constitutes an original contribution to existing knowledge. It is a faithful record of the research work conducted by the candidate under my guidance and supervision.

To the best of my knowledge, this work has not been submitted in part or in full for the award of any degree elsewhere.

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ABSTRACT

Meeting the increasing global demand for electrical energy necessitates inventive approaches that transcend the constraints of conventional centralized power generation methods. One such groundbreaking paradigm with transformative potential in power distribution is Distributed Generation (DG). This project is dedicated to scrutinizing and enhancing the seamless integration of DG into distribution networks, with the ultimate goals of augmenting system efficiency, reliability, and sustainability.

The primary objective of this project is to establish a robust framework for the effective planning and implementation of DG. This entails employing a multifaceted approach that considers technical, economic, and environmental aspects. The proposed methodology aims to identify optimal sites, capacities, and technologies for DG units within the distribution network through the application of state-of-the-art optimization algorithms.

The study commences by providing a comprehensive introduction to the foundational aspects of power systems, ensuring readers have a solid grasp of the principles governing generation, transmission, and distribution networks. It underscores the evolving role of DG in this framework, emphasizing its potential to alleviate the burden on centralized generation facilities and enhance local energy resilience.

Central to DG planning is the judicious selection of technologies and energy sources. This research work conducts a comprehensive evaluation of a diverse array of DG technologies, including, but not limited to, solar photovoltaics, wind turbines, microturbines, and fuel cells. The selection process places significant emphasis on factors such as resource accessibility, environmental impact, and economic feasibility.

An in-depth exploration of the contemporary DG landscape involves a comprehensive investigation into the integration of renewable energy sources. Given the intermittent nature of renewables, the integration of modern energy storage technologies is imperative to ensure a consistent and reliable electricity supply. Integral to this endeavor are Battery Energy Storage Systems (BESS), which play a vital role in efficiently storing and deploying surplus energy. Additionally, research is underway into demand response strategies, offering dynamic load balancing and grid stabilization.

To facilitate the seamless integration of DG, a meticulous analysis of the existing distribution network is undertaken. This encompasses a thorough assessment of power flow characteristics, voltage profiles, and load profiles. Employing advanced modeling and simulation techniques, the dynamic behavior of the system is accurately captured under a spectrum of conditions.

The multi-objective framework guiding the optimization process encompasses a diverse range of performance metrics. These include considerations such as system losses, voltage stability, environmental impact, and economic feasibility. The Pareto frontiers generated by the

optimization process empower stakeholders to make decisions aligned with their specific priorities.

Through extensive simulations on established reference distribution systems, the proposed approach undergoes rigorous validation. The results underscore tangible benefits, including enhanced system efficiency, reduced losses, and improved voltage stability resulting from DG integration. Furthermore, a comparative analysis with conventional centralized generation vividly illustrates the superior performance of the proposed DG-centric approach.

In a nutshell, this study aims to elevate the domain of distributed generation planning within distribution systems. The proposed framework represents a significant stride towards a greener and more resilient power distribution paradigm, harnessing state-of-the-art optimization techniques, seamlessly integrated renewable energy sources, and comprehensive system analysis. The discoveries of this research carry the potential to steer forthcoming progress in this field, ultimately culminating in an electrical grid characterized by heightened reliability, efficiency, and environmental consciousness.

Contents

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List of Abbreviations

Abbreviations	Stands for
ALRPF	Allow reverse power flow
AO	Anyone
AVRPF	Avoid reverse power flow
BCBV	Branch current to bus voltage
BCS	Bilateral Contract Scenario
BDG	Bio-Gass Distributed Generation
BGA	Binary Genetic Algorithm
BIBC	Bus injection to branch current
BLA	Bi-level Approach
CAC	Considering all constraints
CCT	Critical clearing time
CGA	Continuous Genetic Algorithm
CGSA	Classical Grid Search Algorithm
CL	Constant Load
CML	Commercial Load
COP	Cost Optimization
CPLSM	Combined power loss sensitivity method
DABC	Discrete Artificial Bee Colony
ΣDG	Number of Distributed Generator
DHPF	Decoupled harmonic power flow
DS	Dispatchable system
ECIM	Equivalent Current Injection Method
EL	Exhaustive Load Flow
ELR	Energy loss reduction
GSA	Gravitation Search Algorithm
HDG	Hydro DG
HeS	Heuristic search
HL	High load

IB	Immune based
IGA	Improved Genetic Algorithm
IHRA	Improved Hereford Ranch Algorithm
IL	Industrial load
Itr.	Iteration
IVM	Index Vector Method
LaPF	Lagging power factor
LC	Load Concentration
LCCA	Life cycle cost analysis
LDC	Local distribution company
LePF	Leading power factor
LFC	Limited feeder capacity
LFG	Land fill gas
LI	Loss Incentive
LL	Low load
LLC	Line loading capacity
LLR	Line loss reduction
LSM	Loss Sensitivity Method
MGT	Mini Gas turbine
ML	Medium Load
MMNRES	Multi membered non recombinative evolution strategy
MNM	Modified novel method
MPI	Multi objective performance index
MXL	Mixed load
ND	Non differential
NPr	No preference
NPV	Net profit value
PFR	Power flow reduction
PI	Power system performance index
PP	Probabilistic planning
PR	Pollutant reduction
PSBIT	Power Stability Based Index Technique

PSF	Price scaling factor
QR	Quick restoration
RI	Reliability improvement
RL	Residential load
RP	Repeated power flow
RPF	Reverse power flow
SI	Stability improvement
S_L^0	Peak load
SQP	Sequential Quadratic Programming
TI	Total incentive
Tiv	Time invariant
TP	Traditional planning
TSI	Transient stability improvement
Tv	Time variant
UCO	Uncontrolled output
UFC	Unlimited feeder capacity
Vdm	Maximum voltage drop
VL	Voltage limit
Vpm	V % mean
VSIM	Voltage Sensitivity Index Method
Wc	Clipping wind turbine generation output
W_L	Weightage factor for power loss
WoDG	Without Distributed Generation
WSP	Without solar penetration
Wt	Turning off wind turbine generation output
WTBDG	Wind turbine DG + Bio mass DG
W_{V1}	Weightage factor for voltage deviation
W_{V2}	Weightage factor for voltage variation

List of Symbols

Symbols	Stands for
$P_{\mathrm{L}\,(\mathrm{t})}$	Power transmission losses
$P_{i\,(\mathrm{t})}$	Real power at *i*th node at any time t
$P_{J\,(\mathrm{t})}$	Real power at *j*th node at any time t
$Q_{i\,(\mathrm{t})}$	Reactive power at *i*th node at any time t
$Q_{J\,(\mathrm{t})}$	Reactive power at *j*th node at any time t
$V_{i\,(\mathrm{t})}$	Voltage at *i*th node at any time t
$V_{j\,(\mathrm{t})}$	Voltage at *j*th node at any time t
$r_{i\,j}$	Resistance of branch between *i*th and *j*th node
$\delta_{i\,(\mathrm{t})}$	Angle of voltage at *i*th node
$\delta_{i\,(\mathrm{t})}$	Angle of voltage at *j*th node
$P_{R\,(t)}$	Reverse power at time t
$I_{\mathrm{G}\,(t)}$	Current from grid at time t
$V_{\mathrm{G}\,(t)}$	Voltage of grid at time t
$I_{\mathrm{S.}}$	Designated limit of reverse current
$V_{D\,(t)}$	Penalty for deviation of voltage
$V_{\mathrm{Max.}}$	Maximum value of permissible voltage at node

$V_{\text{Min.}}$	Minimum value of permissible voltage at node
$P_{Gi(t)}$	Real power generation at i^{th} node for the time period t
$P_{Di(t)}$	Real power demand for the time period t
$Q_{Gi(t)}$	Reactive power generation at i^{th} node for the time period t
$Q_{Di(t)}$	Reactive power demand for the time period t
$P_{in,i(t)}$	Nonreceptive load at time t
$P_{el,i(t)}$	Receptive load at time t
E_i^{Total}	Energy demand per day
$L_{d,i(t)}$	Load per hour for the time period t
$P_{\text{DG},i}$	Real power injection by DG
P_{DG}^{max}	Maximum value of real power generation by DG
$I_{ij(t)}$	Current flowing between i^{th} and j^{th} Node at t
I_{ij}^{max}	Maximum permissible value of current
Y_{ij}	Admittance matrix between i^{th} and j^{th} Node
θ_{ij}	Angle of impedance between i^{th} and j^{th} Node
I_{sm}	Current of solar PV
$S_{r(t)}$	Solar radiation at t
S_r^r	Rated value of solar radiation for PV

t.p.	Time period
P_i^T, P_j^T	Active power magnitude i^{th} and j^{th} node for the *t.p.* of *T*
r_{ij}	Branch resistance between i^{th} and j^{th} node
$P^T_{BESS\left(\frac{C_i}{D_i}\right)}$	Power of BESS (charging and discharging) at i^{th} node for *t.p. of T*
I^T_{Grid}	Output current the substation transformer at any time *T*
$P^{\text{Max.}}_{BESS}$	Maximum limit of power dispatch
Ψ	Conversion factors from daily to yearly
η_c	Charging efficiency of BESS
P_c^T	Converter loss for *t.p. of T*
I_{ij}^T	Level of current between *i* and *j* bus in hour T
η_d	Discharging BESS efficiency
P^{max}_{PV}	Maximum size of DGs
$E_{BESS,i}$	BESS energy at i^{th} node
V_{Max}, V_{Min}	Limits of node voltages
η	Efficiency of the storage system
$P^{\text{Min.}}_{BESS}$	Minimum limit of power dispatch
V_i^T	Magnitude of the voltage at the i^{th} node during the *t.p. of* T
V^T_{Grid}	Magnitude of grid voltage at any time *T*
E^{Max}_{BESS}	Maximum limit of energy

C	Contract load
I_{ij}^{max}	Thermal limit (maximum) of line between bus i and j (A)
κ_i^T	Allocated load factor for bus *i* at *t.p. of* T
$P_{el,i}^{min}$, $P_{el,i}^{max}$	Limits of responsive load (maximum and minimum)
V_i^T, V_j^T	Node voltage of i^{th} and j^{th} node for the *t.p.* of *T*
$P_{in,i}^T$	Instantaneous load (nonresponsive and responsive)
Q_{Di}^T	Reactive power demand at node i^{th} at any time T
P_{Loss}^T	Power delivery loss for the *t.p.* of *T*
Q_i^T Q_j^T	Reactive power magnitude i^{th} and j^{th} node for the *t.p.* of *T*
R_{PV}^r	Rated PV module radiations
$P_{el,i}^T$	Responsive load at any time T
P_{Di}^T	Real power demand at node i^{th} at any time T
E_i^{Total}	Total demand of energy of the day
$SOC^{Min.}$, $SOC^{Max.}$	SOC limits
P_{Gi}^T	Real power injection at node i^{th}
R_{PV}^T	Solar radiation at time T
χ	Penetration of DR
SOC_i^T	SOC of BESS at bus *i* in hour T

$P_{\mathrm{PV},i}$	Active power injection at node i^{th} at any time T
V_D^T	Voltage deviation penalty
I_{Spc}	Specified reverse current limit
P_R^T	Reverse power flow at any time T
Δt	Change in time
I_{PV}	Solar module current (A)
δ_i^T, δ_j^T	Voltage angle of i^{th} and j^{th} node for the *t.p.* of T
Q_{Gi}^T	Reactive power injection at node i^{th} for any time T
$L_{d,i}^T$	Hourly demand for the *t.p.* of T
$P_{D,i}^0$	Initial real power demand at i^{th} node
$Q_{D,i}^0$	Initial reactive power demand at i^{th} node

Chapter- I
Introduction

1.1 Electric Power System

An electrical power system is an intricate network tasked with generating, transmitting, and distributing electric power to diverse end-users, including residential, commercial, institutional, and industrial clients. The production aspect of this system consists of three fundamental elements: generation, transmission, and distribution [1]. These elements are interconnected through transformers, which regulate voltage levels to ensure efficient operation [2]. Let's delve deeper into the characteristics of each component:

1.1.1 Power Generation:

- The primary objective of the power generation component is to convert energy from both renewable and fossil fuel sources into usable electrical power. This process operates primarily in two modes: Distributed Generation (DG) and Centralized Generation (CG) [3].
- In CG, large power plants generate electricity on a massive scale, which is then transmitted at high voltages. DG, on the other hand, comprises of smaller generators, frequently under the ownership of Independent Power Producers (IPP), producing electricity at low to medium voltage levels. This component also encompasses customer-owned on-site generation systems like solar panels.
- It is crucial to emphasize that DG is encompassed within the central power system.

1.1.2 Power Transmission:

- The power transmission component comprises a network of transmission and sub-transmission lines, often configured in a mesh pattern. Transmission switching stations serve as interfaces between these lines, regulating voltage levels.
- In centralized generation, its principal role involves the efficient conveyance of substantial volumes of electrical power at elevated voltages across substantial distances, spanning from generators to the distribution system [4, 5].
- Additionally, it enhances power supply reliability and reduces the likelihood of electrical outages by offering alternative transmission routes in case of line failures [6].
- This arrangement allows the transmission operator to efficiently manage the use of multiple generators in accordance with their performance and shifts in demand, thereby enhancing operational stability [7].

1.1.3 Power Distribution:

- The distribution system acts as a conduit, transferring electricity from the transmission network to end-user facilities. At substations, the transmitted electricity undergoes a transformation to attain the standard utility voltage prior to being dispatched [6].
- Operating as an intricate web of medium to low voltage lines, it radiates out to end-users, a majority of whom are medium and small-scale consumers.
- Additionally, distributed generation systems with robust backup systems may be integrated into this network [7].
- Figure 1.1 provides an overview of the overall layout of the electrical power system.

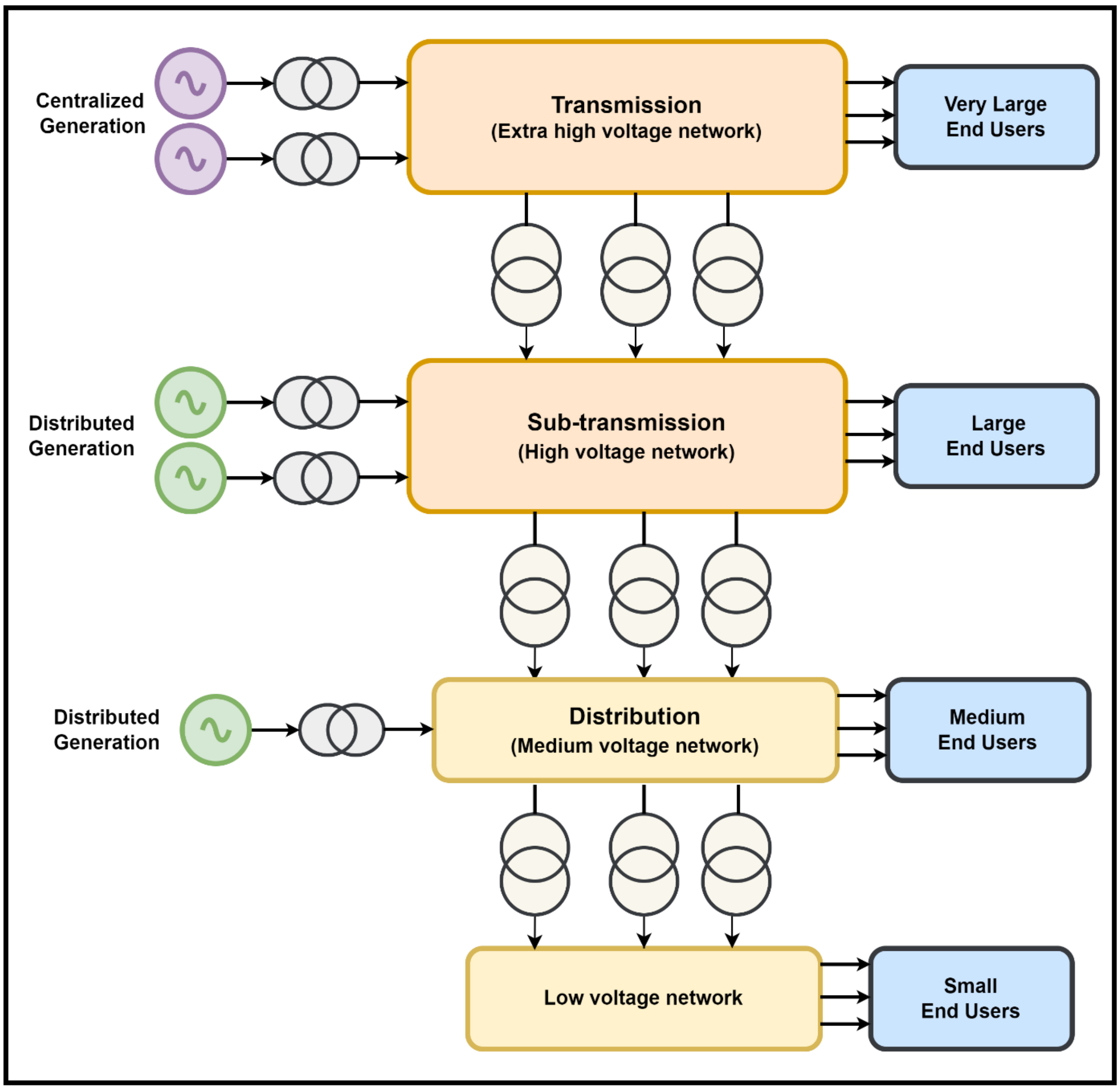

Fig. 1.1: Typical framework of the Electric Power System

1.2 Distributed Generation

Distributed generation (DG) refers to the generation of electricity from multiple small-scale energy sources that are located near to the point of use. DG stands in stark contrast to conventional centralized power plants. It operates on a decentralized model, employing lower-capacity generators that are directly integrated into or located near points of energy consumption within the distribution network [8]. This innovative approach encompasses a diverse range of small-scale technologies, capturing energy from diverse sources, encompassing renewables like solar, wind, geothermal, biomass, biogas, and hydroelectric power, as well as non-renewable resources such as fossil fuels [9].

This dynamic strategy encompasses various technologies such as biomass boilers, combustion turbines, solar photovoltaic cells, solar thermal systems, fuel cells, micro-turbines, internal combustion engines fueled by biogas, geothermal heat pumps, micro-hydro generators, diesel engines, reciprocating engines, and small-scale cogeneration plants [10].

1.2.1 DG Classification

There are several categories of distributed generation, each with its own characteristics and technologies:

Renewable Energy Sources:

- *Solar Photovoltaic (PV) Systems:* Photovoltaic systems directly transform sunlight into electricity through the use of photovoltaic cells.
- *Wind Turbines:* Wind turbines produce electrical power through the conversion of wind energy into rotational kinetic energy, which subsequently drives a generator to generate electricity.
- *Hydroelectric Power:* Small-scale hydroelectric generators make use of the kinetic energy of flowing water to generate electrical power.
- *Biomass and Biogas Systems*: These systems utilize organic matter such as agricultural byproducts, timber, or organic refuse to generate electrical power.

Conventional Fossil Fuel Technologies:

- *Natural Gas Turbines and Engines:* Natural gas turbines and engines utilize natural gas as the primary fuel for electricity generation. They are commonly employed in combined heat and power (CHP) systems.
- *Diesel Generators*: Diesel generators operate by utilizing diesel fuel to power an internal combustion engine, which in turn drives an alternator to produce electricity.

Fuel Cells:

Hydrogen Fuel Cells: These electrochemical systems facilitate the conversion of hydrogen and oxygen into electrical energy, producing water as a resultant byproduct.

Microturbines:

Gas Microturbines: Microturbines of this kind function by utilizing a range of fuels, including natural gas and biogas, in order to generate electrical power.

Energy Storage Systems:

Battery Energy Storage: These systems have the capability to store electrical energy within batteries and subsequently discharge it as required.

Combined Heat and Power (CHP) or Cogeneration:

CHP systems utilize a single energy source to concurrently produce electricity and capture the waste heat generated during electricity generation for practical purposes, thereby enhancing the overall energy efficiency of the system.

Co-generation with Renewable Sources:

Certain renewable technologies, such as biomass and biogas systems, have the capability to be integrated with CHP systems. This integration enables the simultaneous generation of electrical power and valuable thermal energy.

Geothermal Power:

Geothermal systems utilize the Earth's inherent thermal energy to produce electrical power.

Waste-to-Energy (WtE):

These systems utilize diverse processes such as incineration or anaerobic digestion to transform waste materials into energy.

Wave and Tidal Energy:

These technologies harness the energy from ocean waves and tides to generate electricity.

Each category of distributed generation has its own set of advantages and considerations, including factors like environmental impact, scalability, cost, and geographic suitability. The choice of distributed generation technology depends on various factors, including local resources, energy needs, and regulatory environment.

1.2.2 DG Benefits

The proliferation of DG units in distribution systems (DS) is experiencing rapid growth, primarily driven by the escalating global electricity demand. The incorporation of DG within modern power systems is pivotal in enabling consumers to meet their energy needs with enhanced quality and uninterrupted supply. Consequently, DG technologies have garnered substantial recognition for their efficiency and reliability. Below, we delve into the multifaceted technical, economic, and environmental advantages associated with DG integration:

1.2.2.1 Technical Benefits

The integration of DG brings about the following technical advantages within the power system [11-23]:

Reliability Improvement

Optimal placement of DG units within the DS leads to a remarkable enhancement in power system reliability. This outcome is attributed to several factors, including:

- *Improved Power System Reliability:* DG units contribute to a more reliable power system, reducing the susceptibility to disruptions.
- *Reduced Capacity Release:* DG units alleviate the need for excessive capacity release from centralized generation sources during peak demand periods.
- *Improved Generation Diversity:* The integration of diverse DG sources enriches the generation mix, bolstering the overall system's resilience.
- *Peak Power Reduction:* DG units are instrumental in curtailing peak power demand, mitigating the risk of grid overloads.

Voltage Profile Improvement

A paramount concern in radial distribution systems is the suboptimal voltage profile. However, strategic placement of DG units brings about substantial improvements in this regard, encompassing:

- *Voltage Quality Improvement:* DG units enhance voltage quality, reducing voltage fluctuations and irregularities.
- *Voltage Profile Improvement:* The voltage profile across the distribution network experiences a noteworthy uplift, ensuring consistent and stable voltage levels.
- *Reduced Voltage Flicker:* The integration of DG units results in reduced voltage flicker, which can be detrimental to sensitive electrical equipment.
- *Voltage Support and Better Regulation*: DG units provide vital voltage support, contributing to more effective voltage regulation within the DS.

Line Loss/Energy Reduction

DG deployment also leads to notable reductions in line losses, improving energy efficiency. Furthermore, it facilitates better control of reactive power, optimizing the overall power flow within the distribution system.

1.2.2.2 Economical Benefits

The economic advantages of DG integration are substantial and encompass various facets, including [24-33]:

- *Reduced Operational and Maintenance Costs:* Optimal utilization of DG units translates into lower operational and maintenance expenditures.
- *Deferment of Investment in Infrastructures:* DG integration can defer the need for substantial investments in additional infrastructure.

- *Reduction in Losses Associated Costs:* By curbing losses, DG reduces associated costs related to energy wastage.
- *No Fuel Cost with Renewable DG:* Renewable DG sources, such as solar and wind, eliminate fuel costs, as they harness energy freely from nature.
- *Reduction in Right of Way Acquisition Costs*: The need for extensive right-of-way acquisitions is diminished, resulting in cost savings.
- *Reduction in the Cost of Installation:* DG installation costs are often lower compared to conventional centralized generation facilities.
- *Maintenance of Constant Running Costs for Longer Time Periods:* DG units can maintain relatively consistent running costs over extended durations.
- *Reduction in Auxiliaries' Costs:* Ancillary costs associated with DG operations are also reduced.

1.2.2.3 Environmental Benefits

The environmental benefits of DG integration, especially when renewable sources are involved, are of paramount significance [34-46]. These advantages encompass:

- *Reduction in Land Use Effects:* DG, particularly renewable sources like solar and wind, minimizes the environmental impact associated with land use.
- *Reduction in Health Costs with Renewable DG:* The use of renewable DG sources contributes to improved air quality, thereby reducing health-related costs.
- *Environmentally Friendly with Renewable DG:* Renewable DG sources are inherently environmentally friendly, producing negligible direct emissions.
- *Reduction of GHG Emission Pollutants with Renewable DG:* The integration of renewable DG sources significantly reduces greenhouse gas (GHG) emissions, mitigating the adverse effects of climate change.

In conclusion, the integration of DG in distribution systems offers a myriad of technical, economic, and environmental benefits. These advantages not only enhance the reliability and efficiency of power systems but also contribute to cost savings and a more sustainable, eco-friendly energy landscape.

1.3 Motivation of the work:

As per the International Energy Agency (IEA), India is projected to experience the most significant surge in energy demand globally in this decade due to escalating urbanization and industrialization. The demand is expected to increase by 3% annually. Despite endeavors to augment the adoption of renewable energy, it is anticipated to meet up to 60% of the supplementary power demand. However, coal and oil are still anticipated to contribute approximately a third and a quarter of the world's energy, respectively, by the year 2030.

The IEA has projected that India will become the world's most populous country by 2025. This, combined with the concurrent trends of urbanization and industrialization, forms the foundation for a rapid surge in energy demand, with an annual increase of over 3 percent from 2021 to 2030 according to the Stated Policies Scenario (STEPS). India is anticipated to experience the most substantial rise in energy demand compared to any other country.

Despite India's commendable strides in deploying renewable energy sources and implementing efficiency regulations, the sheer scale of its expansion dictates that over the next two decades, the cumulative cost of importing fossil fuels will triple. Notably, a significant portion of this expenditure will be attributed to oil imports.

The construction of large-scale central power plants demands substantial financial investments and intricate, long-term planning. Environmental concerns surrounding nuclear and thermal power plants add another layer of complexity to the situation. Given these challenges, the imperative for distributed power sources, including technologies like fuel cells, wind turbines, solar arrays, small/micro hydro plants, and gas/diesel generators, becomes evident. In the present scenario, adopting a diversified approach is crucial to ensuring the nation's sustained progress.

1.4 Research Gap

The research gap in distributed generation planning within distribution systems pertains to the inadequacy of comprehensive methodologies and tools that consider multi-objective optimization, incorporating various technical, economic, and environmental aspects. Existing studies often focus on singular objectives, such as loss reduction or voltage regulation, without addressing the complex interplay of multiple parameters. Additionally, there is a limited emphasis on the integration of emerging technologies like renewable energy sources, energy storage systems, and advanced grid management techniques.

Moreover, the integration of demand response programs and the incorporation of consumer behavior dynamics in DG planning models represent areas where there is limited research. Understanding how consumer preferences, load patterns, and response to incentives impact the optimal deployment and operation of DG units is crucial for creating more realistic and effective planning strategies.

Additionally, the development of robust decision support tools that can accommodate the evolving regulatory landscape and policy frameworks is an underexplored area. Effective DG planning must consider not only technical and economic factors but also regulatory constraints, grid codes, and market structures. Research in this domain can help bridge the gap between theoretical models and practical implementation.

In summary, the research gap in distributed generation planning in distribution systems revolves around the need for holistic, multi-objective optimization frameworks, empirical validation, consideration of consumer behavior, adaptation to evolving regulatory environments, and the enhancement of system resilience in the context of increasing DG integration. Closing these gaps will contribute to the development of more effective, sustainable, and reliable distribution networks.

1.5 Research Objectives

The proposed research work shall mainly focus on the following aspects:

- **Optimal Placement of DG Units for Power Quality Enhancement in the Distribution System:**

This research objective aims to meticulously investigate and identify the most strategically advantageous locations within the distribution system for the integration of DG units. The primary focus is on how this integration can be harnessed to elevate the overall power quality parameters. This encompasses an in-depth analysis of factors such as voltage regulation, reactive power compensation, and harmonics mitigation.

- **Modeling and Optimization of Size and Location of Renewable DG in the Distribution System:**

This objective delves into the realm of renewable energy sources within the distribution system. It involves developing comprehensive models that encapsulate the dynamics of renewable DG sources. Furthermore, this research endeavors to optimize both the size and the placement of these renewable DG units to ensure maximum efficacy in terms of energy generation, taking into consideration factors like solar radiation patterns, wind speeds, and geographical features.

- **Impact Analysis of Demand Response with the Coordination of DG in the Distribution System:**

This research objective embarks on an exploration of the dynamic interaction between demand response strategies and the integration of DG units within the distribution system. The focus is on discerning how these two vital components can be synchronized to yield synergistic benefits. This encompasses an assessment of load shedding, peak shaving, and load shifting strategies in conjunction with the operation of DG units. The aim is to ascertain how this coordination can bolster the system's resilience, efficiency, and reliability, particularly during periods of high demand.

By meticulously investigating and addressing these research objectives, this study endeavors to contribute significant insights and advancements in the field of distributed generation planning within distribution systems. Each objective is poised to unlock critical knowledge that not only enriches the theoretical understanding of these systems but also offers practical applications and solutions for real-world implementation and enhancement of power distribution networks.

1.6 Organization of Thesis

Chapter I: Introduction

The inaugural chapter serves as the gateway to this comprehensive research endeavor. Within, the overarching scope of the study is delineated, with particular emphasis on presenting the research problem statement. This section also undertakes the crucial task of outlining the objectives and delineating the significance of the study. Furthermore, a concise exposition of the chosen methodology is also included, providing the reader with a preview of the research approach.

Chapter II: Literature Review

This chapter forms the bedrock of the study, offering an in-depth survey of existing scholarship germane to the research topic. This comprehensive review encompasses a critical analysis of preceding research works, encapsulating theoretical frameworks, methodologies employed, and seminal findings. By contextualizing the current research within this broader academic landscape, the literature review furnishes a robust foundation for the ensuing analysis.

Chapter III: Optimal DG Allocation and Impact of Demand Response

Within this chapter, the research pivots towards the crux of the investigation. The primary focus is the judicious placement and sizing of Distributed Generation (DG) units within the distribution network. Additionally, this section is dedicated to probing into the interplay between demand response strategies and the efficacy of DG integration. Through a meticulous examination of these facets, this chapter advances the understanding of how these critical components synergize to fortify the distribution network.

Chapter IV: Optimal DG Allocation in the Coordination of Demand Response and Battery Energy Storage System

Building upon the foundations laid in Chapter 3, this segment extends the discourse to encompass the role of battery energy storage in tandem with DG and demand response. An intricate analysis is undertaken to discern how these integrated elements collaborate to augment the efficiency and dependability of the distribution network. This chapter is instrumental in unraveling the multifaceted dynamics of these components, illuminating their collective impact.

Chapter V: Investigating the Impact of DG on Distribution System Protection and Voltage Regulation

This chapter embarks on a detailed exploration of how the integration of DG affects the protective apparatus and voltage control mechanisms intrinsic to the distribution system. Matters of paramount concern, such as fault currents, overvoltage, and protection coordination, are subjected to rigorous scrutiny. By delving into these intricacies, this chapter furnishes invaluable insights into the intricate interplay between DG integration and the safeguarding of the distribution system.

Chapter VI: Conclusions and Future Scopes

The concluding chapter culminates the research journey, synthesizing the key findings gleaned from the exhaustive investigation. Through a discerning analysis of the results, the chapter draws cogent conclusions that encapsulate the essence of the study. Moreover, this section proffers recommendations for future research avenues, thereby illuminating potential trajectories for further exploration and application of the research findings. This meticulously structured thesis unfolds as a cogent narrative, guiding the reader through a comprehensive exploration of the chosen research domain. Each chapter converges seamlessly, contributing to an exhaustive body of work that advances understanding and offers valuable insights into the dynamic interplay between distributed generation, demand response, and the broader distribution network.

Chapter- II

Literature Review

2.1 General Introduction

In the modern era, distributed generation (DG) has become an integral component of the electric power system, playing a pivotal role due to its significant advantages over conventional centralized generation (CG). These advantages encompass technological, financial, and environmental benefits, as well as enhanced system stability and more efficient resource utilization [10]. DG effectively bridges the gap between electric power generation and the ever-increasing daily load demands.

The transition towards a renewable-powered world is evident in the deliberate and widespread adoption of Distributed Energy Resources (DERs). This shift has led to a departure from the traditional hierarchical structure of CG, marked by a growing emphasis on the utilization and integration of Renewable Energy Sources (RES) [47-51]. Furthermore, the integration of DG with centralized grid generation necessitates an advanced protection system capable of ensuring secure implementation, even in the presence of various power quality constraints [52-54].

A comparative analysis between CG and DG can be drawn based on several key factors:

a) Output Capacity

- CG exhibits a wide range of generation capacities, spanning from 100 MW to 1000 GW [55], whereas DG typically operates within the range of up to 300 MW [56].

b) Technology Utilized

- CG relies on technologies such as hydroelectric, thermoelectric, and nuclear power plants, whereas DG makes use of diverse sources like Diesel engines, Gas engines, and RES [57].

c) Location

- CG facilities are typically located at a distance from consumers, often situated in regions abundant in either non-renewable or renewable resources [58]. In contrast, DG systems are positioned in close proximity to consumer facilities [56].

d) Generation to Distribution

- CG employs step-up transformers for high voltage transmission to substations. From there, step-down transformers facilitate distribution to end-users, effectively minimizing line power losses [59]. DG, on the other hand, may or may not be connected to the grid, making it suitable for low voltage distribution systems [55, 60].

2.2 Employed Strategies for DG Planning

The optimization of DG allocation and size selection in power system networks has been propelled by various factors. These considerations for DG planning encompass technological, economic, and environmental perspectives.

2.2.1 Technological Aspect

DG offers substantial technical advantages, including enhancements in voltage profile, minimization of active and reactive power losses, power factor optimization (PFO), reduction of line losses, and maximization of network MVA capacity. The diverse research endeavors focused on these technological advantages are summarized below:

- *Voltage Profile Enhancement*

Voltage profile enhancement (VPE) stands as a pivotal parameter for ensuring power quality in the distribution system. The penetration level of DG is augmented during optimized allocation in the distribution network to elevate the voltage level. With the presence of DG, VPE is selected as an objective function, yielding significant results by enabling bidirectional power flow to and from the power grid during peak and off-peak load hours [48]. Voltage stability is improved by utilizing the incremental voltage (dv/dp) sensitivities method during DG integration [49]. Additionally, voltage profile and stability are enhanced through techniques such as positive sequence voltage ratio [50], power voltage curve [51], and voltage sensitivity index [52]. The issue of voltage sag is mitigated in low voltage distribution networks during various faults [53]. The relationship between voltage amplitude and injected power is considered to facilitate both VPE and power loss reduction (PLR) [54]. In the Tehran electricity distribution grid [55, 56] and radial distribution networks [57], optimization using the max operator has been employed for this purpose. Authors have proposed a voltage stability index to elevate the voltage level through DG allocation [58]. Incorporating P-V buses [59] and multiple micro turbines [60] has also been shown to improve voltage profiles in distribution networks with renewable energy-based optimized DG allocations. Voltage rise challenges are addressed through DG integration to meet power demands during both time-variant and invariant loads [61].

- *Minimization of Power Losses*

Integrating and strategically allocating DG within the distribution network offers a means to significantly reduce various forms of power losses. This encompasses diminishing network, reactive power, and line loading losses through the optimal sizing and placement of DG within a meshed network [62], and concentrating on load at specific buses [63]. Active and reactive VA injection at selected buses plays a role in reducing total energy losses [52, 53]. In Thailand's voltage distribution system, real-time solar radiation and atmospheric temperature considerations are factored in to reduce real power losses while adhering to power quality constraints [58]. Utilizing a Solar Photovoltaic (SPV) system takes into account voltage limits, effectively reducing power losses [64]. For power injection, selecting a DG size ranging from 10-80% of the system load demand proves effective in reducing actual power losses [65]. Additionally, integration of multiple distributed generation (MDG) systems through continuous and discrete optimization leads to a decrease in actual power losses [66]. ECIM, influenced by power quality parameters, aids in reducing transmission line losses [67]. Wind power generation contributes to both real power injection and reactive power compensation, thereby further minimizing power losses [49]. The computation of approximate losses for each bus, along with compensating the real component of branch currents, results in reduced total power losses [68, 69]. A metaheuristic optimization approach (MHOA) is employed to achieve the minimization of real power losses [70]. This approach also extends to hourly power flow with varying penetration levels in different operational modes of wind turbines [71]. Annual energy losses are curtailed through considerations of the load curve's time-varying characteristics [72], the stochastic behavior of wind speed [73], and the intermittent nature of RES [74], accounting for both avoiding and allowing RPF [75, 76].

- *Optimization of Power Factor*

Optimizing the power factor is another crucial facet of power quality parameter enhancement in the presence of DG. To reduce real power losses, authors undertake the optimization of power factor values, taking into account maximum and minimum operating power factor values, while accommodating inequality boundary conditions and addressing practical and rounding-off concerns [70]. The simultaneous optimization of DG size and power factor is achieved by assuming a predetermined constant power factor value across various load levels [72]. Energy losses are further minimized by optimizing the power factor in a Battery Energy Storage (BES) integrated SPV system across different load levels, with comparisons demonstrated at Unity Power Factor (UPF), lagging power factor, and leading power factor conditions [77]. The impact of power factor variation is illustrated in terms of its effect on power losses and voltage profile, distinguishing between UPF and non-UPF system states [78]. The optimal power factor value is identified by exploring all possible power factor values using curve-fitting techniques and exact solution methods [65]. Additionally, a comparative analysis is presented in [52], comparing UPF with a 0.9 lagging power factor using different DG optimization approaches.

- *Reduction of Total Harmonic Distortion*

Minimizing Total Harmonic Distortion (THD) is a key objective in DG planning. The forward/backward sweep approach is utilized to optimize THD in a distributed system, which includes a combination of passive elements and a harmonic current generator. Furthermore, a harmonic spectrum is developed for a nonlinear (NL) load driven by a deviated frequency driver and a convertible speed driver, with branch current as a function of harmonic current [74]. THD optimization is also carried out in an SPV-based DG system, accounting for various solar radiation levels. THD levels in both voltage and current profiles are measured, considering the background harmonics in an 11-kW grid-connected inverter [58].

2.2.2 Economic Aspect

Cost optimization (COP) forms the bedrock for the planning, implementation, and maintenance of DG in a distribution system. The total cost, comprising installation, maintenance, and sag reduction costs, has been notably reduced through optimal DG allocation, yielding significant results [53]. The minimization of costs for distribution companies (DisCos), coupled with profit maximization, is demonstrated using BLA for DG planning in reference [79]. Reference [80] takes into account the capital cost of DG along with state-dependent costs, while the integration of DG in Japan's East Power Station has successfully reduced fuel costs (considering utilization factors) [81]. Reimbursement time and anticipated profit rates are calculated by formulating a multi-objective (MO) DG optimization that takes into consideration the benefits of both DisCos and owners [82].

2.2.3 Environmental Aspect

Environmental protection stands as a critical facet of human existence on Earth, given the extensive use of fossil fuels in traditional power systems to meet peak demand for end-users. DG presents itself as a potential solution for incorporating natural energy sources into the power system, effectively reducing emissions of greenhouse gases and mitigating climate change [83]. DG holds substantial promise for leveraging RES in power generation and has the capacity to establish a low-carbon emission grid. The assessment of carbon emissions considers the complete life cycle of DG and employs a carbon emission intensity factor. This methodology has resulted in a reduction of up to 1.8 million tons of CO2 emissions [84].

2.3 Optimization Approaches

Optimization approaches can be categorized into the following classification; conventional, modern mathematical, and hybrid.

2.3.1 Conventional Approaches

Conventional optimization approaches encompass traditional, foundational search methods for optimizing the DG allocation. Several researchers have implemented proposed techniques falling within this category. The classification of conventional algorithms is depicted in Figure 2.1 Furthermore, a comprehensive review and data-based assessment of such approaches for DG optimization are presented in Table 2.1.

- *Analytical Method (AM)*

This section reviews various Analytical Methods (AM) used for optimizing DG allocation within a distribution network. One approach involves reducing total power losses through an Equivalent Current Injection Method. This method applies the BIBC matrix and BCBV to determine the value of the injected current. It has been tested on three distribution systems, without considering the admittance matrix and Jacobian matrix [67, 85]. Another technique, the Exact Loss Formula (ELF), is employed for DG optimization. This method is independent of DG type and capable of generating active power and reactive VA [68]. To minimize energy losses in a three-phase unbalanced system, a Feasible Optimization Interval (FOI) approach is utilized. This approach bridges the gap between feeder demand characteristics and the characteristics of SPV-based DG [75]. DG optimization is also achieved through the Power Injection Method (PIM) in dispatchable or non-dispatchable systems, while considering the time-varying nature of load and supply [72]. The FOI technique is further implemented, taking into account RPF and injecting power at coupling nodes. This is followed by the calculation of line losses using Carson equations [78].

The Algebraic Approach (AA) is applied for VPE while in [50], an Iterative Method (IM) is employed to improve power quality parameters and line loadability. Additionally, analytical techniques such as the Primal-Dual Interior-Point Algorithm (MPDIPA) [54], AA [86], Multi-Objective Index (IMO) with Self-Correction Algorithm (SCA) [77], and Heuristic Curve Fitted Method (HCFM) [65] are analyzed for DG optimization. The subsequent utilization of an IA aids in determining the optimal size and location of DG, enhancing the reliability and voltage profile of a distribution network. This approach is evaluated on the IEEE 34 bus system, yielding significant results across various indices [87].

Fig. 2.1: Conventional approaches of DG optimization

- *Exhaustive Search (ES)*

In reference [88], the Brute Force Method (BFM) is employed to integrate the SPV system. This is accomplished using MATLAB programming while taking into account daily load and supply curves, and adhering to the European standard on power quality (EN 50160 standards). The approach employed is similar to the Backward/Forward Sweep Algorithm, which encompasses the large R/X ratio of long feeders by assuming the π model of a distributed system. The DG optimization is a two-stage technique, contingent on supply and load variations. The first stage involves ES, while the second stage utilizes a Clustering Approach (CA) [89]. Power quality parameters are enhanced through the utilization of the Probabilistic Approach (PA) [58] and Weighted ES [90] for optimal DG allocation. Additionally, Monte Carlo simulation and C language are utilized. A Newton-Raphson (N-R) method, in conjunction with IM, is employed for MO optimization to improve cost-effective power quality parameters [77].

- *Linear Programming (LP)*

The utilization of the distribution network undergoes a transformation following the integration of DG. The authors present a methodology for optimizing DG allocation to maximize energy harvesting, considering various power quality and financial constraints. Energy harvesting depends on factors such as DG size, load level, DG location, incurred losses, and financial parameters. Furthermore, limitations arising from financial concerns are addressed by implementing an IM for solving the linear optimization problem [91]. This methodology holds significance in validating the results obtained from nature-inspired optimization techniques. The authors evaluate a genetic algorithm technique for DG allocation in the actual distribution network of Egypt, and the outcomes are validated using LP. Moreover, MO optimization is conducted to optimize various power quality parameters such as LLR, SRI, VPE, and PFR [92].

- *Non-Linear Programming (NLP)*

The integration of DG into the distribution network provides an opportunity for adaptive reactive power compensation, thereby enhancing power quality. In this regard, the authors have introduced an NLP-based DG optimization technique to address the MO function. This technique consolidates various objective functions into a single entity, with a primary focus on reducing power losses and enhancing voltage regulation. Notably, this optimization technique is versatile and can be applied to different types of DGs. It achieves this through the utilization of fuzzification techniques and an appropriate weighting scale, which facilitates a unified approach for a variety of objective functions. The optimization process is executed with the assistance of Constraint Optimization (CONOPT), a component of the General Algebraic Modeling System (GAMS) software, which is specifically designed for continuous power flow simulations [93].

- *Mixed-Integer Linear Programming (MILP)*

In a study by [79], a two-tier approach that encourages collaboration between DisCo and DG owners has been implemented. This bi-level MILP approach involves an upper level that addresses DG placement and the central point of power injection. The lower level focuses on minimizing DisCo payments to the energy market. The decision-making process aims to strike a balance between profit maximization for the owner and payment minimization for DisCo.

- *Mixed-Integer Non-Linear Programming (MINLP)*

MINLP optimization techniques have found application in various research endeavors [51, 94], influencing DisCo investment planning regarding transformer acquisitions and feeder upgrades. A pool market model incorporating Lagrangian multipliers (LM) and line loss sensitivity, considering both equality and inequality constraints, is optimized using GAMS with a Sparse Nonlinear Optimizer solver. This optimization addresses the profit of generation companies and DisCo. Beta and Weibull probability distribution functions are employed to evaluate the probabilistic characteristics of natural sources for DG optimization [51].

- *Dynamic Programming (DP)*

The future-oriented integration of renewable energy-based DG in distributed generation presents a novel aspect of energy generation. To overcome limitations associated with natural sources, a network reconfiguration strategy has been proposed. A Markov decision process is adopted to optimize DG operation, enhancing power quality parameters while considering present and future costs in each step of the Markov model. Dynamic programming is subsequently employed to optimize the proposed recursive model, with evaluations conducted on IEEE 33 and IEEE 123 test systems [95].

- *Optimal Power Flow (OPF)*

Researchers have explored the utilization of the OPF technique for DG allocation [96-100]. The methodology involves employing CONOPT with a generalized gradient method to determine network generation capacities. In highly meshed, reliable systems, NL optimization is used to maximize generation capacities by identifying multiple local optima. The approach begins with no contingencies in the problem formulation, followed by the incorporation of contingencies without constraints and the inclusion of the most violated constraints. Additionally, Fault Level Constraint Optimal Power Flow (FLCOPF) is considered in [96, 97], addressing the sinks source concept and capacity expansion locations (CELs) for profit maximization. Local marginal price, short-run marginal price, and Lagrangian multipliers are incorporated for social welfare and profit maximization [98]. Further extensions include quadratic curves of benefit, bid, and cost, and the consideration of various parties, including DISCOs, sellers, and DG owners, in a two-block (inner and outer) approach for profit maximization. OPF techniques have been employed with genetic algorithms for variable numbers of DG [99] and as ordinal optimization (OO) for a three-level approach [100], where one of all possible solutions outside the search space is within the top α percent with a probability level of P.

- *Load Concentration (LC)*

In reference [63], the Kalman filter algorithm is employed for optimizing DG allocation. This algorithm offers noise rejection and smoothing properties, aiding in solving linear time-varying equations. The process involves initial loss calculation through the N-R method, followed by state vector estimation in the measurement update and time update stages, evaluated through root mean square error calculations. In [101], the concept of equivalent load is applied, utilizing a two-step approach involving Load Centroid (LCn) and Performance Index. The process entails calculating the equivalent load and subsequently using PI to assess active power loss and average node voltage variation.

- *Continuous Power Flow (CPF)*

Incorporating continuous power flow (CPF) into the system enables the identification of the most sensitive buses with respect to continuation parameters and a two-level iterative approach (IA). These sensitive buses are crucial for determining the optimal DG placement, particularly as the system approaches a bifurcation point from a stable point. A CPF-optimized system can serve as a compensator or a significant source for DG units [102].

2.3.2 Modern Mathematical Approaches:

Modern mathematical techniques primarily encompass artificial intelligence methodologies that draw inspiration from the behavior observed in society and nature. These approaches can be specifically categorized, as illustrated in Figure 2.2. Table 2.2 offers an evaluation of advanced mathematical techniques for DG optimization and demonstrates the optimized results (outcomes that have been improved through a process of optimal DG allocation).

Table 2.1 Data-based assessment of DG optimization by adopted conventional approaches

Ref.	Conventional optimization method	Test systems	Different cases	Optimal DG size	Optimal DG location	Strengthened parameters	Compared approaches
[48]	AA	48 km feeder	Vref = 0.94 (p.u.)	144.7 (kVA)	46.8 km	VPE	WoDG
			Vref = 0.95 (p.u.)	292.2 (kVA)	44.8 km		
			Vref = 0.96 (p.u.)	458.3 (kVA)	42.6 km		
			Vref = 0.97 (p.u.)	650 (kVA)	40.1 km		
[50]	IA	IEEE 34	Itr. -1	600 (kVA)	890	PLR, LLC, VPE,	VSIM
			Itr. -2	600 (kVA)	852		
			Itr. -3	1200 (kVA)	814		
[51]	MINLP	IEEE 41	Dispatchable system (0.95 LePF)	4.5 (MVA)	40	VPE	WoDG
			WTDG (0.95 LePF, UPF)	8.8, 1.1 (MVA)	19, 40		
			SPV (0.95 LePF, UPF)	49.7, 1.06, 2.38 (MVA)	19, 28, 40		
[52]	MNM	IEEE 33	UPF	2494.8 (kVA)	6	COP, PLR, VPE	WoDG
		IEEE 69		1832.53 (kVA)	61		
	CPLSM	IEEE 33	UPF	1800 (kVA)	8		
		IEEE 69		1850 (kVA)	61		
	IVM	IEEE 33	UPF	1550 (kVA)	30		
		IEEE 69		1850 (kVA)	61		
	VSIM	IEEE 33	UPF	1000 (kVA)	16		
		IEEE 69		1450 (kVA)	65		
[54]	MPDIPA	IEEE 123	ΣDG =4	65.37,34.75, 12.17, 31.43 (kW)	60, 36, 57,42	PLR, VPE	WoDG
[58]	PA	IEEE 51	SPV ΣDG = 1	0.8 (MW)	38	PLR, VPE, THDR	AM
			SPV ΣDG = 2	0.7, 0.9 (MW)	38,19		
			SPV ΣDG = 2 with THD	0.7, 0.5 (MW)	38, 19		
[65]	HCFM	IEEE 69	UPF	1900 (kVA)	61	PFO, PLR, VPE	AM
			0.85 LaPF	2300 (kVA)	61		
		IEEE 32	0.85 LaPF	2000 (kVA)	29		
[67]	ECIM	IEEE 12	ΣDG=1	0.2272 (MW)	9	PLR	Classical grid search Method
		IEEE 34	ΣDG=1	2.8848 (MW)	21		
		IEEE 69	ΣDG=1	1.8078 (MW)	61		
[68]	ELF	IEEE 30	ΣDG=1	3.3 (MW)	12	PLR	Loss sensitivity, Repeated load flow
		IEEE 33	ΣDG=1	2.49 (MW)	6		
		IEEE 69	ΣDG=1	1.81 (MW)	61		
[72]	PIM	IEEE 69	BΣDG = 2	0.89, 1.05 (MVA)	62,35	ELR, PFO	WoDG
			WTΣDG= 2	0.86, 0.99 (MVA)	62,35		
			WTBΣDG =4	0.49, 0.56, 0.71, 0.82 (MVA)	62, 35, 62, 35		
[75]	FOI	IEEE 29	SPV ΣDG = 1	0.2905 (MW)	17	PLR, VPE	WoDG

Table 2.1 *(continued)*

Ref.	Conventional optimization method	Test systems	Different cases	Optimal DG size	Optimal DG location	Strengthened parameters	Compared approaches
[76]	FOI	IEEE 29	ΣDG =1 (ALRPF)	340.4 (kW)	26	PLR, VPE	AVRPF
			ΣDG=1 (AVRPF)	290.5 (kW)	17		
		IEEE 14	ΣDG =1 (ALRPF)	803.1 (kW)	9		
			ΣDG=1 (AVRPF)	601.7 (kW)	7		
[77]	IMO & SCA	IEEE 33	SPV + BES at UPF	4.336 (MW)+ 1.803 (MW)	12, 20, 24	PFO, PLR, VPE	Standard IEEE 1547
			SPV + BES at LaPF	4.336 (MW)+ 1.804 (MW)	12, 20, 24		
[79]	BLA	IEEE 34	HL	1.5 (MW)	21	COP	WoDG
			ML	1.5 (MW)	24		
			LL	1.5 (MW)	21		
[85]	BIBC, BCBV	IEEE 33	Injecting P only	0.981, 0.981, 0.981, 0.325 (MW)	12, 30, 24, 5	PFO, PLR, VPE	Repeated power flow
			Injecting P & Q	1.16, 1.14, 1.13, 0.29 (MW)	30, 11, 24, 31		
		IEEE 69	Injecting P only	1.01, 0.797, 0.511, 0.318 (MW)	61, 62, 17, 50		
			Injecting P & Q	1.23, 0.99, 0.61, 0.88 (MW)	61, 62, 17, 15		
[86]	AM	IEEE 30	ΣDG =1	15 (MW)	5	PLR	WoDG
[87]	IA	IEEE 33	ΣDG = 2	2.7, 0.39 (MW)	6, 30	VPE, PLR	FFM, CS
[88]	BFM	IEEE 30	ΣDG =1	1 (MW)	9	PLR	Heuristic search
[89]	CA & ES	24 Node	ΣDG = 5	40, 100, 15, 100, 400 (kW)	4, 7, 9, 11, 13	COP, PLR, VPE	GA, MINLP
[90]	ES	IEEE 6	ΣDG= 2	3.4, 0.85 (MW)	3, 5	PLR, VPE	WoDG
		IEEE 14	ΣDG=2	25.9, 25.9 (MW)	10, 14		
		IEEE 30	ΣDG = 7	16.194, 8.097, 10.796, 8.097, 5.398, 2.699, 5.398 (MW)	17, 18, 20, 24, 26, 27, 30		
[91]	LP	IEEE 7	BΣDG = 1	8 (MW)	7	COP, PLR, VPE	WoDG
			ΣDG = 1 (LFG)	650 (kW)	3		
			HΣDG = 1, 2, 3	2, 1.5, 0.6 (MW)	2, 3, 2		
			WTGn = 1, 2, 3	4.5, 8.5, 9.4 (MW)	7, 2, 6		
[96]	OPF	IEEE 12	FLCOPF (NPr)	1.8, 30.7, 14.3 (MVA)	1, 10, 11	COP, PLR	IM
			Direct FLCOPF (NPr)	0, 30.9, 17.6 (MVA)	1, 10, 11		
			FLCOPF (CEL-1)	2.6, 30.7, 11.7 (MVA)	1, 10, 11		
			Direct FLCOPF (CEL-1)	20.7, 2.3, 17.7 (MVA)	1, 10, 11		
[97]	FLCOPF	IEEE 12	OPF (NPr)	12.3, 52.3, 38.2 (MVA)	1, 10, 11	COP, PLR	OPF
			FLCOPF (NPr)	13.6, 49.1, 38.4 (MVA)	1, 10, 11		
			OPF (@ bus 1)	34.9, 52, 11.6 (MVA)	1, 10, 11		
			FLCOPF (@ bus 1)	35.9, 48.8, 12.2 (MVA)	1, 10, 11		

Table 2.1 *(continued)*

Ref.	Conventional optimization method	Test systems	Different cases	Optimal DG size	Optimal DG location	Strengthened parameters	Compared approaches
[98]	OPF	IEEE 14	ΣDG = 1	202.62 (MW)	4	COP, PLR	WoDG
			ΣDG = 2	195.05 (MW)	4		
			ΣDG = 3	141.28 (MW)	9		
			ΣDG = 4	41.94 (MW)	14		
			ΣDG = 5	50.38 (MW)	14		
			ΣDG = 6	42.84 (MW)	14		
			ΣDG = 7	25.33 (MW)	14		
[100]	OPF	IEEE 69	ΣDG = 3 (P=99%, α=0.1)	2.6614 (MW)	26, 35, 62	COP, PLR	WODG
			ΣDG = 5 (P=99%, α=0.1)	3.9761 (MW)	4, 26, 40, 49, 62		
			ΣDG = 7 (P=99%, α=0.1)	5.5305 (MW)	4, 26, 30, 35, 40, 49, 65		
			ΣDG = 9 (P=99%, α=0.1)	6.0027 (MW)	4, 13, 17, 26, 30, 40, 49, 58, 52		
			ΣDG = 3 (P=99.999 %, α=0.01)	2.6614 (MW)	26, 35, 62		
			ΣDG = 5 (P=99.999 %, α=0.01)	4.0069 (MW)	4, 26, 40, 49, 62		
			ΣDG = 7 (P=99.999 %, α=0.01)	5.5305 (MW)	4, 26, 30, 35, 40, 49, 65		
			ΣDG = 9 (P=99.999 %, α=0.01)	6.0027 (MW)	4, 13, 17, 26, 30, 40, 49, 58, 52		
[101]	LC	IEEE 13	LCn @ 5	2, 1 (MW)	5, 11	PLR, VPE	Heuristic search
		IEEE 25	LCn @ 12	2, 2, 2, 0.5(MW)	12, 15, 14, 7		
			LCn @ 17	2, 1.5 (MW)	17, 22		
		IEEE 30	LCn @ 2	50, 50, 50, 10(MW)	2, 9, 6, 28, 13		
[102]	CPF	IEEE 34	ΣDG = 1	25 (MW) and 20 (MVA)r	26	PLR, LLC, VPE	WoDG
			ΣDG = 2	25 (MW) and 20 (MVA)r	26, 33		
			ΣDG = 3	25 (MW) and 20 (MVA)r	26, 33, 17		
[133]	N-R & IS	IEEE 6	ΣDG=1	6 (MW)	3	COP, PLR, VPE	AA
		IEEE 14	ΣDG=1	16 (MW)	8		
		IEEE 30	ΣDG=1	35 (MW)	11		

- *Evolutionary Programming (EP)*

Evolutionary Programming (EP) is a well-established artificial intelligence optimization algorithm inspired by natural processes involving metamorphosis, competition, and evolution. It stands out for its proficiency in handling non-continuous, irregular, and nondistinct optimization problems, setting it apart from conventional methods. In a study focused on reactive power planning, EP was employed with a probability transition rule [103]. The procedure involved key stages: initialization, statistics, mutation, completion, and determination. The authors demonstrated the effectiveness of EP on a 12.66 kV IEEE 69 test system, considering two modes of operation: one involving the deactivation of a DG based on a wind turbine (WTDG), and the other entailing clipping of the output through an index-based scheme. Sensitivity analysis was conducted while maintaining the ratio of dispatched wind energy to load (WPDLR) within specified limits [71].

- *Genetic Algorithm (GA)*

Genetic Algorithm (GA), a part of the broader EP class, has found extensive application in evaluating optimal DG allocations within power systems [104]. It stands out by emulating natural selection processes, incorporating steps such as mutation, crossover, and selection to achieve superior optimization outcomes. GA has been deployed in various scenarios, such as NL optimization within a Tehran regional electricity company, focusing on financial objectives including the pricing of power connectors and unprovided energy by the system [57]. Additionally, it has been employed in linear problem optimization to enhance power quality parameters in the West Delta sub-transmission network [92]. The approach involves minimizing the voltage sag effect, calculated using the voltage divider rule, while simultaneously minimizing line losses and achieving cost savings, all within the constraints of power flow and voltage levels. Stochastic optimization techniques were used to determine the optimal size of DG, with consideration given to the point of common coupling during different fault conditions [53]. The study considered various load models in the optimization results, accounting for the source as a negative sink and incorporating index-based performance evaluation [105]. GA has been integrated with OPF [99] and AM [59] for DG optimization. In another study [106], a step-by-step approach was employed to optimize the size and location of DG in main and sub-network distribution systems. This was done using a single-step restoration strategy, supplied by utility-owned DG, to address power outage issues stemming from cold load pick-up conditions. Additionally, a non-dominated sorting GA (NSGA) and forward/backward sweep method were applied in [74] to allocate renewable DG and non-renewable DG (NRDG) and select their sizes. Zonal division of peak load [107], moment method, and central limit theorem [108] were incorporated into DG planning to optimize cost, power quality parameters, and reliability. Furthermore, SPV and WTDG were characterized as DG sources in a study focused on optimizing Weibull reliability and maintenance costs, ultimately minimizing the annual operating cost (AOC).

- *Tabu Search (TS)*

Introduced in 1986, Tabu Search (TS) operates on the principle of prohibiting moves that would lead to cycling, resulting in a powerful search method with a memory mechanism. This approach involves saving tabu information from bottom to top in a tabu list. In the context of DG placement optimization, TS employs three simultaneous algorithms targeting residential, commercial, and industrial loads. These algorithms encompass rounding calculations, local minimum identification, and optimal installation processes [109]. The TS procedure consists of stages such as initialization, finding neighborhood solutions, calculating losses, iterations, and updating the current solution until a maximum iteration limit is reached to achieve optimization. If a neighborhood solution proves superior to the current set of values, it is adopted, satisfying the aspiration outlined in the tabu list. The authors propose a methodology that optimizes both DG resources and reactive power resources, involving short-term, intermediate-term (keeping the best solution to date), and long-term memory (considering more than three successive iterations). This methodology incorporates controlled output (CO) and Z scenarios [110]. In this work, a forbidden move, which entails adding a new move while removing an old one, results in an updated solution in the next iteration of the tabu list. The length of the tabu list is directly proportional to the improved solution.

- *Harmony Search (HS)*

The Harmony Search (HS) heuristic technique, introduced by Geem et al., draws inspiration from the process of musical improvisation to find the optimal condition, akin to a musician's artistic judgment. Musicologist Tirro and French composer Jean Philippe Rameau contributed to the foundation of this technique, drawing from the classical method of harmony applied to the Traveling Salesman Problem (TSP) [111]. An improved multi-objective harmony search (IMOHS) is proposed for optimizing DG placement, offering a qualitative comparison with NSGA II. IMOHS incorporates a search process using a novel global HS, which incorporates mutation probability and excludes the harmony memory considering rate parameters. The technique primarily involves two steps: domination rank and crowding distance. When comparing two harmonies, if one harmony dominates the other, the non-dominated harmony is stored in the harmony memory, while the dominated harmony is not discarded and is given a second chance for improvisation [112].

- *Simulated Annealing (SA)*

In 1983, Kirkpatrick et al. researched the Simulated Annealing (SA) optimization technique, which consists of four steps: concise configuration, random selection, determining function, and annealing process schedule. The authors demonstrated five DG applications to extract various benefits of DG allocation in the distribution network using simulated annealing optimization technique. Load flow analysis is employed to calculate voltage drops and power losses using a multi-objective function. This technique is evaluated on the IEEE 33 test system, concluding that increased penetration of renewable energy is viable in a radial power system. The results showcase the optimal size and location of DG considering the number of DG units [113].

- *Imperialist Competitive Method (ICM)*

In references [114-117], an optimization technique based on the concept of imperialism and the competition among empires is implemented. The colonies approach their imperialist, and the cost of each empire is calculated to determine the exchange of positions from weaker to stronger empires, ultimately resulting in the existence of a single optimized value for DG. Subsequently, the profit of distribution network operators is maximized and applied in the UK under Ofgen. This includes considerations for power flow constraints, operating limits, voltage profiles, feeder capacities, and the number of DG steps, with crossover and mutation probability functions programmed in MATLAB [116]. In [117], losses are computed using the load flow technique, employing KVL and KCL to measure upstream voltage, resulting in complex power measurements. The ICM is then applied for DG optimization in a zonal distribution network using islanding operation for sensitive loads.

- *Ant Colony Optimization (ACO)*

Ant Colony Optimization (ACO) is characterized by several distinct stages, including initialization, cost function calculation, constraint assignment, feasible state selection, and neighborhood structure. It also possesses properties such as search behavior, memory storage, feasible neighborhood definition, termination conditions, probabilistic decision-making, ant routing table, and pheromone update. ACO is implemented to restructure the distribution network framework with the goal of minimizing power losses. ACO demonstrates the ability to avoid premature convergence and being trapped in local optima. The technique is tested and applied to the IEEE 33 bus system, yielding significant results in reducing power losses compared to a non-restructured distribution network. Additionally, the convergence time indicates faster solution convergence using this technique. Furthermore, network losses are reduced from 140 kW to 110 kW by reconfiguring DG in the distribution system [118].

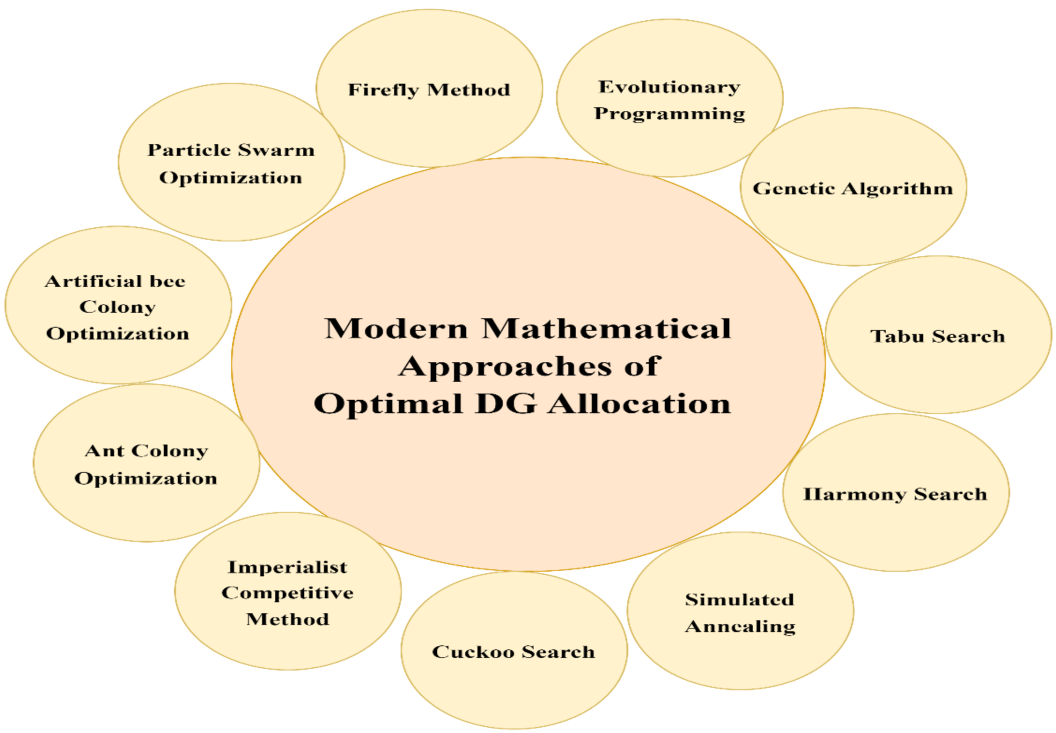

Fig.2.2: Modern mathematical approaches of DG optimization

- *Artificial Bee Colony (ABC)*

Karboga introduced an optimization technique based on the collective behavior of honey bees, consisting of three main components: food source, searchers, and non-searchers. These components exhibit self-organizational behavior through alternate feedback, random search, and information sharing. A bi-level approach employing the ABC optimization technique is applied to the IEEE 33 system for DG allocation. The process involves locating the DG followed by optimizing its size in four different cases to obtain possible outcomes with reduced computation time [119]. Additionally, indexes are incorporated into the ABC optimization to enhance power quality parameters. The authors also address the reformation of industrial and commercial processes by including the distribution loss index in the objective function, considering its high prevalence in Iran [120].

- *Particle Swarm Optimization (PSO)*

In 1995, Kennedy et al. investigated the PSO technique, which is another optimization approach inspired by social behavior simulations, connecting artificial life to bird flocking, fish schooling, and swarming behavior. PSO utilizes basic mathematical operators with minimal memory space and high speed. The technique involves concepts like velocity matching, craziness, cornfield vector, auxiliary variable removal, multidimensional search, and distance acceleration, resulting in improved versions. PSO is rooted in social concepts and swarm intelligence principles such as proximity, quality, diverse response, stability, and adaptability. The authors also delve into various modified versions of PSO, including multi-objective PSO (MPSO), constraint handling PSO, stretching PSO, cooperative PSO, comprehensive learning PSO, and hybrid PSO. These versions, such as Tribal PSO (TPSO) with OO [37], constriction factor PSO [78], and MPSO [82, 121], are applied to optimize renewable source-based DG. Additionally, MPSO is employed to optimize power quality parameters while considering constraints like expected rate of return (ERR), yielding results in terms of the total loss power index (TLPI). The optimization process involves the use of synchronous compensators, synchronous generators, and synchronous-based DG units [122]. Continuous and discrete optimization using the N-R method is integrated for DG optimization and penalty factor calculation [66].

- *Cuckoo Search (CS)*

Researchers Yang et al. proposed an optimization technique based on the communal behavior of a cuckoo bird, combined with Levy flight behavior to achieve improved results. CS involves three steps: cuckoo breeding behavior, Levy flight, and search. In this process, a cuckoo bird randomly searches for a nest, places its egg, and if the host bird deems the egg unfit for the nest, it will reject the cuckoo's egg. CS is applied to optimize renewable energy-based DG to attain technical, financial, and societal advantages. Tests are conducted on IEEE 22 and IEEE 69 bus systems, considering mono, dual, and multi-DG injections. The proposed technology's results are effectively compared with the established PSO technique [123]. The authors recommend CS for optimizing the objective function, which includes improved voltage profiles and reduced power losses with different weightage factors: (WL), (WV1), and (WV2) [124]. Additionally, the evaluation of indices based on voltage is emphasized for power quality. The outcomes are significant and compared with well-established GA and PSO.

- *Firefly Method (FFM)*

The Firefly Method (FFM) draws inspiration from the illuminating behavior of fireflies, operating on three fundamental assumptions: all fireflies are of the same type and emit light signals to attract others, the strength of attraction is directly proportional to the brightness of the light, and a firefly will move towards a brighter one. In the absence of a brighter light source, a firefly will take a random step in the search space. A modified version of FFM is applied to DG allocation for both active and reactive power compensation, in conjunction with shunt capacitors. The FFM optimization technique addresses four different compensation scenarios in the distribution

Table 2.2 Data-based assessment of DG optimization by adopted modern mathematical approaches

Ref.	Modern mathematical optimization method	Test systems	Different Cases	Optimal DG sizes	Optimal DG locations	Strengthened Parameters	Optimized Results	Compared Approaches
[49]	DE	IEEE 6	ΣDG = 2	0.48995, 0.63858 (p.u.)	3, 6	PLR, VPE	0.020545 p.u.	Base Care WoDG, BBPSO, MMNRES
		IEEE 30	ΣDG = 6	0.16362, 0.11973, 0.21795, 0.20327, 0.013192, 0.29578 (p.u.)	16, 18, 19, 23, 25, 27		0.088605 p.u.	
[53]	GA	IEEE 34	ΣDG = 4	500 (kW) each	20, 25, 8, 17	COP, PLR, VPE	102.76 (kW)	
		IEEE 30	ΣDG = 5	510 (kW) each	18, 11, 25, 21		104.6 (kW)	
[55]	GA	IEEE 13	V % Mean = 98.823	3200 (kW)	13	PLR, VPE	100.25 (kW)	
			V % Mean = 98.81	1600, 1600 (kW)	13, 9		92.9 (kW)	
[56]	GA	IEEE 13	V % Mean = 98.823	3200 (kW)	13	PLR, VPE	100.25 (kW)	
			V % Mean = 98.81	1600, 1600 (kW)	13, 9		92.9 (kW)	
[61]	GA	IEEE 12	ΣDG = 1 (Tiv)	0.24 (MW)	9	COP, PLR, VPE	0.0046 (MW)	WoDG
			MDG (Tiv)	0.0755, 0.0484, 0.0676, 0.0594 (MW)	6, 8, 9, 10			
			ΣDG = 1 (Tv)	0.13 (MW)	9		0.0035 (MW)	
			MDG (Tv)	0.0401, 0.0601, 0.0401, 0.0267 (MW)	6, 8, 10, 12			
[62]	IHRA	IEEE 6	ΣDG =4	15 (MW)	2, 3, 4, 6	PLR	0.0498 (MW)	GA
		IEEE 14	ΣDG =4	26 (MW)			11.12%	
		IEEE 30	ΣDG = 4	28.3 (MW)			9.08%	
[66]	PSO	IEEE 69	ΣDG = 1	1904.2 (kW)	61	PLR	23.9 (kW)	SQP
			ΣDG = 2	1582, 322 (kW)	61, 21		13.6 (kW)	
			ΣDG = 3	1278, 301, 324 (kW)	61, 64, 21		12.8 (kW)	
[70]	ABC	IEEE 69	ΣDG=1 , load = 3802 (kW) + 2694 (kVA)r	2200 (kVA)	61	COP, PFO, PLR	23.9199 (kW)	GA, ELF
			ΣDG=1, load = 150 %	3400 (kVA)	61		54.7271 (kW)	
			MDG, load = 3802 (kW) + 2694 (kVA)r	2100, 600 (kVA)	61, 17		7.99901 (kW)	
			MDG, load = 150 %	3200, 900 (kVA)	61, 17		17.9966 (kW)	
			ΣDG=1 + capacitor (load = 100%)	2200 (kVA), 300 (kVA)r	61, 18		18.5512 (kW)	
			ΣDG=1 + capacitor load = 150 %)	3300 (kVA), 600 (kVA)r	61, 16		42.1286 (kW)	
			Active Power DG (load = 100 %)	1800 (kW) + 1350 (kVA)r	61		23.282 (kW)	
			Active Power DG (load = 150 %)	2700 (kW) + 1950 (kVA)r	61		53.2194 (kW)	
			DG size is fixed	1000 (kVA)	61		80.29 (kW)	

Table 2.2 *(continued)*

Ref.	Modern mathematical optimization method	Test systems	Different Cases	Optimal DG sizes	Optimal DG locations	Strengthened Parameters	Optimized Results	Compared Approaches
[71]	EP	IEEE 69	Wc, WPDLR = 0	0.25 (MW) each (1 SPV, 1 WTDG)	53	PLR, VPE	65.69 (MWh)	GA, ES
			Wc, WPDLR = 0.1	0.25 (MW) each (1 SPV, 1 WTDG)	51, 53		51.16 (MWh)	
			Wc, WPDLR = 0.2	0.25 (MW) each (1 SPV, 1 WTDG)	54, 50		44.81 (MWh)	
			Wc, WPDLR = 0.3	0.25 (MW) each (1 SPV, 1 WTDG)	53, 50		42.58 (MWh)	
			Wc, WPDLR = 0.4	0.25 (MW) each (1 SPV, 1 WTDG)	53, 50		42.17 (MWh)	
			Wt, WPDLR = 0	0.25 (MW) each (1 SPV, 1 WTDG)	53		65.69 (MWh)	
			Wt, WPDLR = 0.1	0.25 (MW) each (1 SPV, 1 WTDG)	53, 53		61.4 (MWh)	
			Wt, WPDLR = 0.2	0.25 (MW) each (1 SPV, 1 WTDG)	53, 53		56.04 (MWh)	
			Wt, WPDLR = 0.3	0.25 (MW) each (1 SPV, 1 WTDG)	54, 50		48.17 (MWh)	
			Wt, WPDLR = 0.4	0.25 (MW) each (1 SPV, 1 WTDG)	53, 50		43.79 (MWh)	
			Wc, WPDLR = 0	0.125 (MW) each (2 SPV, 2 WTDG)	53, 54		65.69 (MWh)	
			Wc, WPDLR = 0.1	0.125 (MW) each (2 SPV, 2 WTDG)	53, 54 and 51, 53		51.14 (MWh)	
			Wc, WPDLR = 0.2	0.125 (MW) each (2 SPV, 2 WTDG)	52, 54 and 50, 53		44.7 (MWh)	
			Wc, WPDLR = 0.3	0.125 (MW) each (2 SPV, 2 WTDG)	50, 53 and 50, 53		42.53 (MWh)	
			Wc, WPDLR = 0.4	0.125 (MW) each (2 SPV, 2 WTDG)	53, 54 and 50, 52		42.15 (MWh)	
			Wt, WPDLR = 0	0.125 (MW) each (2 SPV, 2 WTDG)	53, 54		65.69 (MWh)	
			Wt, WPDLR = 0.1	0.125 (MW) each (2 SPV, 2 WTDG)	54, 54 and 53, 53		58.43 (MWh)	
			Wt, WPDLR = 0.2	0.125 (MW) each (2 SPV, 2 WTDG)	52, 54 and 52, 53		48.64 (MWh)	
			Wt, WPDLR = 0.3	0.125 (MW) each (2 SPV, 2 WTDG)	53, 53 and 50, 51		44.27 (MWh)	
			Wt, WPDLR = 0.4	0.125 (MW) each (2 SPV, 2 WTDG)	51, 54 and 50, 53		42.59 (MWh)	
[74]	GA	IEEE 31	NRDG	1.5, 0.5, 1, 1.5, 1.5 (MW)	8,12,13,28,30	PLR, THDR	11960 (MWh)	WoDG
			NRDG + WTDG	1.5, 0.7, 1.4, 0.6, 0.6 (MW)	8,15,17,20,30		12784 (MWh)	
			NRDG + SPV	1.15, 0.3, 0.4, 0.85, 0.3 (MW)	12,13,15,17,31,		15410 (MWh)	
			NRDG + WTDG + SPV	0.3, 1.5, 1.4, 0.8, 1.5 (MW)	6,12,28,30,31		15121 (MWh)	

Table 2.2 *(continued)*

Ref.	Modern mathematical optimization method	Test systems	Different Cases	Optimal DG sizes	Optimal DG locations	Strengthened Parameters	Optimized Results	Compared Approaches
[78]	PSO	IEEE 16	ΣDG = 1	12.97 (MW)	9	COP, PFO, PLR, VPE	168.1 (kW)	IAM
			ΣDG = 2	12.97, 5.86 (MW)	9, 6		111.7 (kW)	
			ΣDG = 3	13.1, 5.897, 4.29 (MW)	9, 6, 16		76.4 (kW)	
			ΣDG = 1	2.591 (MW)	6		111.1 (kW)	
			ΣDG = 2	1.002, 1.0195 (MW)	12, 30		87.5 (kW)	
			ΣDG = 3	0.88, 1.0928, 1.0098 (MW)	13, 24, 30		73.2 (kW)	
			ΣDG = 1	1.8062 (MW)	61		78.6 (kW)	
			ΣDG = 2	1.8062, 0.511 (MW)	61, 17		67 (kW)	
			ΣDG = 3	1.8062, 0.511, 0.719 (MW)	61, 17, 50		65.5 (kW)	
[81]	ABC	IEEE 30	ΣDG = 1	200 (MW)	17	COP, PR		Without solar penetration
			ΣDG = 2	136, 97 (MW)	5, 23			
			ΣDG = 3	198, 127, 176 (MW)	14, 22, 23			
			ΣDG = 4	68, 109, 1193, 102 (MW)	11, 13, 26, 29			
[82]	PSO	IEEE 33	ERR = 15 %	1, 1, 0.9 (MW)	7, 33, 15	PLR, RI, SI VPE	TLPI = 0.1642 p.u.	WoDG
			ERR = 20 %	0.9, 0.9, 1 (MW)	6, 32, 14		TLPI = 0.1568 p.u.	
			ERR = 25 %	0.9, 0.9, 1 (MW)	6, 32, 14		TLPI = 0.1568 p.u.	
			ERR = 30 %	0.9, 0.9, 1 (MW)	6, 32, 14		TLPI = 0.1568 p.u.	
			ERR = 35 %	1, 1, 0.9 (MW)	6, 32, 13		TLPI = 0.1479 p.u.	
			ERR = 40 %	1, 1, 0.9 (MW)	7, 31, 13		TLPI = 0.14665 p.u.	
			ERR = 45 %	1, 1, 1 (MW)	6, 29, 12		TLPI = 0.162 p.u.	
			ERR = 50 %	1, 1, 1 (MW)	6, 29, 12		TLPI = 0.1635 p.u.	
[92]	GA	IEEE 52	GA (VPE = 24.4 %, SRI = 63.1 %)	0.3105 p.u.	50	LLR, SRI, VPE, PFR	PFR = 42.016 % , LLR = 81.5 %	LP
			LP (VPE = 24.26 %, SRI = 63.075 %)	0.3 p.u.	50		PFR = 42.709 % , LLR = 80.7 %	
[105]	GA	IEEE 13	CL	0.63 p.u.	7	PLR	0.0161 p.u.	WoDG
			IL	0.61 p.u.	8		0.0167 p.u.	
			RL	0.59 p.u.	8		0.0167 p.u.	
			CML	0.58 p.u.	8		0.0171 p.u.	
			MXL	0.62 p.u.	8		0.0168 p.u.	
		IEEE 37	CL	0.62 p.u.	14		0.001889 p.u.	
			IL	0.63 p.u.	25		0.00166 p.u.	
			RL	0.63 p.u.	25		0.001664 p.u.	
			CML	0.63 p.u.	25		0.001646 p.u.	
			MXL	0.63 p.u.	25		0.001663 p.u.	

Table 2.2 *(continued)*

Ref.	Modern mathematical optimization method	Test systems	Different Cases	Optimal DG sizes	Optimal DG locations	Strengthened Parameters	Optimized Results	Compared Approaches
[106]	GA	IEEE 33	ΣDG =2	700, 500 (kVA)	10, 31	QR, PLR	-	WoDG
[107]	GA	IEEE 39	MGT	500 (kW)	36	COP, RI	AOC = 141920 $ / year	WoDG
			MGT	1000 (kW)	19		AOC = 236520 $ / year	
[108]	GA	IEEE 97	WTΣDG-1	1 (MVA)	Any bus	COP, PR, RI	AOC = 15000 $ / (MVA)	WoDG
			WTΣDG-2	1.5 (MVA)	Any bus		AOC= 12750 $ / (MVA)	
			WTΣDG-3	2 (MVA)	Any bus		AOC= 10500 $ / (MVA)	
			SPV ΣDG-1	16 (MVA)	Any bus		AOC= 20500 $ / (MVA)	
			SPV ΣDG-2	18 (MVA)	Any bus		AOC= 18750 $ / (MVA)	
			SPV ΣDG-3	19 (MVA)	Any bus		AOC= 19625 $ / (MVA)	
[109]	TS	Model 1 (1 S/S, 4 Feeder and 28 Sections)	AL-1 (ΣDG=10)	4000 (kW)	-	PLR	1725 (kW)	SA
			AL-2 (ΣDG=10)	4000 (kW)			1823 (kW)	
			AL-3 (ΣDG=10)	4000 (kW)			1823 (kW)	
		Model 1 (1 S/S, 4 Feeder and 28 Sections)	AL-1 (ΣDG=20)	4000 (kW)			1211 (kW)	
			AL-2 (ΣDG=20)	4000 (kW)			1292 (kW)	
			AL-3 (ΣDG=20)	4000 (kW)			1299 (kW)	
		Model 2 (4 S/S, 6 Feeder and 78 Sections)	AL-2 (ΣDG=15)	13.7 (kW)			26554 (kW)	
			AL-3 (ΣDG=15)	13.7 (kW)			35250 (kW)	
		Model 2 (4 S/S, 6 Feeder and 78 Sections)	AL-2 (ΣDG=35)	14.9 (kW)			13044 (kW)	
			AL-3 (ΣDG=35)	14.9 (kW)			18647 (kW)	

Table 2.2 *(continued)*

Ref.	Modern mathematical optimization method	Test systems	Different Cases	Optimal DG sizes	Optimal DG locations	Strengthened Parameters	Optimized Results	Compared Approaches
[110]	TS	IEEE 33	UCO, SL0 = 3715 + j 2300 (kVA)	275, 325, 150, 100, 450 (kW)	8, 16, 24, 27, 32	COP, PLR, VPE	54.43 (kW)	
			S_L^{1} = 0.8 (3715 + j 2300) (kVA)	275, 325, 150, 100, 450 (kW)	8, 16, 24, 27, 32		22.87 (kW)	
			S_L^{2} = 0.6 (3715 + j 2300) (kVA)	275, 325, 150, 100, 450 (kW)	8, 16, 24, 27, 32		6.93 (kW)	
			S_L^{3}= 0.4 (3715 + j 2300) (kVA)	275, 325, 150, 100, 450 (kW)	8, 16, 24, 27, 32		5.47 (kW)	
			S_L^{4} = 0.2 (3715 + j 2300) (kVA)	275, 325, 150, 100, 450 (kW)	8, 16, 24, 27, 32		17.46 (kW)	
			CO, SL 0 = 3715 + j 2300 (kVA)	275, 400, 75, 50, 500 (kW)	8, 16, 24, 27, 32		50.32 (kW)	
			S_L^{1} = 0.8 (3715 + j 2300) (kVA)	275, 400, 75, 50, 500 (kW)	8, 16, 24, 27, 32		21.59 (kW)	
			S_L^{2} = 0.6 (3715 + j 2300) (kVA)	275, 400, 75, 50, 500 (kW)	8, 16, 24, 27, 32		7.88 (kW)	
			S_L^{3}= 0.4 (3715 + j 2300) (kVA)	275, 225, 75, 50, 325 (kW)	8, 16, 24, 27, 32		3.24 (kW)	
			S_L^{4} = 0.2 (3715 + j 2300) (kVA)	175, 75, 75, 50, 125 (kW)	8, 16, 24, 27, 32		0.67 (kW)	
			CO with 300 (kW), 300 (kVA)r Source, SL 0 = 3715 + j 2300 (kVA)	300, 300, 125, 275, 300 (kW)	8, 16, 24, 27, 32		53.1 (kW)	
			S_L^{1} = 0.8 (3715 + j 2300) (kVA)	300, 300, 125, 250, 300 (kW)	8, 16, 24, 27, 32		22.7 (kW)	
			S_L^{2} = 0.6 (3715 + j 2300) (kVA)	300, 300, 125, 250, 300 (kW)	8, 16, 24, 27, 32		6.83 (kW)	
			S_L^{3}= 0.4 (3715 + j 2300) (kVA)	200, 125, 125, 215, 75 (kW)	8, 16, 24, 27, 32		2.68 (kW)	
			S_L^{4} = 0.2 (3715 + j 2300) (kVA)	250, 225, 125, 250, 225 (kW)	8, 16, 24, 27, 32		0.8 (kW)	
[112]	HS	IEEE 33	Load = 3.72 (MW), 2.3 (MVA)r	0.9369, 0.6672, 1.0117 (MW)	6, 14, 24, 31	PLR, VPE	0.06783 p.u.	GA/ PSO, GA, PSO
		IEEE 69	Load = 3.8 (MW), 2.69 (MVA)r	1.4552, 0.4769, 0.3124 (MW)	61, 64, 21		0.0105 p.u.	
[115]	ICM	IEEE 33	ΣDG =1	200 (kW)	-	PLR	201.38 (kW)	GA
		IEEE 69	ΣDG =1	200 (kW)			211.45 (kW)	

Table 2.2 *(continued)*

Ref.	Modern mathematical optimization method	Test systems	Different Cases	Optimal DG sizes	Optimal DG locations	Strengthened Parameters	Optimized Results	Compared Approaches
[116]	ICM	IEEE 69	ΣDG = 3	0.385, 1.186, 1 (MW)	26, 35, 62	PLR	LI = 7.535	GA + OPF, OO, IB, PSO, GA, GAMS, IGA
			ΣDG = 5	1.059, 0.85, 0.873, 0.717, 0.9 (MW)	4, 26, 40, 48, 62		LI = 9.438	
			ΣDG = 7	0.998, 0.686, 0.676, 0.871, 0.719, 0.811, 0.75 (MW)	4, 17, 27, 40, 48, 58, 65		LI = 9.837	
			ΣDG = 9	0.996, 0.752, 0.645, 1.258, 0.496, 0.498, 0.406, 0.855, 0.73 (MW)	4, 17, 27, 30, 35, 41, 50, 58, 65		LI = 9.769	
[117]	ICM	IEEE 33	ZONE-1	941.5 (kW)	30	PLR, VPE	34.52 (kW)	WoDG
			ZONE-2	603.091 (kW)	14		4.82 (kW)	
			ZONE-3	691.607 (kW)	25		2.41 (kW)	
[119]	ABC	IEEE 39	ΣDG =1	2.5775 (MW)	6	PLR, VPE	105.02(kW)	AM
			ΣDG =2	1.9707, 0.5757 (MW)	6, 15		89.96(kW)	
			ΣDG =3	1.7569, 0.5757, 0.7826 (MW)	6, 15, 25		79.25(kW)	
			ΣDG =4	1.0765, 0.5757, 0.7824, 0.6538 (MW)	6, 15, 25, 32		66.58(kW)	
[120]	ABC	IEEE 33	ΣDG =1	2.3970 p.u.	5	LLC, PLR, VPE	0.06 p.u.	WoDG
			ΣDG =3	1.0645, 0.7322, 0.9823 (p.u.)	29, 13, 23		0.013 p.u.	
			ΣDG =5	1.39, 0.66, 0.52, 0.73,0.74 (p.u.)	1, 24, 14, 7, 30		0.007 p.u.	
[121]	PSO	IEEE 12	WTΣDG = 2	336 (kW)	8	PFO, PLR, VPE	14.7 (kVA)	GA, AM, PSBIT
		IEEE 15	WTΣDG = (4 + 3)	1176 (kW)	4, 7		54.8 (kVA)	
		IEEE 33	WTΣDG = (5 + 3 + 5 + 5)	2873 (kW)	7, 16, 24, 30		127.1 (kVA)	
		IEEE 69	WTΣDG = (4 + 2 + 6 + 6 + 4)	3696 (kW)	7, 9, 48, 62, 64		131.3 (kVA)	
		IEEE 12	SPV = (4 + 3)	370 (kW)	5, 10		12..5 (kVA)	
		IEEE 15	SPV = (4 + 4 + 5 + 3 + 4 + 4)	1267 (kW)	5, 6, 8, 9, 12, 15		50.9 (kVA)	
		IEEE 33	SPV = (6 + 6 + 3 + 6 + 6 + 6 + 6 + 6 + 6 + 6)	2693 (kW)	8, 13, 16, 17, 20, 24, 25, 27, 31, 33		127 (kVA)	
		IEEE 69	SPV = (3 + 5 + 5 + 6 + 5 + 6 + 5 + 6 + 6 + 5 + 6)	3062 (kW)	6, 8, 12, 26, 52, 53, 59, 61, 62, 65, 68		148.6 (kVA)	
[124]	CS	IEEE 38	Wv1 = 1 & WL = Wv2 = 0	10, 20, 30, 40 (MW)	18, 8, 27, 36	PLR, VPE		Binary GA, continuous GA, PSO, WoDG
			WL = 1 & Wv1 = Wv2 = 0	10, 20, 30, 40 (MW)	24, 29, 7, 18			
			Wv1 = 1 & WL = Wv1 = 0	10, 20, 30, 40 (MW)	29, 8, 12, 15			
			Wv1 = 0.5 & WL = Wv2 = 0.25	10, 20, 30, 40 (MW)	34, 30, 16, 9			
		IEEE 69	Wv1 = 1 & WL = Wv2 = 0	10, 20, 30, 40 (MW)	30, 44, 59, 29			
			WL = 1 & Wv1 = Wv2 = 0	10, 20, 30, 40 (MW)	58, 51, 38, 19			
			Wv1 = 1 & WL = Wv1 = 0	10, 20, 30, 40 (MW)	32, 68, 63, 31			
			Wv1 = 0.5 & WL = Wv2 = 0.25	10, 20, 30, 40 (MW)	9, 67, 55, 40			

Table 2.2 *(continued)*

Ref.	Modern mathematical optimization method	Test systems	Different Cases	Optimal DG sizes	Optimal DG locations	Strengthened Parameters	Optimized Results	Compared Approaches
[126]	FF	IEEE 69	ΣDG = 1	1.8753 (MW)	61	PLR, VPE	0.0832 (MW)	GA
			ΣDG = 2	1.7496, 0.9269 (MW)	61, 67		0.0747 (MW)	
[134]	HA	IEEE 9	HL	4, 2, 4, 4 (MVA)	2, 4, 5, 8	COP, PLR	2.42 (MVA)	Bilateral contract scenario
			ML	2, 4, 4 (MVA)	4, 5, 8			
			LL	4, 1, 4, 4 (MVA)	1, 3, 6, 7			
			PSF = 0.7 - 1.66	4, 4, 4, 3 (MVA)	2, 5, 8, 4			
			PSF = 0.7 - 1.75	4, 4, 4, 3, 2, 1 (MVA)	2, 5, 8, 4, 7, 1			
[135]	GA	IEEE 16	HL	0.62 p.u.	7	PLR	5.76 p.u.	WoDG
			ML	0.53 p.u	7		2.63 p.u.	
			LL	0.4 p.u.	7		1.7 p.u.	
		IEEE 37	HL	0.5 p.u.	15		14.12 p.u.	
			ML	0.47 p.u.	15		6.2 p.u.	
			LL	0.63 p.u.	15		3.45 p.u.	
		IEEE 75	HL	0.45 p.u.	32		29.93 p.u.	
			ML	0.63 p.u.	30		13.06 p.u.	
			LL	0.59 p.u.	30		8.09 p.u.	
[136]	MVO	IEEE 33	ΣDG = 1	2500 (kW)	6	VPE, PLR	0.941 (p.u.), 111.01 (kW)	MFO, PSO, HPSO
			ΣDG = 2	852.06, 1156.95 (kW)	13, 30		0.9684 (p.u.), 87.16 (kW)	
[137]	MALO	IEEE 33	ΣDG = 5	220, 50, 30, 20, 1020 (kW)	5, 9, 12, 23, 30	VPE, PLR	0.083, 74.96 kW	WoDG
[138]	PSO	IEEE 33	ΣDG = 5 (OIW)	2.8171 (MW) each	6, 10, 18, 22, 31	VPE, PLR	112.691 (kW)	WoDG
			ΣDG = 5 (RIW)	2.9109 (MW) each			112.558 (kW)	
			ΣDG = 5 (GLBIW)	2.7947 (MW) each			112.719 (kW)	
			ΣDG = 5 (TVIW)	2.8201 (MW) each			112.534 (kW)	
[139]	MCPSO	IEEE 30	ΣDG = 1	46.95 (MW)	23	VPE, PLR	12.93 (MW)	AM, PSO
		IEEE 14	ΣDG = 1	34 (MW)	14		10.093 (MW)	
[140]	PSO	IEEE 34	ΣDG = 1	3 (MW)	8	VPE, PLR	167 (kW)	WoDG
[141]	CPSO	IEEE 14	ΣDG = 1	33.95 (MW)	6	VPE, PLR, COP	10.81 (MW)	IA, ELF, PSO

network: absence of a compensator, presence of a shunt capacitor, presence of DG, and presence of integrated DG and shunt capacitor. This modified approach is evaluated on the IEEE 85 test system, yielding significant improvements compared to PSO and MINLP [125]. Furthermore, the optimization of DG size and allocation takes into account voltage profile and line losses. This evaluation is conducted on the IEEE 69 radial distribution system and the results demonstrate comparable efficacy to Genetic Algorithms (GA) [126].

2.3.3 Hybrid Approaches

In the domain of Optimal planning of DG, researchers have advocated for the application of heterogeneous hybrid AI techniques. These approaches are engineered to tackle progressively intricate challenges in DG planning. They involve the amalgamation of two optimization methods, operating either consecutively or concurrently. Within this hybrid category, GA is coupled with TS to create GATS [127]. It is also integrated with PSO to yield GAPSO [128]. Moreover, it is combined with OPF to produce GAOPF [129], and harmonized with a fuzzy approach to form FZ [130]. Another integrated approach encompasses the evaluation of GA and TS for the optimization of the objective function, utilizing GA chromosomes and TS neighbors [127].

GAPSO, employing GA for DG allocation and PSO for size optimization with population sizes of 30 and 20, respectively, is deployed for the optimization of power quality parameters [128]. GAOPF leverages GA to ascertain decision variables, after which OPF is executed to ascertain the optimal solution. In [131], the Jumping Frog PSO (JFPSO) method is employed to pinpoint optimal DG locations through OPF optimization. The PSO process, considering voltage level deterioration, is succeeded by a hybrid optimization technique involving Gravitational Search Algorithm (GSA) [132]. Moreover, a heightened level of transient stability is achieved through the implementation of a cascade process involving PSO and Shuffled Frog Leaping (SFL) with the Critical Clearing Time (CCT) index. This is executed using Dlg SILENT software [60]. Furthermore, a fusion of Fuzzy Logic (FZ) with TS (FZTS) is applied for MO optimization of the fitness function for the integration of DG [69]. For a comprehensive overview of these hybrid optimization techniques, please consult Table 2.3, which provides detailed information on the techniques adopted, the test systems utilized, optimized results, and comparisons with other optimization techniques.

2.4 Renewable Energy

Leveraging established renewable energy resources (RER), DG constitutes a pivotal phase in the modernization of existing power grids. The heightened attention towards DG in today's energy landscape is prompted by the diminishing reservoirs of conventional fossil fuels, escalating environmental apprehensions, and soaring fuel expenses. Through the deployment of smaller-scale technologies capable of harnessing a diverse range of energy sources including hydro, wind, solar, fuel cells, ocean energy, geothermal, biomass, and non-RER options, it signifies a departure from the dependency on centralized generation. Traditional fossil fuel-based power generation remains the predominant source of global energy supply. However, this comes at the cost of jeopardizing ecosystems and public health due to the emission of hazardous pollutants. The persistent reliance on non-renewable energy sources has been associated with severe repercussions, encompassing climate change, depletion of the ozone layer, heightened vulnerability to natural calamities, endangerment of species, public health hazards, air quality degradation, and the emergence of novel diseases. DG stands as a potent means to seamlessly integrate renewable energy resources into state-of-the-art power systems, thereby fostering the generation of sustainable, eco-friendly energy.

The intermittent nature of specific resources, notably wind and solar energy, poses a substantial challenge in the incorporation of renewable energy sources within DG planning. The availability of these sources is contingent upon local environmental and geographical factors. Therefore, to ensure the smooth integration of DG and sustainable energy sources, the implementation of demand response initiatives and energy storage technologies is imperative.

Table 2.3 Data-based assessment of DG optimization by hybrid approaches

Ref.	**Hybrid optimization method**	**Test systems**	**Different Cases**	**Optimal DG sizes**	**Optimal DG locations**	**Strengthened Parameters**	**Optimized Results**	**Compared Approaches**
[14]	FZ + AM	IEEE 12	-	0.22 (MW)	9	PLR, VPE	0.01077 (MW)	WoDG
		IEEE 33		2.59 (MW)	6		0.111 (MW)	
		IEEE 69		1.87 (MW)	61		0.0832 (MW)	
[16]	GA + AM	IEEE 4	Vdm = 0.007422 p.u.	4000, 3000 (kW)	3,4	COP, RI, VPE	74.26 (kW)	WoDG
			Vdm = 0.007422 p.u.	3000, 2000 (kW)	12, 7		129.37 (kW)	
[20]	PSO + SFL	IEEE 33	CL	312.8, 334.4, 323, 279, 200 (kW)	14, 16, 33, 8, 31	PLR, VPE, TSI	0.053273 (MW)	PSO, SFL
			MXL	275.1, 252.3, 306.2, 237.6, 290 (kW)	33, 12, 14, 26, 13		0.055567 (MW)	
[21]	FZ + AM	IEEE 33	VL > ± 5%	2.4818 (MW)	6	PLR, VPE	110.6318 (kW)	WoDG
			VL ± 5%	3.15 (MW)	6		115.2 (kW)	
[26]	PSO + FZ	IEEE 33	ΣDG = 1	1.2931 (MW)	32	PLR, VPE	127.0919 (kW)	PSO
			ΣDG = 2	0.3836, 1.1506 (MW)	32, 30		117.3946 (kW)	
			ΣDG = 3	0.2701, 1.1138, 0.1503 (MW)	32, 30, 31		117.3558 (kW)	
			ΣDG = 4	0.2706, 0.8432, 0.1503, 0.5982 (MW)	32, 30, 31, 18		90.4794 (kW)	
[30]	MINLP + OPF	IEEE 41	PP	4.4, 1.1, 2.2 (MW)	19, 23, 40	PLR, VPE	1079.7 (MW)h	WoDG
			TP	6.6, 5.5, 9.9 (MW)	19, 23, 40		1527.2 (MW)h	
[37]	TPSO + OO	IEEE 86	TRIBE PSO (SPV + BDG)	200, 200 (kVA)	61, 85	COP	Total cost = 9355000 $	TRIBE PSO, OO
			OO (SPV + BDG)	400, 100 (kVA)	72, 85		9504000 $	
			TRIBE PSO + OO (SPV + BDG)	200, 200 (kVA)	61, 82		9355000$	
[50]	NLP + OPF	IEEE 34	ΣDG = 2	3112, 6.613 (MW)	17, 18	PLR, VPE	0.279 (MW)	WoDG
[56]	GA + OPF	IEEE 69	ΣDG = 3	2.661 (MW)	26, 35, 62	COP, PLR	TI (£ / h) = 8.72	
			ΣDG = 5	4.067 (MW)	4, 26, 35, 40, 62		TI (£ / h) = 10.73	
			ΣDG = 7	4.566 (MW)	5, 13, 27, 35, 40, 57, 65		TI (£ / h) = 11.27	
			ΣDG = 9	4.833 (MW)	4, 6, 13, 21, 27, 35, 40, 57, 62		TI (£ / h) = 11.51	

Table 2.3 *(continued)*

Ref.	Hybrid optimization method	Test systems	Different Cases	Optimal DG sizes	Optimal DG locations	Strengthened Parameters	Optimized Results	Compared Approaches
[79]	PSO + CPF	IEEE 33	ΣDG = 1	3.0317 (MW)	12	PLR	70.949 (kW)	WoDG
			ΣDG = 2	0.9143, 1.5345 (MW)	27, 22		29.82 (kW)	
		IEEE 69	ΣDG = 1	2.2215 (MW)	56		23.594 (kW)	
			ΣDG = 2	0.6247, 2.1213 (MW)	53, 56		7.342 (kW)	
[84]	GA + TS	IEEE 13	BDG	300 (kW)		PLR	84.6 (kW)	GA
			WTDG	200 (kW)			83.5 (kW)	
			SPV	80 (kW)			95.2 (kW)	
		IEEE 34	BDG	200 (kW)			220.9 (kW)	
			WTDG	200 (kW)			195.7 (kW)	
			SPV	200 (kW)			141.4 (kW)	
[85]	GA + PSO	IEEE 33	ΣDG = 4	0.6639, 0.6628, 1.0232, 0.8671 (MW)	32, 14, 24, 26	PLR	0.0682 p.u.	GA, PSO
[86]	GA + OPF	IEEE 9	UFC	2 (4 (MVA) & 1 (MVA))	4, 8	COP, PLR	52.73 GWh	MINLP
			LFC	1 (4 & 1), 2 (2 & 1), 1 (1 & 1) (MVA)	2, 4, 7, 1		45.35 GWh	
			CAC	3 (4 & 1), 1 (3 & 1) (MVA)	2, 4, 8, 1		31.55 GWh	
[87]	GA + FZ	IEEE 6	ΣDG = 1	8.5 (MW)	3	COP, PLR	0.112 (MW)	WoDG
		IEEE 30	ΣDG = 2	40, 35 (MW)	10, 6			
[88]	PSO + OPF	IEEE 30	ΣDG = 3	9.75, 9.26, 8.81 (MW)	19, 24, 30	COP, PLR	11.05 (MW)	
			ΣDG =5	9.95, 7.85, 6.23, 2.01, 7.75 (MW)	7, 19, 24, 26, 30		10.92 (MW)	
			ΣDG= 7	8.78, 7.15, 2, 2, 4.52, 2.01, 7.73 (MW)	7, 19, 21, 23, 24, 26, 30		10.91 (MW)	
			ΣDG = 9	7.78, 5.34, 2, 2, 2, 2, 3.67, 2, 7.21 (MW)	7, 18, 19, 21, 22, 23, 24, 26, 30		10.9 (MW)	
[89]	PSO + GSA	IEEE 69	Test Case 1 (Tiv)	0.2, 1, 1.8 (MW)	21, 49, 61	LLC, PLR, PR, VPE	MPI = 0.5463	PSO, GSA
			Test Case 1 (Tv)	0.9, 0.2, 1.3 (MW)	4, 21, 61		MPI = 0.6014	
			Test Case 2 (Tiv)	0.3, 1.2, 1.8 (MW)	21, 49, 61		MPI = 0.4495	
			Test Case 2 (Tv)	1.3, 1.8, 0.2 (MW)	21, 49, 61		MPI = 0.4909	
			Test Case 3 (Tiv)	1.7, 0.8, 0.8 (MW)	3, 60, 61		MPI = 0.6888	
			Test Case 3 (Tv)	1.6, 0.8, 0.3 (MW)	3, 61, 64		MPI = 0.7131	
			Test Case 3 (Tiv)	0.3, 0.2, 1 (MW)	21, 61, 48		MPI = 0.4771	
			Test Case 3 (Tv)	0.6, 1.5, 0.6 (MW)	50, 61, 47		MPI = 0.5282	

Table 2.3 *(continued)*

Ref.	Hybrid optimization method	Test systems	Different Cases	Optimal DG sizes	Optimal DG locations	Strengthened Parameters	Optimized Results	Compared Approaches
[99]	ABC+TLBO	IEEE 33	WTΣDG-1	2558.5 (kW)	6	VPE, PLR, COP,	67.83 (kW), 35971$	EA, GA, PSO
			WTΣDG-2	858.3, 1089.1 (kW)	13, 30		28.63 (kW), 15049$	
			WTΣDG-3	1069.9, 1029.9, 793.8 (kW)	13, 30, 24		11.74 (kW), 6171$	
			SPV ΣDG-1	2590.2 (kW)	6		111.027 (kW), 58536$	
			SPV ΣDG-2	851.5, 1157.6 (kW)	13, 30		87.16 (kW), 45814$	
			SPV ΣDG-3	801.7, 1053.6, 1091.3 (kW)	13, 30, 24		72.78 (kW), 38256$	
[100]	ALO+PSO+FLC	IEEE 33	SPV ΣDG = 2, UPF	385, 2154 (kW)	32, 7	PLR, COP	90.98 (kW), 12062 $	PSO, ALO+PSO
			WT ΣDG = 2, UPF	951, 696 (kW)	31, 17		89.3 (kW), 8496 $	
			SPV ΣDG = 2, LaPF=0.85	924+j1223, 665+j710 (kVA)	32, 14		47.6 (kW), 8037 $	
			WT ΣDG = 2, LaPF=0.85	993+j1667, 606+j913.5 (kVA)	8, 30		35.5 (kW), 8038 $	
			SPV ΣDG = 2, LePF=0.85	1669-j413, 1179-j29 (kVA)	7, 30		116 (kW), 13710 $	
			WT ΣDG = 2, LePF=0.85	2300+j273, 934-j38 (kVA)	4, 30		109 (kW), 15611 $	
[101]	GOA+CS	IEEE 33	ΣDG = 1, Half load=50%	1716 (kW)	2	VPE, PLR, COP	123.62 (kW), 34.33$	GA, PSO, GOA, CS
		IEEE 33	ΣDG = 1, Full load	926.99 (kW)	24		139.59 (kW), 18.5$	
		IEEE 33	ΣDG = 1, 150% load	926.99 (kW)	24		139.59 (kW), 18.5$	
		IEEE 69	ΣDG = 1, Half load=50%	1930.7 (kW)	17		141.43 (kW), 38.6 $	
		IEEE 69	ΣDG = 1, Full load	1990.7 (kW)	6		147.66 (kW), 39.8$	
		IEEE 69	ΣDG = 1, 150% load	1890.6 (kW)	12		151.66 (kW), 37.8$	

2.5 Renewable DG planning

The modern power system architecture, particularly those integrating renewable DG, encompasses several distinct phases in its planning and execution. These stages encompass the design of the DG system, the assessment of renewable energy resources, load surveys, the formulation of an energy storage framework, the utilization of optimization methodologies, and the analysis of the resultant optimization outcomes. Figure 2.3 provides a sequential depiction of the crucial elements involved in the planning of renewable DG systems.

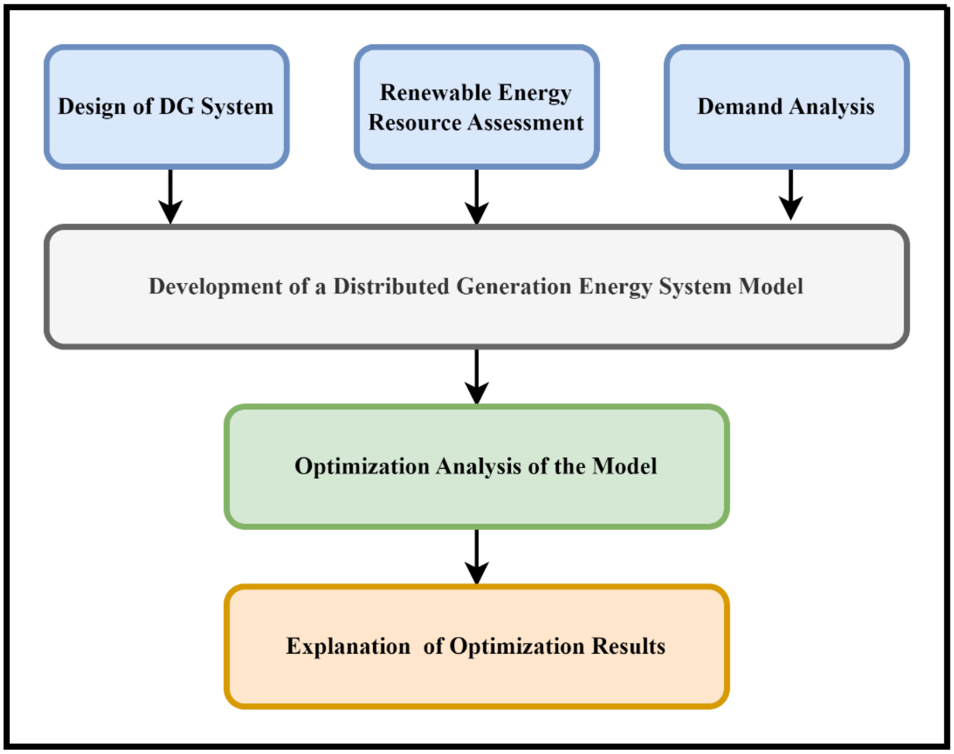

Fig.2.3: Orderly progression of vital components in DG planning framework

2.5.1 DG System Design

The designs of DG systems encompass a variety of methodologies concerning energy generation, battery storage, and bus scheduling. These systems can employ either renewable or non-renewable resources for energy production. Renewable sources encompass technologies like solar photovoltaic systems, wind power generation, crop-based generation, biomass generation, and fuel cells. On the other hand, fossil fuel-based generation encompasses a spectrum of combustion engine designs [145].

Despite the intermittent nature of certain renewable sources, there exist several reliable configurations for integrating renewable energy generation, consumption, and storage. For instance, in a hybrid DG system, energy can also be derived from biomass and biogas, presenting an additional viable option.

The following outlines descriptions and advantages of different bus planning methodologies:

- *DC-bus Architecture:*
    - *Description:* The DC-bus architecture is characterized by its straightforward installation process. It involves channeling the generated energy to a DC bus to power DC loads. Additionally, inverters can be employed to convert and supply AC when needed.

- *Benefits:* This configuration simplifies the installation process, making it a practical choice for systems primarily operating with DC loads. It offers efficiency in powering DC devices directly.

Table 2.4 Technologies associated with DG [146]

Methodologies	**Explanation**
Dispersed Heat Methodologies	
Solar heating of water	Solar thermal collector is used to convert sunlight into boiled water.
Heat pump	Water heating by using the temperateness deposited for a thermal reservoir.
Biomass	Water and surface heating by burning the biomass ingredients.
Dispersed Energy Generation Methodologies	
Solar PV array	Designed to convert solar heat into electricity.
Wind mills	Designed to transform wind energy into electricity.
Micro-wind	Small-scale windmill up to 100 kW.
Micro-hydro	Designed to convert kinetic energy of water into electricity.
Biomass	Designed to extract electricity via landfill gas production and up to 40 MW.
Hybrid Heat and Power Methodologies	
Biomass	Energy generation from 100 kW biomass to 85 MWth / 20 Mwe.
Upto 1 MW	Small-scale energy distribution for residential and commercial purpose.
1 MWe-10 MWe	Mid-level energy distribution for community and industry.
>10 MWe	High-level energy distribution for industries.

- *AC-bus Architecture:*
    - *Description:* The AC-bus architecture utilizes generated energy to energize an AC bus, which subsequently caters to AC demand. Nevertheless, it's worth noting that access to the DC supply is still achievable through the use of converter devices.

- *Benefits:* This setup is conducive for systems predominantly utilizing AC loads. It allows for efficient utilization of generated AC power while still providing access to the underlying DC source.

- *Hybrid AC-DC Bus Architecture:*
  - *Description:* The hybrid AC-DC bus architecture enables the concurrent provision of both AC and DC power, resulting in enhanced overall system efficiency. It employs both inverters and rectifiers to facilitate the storage and distribution of energy in both AC and DC formats.
  - *Benefits:* This configuration offers versatility by allowing the system to provide power in both AC and DC forms. It leverages the strengths of both architectures, leading to increased overall efficiency and adaptability to various load types.

2.5.2 Renewable Energy Resource Assessment

Establishing a comprehensive framework for the assessment of natural energy resources is crucial for the design and deployment of renewable DG systems. While environmentally sustainable, these resources exhibit lower reliability compared to conventional fossil fuel-based electricity generation. Effectively addressing this intermittent nature is paramount for optimizing the utilization of green energy. The availability of these resources is contingent on regional climatic conditions, seasonal variations, soil characteristics, geographical dimensions, and forecasted weather patterns. Furthermore, the pronounced intermittency observed in solar and wind power generation poses challenges in constructing precise assessment models for these forward-looking strategies. In contrast, biomass-based energy generation, while influenced by weather conditions, offers the advantage of ensuring continuous energy production through proper feedstock storage practices.

In this study, the authors investigated the influence of geographical and ecological elements on the utilization of natural resources for distributed energy generation in the Visayas, Philippines. Specifically, wind and SPV power generation were analyzed. The assessment of yearly energy output considered ecological variables like optimal monthly positioning of PV panels, average solar irradiance levels, and mean monthly wind velocities [147].

To enhance the reliability assessment of renewable distributed energy sources, a novel indexing system was introduced. This system integrates the least path strategy with conventional fault consequence assessment techniques. Additionally, the study developed two-state and three-state models aimed at enhancing stability, contingent on the seamless integration of the distribution network. These outcomes were compared with scenarios lacking DG integration [148].

To mitigate the increased intermittency associated with wind and solar power generation, the utilization of both experimental atmospheric data and predictive climatological data has been proposed [149].

- *Experimental atmospheric data:* It can be sourced from various outlets such as on-site measurements, previously published studies, experimental atmospheric observatories, privatelyfunded enterprises, as well as government organizations. These sources offer valuable insights into the intermittent natural energy source atmospheric conditions. Pertaining to solar energy, this encompasses metrics like global solar radiation statistics, power output of solar photovoltaic arrays, daily horizontal solar irradiance, solar intensity, hourly solar radiation, and the relative frequency of global solar radiation. Wind speed data characterization covers parameters such as hourly mean wind speed, monthly average wind speed, daily wind energy, and the relative frequency of wind speed.

- *Forecasting Climatological Data:* Accurate prediction of climatological data is paramount in mitigating challenges associated with renewable energy generation and determining the necessary reserve fuel levels. This need arises due to various factors including limited availability of meteorological statistical services and expertise in certain regions, financial constraints constraining comprehensive climate data gathering, and the lack of a measurement infrastructure hindering continuous data acquisition over prolonged durations.

Table 2.5 Cataloguing of RES forecast boundaries with outcomes [150]

Group	Dimension of Forecast Boundary	Outcomes
Extreme Short Period	Seconds to Hour	- Clearance Cost of Energy Production
		- Real-Time Monitoring of Grid Operation and Optimization
Diminutive Period	Hour to Hours	- Fund Arrangement of Load Scheduling
		- Reliable Load Announcements with Justification
Intermediary Period	Hours to Week	- Unit Assurance Conclusions
		- Reserve Precondition Verdicts
		- Generation Dynamic/Inert Mode Pronouncements
Prolonged Period	Week to Year and Above	- Operational Budget Optimization
		- Forecasting and Supervision of Processes
		- Prospective Observations on Wind Power Projects

2.5.3 Demand Response

In the context of DG systems, the Demand Response (DR) program plays a pivotal role, enabling consumers to adjust their energy consumption patterns, thereby transitioning from periods of high-load to low-load demand, consequently leading to cost savings on electricity bills. In many contemporary power systems across various countries, there is a predominant reliance on decentralized renewable energy sources for small-scale power generation. This reliance on intermittent renewable energy sources necessitates the implementation of a demand response mechanism as an auxiliary measure to manage and balance energy supply and demand effectively. Historically, end-user energy consumption was primarily regulated by utility providers, as there was limited information available regarding cost tariffs and incentive structures for demand response within traditional power networks. The emergence of prosumers has significantly influenced the management and execution of energy distribution, reflecting the evolution of the contemporary energy landscape. Moreover, consumers are typically categorized into three main groups: industrial, commercial, and residential. These entities now have the flexibility to shift their energy consumption from peak demand periods to off-peak times, reduce their load during periods of elevated energy prices, or utilize on-site generation to fulfill their energy requirements.

The benefits of this plan encompass financial gains, risk evaluation, system stability, effective commercial deployment, expanded user amenities, reduced expenses, and environmental merits. The demand response scheme entails various cost elements including equipment investments, response tactics, operational complexities, potential revenue reductions, postponed expenses, communication outlays, tariff frameworks, monitoring expenditures, incentive distributions, evaluation costs, and customer education [151, 152]. Figure 2.4 delineates the classification of the demand response scheme.

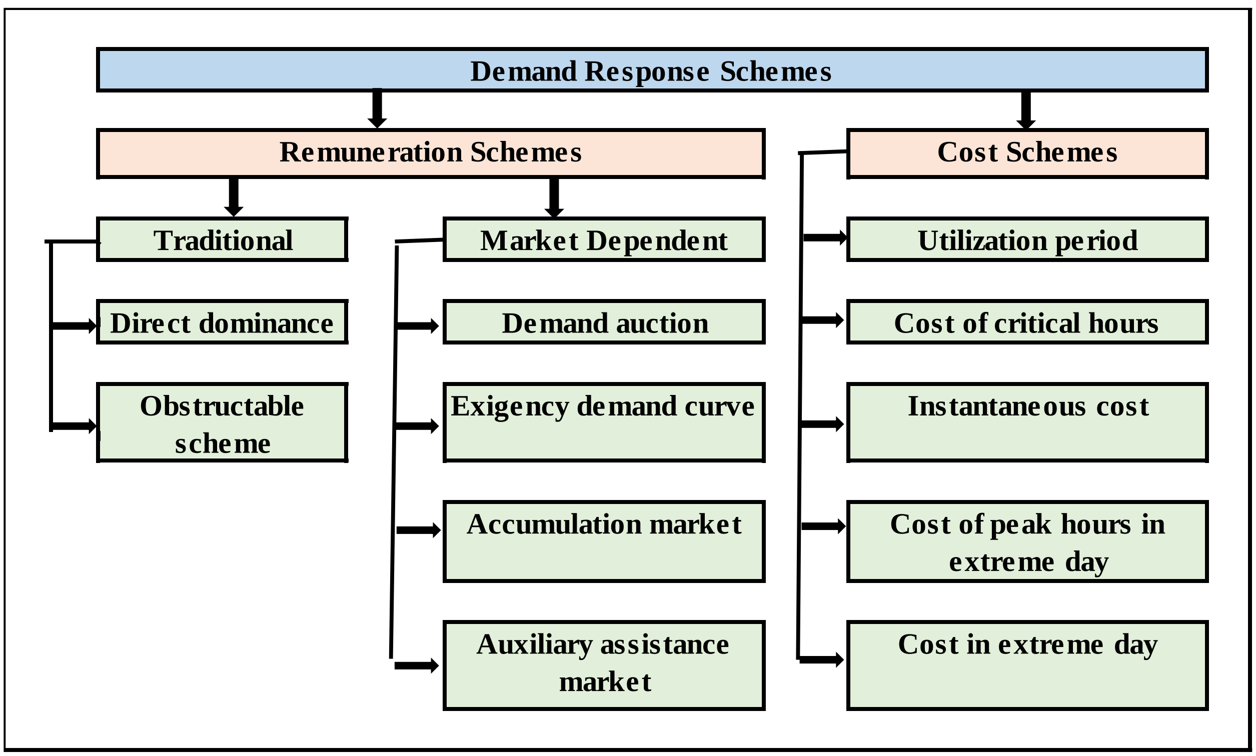

Fig. 2.4: Classification of demand response schemes.

2.5.4 Battery Storage

Incorporating energy storage is imperative for the optimal integration of renewable DG systems. This is crucial in order to enhance the penetration of DG and effectively address the intermittent generation patterns observed in solar and wind power systems. Achieving a sustainable and environmentally-friendly energy landscape hinges on the efficient storage of electrical energy. Energy storage systems encompass various categories including electrical, mechanical, chemical, and thermal storage methodologies. Each of these approaches has undergone comprehensive evaluations with regard to their respective merits, limitations, and practical applications. Additionally, assessments have been conducted on aspects such as technology, charge storage density, retrieval efficiency, costs, and other pertinent considerations. The seamless implementation of battery storage encounters several obstacles:

- Adherence to distribution company guidelines and practices, which may not always align with the integration of energy storage solutions.
- The significant capital investment, operational expenses, and maintenance costs associated with large-scale energy storage systems.
- Limited awareness among stakeholders regarding the benefits offered by battery storage solutions.

Furthermore, the regulatory framework for electricity pricing, often set by administrative bodies, may not sufficiently incentivize energy conservation through storage. Shareholders may express hesitancy due to the higher initial costs linked to storage infrastructure. Additionally, the absence of robust incentives for energy conservation practices, coupled with limited availability of comprehensive literature, further inhibits the widespread adoption of such systems [153]. Figure 2.5 provides a categorization of energy storage (ES) systems.

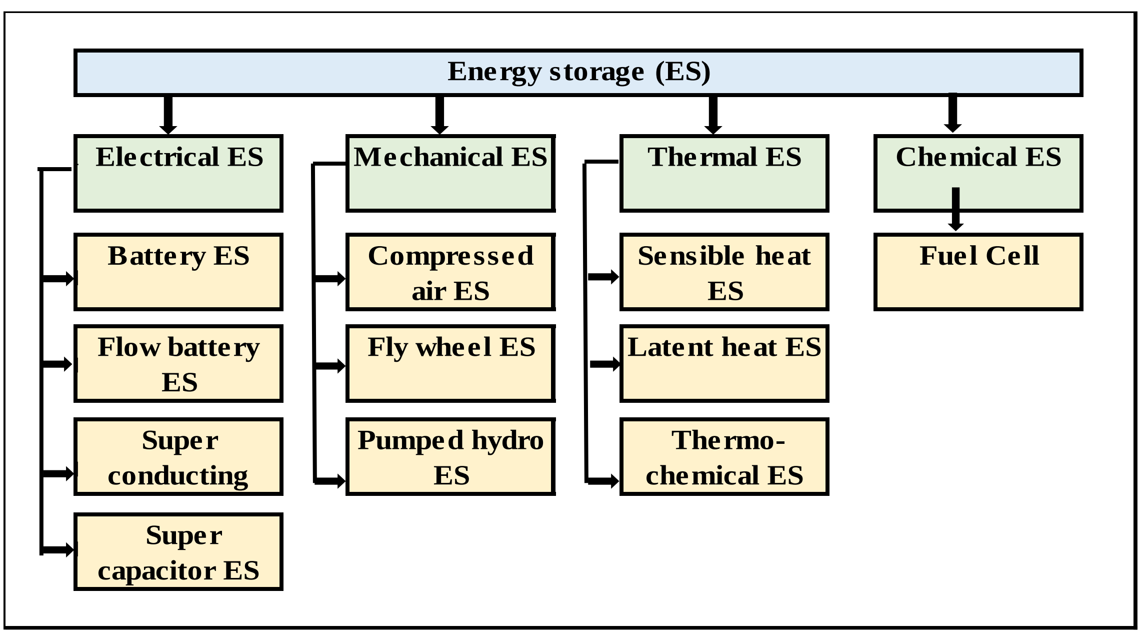

Fig. 2.5: Cataloguing of energy storage system.

2.5.5 Optimal Allocation of Renewable DG

The optimization technique employed in this research paper is the Moth Swarm algorithm, utilized to enhance frequency regulation in DG systems. This approach incorporates a combination of PI-PD controllers, as well as technologies like energy storage, electric vehicles, and renewable sources such as solar and wind power. Within this setup, the PI controller operates in the primary stage, while the PD controller takes charge in the secondary stage. When compared to conventional PID controllers, known for yielding unstable transient responses, this cascaded control scheme effectively reduces the system's steady-state error. MATLAB and SIMULINK were employed to implement this strategy, leveraging parameters like gain and time constants specific to various components including solar photovoltaic systems, wind turbines, fuel cells, diesel engine generators, and electric motors [154]. This enables a refined and optimized frequency regulation process in DG systems. To facilitate the seamless integration of distributed SPV systems, a battery storage configuration has been proposed. This design aims to mitigate challenges arising from the intermittent nature of renewable energy sources, while enhancing grid flexibility even in the event of disruptions at various scales, encompassing power plants, substations, and circuits. Various battery storage systems have been developed, including in-building distributed storage, circuit/distribution storage, substation/microgrid storage, power plant storage, and utility/grid storage, each operating on distinct principles. The outcomes of this study entail heightened renewable energy penetration coupled with augmented grid resilience achieved through the optimal integration of battery storage technologies [155].

The authors have advocated for a mathematical approach to enhance power quality and voltage through the incorporation of DG into power distribution. This integration has been realized using a versatile multi-level switch. Considerations have been made for the feeder's capability to manage power and loading frequency to effectively assimilate DG and maintain feeder equilibrium. To address potential limitations of the flexible multi-level switch, a control framework has been devised, incorporating a PI controller and a steady-state reverse model [156]. In the context of a prospective smart grid, a coordinated scheduling scheme for renewable DG has been delineated. This strategy aims to address disruptions stemming from intermittent renewable energy sources. Initially, renewable virtual resources are employed to enact procedural steps, with subsequent simulations used to refine the strategy's framework. The proposed model demonstrates how pumped storage energy can mitigate the erratic nature of renewable energy supply, enabling precise forecasting with source shedding for profit maximization [157]. A distinctive filter has been developed to forecast distributed solar power generation while accounting for proximity-induced influences on energy systems. The model also accommodates one-minute resolution intermittency caused by cloud formation and propagation. This bi-level methodology incorporates the estimation of PV power and lower-frequency measurements of sampled data [158]. The authors introduced a novel framework aimed at mitigating distribution energy losses by delivering electrical energy at a unity power factor level. Additionally, they implemented a dumping cost methodology to evaluate soil contamination. Consequently, the approach has led to a reduction in the overall expense of managing power congestion, thereby enhancing the feasibility of prospective smart city power initiatives [159].

Solar PV DGs, acting as reactive elements, have shown significant enhancements in voltage regulation within distribution systems, all without reliance on feedback assessment or information exchange. In this demonstrated approach, the backward/forward sweep algorithm has been employed, taking into consideration factors such as solar energy irradiance levels and ambient temperature [160]. The research paper proposed an innovative approach to address the high cost associated with acquiring infrastructure space. This involves repurposing unused land adjacent to motorways, water storage facilities, and railroad tracks, while ensuring fair compensation for landowners. Additionally, a geographic information system has been developed to assist in identifying suitable land parcels [161]. Recognizing the unpredictability of climatological and atmospheric conditions and its impact on renewable DG, the authors introduced an enhanced predictive technique. This adaptive subgroup selection method operates in two stages, utilizing a binary genetic algorithm for feature selection and a regression-based vector for estimating the suitability level of the predictor. Comparative analysis with conventional prediction methods demonstrates a substantial 58.4% improvement in accuracy [162].

The research paper conducted an assessment of wind power generation as a DG source to cater to the energy requirements of rural America. A case study approach is employed, encompassing two distinct periods: the pre-wind era (2009-2015) and the post-wind era. The study employs graphical representations to illustrate the shifts in consumption patterns among residential, commercial, and industrial users over the last five years. Furthermore, the analysis incorporates crucial factors such as wind speed, air temperature, and load demand, as referenced in [163].

The research paper explored the feasibility of utilizing wind power generation as distributed energy sources in the event of atypical power outages through a simulated testing process. This investigation was substantiated using a seven-scenario system, encompassing configurations both with and without DG, located downstream, midstream, and upstream. Additionally, it encompassed four distinct types of wind power generation [164].

To capitalize on the potential of renewable energy sources, particularly in light of the proliferation of large-scale heat pump projects, numerous countries find it imperative to revamp their conventional grid systems. In this regard, a mathematical model has been devised with the dual objectives of maximizing profits and minimizing costs. The primary aim of this model is to efficaciously integrate heat pumps with wind power generation into the existing distribution network [165].

In the context of distribution networks, wind power generation has been deployed as a DG resource to enhance voltage profiles, reduce losses, and contribute to environmental benefits. An optimization strategy rooted in power control curve optimization has been employed to regulate windmill rotor speeds, aiming to achieve optimal characteristics related to energy losses and voltage quality [166].

In the pursuit of optimizing DG size and placement, a multi-objective function has been proposed. This function accounts for various factors including operational costs, capital expenses, environmental impacts, costs associated with wind and solar power curtailment, as well as constraints such as voltage levels, current limits, power flow equations, and DG capacity. Notably, PSO has been successfully applied in optimizing gas-fueled microturbine generators, SPV systems, and wind turbines [167].

2.6 Conclusion

The literature concludes that DG plays a pivotal role in enhancing the characteristics of power systems. It encompasses a plethora of optimization techniques deployed in DG allocation to meet specific constraints. Furthermore, it serves as a tool to bolster the stability, reliability, and consistency of the distribution network. Additionally, it facilitates the analysis of intricacies involved in optimizing algorithms.

This literature provides a comprehensive review of various optimization techniques, offering a comparative analysis of conventional, modern mathematical, and hybrid methods employed for optimizing significant parameters of DG. These optimizations aim to achieve technological, financial, and environmental benefits with optimized result parameters. Conventional approaches, while simple, easy to execute, and highly precise, suffer from slow convergence optimization due to single-objective focus. On the other hand, modern mathematical approaches excel in solving multi-objective complex problems, albeit with challenges such as increased coding complexity, diverse settling parameters, and potentially rapid convergence. Hybrid optimization approaches, while capable of handling more intricate problems with swifter convergence, may entail greater complexity and have a smaller existing body of literature.

The reviewed studies strongly indicate that integrating renewable energy sources can greatly amplify the benefits of DG planning in distribution networks. However, this integration underscores the need for a reliable assessment tool for renewable energy. Overcoming the intermittent nature of renewable energy sources demands effective energy storage solutions, potentially leading to the mitigation of intermittency.

Furthermore, it is worth noting that demand response has not received significant attention from researchers. Given the high costs associated with energy storage systems, demand response emerges as a pivotal element in the development of smart distribution systems. There exists a promising opportunity to develop a system that encompasses the planning and optimal dispatch of renewable DG in tandem with energy storage and demand response mechanisms.

Chapter- III

Optimal DG Allocation and Impact of Demand Response

3.1 Introduction

Two essential components of a smart grid system are distributed generation DG and demand response (DR). The types of DG may be renewable or nonrenewable energy sources. The optimal placement of solar photo voltaic (SPV) in the distribution network (DN) is contingent on a number of parameters, including the location of the loads, the available solar resources, and the DN's capacity. The investigation of the effect of DR on the optimal location of SPV systems in the DN is an important topic that has gained considerable attention in recent years.

DR refers to the capacity of consumers to modify their electricity use in response to price fluctuations or other signals. Integration of DR into the DN can aid in the reduction of peak demand, improvement of the grid's dependability, and reduction of the need for expensive infrastructure investments [168]. Many methods exist for analyzing the influence of DR on the optimal placement of SPV plants in the DN.

- *Capacity planning*: DR can help to reduce the peak demand on the DN, which can in turn reduce the need for additional generation capacity. This can impact the optimal placement of SPV systems in the network, as the capacity requirements may be lower.
- *Load profile*: DR can also impact the load profile of the network, which can impact the optimal placement of SPV systems. For example, if DR results in a shift in the peak load to a different time of day, the optimal placement of SPV systems may be different.
- *Voltage stability*: The integration of SPV systems in the DN can impact the voltage stability of the network. DR can help to manage voltage fluctuations by adjusting the consumption in response to changes in voltage. This can impact the optimal placement of SPV systems, as the locations that can provide the most benefit in terms of voltage stability may change [169].
- *DN configuration*: The optimal placement of SPV systems in the DN also depends on the network configuration. DR can impact the network configuration by reducing the need for additional infrastructure upgrades or by changing the location of the loads. This can impact the optimal placement of SPV systems.

The relationship between energy generation from an SPV system and other parameters is influenced by factors such as solar irradiation, panel efficiency, system orientation, shading, and temperature. These parameters also affect power quality [170,171].

In ref. [172], the authors proposed an integrated technique for incorporating renewable distributed generation (RDG) and DR into the planning of low-carbon sustainable distribution systems. In comparison to standard planning paradigms, the results illustrate the efficacy of the suggested methodology in enhancing the efficiency of RDG operations and reducing the CO_2 footprint of DN. The methodology provides a balance between economic and environmental benefits, and it has been demonstrated that the integration of RDG and DR choices in distribution system planning is beneficial in reducing carbon emissions and minimizing costs. This study utilizes an interior-point-method-embedded discrete genetic algorithm to effectively and accurately solve the model.

In ref. [173], the authors demonstrated that how temperature-controlled loads (TCL) demand flexibility can be used as part of a DR management architecture to improve the reliability and affordability of the power system. Using temperature measurements and consumer preferences, the study measures how flexible TCL demand is and predicts that solar power generation will make DR more reliable. The proposed distributed DR management architecture simplifies optimization and enhances optimality, resulting in reduced power consumption during peak reduction and emergency DR requests and low variability during capacity firming requests. Different DR requests are measured using two indices: DR reliability and consumer comfort. The proposed technique is implemented on Energy Plus-Matlab co-simulation.

In ref. [174], the authors proposed a structure for a solar photovoltaic-based microgrid (PV-MG) and looks into how DR affects the problem of optimizing its dispatch. The objective is to minimize the total cost of running PV-MG and moving energy around in ESS while taking into account different constraints on equality and inequality. The case study shows that the proposed optimization model works well to optimize the dispatch of the PV-MG and that the non-dominated sorting genetic algorithm-II works well to get Pareto solution sets. At the end of the paper, the typical dispatch schemes are looked at to see if the established optimization model is reasonable and works.

The authors of ref. [175] proposed a two-stage robust microgrid coordination strategy to address the difficulties of managing uncertain renewable DG resources and load demands in microgrids. Price-based demand response (PBDR) is scheduled daily, and dispatchable DG such as microturbines is changed hourly to maintain power balance and obtain economic benefits. Coordination of the PBDR and multiple DG units is proposed using a two-stage robust optimization model with guaranteed robustness against uncertainty. The simulation results demonstrate that the proposed strategy can deal with the unpredictability of renewable energy and demand while optimizing microgrids. The optimization is demonstrated with the use of column-and constraint generation algorithm

In ref. [176], the authors proposed and concluded the potential of DR and photo voltaic distributed generation (PVDG) can be measured, which helps plan sustainable DN with the help of end users. Changes to the rules, like the optional time of use tariff in Brazil, are needed to boost both DR and PVDG at the same time. The rational use of electricity, which is based on economic efficiency, is the basis of the method. This method gives a complete framework for the benefits and challenges of incorporating DR and/or PVDG into planning for power utilities. By doing a thorough analysis of the power grid and figuring out how cost-effective DR and/or PVDG are, power companies can figure out the best and most cost-effective ways to meet their customers' energy needs. The open distribution system simulator is used to conduct the simulations.

In ref. [177], the authors presented the method for sizing PV and ESS while taking DR into account gives a complete way to optimize the operation of PV and ESS systems while meeting the electricity needs of consumers. By taking into account the cost for PV and ESS systems, variation of daily load, and power utilities can make informed decisions about the optimal size of PV and ESS systems that will minimize the total cost of the system while meeting consumers' electricity needs. The MILP model was implemented in GAMS v.24.1.3 and solved using CPLEX v.12 as the solver.

In ref. [178], transmission expansion planning (TEP) has traditionally been done based on peak demand, but this may not be the best or most efficient way to do it. DR and DG are being considered as ways to deal with this. These things can have a big effect on how controllable and cost-effective power systems are, both in the short and long term. The proposed framework was realized by differential evaluation program.

In ref. [179], the authors used a direct approach of load flow to optimize the size and location of SPV-based DGs in the primary distribution system. The objectives include reducing power loss, improving voltage profile, and gaining economic benefits. DGs are placed at a single location to enhance system performance, and the estimated optimal size of a DG becomes a constraint for locating the SPV-based DGs.

In ref. [180], the authors suggested the optimal operating method for renewable energy-supported isolated microgrids. It employs carbon capture-based technologies to reduce CO2 impact and incorporates an emission-averse model. A fee is imposed due to CO2 emissions from diesel engines. The study compares a carbon capture unit with a fossil fuel-based unit, considering renewable energy penetration and carbon emission factors. Results show the microgrid's highest profitability at 40% RE penetration, with increased emission factors negatively affecting economics at that level.

3.2 Formulation of Problem

In this chapter, the following objectives have been considered for the realization of the proposed framework:

Minimizing power ditribution losses in a distribution network is a crucial aspect of efficient power system operation. Power losses occur due to resistance in the wires, which leads to a voltage drop and energy loss as electricity is transmitted from the source to the end-users. Hence, minimizing power loss is one of the objective functions, defined as follows. [181]:

$$£_1 = \sum_{t=1}^{24} P_{\mathrm{L\,(t)}} \tag{1}$$

$$P_{\mathrm{L\,(t)}} = \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_{ij\,\mathrm{(t)}}\left(P_{i\,\mathrm{(t)}} P_{J\,\mathrm{(t)}} + Q_{i\,\mathrm{(t)}} Q_{J\,\mathrm{(t)}}\right) + \beta_{ij\,(t)}\left(Q_{i\,\mathrm{(t)}} P_{j\,\mathrm{(t)}} - P_{i\,\mathrm{(t)}} Q_{j\,\mathrm{(t)}}\right) \forall t \tag{2}$$

where $\alpha_{ij\,\mathrm{(t)}} = r_{ij} \cos\left(\delta_{i\,\mathrm{(t)}} - \delta_{j\,\mathrm{(t)}}\right) / V_{i\,\mathrm{(t)}} V_{j\,\mathrm{(t)}}$ and $\beta_{ij\,\mathrm{(t)}} = r_{ij} \sin\left(\delta_{i\,\mathrm{(t)}} - \delta_{j\,\mathrm{(t)}}\right) / V_{i\,\mathrm{(t)}} V_{J\,\mathrm{(t)}}$

Reverse power flow occurs when DG units generate more power than the local load demands, causing excess power to flow back into the grid. This can cause stability and safety issues in the DN, as well as increase the risk of voltage fluctuations and equipment damage. Hence, DG integration considers reversing power flow.

$$£_2 = \sum_{t=1}^{24} P_{R\,(t)} \tag{3}$$

$$P_{R\,(t)} = \begin{cases} 0, & \text{if } I_{\mathrm{G}\,(t)} \geq I_{\mathrm{S}} \\ \mathrm{Re}\left(V_{\mathrm{G}\,(t)}\, I^{*}_{\mathrm{G}\,(t)}\right) & \text{if } I_{\mathrm{G}\,(t)} < I_{\mathrm{S}.}\,. \end{cases} \tag{4}$$

Node voltage deviation refers to the difference between the actual voltage level and the desired or nominal voltage level at a particular node in an electrical power system. Voltage deviation can be caused by various factors, including load variations, reactive power flow, and voltage drop in the transmission and distribution lines. Voltage deviations can cause several issues in the power system, including reduced system efficiency, increased losses, and damage to equipment. Large voltage deviations can lead to equipment failures, voltage collapse, and blackouts. The objective of violation of voltage limits can be stated as follows [182]:

$$£_3 = \left(1 + \textstyle\sum_{t=1}^{24} V_{D\,(t)}\right) \tag{5}$$

$$V_{D\,(t)} = \begin{cases} \left|V_{\mathrm{Min}} - V_{i\,(t)}\right| \text{ if } V_{i\,(t)} < V_{\mathrm{Min.}} \\ 0 \quad \text{if } V_{\mathrm{Min.}} \leq V_{i\,(t)} \leq V_{\mathrm{Max.}} \\ \ell \quad \text{if } V_{i(t)} > V_{\mathrm{Max.}} \end{cases} \tag{6}$$

where ℓ is the large value or unacceptable value.

3.3 Objective Function

To achieve the objectives, it is necessary to employ a fitness function that incorporates weighted factors for different objective functions. Fitness function (Υ_1) for level 1 optimization:

$$min(\Upsilon_1) = \varphi \times M \times £_3 \tag{7}$$

where $M = £_1 + £_2$ and φ is the daily to yearly conversion product. $£_1$ and $£_2$ are relevant to the power and $£_3$ is relevant to voltage.

The DR planning and scheduling approach of DGs is taken into consideration at level 2 of the optimization objectives. The following objective function will be taken into consideration for level 2 of the optimization problem:

$$min(\Upsilon_2) = M \times £_3 \tag{8}$$

In this context, the fitness function for level 2 is denoted by Υ_2.

It is vital to have a dispatch strategy, which is determined upon by the DR aggregator. In the level 2 of optimization, the dispatch strategies of SPV and DR are considered. This helps to minimize the aforementioned fitness function.

3.4 Demand Response

A demand response aggregator (DRA) is a third-party entity that works with energy consumers to manage their energy consumption during periods of peak demand. The aggregator coordinates with multiple consumers to reduce their electricity consumption during peak demand periods and sells the reduced energy consumption back to the grid operator or utilities as a form of DR. The DRA acts as an intermediary between the grid operator and the energy consumers. It helps the consumers reduce their energy consumption during peak hours by offering financial incentives, such as reduced electricity rates, to those who agree to participate in demand response programs. The aggregator then aggregates the reduced energy consumption from multiple consumers and sells it back to the grid operator or utilities. The DRA uses various technologies and strategies to manage energy consumption, such as automated demand response systems, smart thermostats, and energy management systems. These technologies allow the aggregator to remotely control and adjust energy consumption in real-time, based on grid conditions and market prices [183].

DRAs play a critical role in helping grid operators manage peak demand, reduce energy costs, and improve system reliability. By incentivizing energy consumers to reduce their energy consumption during peak periods, demand response aggregators help to balance the supply and demand of electricity and reduce the need for additional generation capacity.

The following are some of the DR restrictions that are taken into consideration:

$$P_{i(t)} = \left(P_{Gi(t)} - P_{Di(t)}\right) \forall t, i \tag{9}$$

$$Q_{i(t)} = \left(Q_{Gi(t)} - Q_{Di(t)}\right) \forall t, i \tag{10}$$

$$P_{Di(t)} = \left(P_{in,i(t)} + P_{el,i(t)}\right) \forall t, i \tag{11}$$

$$\sum_{i=1}^{N} \sum_{t=1}^{24} \left(P_{in,i(t)} + P_{el,i(t)}\right) \times \Delta t = E_i^{Total} \tag{12}$$

$$P_{el,i}^{min} \leq P_{el,i(t)} \leq min\left(\left(C - P_{in,i(t)}\right), P_{el,i}^{max}\right) \forall t \tag{13}$$

$$P_{el,i}^{max} = \mu \sum_{t=1}^{24} L_{d,i(t)} \tag{14}$$

Where C and μ is the contract load and DR penetration rate respectively.

Participants in mandatory DR programs are liable to face financial penalties if they fail to adjust their electricity consumption as instructed by the aggregator. The scheduling of demand should aim to strike a balance between the total electricity consumption and the available resources throughout the day. Rather than simply reducing overall consumption, the objective of DR is to reshape the demand profile. The total demand at any given time, denoted as t, is the sum of all types of loads, including both receptive and non-receptive loads, as shown in equation 11. The receptive load shifts the demand as per the instructions of the DRA.

Equation 12 illustrates the scheduling constraints that must be followed to meet the responsive demand while ensuring it does not significantly impact the overall daily demand. The lower and upper limits of the responsive demand are represented by equation 13.

The peak value of the responsive demand is influenced by the level of DR penetration, and further details regarding this relationship can be found in equation 14.

3.5 Objective Constraints

- *Constraint for SPV output:* The constraint for SPV generation limit is given as:

$$0 \leq P_{\mathrm{DG},i} \leq P_{DG}^{max} \forall i \tag{15}$$

- *Constraint for feeder:* The constraint for the thermal limits is given as:

$$I_{ij(t)} \leq I_{ij}^{max} \ \forall t, i, j \tag{16}$$

- *Constraints for power balance:* The constraints for real power and reactive power are given as:

$$P_{i(t)} = V_{i(t)} \sum_{j=1}^{N} V_{j(t)} Y_{ij} \cos\left(\theta_{ij} + \delta_{j(t)} - \delta_{i(t)}\right) \forall t, i \tag{17}$$

$$Q_{i(t)} = -V_{i(t)} \sum_{j=1}^{N} V_{j(t)} Y_{ij} \sin\left(\theta_{ij} + \delta_{j(t)} - \delta_{i(t)}\right) \forall t, i \tag{18}$$

3.6 Modeling of Demand

The demand modeling of the system is given in the following equations:

$$P_{D,i(t)} = \Omega_{i(t)} P_{D,i}^{0} \forall t, i \tag{19}$$

$$Q_{D,i(t)} = \Omega_{i(t)} Q_{D,i}^{0} \forall t, i \tag{20}$$

where $\Omega_{i(t)}$ is the assigned load factor for the time period t.

3.7 Modeling of PV Output

Solar power generation is dependent on several other elements as well. These factors include the type of panel and its area, the angle at which the panel is tilted, and the amount of solar radiation that is received. To facilitate this analysis, it is assumed that all other factors will remain identical during the specified time. The transformation of the current in relation to the rated voltage may be found as follows:

$$I_{sm(t)} = \begin{cases} I_{sm} \text{ if } S_{r(t)} \geq S_r^r \\ I_{sm} \times S_{r(t)} / S_r^r \text{ if } S_{r(t)} < S_r^r \end{cases} \tag{21}$$

3.8 Optimization Technique

Particle Swarm Optimization (PSO) is a way for computers to find the best answer to a problem by imitating the way animals act. Each particle in the swarm is a possible answer to the optimization problem, and its position and speed change are based on what it has learned and what the whole swarm has learned. The objective function tells the swarm where each particle should go. During each iteration, the PSO method uses a particle's current position, its best position from before, and the best position found by any other particle in the swarm to change its speed and location [184]. This process keeps going until there is a reason to stop. At Level 1, optimal decision-making occurs to determine the key planning variables, including the location and size of PV systems. Meanwhile, at Level 2, the focus shifts to optimizing the hourly dispatch of DR

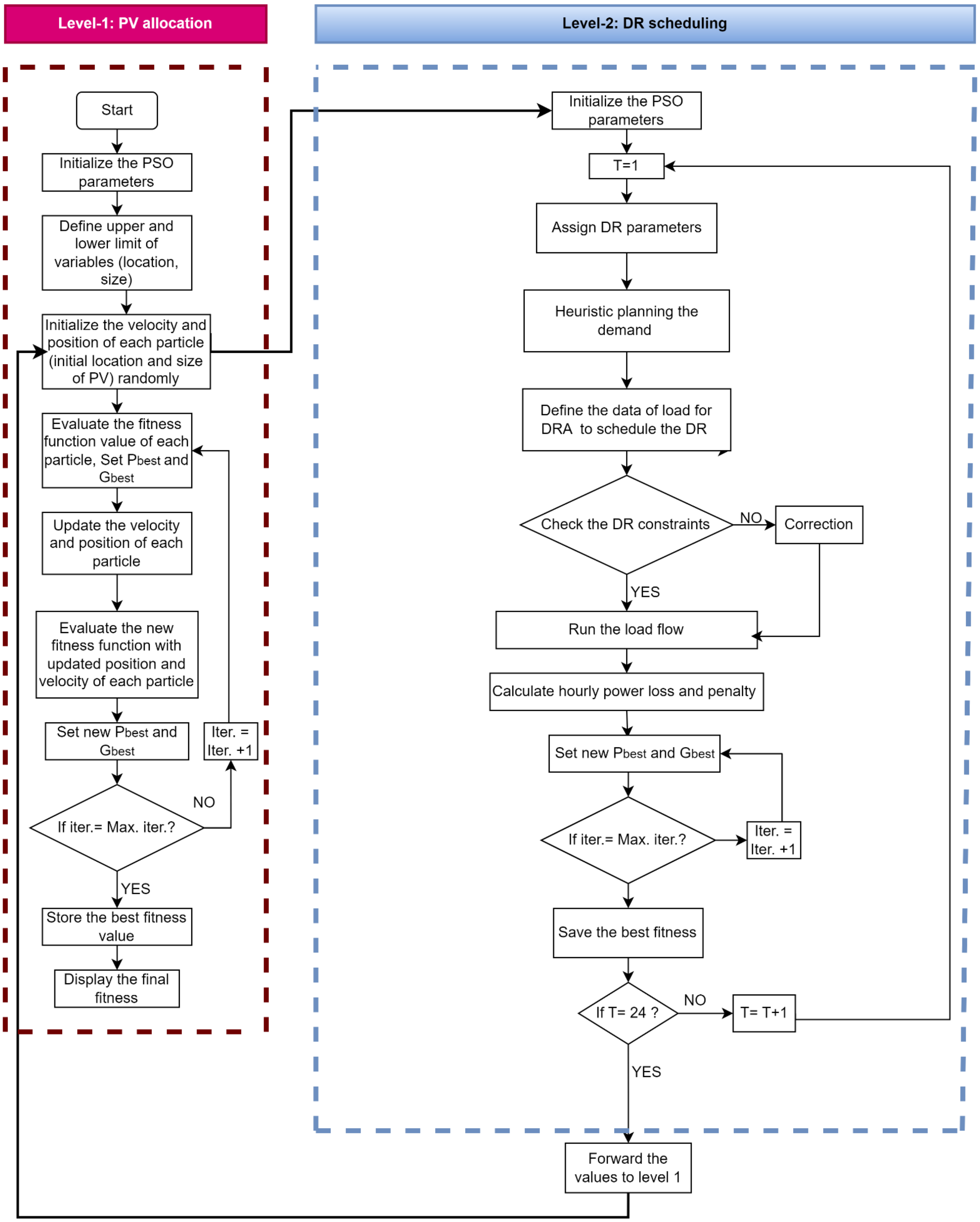

Fig. 3.1: Framework of proposed bilevel optimization approach.

programs. This optimization aims to maximize the operational advantages for the distribution system operator (DSO). Any evolutionary method can be used to solve the difficult problem of multilevel optimization. Based on a review of the relevant published material, it has been found that PSO is the most common way to solve the DG planning optimization problem [185,186]. The simulation parameters for the optimization technique are given in the table 3.1.

Table 3.1. Simulation parameters of proposed bilevel optimization technique.

Parameters	Level-1	Level-2
Swarm size	20	50
Inertia weight	1	1
Inertia Weight Damping Ratio	0.99	0.99
Personal Learning Coefficient	1.5	1.5
Global Learning Coefficient	2	2
Maximum Number of Iteration	50	50

3.9 Results

On the IEEE 33 bus system, the multilevel optimization method that has been suggested will be used [187]. The test system is shown in figure 3.2. In this study, the effects of DR technologies are shown and analyzed so that a solution to the problem of finding the optimal way to transmit power in different situations and with different constraints can be found. The objective of this research is to improve the efficiency of power distribution. Using MATLAB software and a computer with an i3 core processor and 12 gigabytes of random-access memory, the optimization objectives are resolved with the help of proposed optimization techniques.

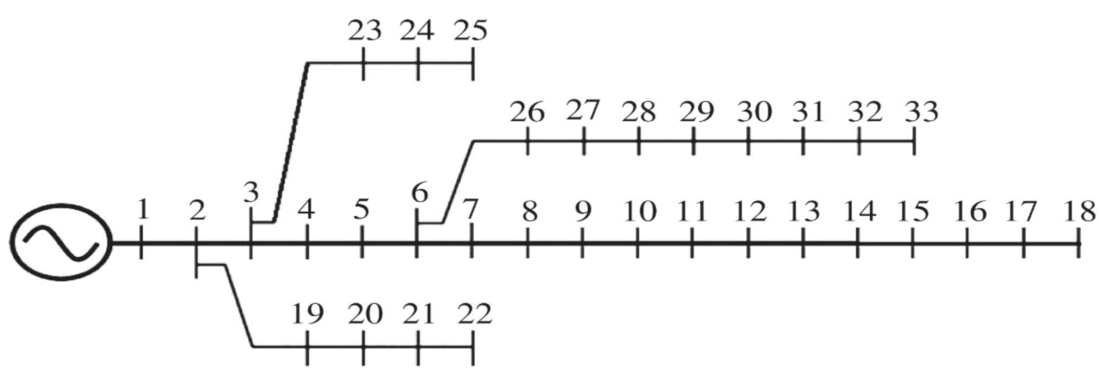

Fig. 3.2: IEEE 33 bus system

3.9.1 Base Case

This scenario considers the base case to demonstrate effectiveness of a recommended technique for incorporating SPV into a 33-bus radial distribution system. The objective functions of the research are based on the consumption pattern of a typical day [188], and the annual energy loss is calculated using the average daily energy loss. The results show the difference between the highest and lowest possible demand, the minimum mean voltage, and the annual energy losses for the base scenario. The lowest demand period is around 5:00 a.m., while the highest demand period is around 8:00 p.m. According to tables 3.2 and 3.3, the difference between the highest and lowest possible demand, the minimum mean voltage, and the annual energy losses for this base scenario are respectively 5397.73 kW, 0.978178 p.u., and 1426 MWh.

3.9.2 DG Integration

In this case, the authors optimized the placement of DG in a DN using SPV installations. The results showed that incorporating DGs into an optimized method improved power quality parameters such as annual energy loss and minimum mean voltage. The annual energy loss decreased by approximately 21.8%, and the minimum mean voltage increased from 0.978178 to 0.99634 p.u. The optimal size for SPV installations and their locations are outlined in table 3.3, and the effect of DGs on the pattern of demand, voltage, and active power losses were illustrated in figures 3.3, 3.4, and 3.5, respectively.

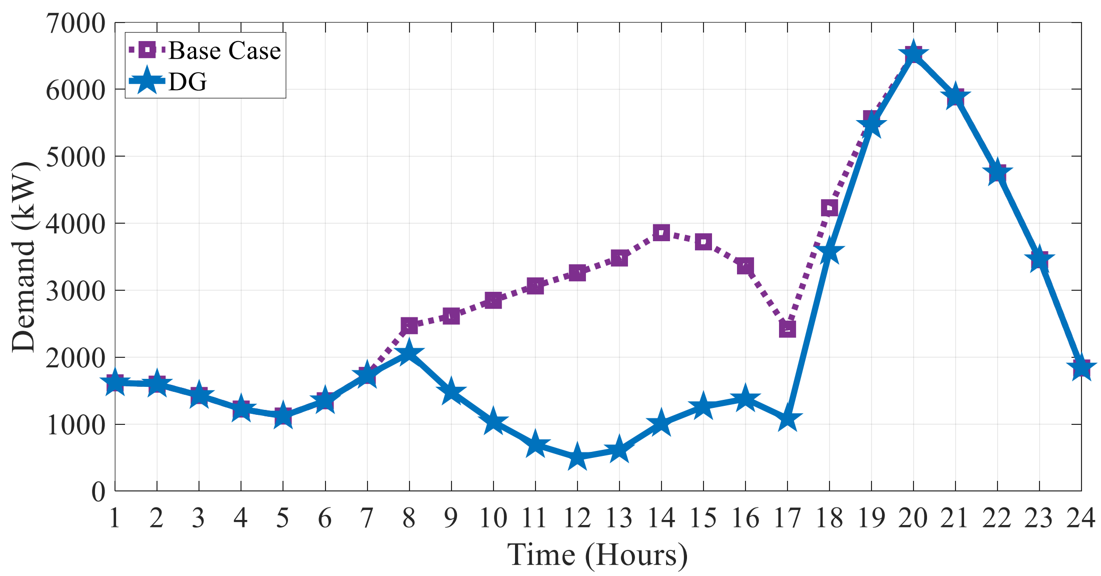

Fig. 3.3: Impact of DGs (PSO optimized) on demand pattern

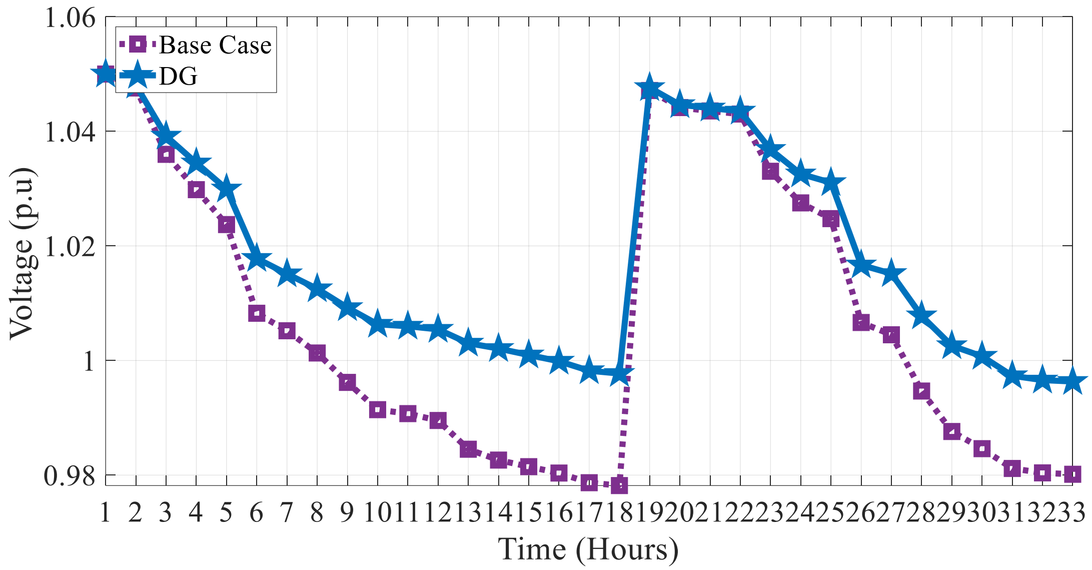

Fig. 3.4: Impact of DGs (PSO optimized) on voltage pattern

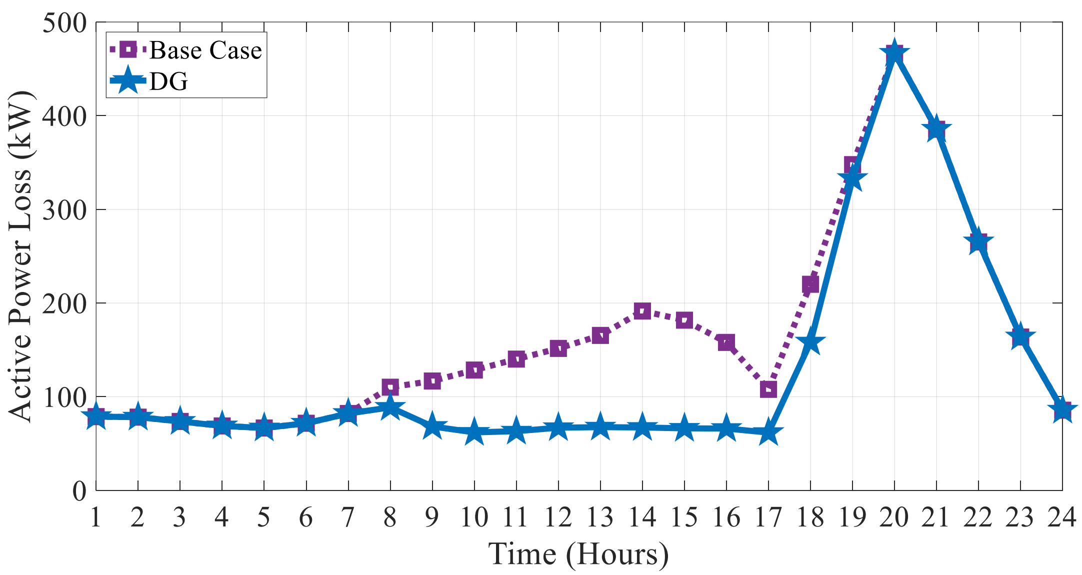

Fig. 3.5: Impact of DGs (PSO optimized) on active power losses

3.9.3 DR Implementation

This study evaluates the significance of DR approach in the absence of DG coordination. Two levels of demand elasticity are assumed and benchmarked. DR rate refers to market demand elasticity. In this case, DR rate of 10% and 20% are considered without DG placement. Results show that DR reduces peak demand by 14.72% for a 10% DR rate and 18.32% for a 20% DR rate, and yearly energy loss by 5.96% to 8.2%. DR also reduces active power losses and increases peak-to-valley disparity. Even without DG, DR can be effective. Figure 3.6 to figure 3.11 demonstrate the effects of 10% and 20% DR rates on demand, voltage, and active power losses. There is negligible impact of DR rate on the voltage profile of the test system as shown in figure 3.7 and figure 3.10.

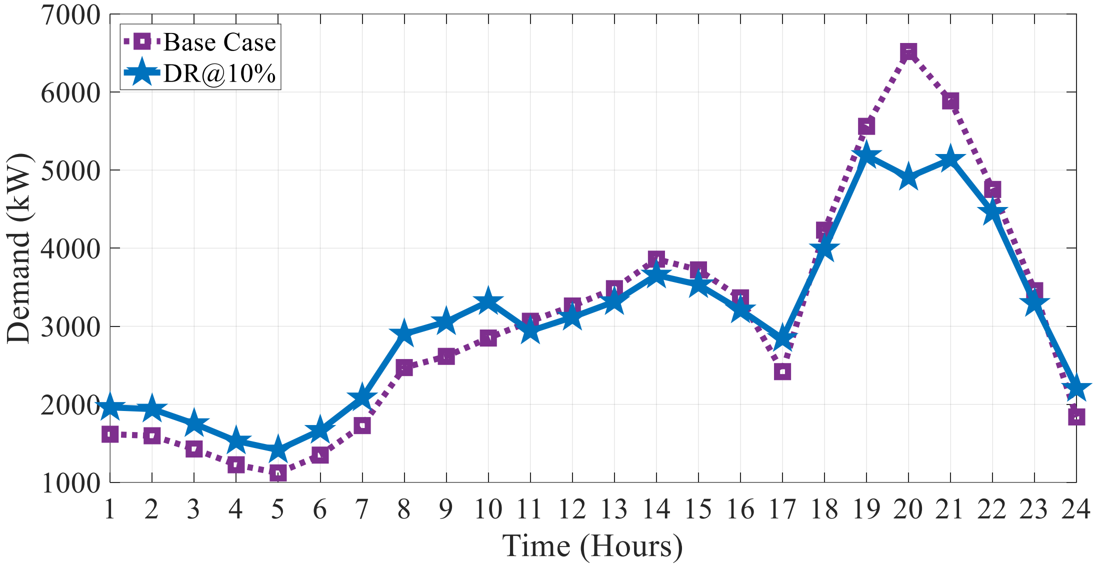

Fig. 3.6: Impact of 10% DR rate on demand pattern

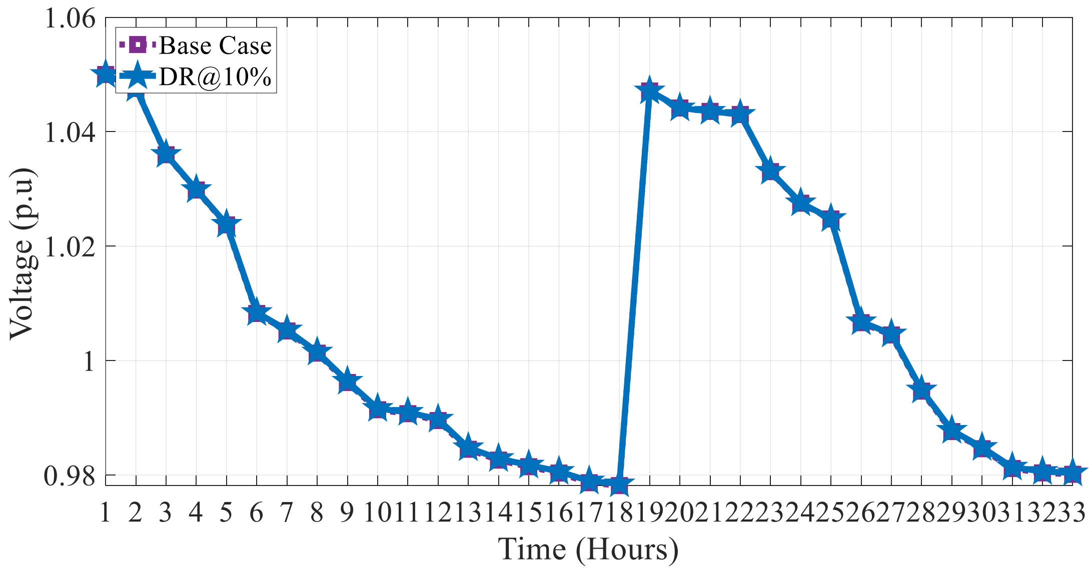

Fig. 3.7: Impact of 10% DR rate on voltage pattern

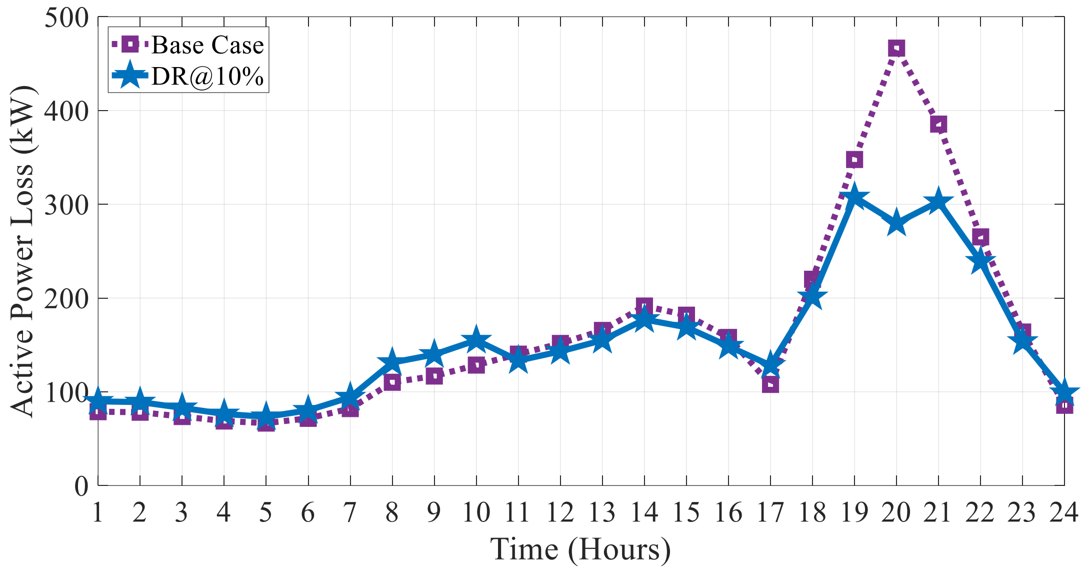

Fig. 3.8: Impact of 10% DR rate on active power losses

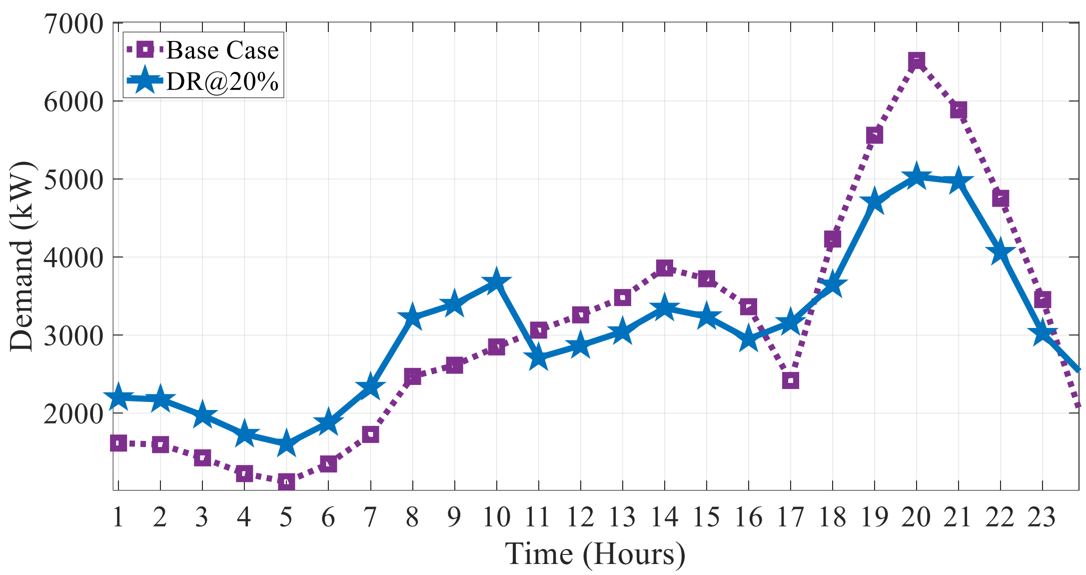

Fig. 3.9: Impact of 20% DR rate on demand pattern

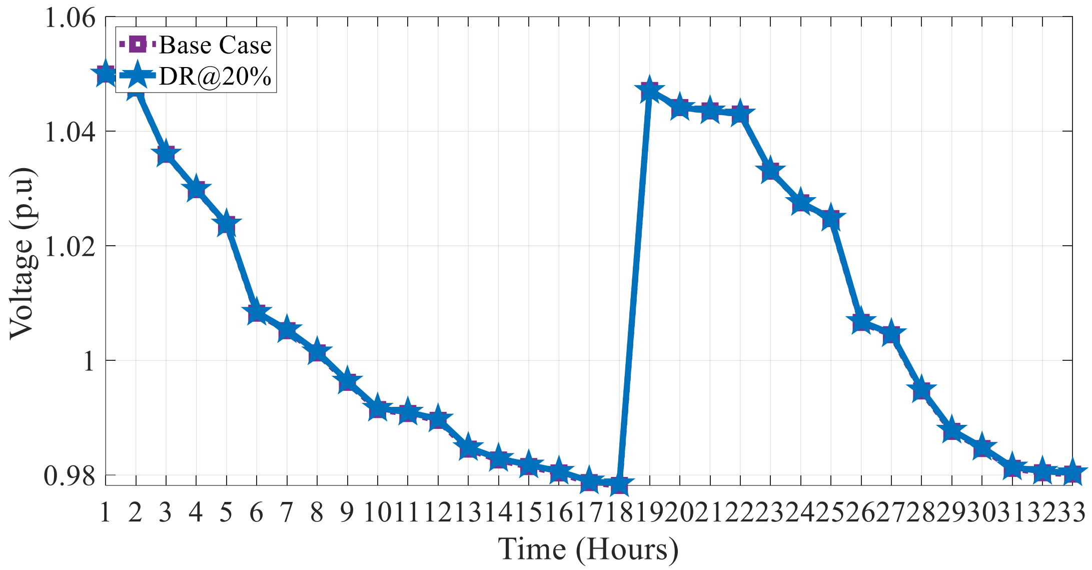

Fig. 3.10: Impact of 20% DR rate on voltage pattern

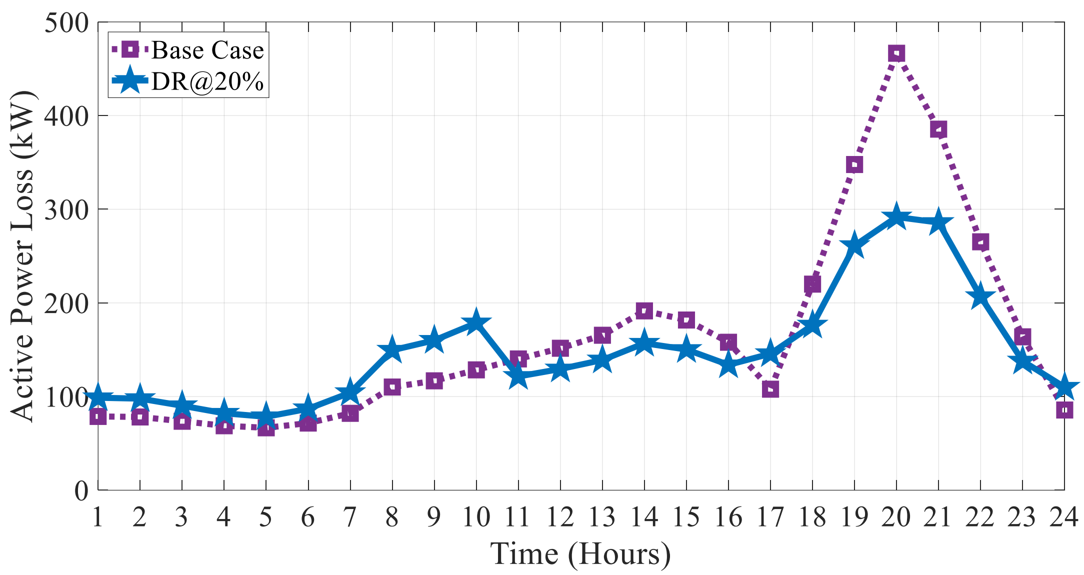

Fig. 3.11: Impact of 20% DR rate on active power losses

3.9.4 DG Integration with DR Coordination

In this case, after incorporating DGs into DR coordination and planning under system constraints, the analysis is done. This scenario integrates DGs with DR scheduling while considering system constraints. High DR rates and smaller DGs increase system performance. Annual energy loss has decreased significantly. The lowest mean voltage has increased from cases 1 and 2 by 29.03% to 33.31%, depending on the degree of DR rates. The load profile is flatter because DGs reduce the gap from maximum to minimum demand. Figure 12 to figure 14 show that DGs with a 10% DR rate affect demand, voltage, and active power losses. Figure 15 to figure 17 show how DGs with a 20% DR rate affect demand, voltage, and active power losses.

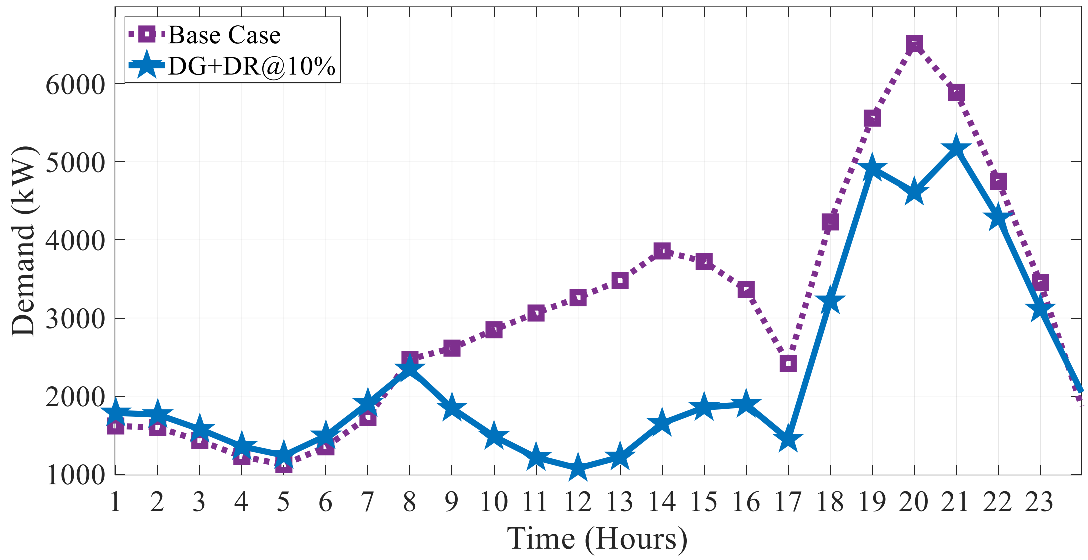

Fig. 3.12: Impact of DG and 10% DR rate (PSO optimized) on demand pattern

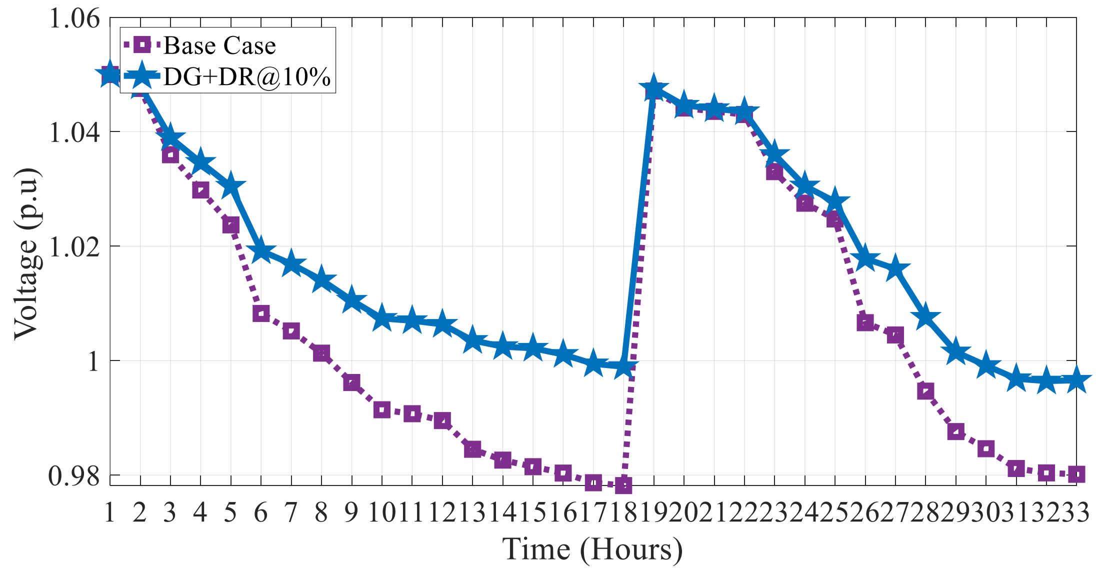

Fig. 3.13: Impact of DG and 10% DR rate (PSO optimized) on voltage pattern

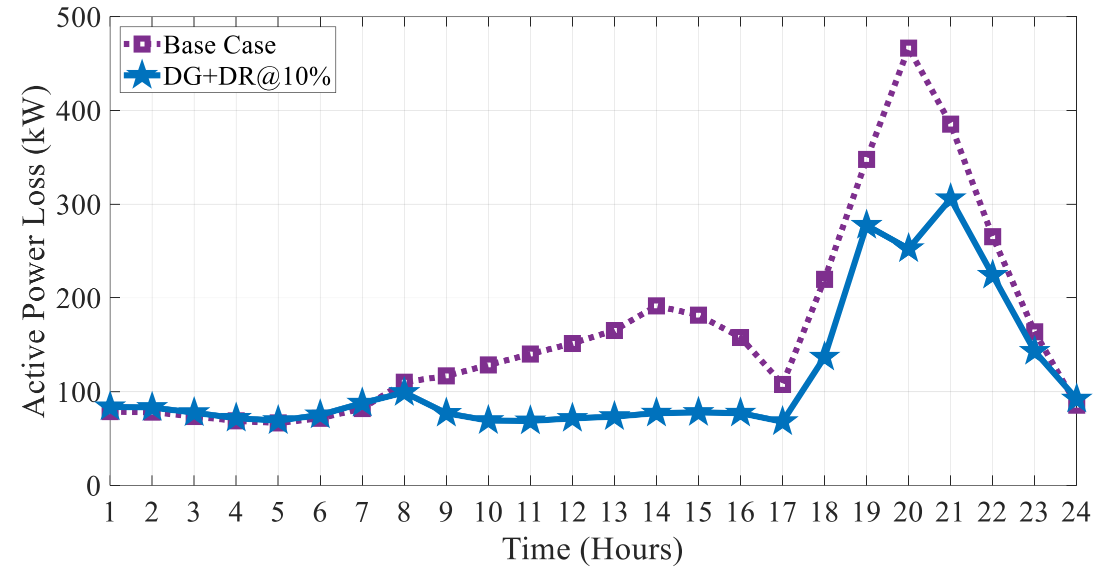

Fig. 3.14: Impact of DG and 10% DR rate (PSO optimized) on active power losses

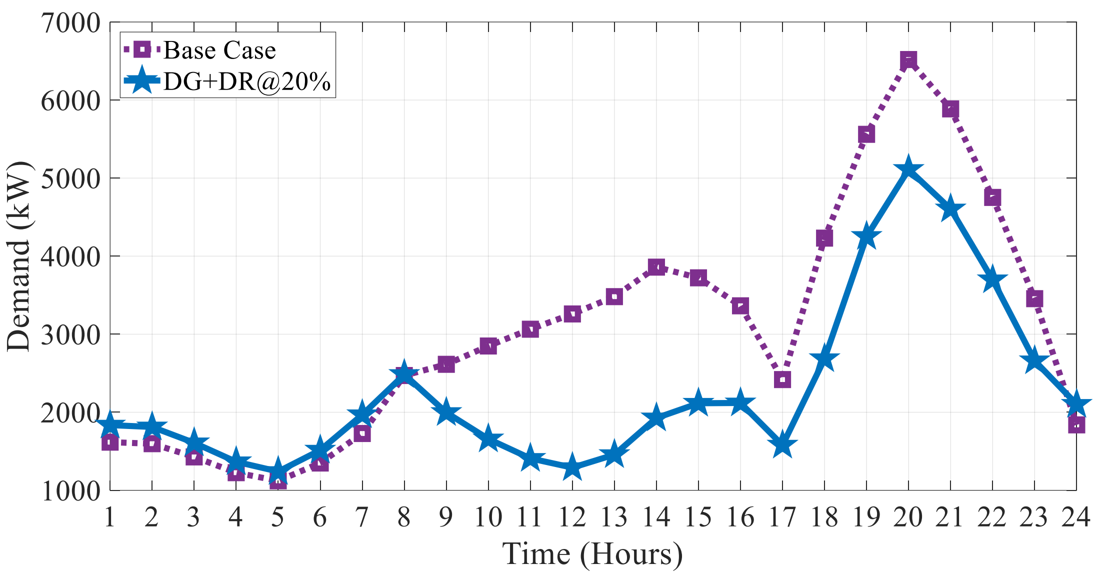

Fig. 3.15: Impact of DG and 20% DR rate (PSO optimized) on demand pattern

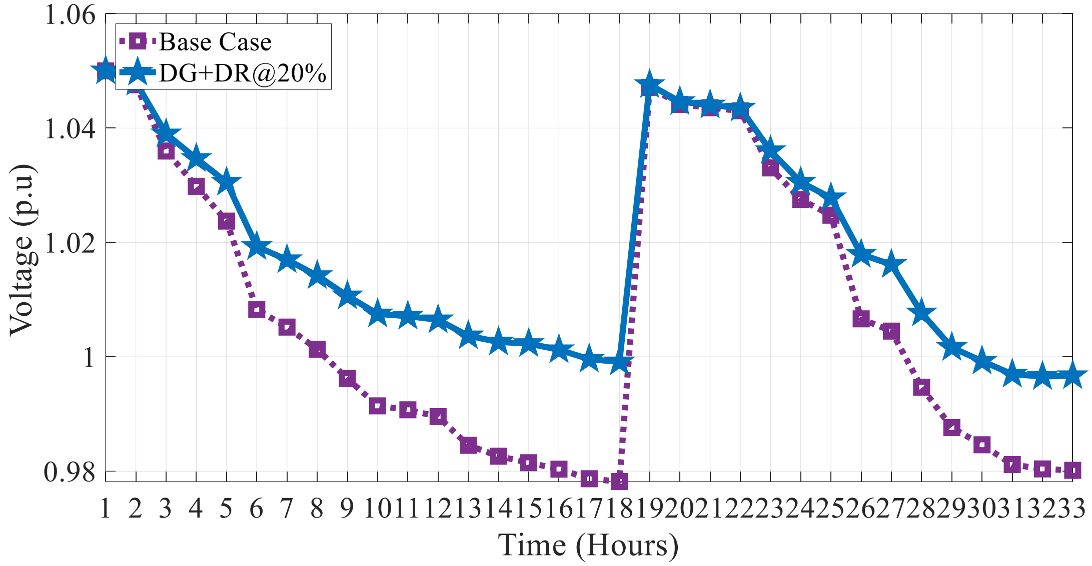

Fig. 3.16: Impact of DG and 20% DR rate (PSO optimized) on voltage pattern

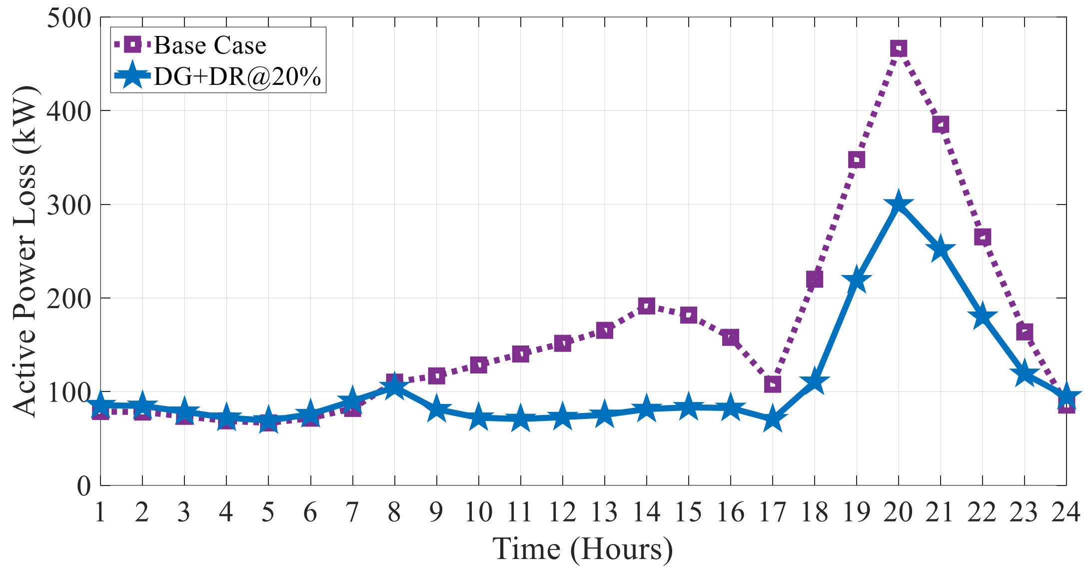

Fig. 3.17: Impact of DG and 20% DR rate (PSO optimized) on active power losses

Table 3.2 Effect of the coordination of DR with optimally integrated SPV on demand.

Case No.	Category	Maximum Demand (kW)	Maximum Demand Mitigation %	Difference between Maximum to Minimum Demand (kW)	% Of Maximum Loss Mitigation at 8:00 PM
1	Base Case	6519	0	5397.73	0
2	DG	6519	0	6016.39	0
3	DR@10%	5548	16.1	4166.14	36.09
	DR@20%	5321	18.42	3730.6	42.77
4	DG+DR@10%	5370	17.33	4322.87	33.69
	DG+DR@20%	4790	26.78	3540.31	45.69

Table 3.3 Outcomes of the coordination of DR with optimally integrated SPV.

Case No.	Category	Optimal Allocation of DG (Bus No., kW)	Annual Losses (MWh)	Reduced losses / Year (%)	DG Penetration (%)
1	Base Case		1426		
2	DG	17(1344)-32(1690)-25(1092)	1098	23	68.76
3	DR@10%		1302	8.69	
	DR@20%		1290	9.53	
4	DG+DR@10%	7(1086)-15(1902)-32(914)	996	30.15	65.03
	DG+DR@20%	18(408)-29(1816)-11(1602)	934	34.5	63.76

3.10 Conclusion

While DGs have proven effective in reducing annual energy losses, it is important to consider their potential negative impact on load profile flattening. As the penetration of DGs increases, voltage levels can rise, leading to reverse power flow back into the grid. These challenges highlight the limitations of high DG penetration within the DN. Incorporating DR helps to balance the load profile, minimize the gap between peak and off-peak load demands, and alleviate strain on the system. Put simply, a higher DR rate can improve demand normalization efficiency, especially in cases where the penetration level of SPV systems is lower. As per the implemented framework, the mitigation of maximum demand, reduced energy losses per year, and DG penetration are 26.78%, 34.5%, and 67.76%, respectively. These are the maximum level achieved from case 1 to case-4.

In conclusion, the impact assessment of DR on the optimal placement of SPV systems in the DN has shown significant potential for improving the efficiency and effectiveness of renewable energy integration. The use of DR strategies can help reduce peak demand and enhance the flexibility of the distribution network, allowing for increased penetration of SPV systems while minimizing grid congestion and overloading.

Through simulation studies and empirical analyses, it has been demonstrated that the integration of demand response mechanisms can lead to enhance the power quality parameters and increased penetration level of renewable energy sources. The findings of the impact assessment provide useful insights for policymakers, utilities, and other stakeholders involved in the planning and management of DN.

While further research is needed to fully explore the potential of DR on SPV placement, it is clear that the incorporation of DR into energy systems planning and design will be an essential component of meeting future energy needs sustainably. Ultimately, the impact assessment of DR on the optimal placement of SPV systems highlights the importance of adopting a holistic approach to energy systems planning that considers the interaction between different components of the energy system and the potential for innovative solutions to address complex challenges.

Chapter- IV

Optimal DG Allocation in the Coordination of Demand Response and Battery Energy Storage System

4.1 Introduction

In the modern era, a smart grid is required to increase the penetration of renewable energy resources with the use of real-time information and advanced communication technologies for the execution of its objectives. The smart grids allow for communication in both directions between the customers and the sources of energy generation [189]. Many studies have been done on the responsive load that is based on dynamic pricing, and they have all come to the same conclusion: the shifting of load from peak to valley hours of demand in the coordination of renewable energy resources gives prosumers the most benefits [183, 190, 191]. The fast developments in technology for small-scale generation have pushed distribution system operators (DSOs) to expand the percentage of distributed generators (DGs) in distribution networks (DN). The optimal size and location of DGs are required to enhance the performance of DN. This is because it has been shown that not allocating resources in the optimal way is counterproductive [192-194]. Through the optimal incorporation of DGs, a number of goals have been accomplished, including the enhancement of power quality, the improvement in voltage profile, the reduction of pollutants in the atmosphere, the improvement in system stability and reliability, and many more. But traditional distribution systems aren't set up to handle a large number of renewable energy sources because these sources can't be controlled, are unpredictable, and change over time [186]. It is advised to adopt one of the potential remedies known as battery energy storage systems (BESS) to raise the penetration level of power from nondispatchable DGs in DN [195–198]. Numerous studies have been conducted for the modelling and optimal energy management of BESS to reinforce the penetration level of DGs. It has come to our attention that significant efforts are being put into optimizing the capacity of BESS, but the optimal location is not considered in the objective function [195, 196]. To optimize the performance of DN, it is strongly suggested to formulate and find the optimal solution for the location and size of BESS at the same time. There is a paucity of research on simultaneous deployment and sizing of BESS in the existing body of academic literature. The advantages of DSO are enhanced by optimally identifying the size and position of BESS [197]. The optimization of the size and location of BESS also includes the minimization of power losses, the minimization of cost functions, and the maximization of energy arbitrage profits, among other accomplishments [198]. The implications of optimized capacity and location of BESS are evaluated for wind energy and hydro energy-based hybrid power plants in the coordination of BESS [199]. The authors did the research on how the reconfiguration of a network influences the size of BESS and where it is located [200]. Despite this, BESS is a costly option for DSO since it requires more investment and increases the overall cost of operating the system. The life cycle of BESS is dependent on the selection of the depth of discharge (DOD) as well as the charging and discharging cycles of the storage system. [201]. According to the research that has been conducted, a high penetration of DGs may be supported by a large BESS that is optimally situated.

Nevertheless, an increase in the size of the BESS places an additional cost burden on the DSO. Because of these problems, researchers are looking into possible other ways to run DR, with the goal of taking some of the pressure off of BESS. The DR has done a good job of meeting many of the prospective of the smart grid [202-204]. Communication and consumer coordination through price-based demand response is one method for reducing the costs associated with energy consumption and the reoccurrence of the peak [202]. The utilization of DR has demonstrated improved technological advantages for the DN in Finland, including reductions in power losses and an improved voltage profile [203]. The authors demonstrated a DR-coordinated approach in DG allocation to mitigate the impact of renewable energy sources' intermittent nature [204].

DR is adopted to reduce demand and supply imbalances, as well as to limit the risks posed by the constraints imposed on DG owners. In the research carried out by the authors [205], the simultaneous deployment of DR and DG loads on the DN was investigated. The authors demonstrated a coordinated approach of DGs and DR in order to optimize the advantages for a variety of utility stakeholders [206, 207]. Based on the research mentioned above, demand response can work well when there are regulated loads, dynamic pricing, and renewable resources. After conducting an in-depth analysis of the relevant published research, the authors came to the conclusion that incorporating DGs and BESS into distribution networks results in a notable increase in the efficiency of those networks. The DR not only enables a high penetration of distributed generation but also offers significant benefits to all parties involved in the smart grid, including customers, distribution service operators (DSOs), generating firms, and aggregators. It is clear from the available research that the optimal allocation of DGs in the coordination of DR has been examined. However, the optimized allocation of DGs in the existence of DR has not been researched with the incorporation of BESS. As a result, the purpose of this research is to explore the function of DR as well as its advantages in order to best integrate DGs and BESS in the DN. Because the potency of DR depends upon the level of consumer participation, as a result, research is being done to determine how the appropriate size and placement of PV and BESS systems are affected by the various DR rates. A multilevel optimization framework is utilized for the objective of optimally and concurrently integrating PVs and BESS in the synchronization with DR planning in DN.

This research chapter takes a number of different objectives into consideration, some of which are to minimize the amount of energy lost in the feeders and the amount of energy converted in the BESS; to minimize the amount of voltage deviation; and to minimize the amount of reverse power flow, all while making the most of the BESS and DR in the presence of high PV penetration. To demonstrate how effectively DR works, many test scenarios have been investigated, and a recommended framework has been applied to a typical 33-bus test data set. This was done in order to demonstrate how well DR works.

4.2 Problem Conceptualization

In this study, the following objectives have been examined for the optimal allocation of PV and BESS in the effective synchronization of DR panning in DN.

4.2.1 Minimization of Power Losses

The amount of power that is lost during delivery is often rather significant in DS. There is significant potential for a reduction in power loss to be achieved with the implementation of a number of technological advancements, including the integration of DGs, the effective functioning of BESS, and the coordination of DR. A significant amount of power loss in any distribution system has an immediate and direct impact on the annual income of the utility, which in turn has repercussions for all of the stakeholders. Therefore, minimizing power loss is taken into consideration as one of the goal functions, which are defined as follows [181]:

$$f_1 = \sum_{T=1}^{24} P_{\text{Loss}}^T \tag{1}$$

$$P_{\text{Loss}}^T = \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_{ij}^T \left(P_i^T P_j^T + Q_i^T Q_j^T\right) + \beta_{ij}^T \left(Q_i^T P_j^T - P_i^T Q_j^T\right) \forall T \tag{2}$$

where $\alpha_{ij}^T = r_{ij} \cos\left(\delta_i^T - \delta_j^T\right) / V_i^T V_j^T$ and $\beta_{ij}^T = r_{ij} \sin\left(\delta_i^T - \delta_j^T\right) / V_i^T V_j^T$

4.2.2 Minimization of Reverse Power Flow

It is anticipated that the proportion of renewable sources will rise in the years to come in order to achieve the global green energy targets and reduce greenhouse gas emissions. However, the rising penetration of renewable energy sources might result in a reverse flow of power during low demand hours. This will increase the operational complexity for DSO, and certain protection difficulties. As a result, one of the goals of DG integration is to take into consideration the possibility of reversing the flow of electricity. The goal of the power flow in the opposite direction might be stated as:

$$f_2 = \sum_{T=1}^{24} P_R^T \tag{3}$$

$$P_R^T = \begin{cases} 0, & \text{if } I_{\text{Grid}}^T \geq I_{\text{Spc}} \\ \text{Re}\left(V_{\text{Grid}}^T I_{\text{Grid}}^{T*}\right) & \text{if } I_{\text{Grid}}^T < I_{\text{Spc.}}. \end{cases} \tag{4}$$

4.2.3 Minimization of BESS Conversion Losses

The development of converters and battery storage systems has been the subject of a large amount of study as of late. The minimization of converter losses is required for effective integration of BESS. Therefore, taking into consideration the conversion losses of charging-discharging period of BESS is also one of the objectives. The formula for BESS loss may be written as:

$$f_3 = \left(\sum_{T=1}^{24} P_c^T\right) \tag{5}$$

$$P_c^T = (1 - \eta) P_{BESS\left(\frac{C_i}{D_i}\right)}^T \tag{6}$$

4.2.4 Node Voltage Deviation

In order to preserve the reliability of the power supply, it is necessary for the DS to function within the parameters of an acceptable voltage range. In most cases, a penalty function is responsible for accounting for the exceeding of voltage restrictions. It is possible to count this penalty function as one of the objectives as well.

The purpose of exceeding the voltage limit can be stated as follows [208]:

$$f_4 = (1 + \sum_{T=1}^{24} V_D^T) \quad (7)$$

$$V_D^T = \begin{cases} \left|V_{\text{Min}} - V_i^T\right| \text{ if } V_i^T < V_{\text{Min.}} \\ 0 \quad \text{if } V_{\text{Min.}} \leq V_i^T \leq V_{\text{Max.}} \\ \ell \quad \text{if } V_i^T > V_{\text{Max.}} \end{cases} \quad (8)$$

l denotes an arbitrarily large positive integer. A big value denotes an undesirable solution. A rise in voltage that is beyond the maximum working limit is a major problem, which is an essential point to keep in mind [169]. As a result of the low demand case, the rise in voltages may continue to worsen, eventually reaching such high levels that it may have an effect on the protection shield and insulation collapse may happen in a number of the equipment that are linked. Increased voltage is the primary barrier that prevents a deeper penetration of DGs in DN. Because of this, hard constraint was employed whenever there was a violation of the higher voltage limit. However, compared to the maximum voltage, the minimum voltage has been treated as more of a flexible limitation. It means that there can be a small deviation from the minimum voltage as long as there is a good penalty factor.

4.2.5 Fitness Function

To achieve the required objectives, it is required to make a fitness function having the weightage factor of different objective functions. For level 1 of optimization, the fitness function ($F_{\ell 1}$) is given as:

$$min(F_{\ell 1}) = \Psi \times L \times f_4 \quad (9)$$

$$\text{where } L = f_1 + f_2 + f_3$$

The level 2 of the optimization objectives involves taking into consideration the DR planning and scheduling methods of DGs and BESS. In this stage, the BESS conversion losses are irrelevant and have no impact. Because of this, the following objective function will be taken into consideration for level 2 of the optimization problem:

$$min(F_{\ell 2}) = \kappa \times f_4 \quad (10)$$

$$\text{where} \quad \kappa = f_1 + f_2$$

In this context, the fitness function for level 2 is denoted by $F_{\ell 2}$.

It is vital to have a dispatch strategy, which is determined upon by the DR aggregator. This helps to minimize the aforementioned goal function.

4.2.6 Demand Response Aggregator

The DR system that has been developed takes into account the advantages that many stakeholders, such as DSOs and consumers, enjoy. The DR aggregator has an impact on how customers schedule their demand in accordance with their participation in DR, and this scheduling is also subject to a number of different technological restrictions. This study focuses the majority of its attention on the technological challenges faced by the DS as a direct result of the widespread use of PVs. In its most basic form, DR implementation makes use of the information provided by dynamic tariff and, based on that information, schedules the load in order to achieve the greatest possible reduction in set technical targets. The financial objectives are not considered for this study; rather, attention is directed toward the technological problems.

The load is scheduled by DR aggregator after collecting the relevant information of responsive and nonresponsive load demand and it is the mandatory part of this program.

Participants in obligatory DR programs are subject to financial penalties if they fail to adjust their load in accordance with the instructions given by the aggregator. The scheduling of demand should strike a balance between total consumption and available resources throughout the day. In place of demand reduction or reduction in overall consumption, the objective of DR is to restructure demand. The complete demand at any time T is equal to the sum of all types of loads (responsive and nonresponsive) and represented in equation 13.

Equation 14 depicts the scheduling restrictions that must be adhered to in order to meet responsive demand without having an impact on the overall demand of an entire day. The lowest and maximum values of the responsive demand are both represented by equation 15.

The peak value of responsive demand is dependent on the penetration level of DR and such details are given in equation 16. The following are some of the DR limitations that are taken into consideration [182]:

$$P_i^T = (P_{Gi}^T - P_{Di}^T)\forall T, i \tag{11}$$

$$Q_i^T = (Q_{Gi}^T - Q_{Di}^T)\forall T, i \tag{12}$$

$$P_{Di}^T = \left(P_{in,i}^T + P_{el,i}^T\right)\forall T, i \tag{13}$$

$$\sum_{i=1}^{N} \sum_{T=1}^{24} \left(P_{in,i}^T + P_{el,i}^T\right) \times \Delta t = E_i^{Total} \tag{14}$$

$$P_{el,i}^{min} \leq P_{el,i}^T \leq min\left(\left(C - P_{in,i}^T\right), P_{el,i}^{max}\right)\forall T \tag{15}$$

$$P_{el,i}^{max} = \chi \sum_{T=1}^{24} L_{d,i}^T \tag{16}$$

The optimal solution to the optimization issue is a vector of responsive load schedules with a length of T and is represented as:

$$P_{el} = [P_{el}^1, P_{el}^2, P_{el}^3, P_{el}^4 \dots \dots \dots \dots \dots \dots \dots \dots P_{el}^T]\forall T.$$

4.2.7 Objective constraints

The objective functions are constrained in a variety of ways by both technical and operational considerations. These restrictions can be represented numerically as follows:

- *PV generation limit constraint*

The constraint for PV generation limit is given as:

$$0 \leq P_{\mathrm{PV},i} \leq P_{PV}^{max}\forall i \tag{17}$$

- *BESS constraints*

The constraints of BESS are given as:

$$0 \le E_{BESS,i} \le E_{BESS}^{\text{Max}} \forall i \tag{18}$$

$$P_{BESS}^{\text{Min.}} \le P_{BESS(C_i/D_i)}^{T} \le P_{BESS}^{\text{Max.}} \forall T, i \tag{19}$$

$$SOC^{\text{Min.}} \le SOC_i^T \le SOC^{\text{Max.}} \forall T, i \tag{20}$$

$$SOC_i^T = \begin{cases} SOC_i^{T-1} + P_{BESS(\mathrm{C}_i/\mathrm{D}_i)}^{T} \eta_c \Delta t / E_{BESS}^{R} & \text{if } P_{BESS(\mathrm{C}_i/\mathrm{D}_i)}^{T} > 0 \\ SOC_i^{T-1} + P_{BESS(\mathrm{C}_i/\mathrm{D}_i)}^{T} \Delta t / \eta_d E_{BESS}^{R} & \text{else} \end{cases} \tag{21}$$

$$\sum_{T=1}^{24} \eta_c P_{BESS(C_i/D_i)}^{T} + P_{BESS(C_i/D_i)}^{T} / \eta_d = 0 \tag{22}$$

Equation 18 represents the limitations of energy while equation 19 represents the limitations of power dispatch. The limits of SOC are given in equation 20 and SOC status is presented in equation 21. SOC balancing constraints are demonstrated in equation 22. All the above equations are at specific node and time.

- *Feeder Constraint*

The constraint for the thermal limits is given as:

$$I_{ij}^{T} \le I_{ij}^{max} \forall T, i, j \tag{23}$$

- *Power balance constraints*

$$P_i^T = V_i^T \sum_{j=1}^{N} V_j^T Y_{ij} \cos\left(\theta_{ij} + \delta_j^T - \delta_i^T\right) \forall T, i \tag{24}$$

$$Q_i^T = -V_i^T \sum_{j=1}^{N} V_j^T Y_{ij} \sin\left(\theta_{ij} + \delta_j^T - \delta_i^T\right) \forall T, i \tag{25}$$

The actual and reactive power balance restrictions are shown by equations 24 and 25 respectively.

4.2.8 Demand Modeling

The demand modeling of the system is given in the following equations:

$$P_{D,i}^{T} = \kappa_i^T P_{D,i}^{0} \forall T, i \tag{26}$$

$$Q_{D,i}^{T} = \kappa_i^T Q_{D,i}^{0} \forall T, i \tag{27}$$

4.2.9 PV Generation Modeling

Solar power generation is dependent on a number of other factors as well, such as the type of panel and its area, the angle at which it is tilted, and the amount of solar radiation that is received. For the purposes of this study, during a specific period of time, it is assumed that all other parameters remain unchanged. The transformation of the current in relation to the rated voltage may be found as follows:

$$I_{pv}^{T} = \begin{cases} I_{PV} \text{ if } R_{PV}^{T} \geq R_{PV}^{r} \\ I_{PV} \times R_{PV}^{T}/R_{PV}^{r} \text{ if } R_{PV}^{T} < R_{PV}^{r} \end{cases} \tag{28}$$

4.3 Optimization Technique

As discussed in previous case, the presented optimization objectives required such a optimization technique that can solve the complex nonlinear problem. The adoption of a multilevel optimization context is required by the presence of BESS since it takes into consideration both the limits associated with SOC levels and their accessibility. The optimal allocations of PVs and the BESS are determined at the first level of optimization. At the second level of optimization, the hourly power scheduling of BESS in the synchronization of DR programs is determined. This is done to make sure that the operational gains from DSO are used to their fullest extent. Any evolutionary method can be utilized to address the difficult multilevel optimization issue that has to be solved. According to a review of the relevant published material, it has been determined that GA is the method that is utilized most frequently for tackling the DG planning optimization problem [185]. As a result, the optimization goal presented in this work has been met at both levels by using GA.

The GA is an optimization approach that has the capability to search for a global or near-global solution to difficult optimization issues involving power systems, and it is a population-based meta-heuristic technique. Here are the things that need to be done to improve the multilevel optimization that is being thought about:

I. Set the initial values for the parameters and variables that are used in level 1 optimization. It includes locations, sizes of PVs and BESS, maximum generation, crossover, and mutation rate of the proposed optimization technique.

II. Upgrade the sizes and locations of PV that have been determined heuristically.

III. Apply the calculated load factor κ_i^T to the P_{Di}^T and Q_{Di}^T for a period of 24 hours.

IV. The level 2 gets the most up-to-date location, size of BESS P_{Gi}^T, P_{Di}^T, and Q_{Di}^T so that BESS and DR can be managed as well as possible.

V. For the level 2, the arrangement of responsive load and BESS power dispatch over a period of twenty-four hours are seen as the variables.

VI. At the level 2, the scheduling of BESS and DR is started subsequently getting the outcomes from first level subjected to various constraints of the system.

VII. Execute the load flow to find out how much power is lost and how much voltage is at each node.

VIII. Perform another round of updates to P_{Gi}^T (BESS discharging) and P_{Di}^T (BESS charging and also depends on the planning of responsive loads) in accordance with the BESS and DR schedules that were optimized in level 2.

IX. The level 1 controller receives upgraded variables like P_{Gi}^{T}, P_{Di}^{T}, SOC, and BESS power in order to optimize the objective of equation 9.

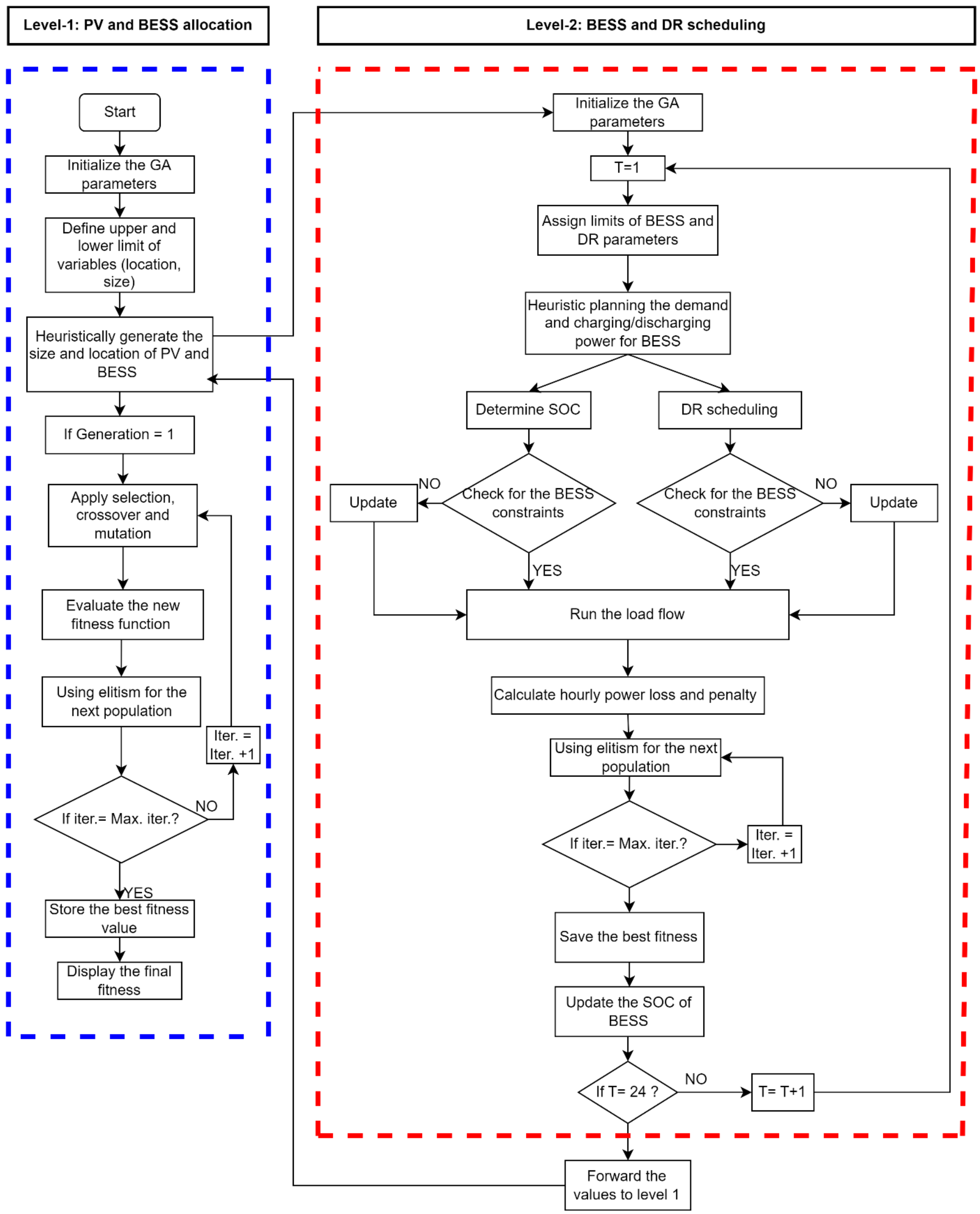

Fig. 4.1: Flow chart for multilevel optimization approach

X. Perform the load flow to find out the energy losses in addition the level of voltages at different nodes, it is necessary to evaluate the performance of level-1 optimization function.

XI. Preserve the level 1 population with the highest fitness and its matching best population.

The flow chart that is given in Figure 4.1 illustrates both the upper and lower levels' structures in great detail. The scheduling of BESS will depend upon the optimized value of dispatch power and the present value of SOC. The value of DOD is assumed to be 20% of the peak value of DOD and, primarily, the value of SOC is equal to the value of DOD. The optimal power dispatch and SOC will determine how the BESS charges and drains.

4.4 Results and Discussions

The proposed multilevel optimization technique is implemented on the IEEE 33 bus system [187]. In this research, the effects of DR technologies are shown and analyzed in order to solve the optimal power dispatch problem in a number of different scenarios and with a number of different constraints. The optimization objectives are solved with the help of proposed optimization techniques by using MATLAB software on i3 core processor having 12 GB RAM. PV is considered as DG during the optimal planning of power dispatch with the coordination of BESS and different DR rates. The details about the simulation settings for the multilevel optimization is given in Table 4.1. Additionally, the values of base voltage, nominal active demand, nominal reactive demand, power loss, $Vmin$, $Vmax$, P_{BESS}^{Min}, P_{BESS}^{Max}, SOC^{Min}, $SOC^{\mathrm{Max.}}$, $DG^{\mathrm{Max.}}$ and E_{BESS}^{Max} are 12.66kV, 3715 kW, 2300 kVAr, 202.7 kW, 0.95 pu., 1.05 pu, -1 MW, 1 MW, 0,1, 2 MW and 5MWh respectively.

Table 4.2 demonstrates how the DR rates impact the overall performance of the DS. The participation of different customers in various DR programs is reflected in the various DR rates. In this case study, we are assuming that type DR programs are required. Participants in mandated DR programs are required to pay the fine / penalty if they did not coordinate their usage in accordance with the DR aggregator's instructions. As a result, it is essential for the DR aggregator to monitor, control, and advise the consumers on scheduling the demand in accordance with the implemented DR rate. The outcomes of the optimal planning of power dispatch in the coordination of DG, DR, and BESS are given in table 4.3. Once the recommended technique is put into place, significant reductions in yearly energy loss, reverse power flow, and voltage variations are seen. As an illustration of the effectiveness of the suggested technique, we present several case studies and their respective results.

Table 4.1: Simulation parameters of multilevel optimization technique.

Parameters	**Level-1**	**Level-2**
Population size	20	50
Maximum generation	50	150
Crossover rate	0.9	0.9

Mutation rate	0.03	0.03

Table 4.2: Effect of the coordination of DR with optimally integrated renewable DG and BESS on demand.

Case No.	Category	Maximum Demand (kW)	Maximum Demand Mitigation %	Difference between Maximum to Minimum Demand (kW)	% Of Maximum Loss Mitigation at 20:00 h
1	Base Case	6519	-	5397.73	-
2	DG	6519	-	6016.39	-
3	DR@10%	5559.3	14.7216	4166.14	25.496
	DR@20%	5324.7	18.3204	3730.6	30.9725
4	DG+DR@10%	5375.66	17.5386	4322.87	29.807
	DG+DR@20%	4794.57	26.45	3540.31	42.3061
5	DG+BESS	4357.32	33.1597	4100.89	76.6233
6	DG+BESS+DR@10%	3811.44	41.5334	3299.7	77.0661
	DG+BESS+DR@20%	3291.08	49.5156	2498.53	76.8366

Table 4.3: Outcomes of the coordination of DR with optimally integrated renewable DG and BESS.

Case No.	Category	Optimal Allocation of DG (Bus No., kW)	Optimal Allocation of BESS (Bus No., kWh)	Annual Losses (MWh)	Reduced losses / Year (%)	DG Penetration (%)	Average Voltage level (p.u.)
1	Base Case	-	-	1426	-	-	0.978178
2	DG	14(1343)-30(1706)-25(1078)	-	1115	21.809	69.44	0.996344
3	DR@10%	-	-	1341	5.96	-	0.978444
	DR@20%	-	-	1309	8.204	-	0.978547
4	DG+DR@10%	15(1163)-7(1876)-33(904)	-	1012	29.03	66.33	0.9964
	DG+DR@20%	18(418)-29(1820)-11(1636)	-	951	33.31	64.56	0.996575
5	DG+BESS	16(1903)-32(1653)-7(1849)	13(2697)-33(4593)-16(3773)	827	42.0056	90.93	1.01249
6	DG+BESS+DR@10%	16(1528)-32(1729)-26(1828)	16(4529)-33(4386)-18(982)	789	44.6704	84.75	1.01226
	DG+BESS+DR@20%	17(988)-11(2022)-30(1797)	16(4591)-33(4388)-18(985)	759	46.7742	80.11	1.01263

4.4.1 Case 1: Base Case

The purpose of include this scenario in the discussion is to provide a foundation for demonstrating how successful the suggested approach is. In this analysis, neither PV nor BESS are considered for the 33-bus radial DS. In this particular instance, the DSO obtains all of the necessary power from the grid. The consumption pattern of an average day was obtained from reference [188], and it has been accounted for in each of the proposed objective functions in this chapter. The average daily energy loss is used in the calculation of yearly energy loss so that the study may be completed more quickly. According to Tables 4.2 and 4.3, the difference between the maximum and minimum demand, the minimum mean voltage, and the yearly energy losses are respectively 5397.73 kW, 0.978178 p.u., and 1426 MWh for this base scenario. The peak demand occurrence is 20:00 of the evening hours around while the valley point is around 5:00 in the morning hours.

4.4.2 Case 2: DG Allocation

In this scenario, the penetration level and locations of DGs are calculated at first level of optimization. The remaining information remains unaltered. According to Tables 4.2 and 4.3, the difference between the maximum and minimum demand, the minimum mean voltage, and the yearly energy losses are 6016.39 kW, 0.99634 p.u., and 1115 MWh respectively, for this particular instance. The peak demand remains same as shown in figure 4.2. This is due to the fact that the availability of solar generation is different from the availability of peak demand. Another valley point can be seen between the hours of 10:00 and 15:00, and this one is caused by the high penetration of distributed generation (DG), which lowers the demand placed on the grid. It may be concluded that the integration of DGs in optimized way enhance the power quality parameters. In this particular instance, the yearly energy loss has been shown to have decreased by around 21.8%, and the minimum mean voltage has increased from 0.978178 to 0.99634 p.u. Table 4.3 outlines the optimal dimensions for PV installations within DS, as well as their placement. The impact of DGs on the demand pattern, voltage pattern, and active power losses are demonstrated in figure 4.2, figure 4.3, and figure 4.4 respectively.

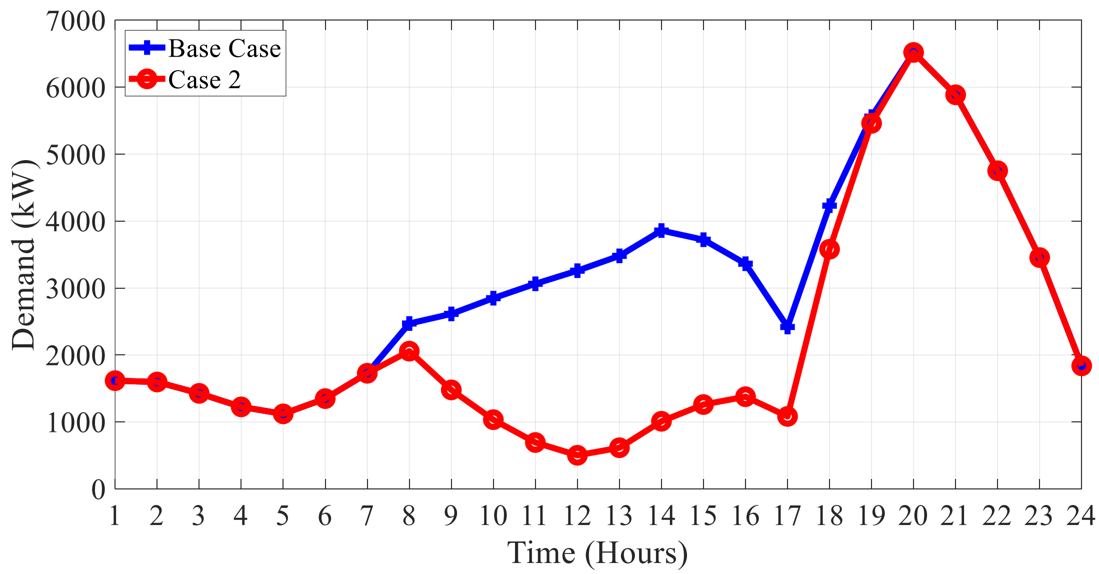

Fig. 4.2: Impact of DGs (GA optimized) on demand pattern

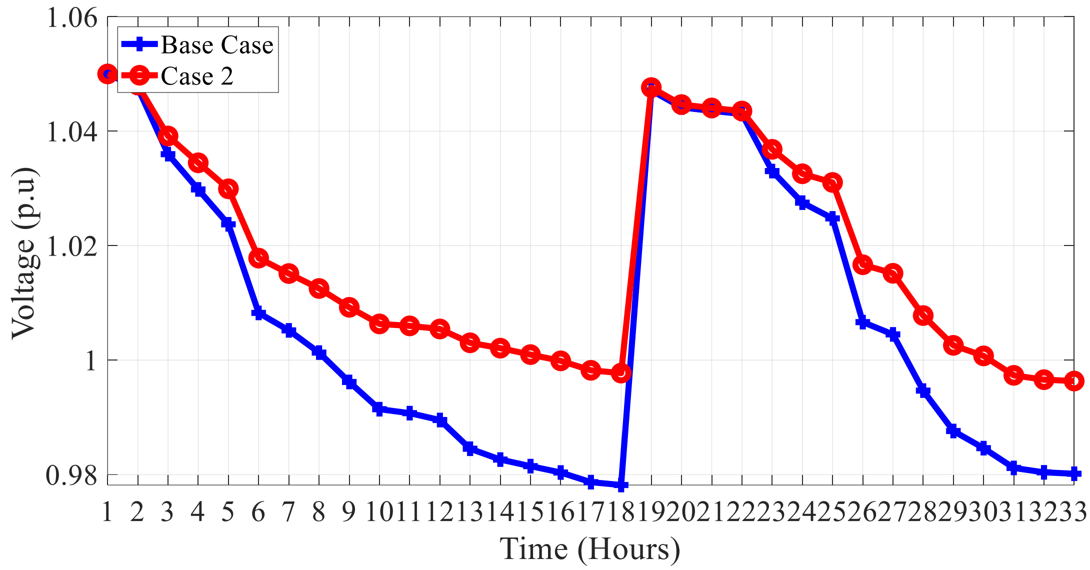

Fig. 4.3: Impact of DGs (GA optimized) on voltage pattern

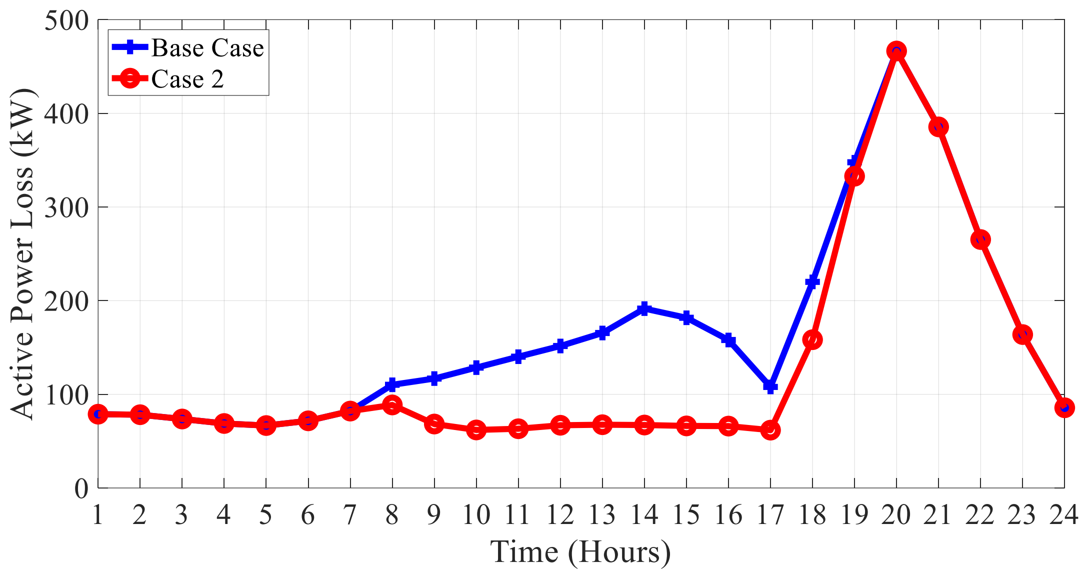

Fig. 4.4: Impact of DGs (GA optimized) on active power losses

4.4.3 Case 3: DR Approach

In this particular scenario, the significance of the DR approach by itself is evaluated for the base case, which does not involve the coordination of DGs or BESS. In this particular scenario, we will suppose that there are two distinct steps of demand elasticity namely, 10% and 20%. Such a demand elasticity is referred as the DR rate. The DR indicates that there is the load that is elastic and may be delivered at any moment that is suitable while taking into consideration the total demand and pricing scenario. It is recommended that power be delivered at the time of demand regardless of the price because the remaining portion of the load is inelastic. It has been noticed that the inclusion of various amounts of elastic load in DR exhibits substantial improvement in comparison to the basic scenario. It is important to keep in mind that the reduction in peak demand is 14.72% and 18.32 % for the DR rates of 10% and 20%, respectively, and that the reduction in yearly energy loss is found in the range of 5.96 % to 8.2 %. As a result, it is clear that DR allows for a reduction in yearly loss as well as an improvement in peak-to-valley difference. This scenario demonstrates that DR is successful even when DGs are not taken into consideration. The impact of a 10% DR rate on the demand pattern, voltage pattern, and active power losses is demonstrated in figure 4.5, figure 4.6, and figure 4.7 respectively. Additionally, the impact of a 20% DR rate on the demand pattern, voltage pattern, and active power losses is demonstrated in figure 4.8, figure 4.9, and figure 4.10 respectively. It can be stated that there is a negligible impact of DR on the voltage profile in the absence of DG integration.

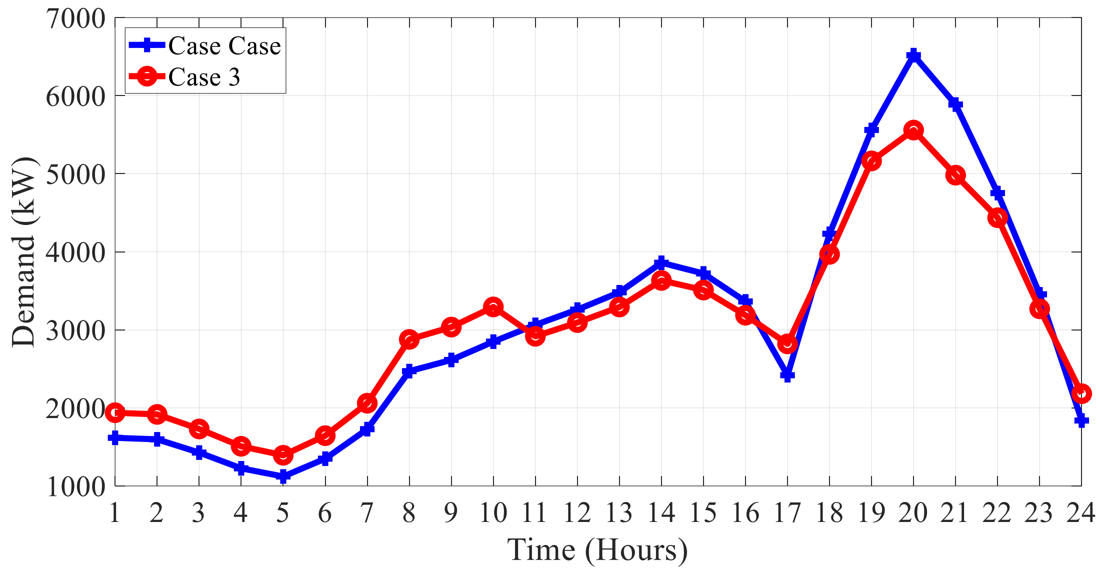

Fig. 4.5: Impact of 10% DR rate on demand pattern

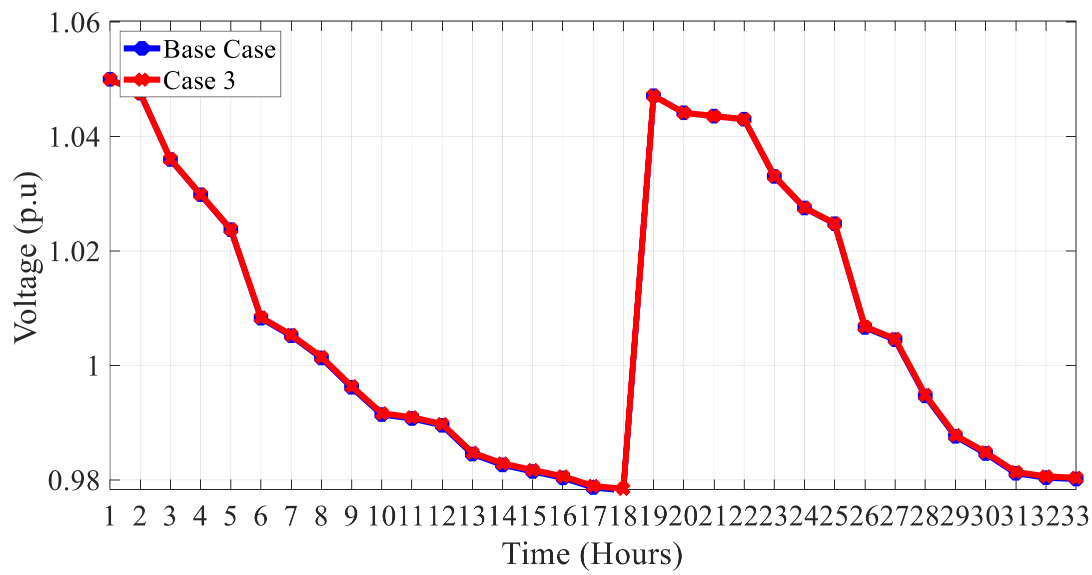

Fig. 4.6: Impact of 10% DR rate on voltage pattern

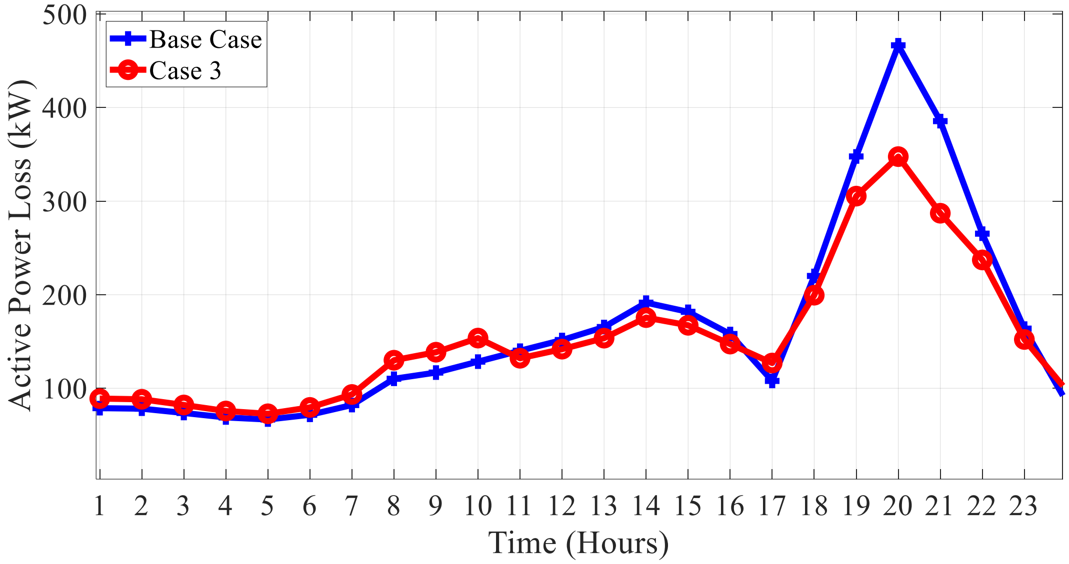

Fig.4.7: Impact of 10% DR rate on active power losses

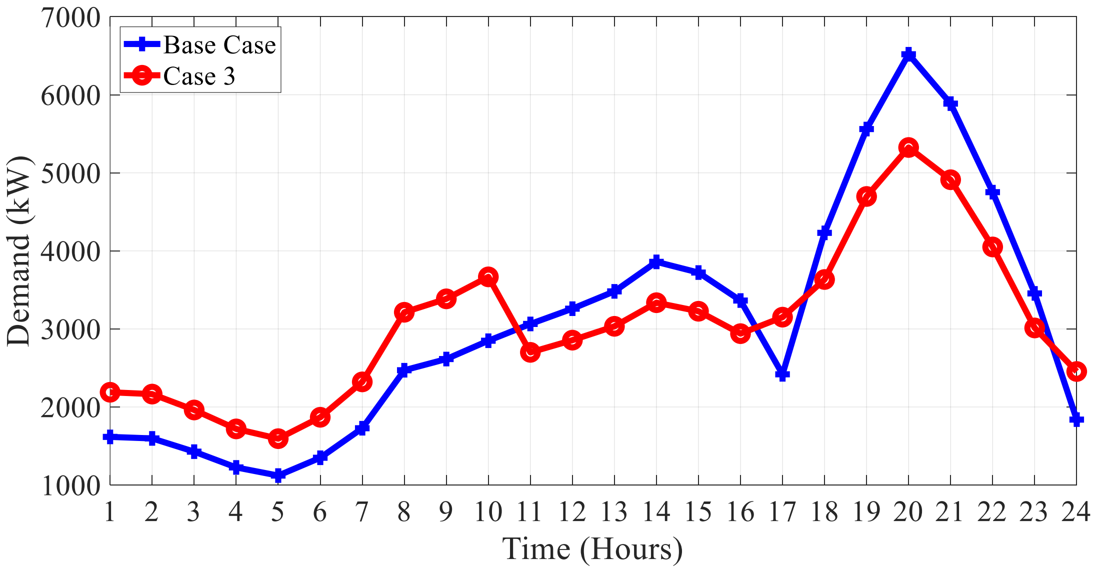

Fig. 4.8: Impact of 20% DR rate on demand pattern

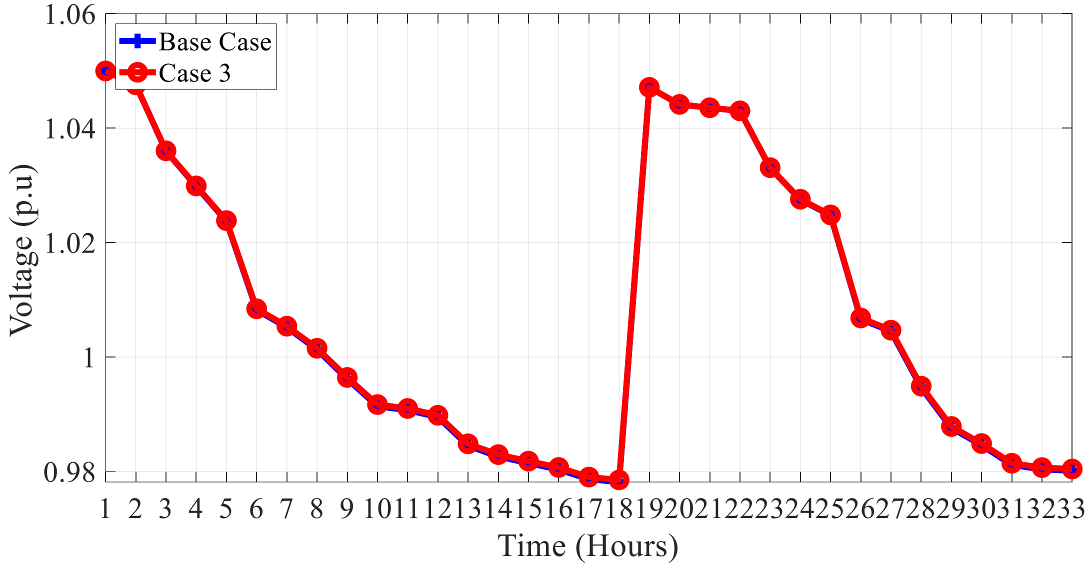

Fig. 4.9: Impact of 20% DR rate on voltage pattern

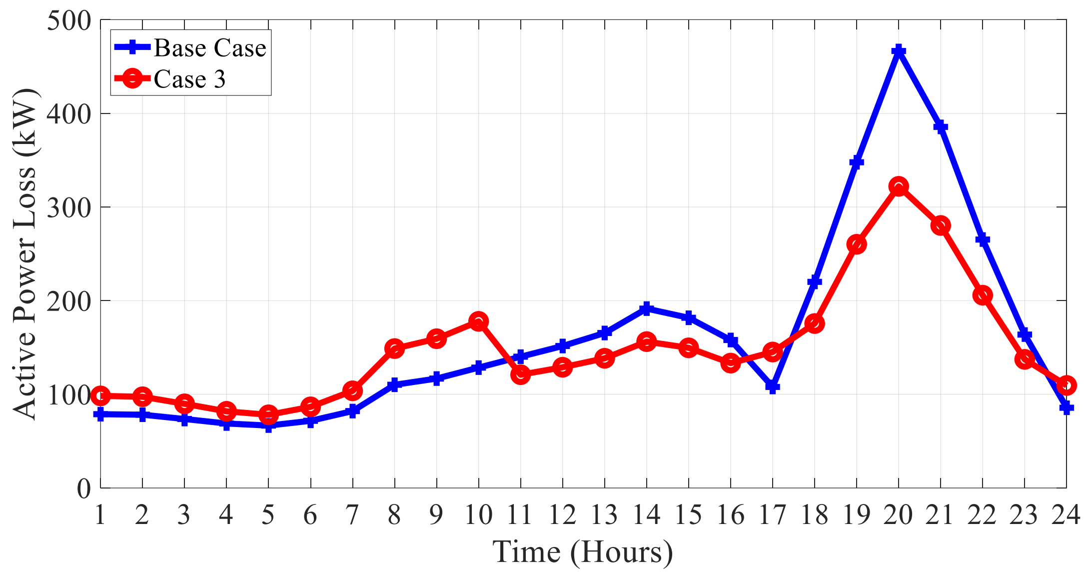

Fig. 4.10: Impact of 20% DR rate on active power losses

4.4.4 Case 4: DG and DR

In this scenario, the analysis is done after the incorporation of DGs in the coordination and planning of DR subjected to the various system constraints. In this scenario, the integration of DGs with the scheduling of DR is carried out while taking into account the limitations imposed by the systems. It has been noticed that the implementation of DR results in a considerable enhancement of the benefits that DGs provide. Moreover, the system performance can be boost with the high DR rates while the presence of lower size DGs. The yearly energy loss has seen a tremendous improvement in its decrease. It ranges from 29.03% to 33.31% depending on the degree of DR rates, and the lowest mean voltage has also seen a significant increase in comparison to cases 1 and 2. When compared to the result produced by employing DGs alone, the difference between maximum-to-minimum demand is significantly decreased, which results in a load profile that is more level. The impact of a DGs and 10% DR rate on the demand pattern, voltage pattern, and active power losses is demonstrated in figure 4.11, figure 4.12, and figure 4.13 respectively. Additionally, the impact of a DGs and 20% DR rate on the demand pattern, voltage pattern, and active power losses is demonstrated in figure 4.14, figure 4.15, and figure 4.16 respectively.

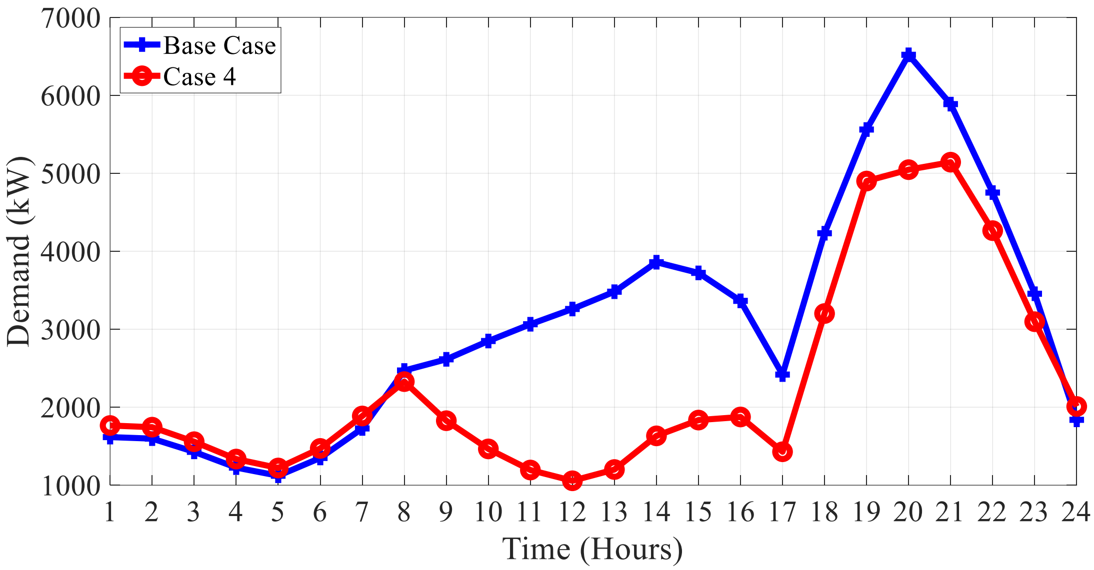

Fig. 4.11: Impact of DG and 10% DR rate (GA optimized) on demand pattern

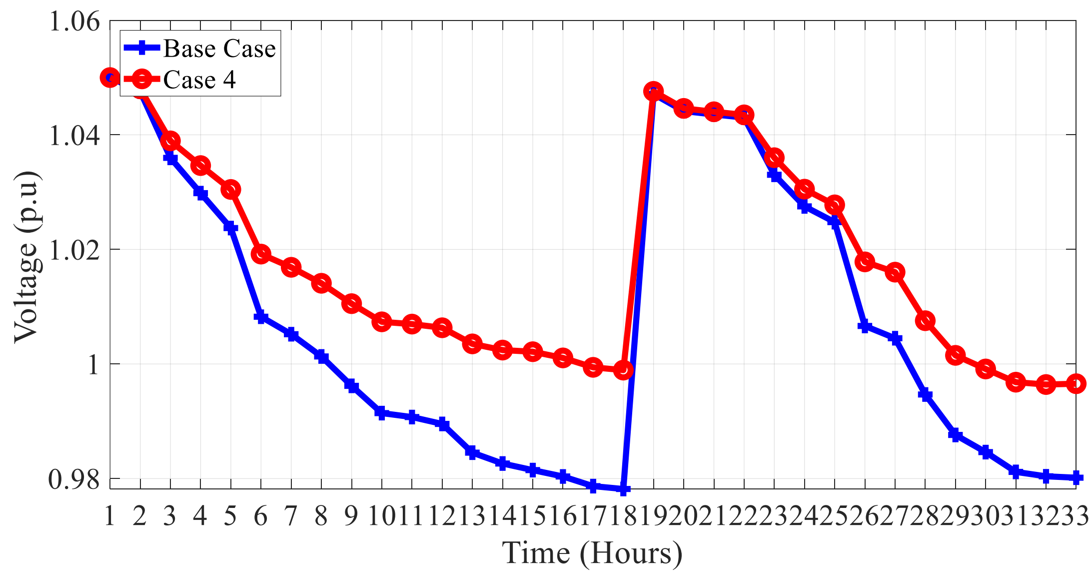

Fig. 4.12: Impact of DG and 10% DR rate (GA optimized) on voltage pattern

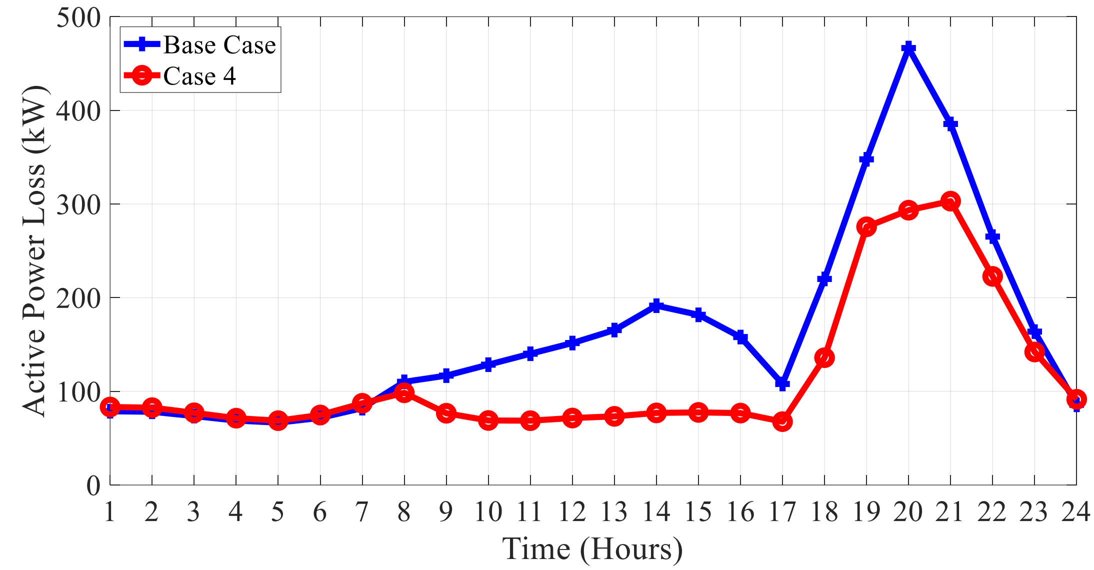

Fig. 4.13: Impact of DG and 10% DR rate (GA optimized) on active power losses

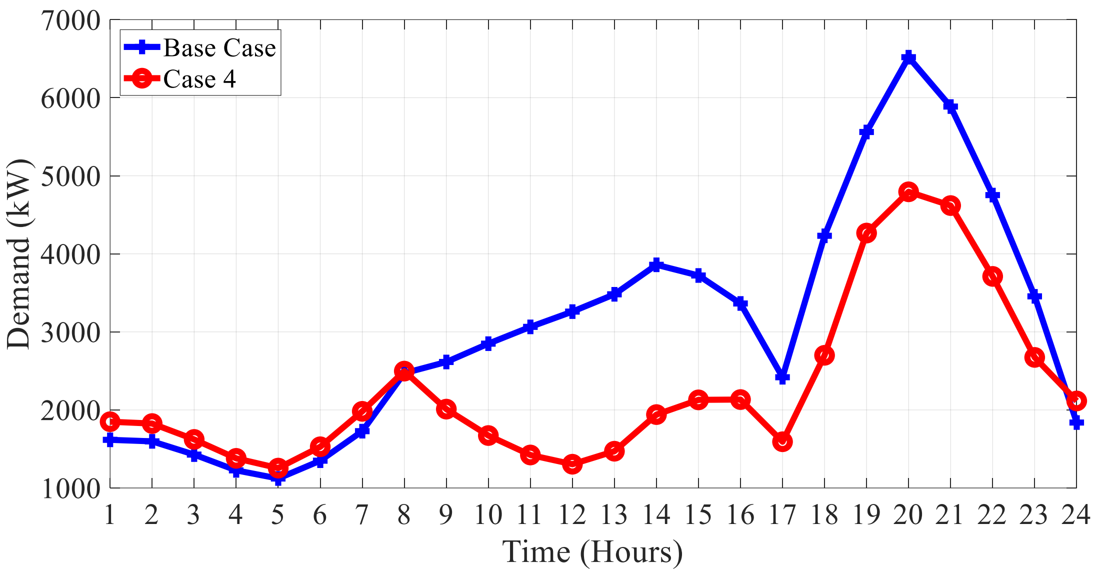

Fig. 4.14: Impact of DG and 20% DR rate (GA optimized) on demand pattern

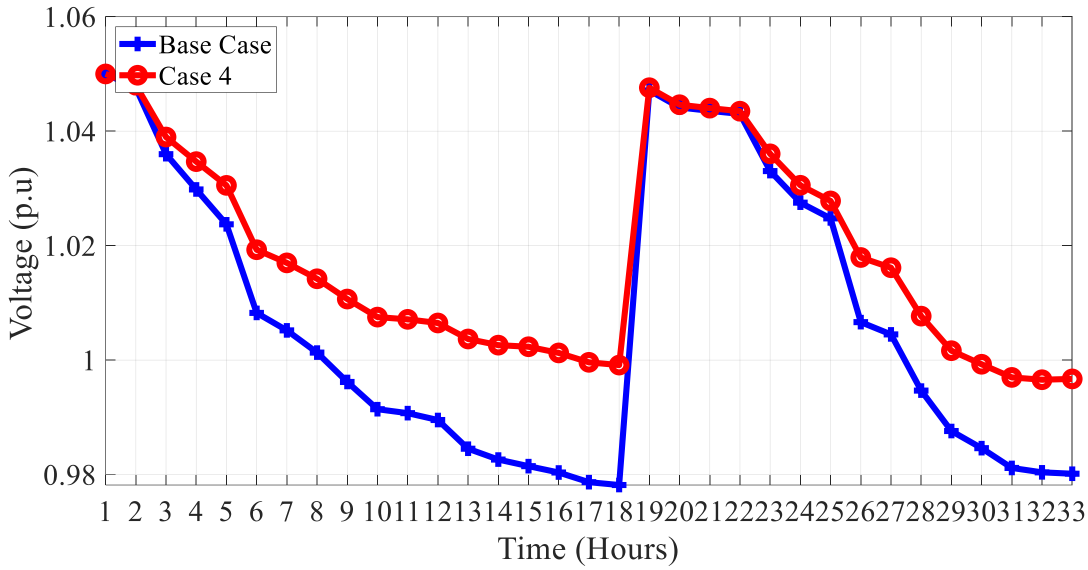

Fig. 4.15: Impact of DG and 20% DR rate (GA optimized) on voltage pattern

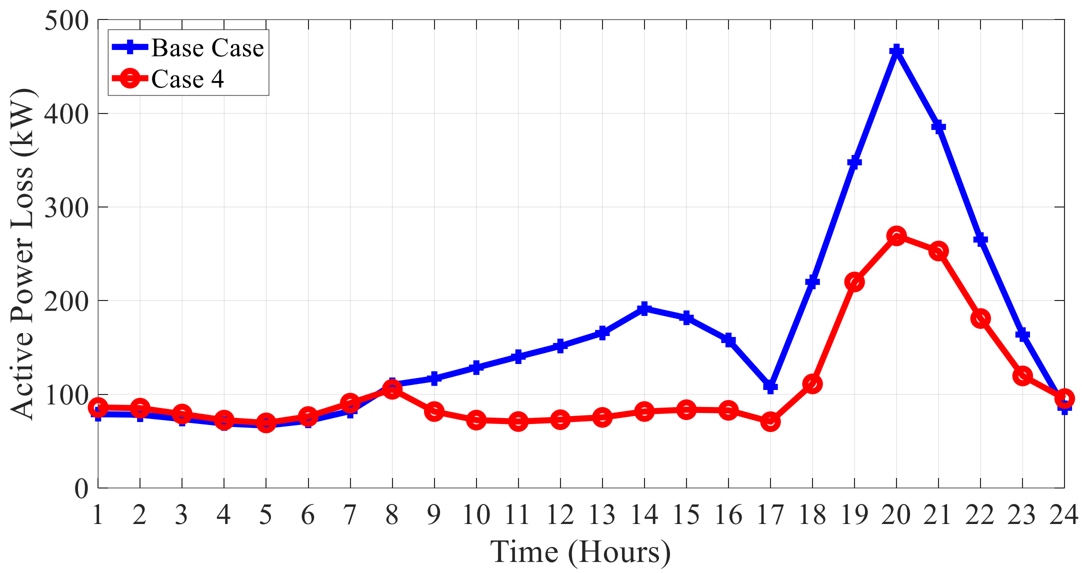

Fig. 4.16: Impact of DG and 20% DR rate (GA optimized) on active power losses

4.4.5 Case 5: DG and BESS

An assessment of the influence of BESS alone on optimal DG allocation has been conducted. Table 4.3 outlines the appropriate placement and dimensions of the BESS that were determined. The planning and scheduling of BESS for the charging and discharging are executed in such a pattern that can enhance the voltage profile and reduce the energy losses of the network. In this case, the ideal BESS is coordinated with DGs in order to reduce the detrimental effects of excessive penetration as much as possible. As can be seen in Table 4.2, this technique brings the yearly energy loss down to 42% and produces a flatter load curve than case-2, which was previously thought to be impossible. The results of the application make it abundantly evident that BESS also contributes to increased optimal penetration of DGs (90.93% as opposed to 69.44%). The impact of a DGs and BESS on the demand pattern, voltage pattern, active power losses, and BESS energy storage is demonstrated in figure 4.17, figure 4.18, and figure 4.19 respectively.

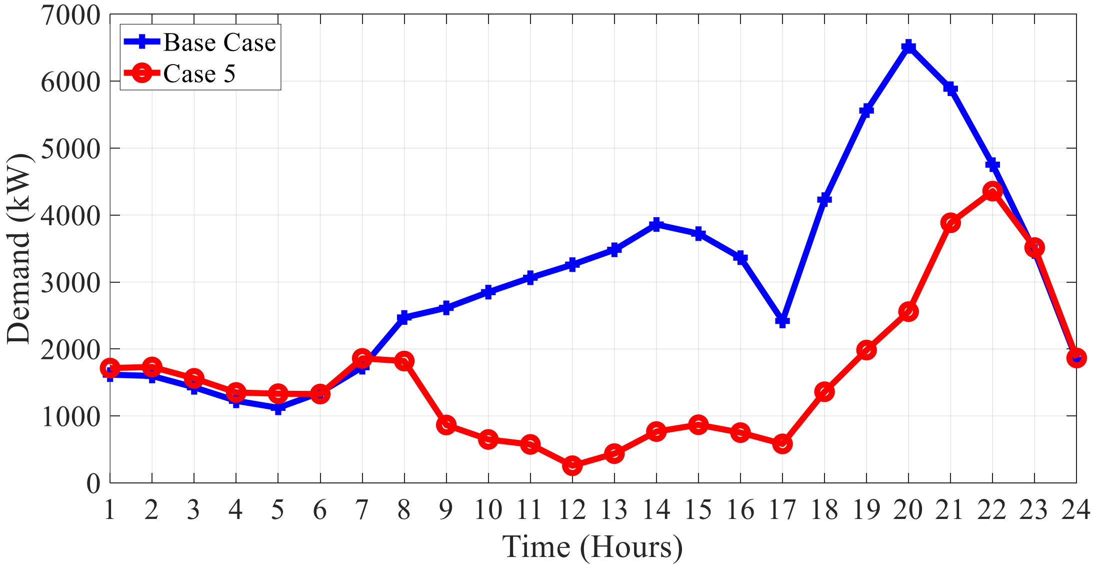

Fig. 4.17: Impact of DG and BESS (GA optimized) on demand pattern

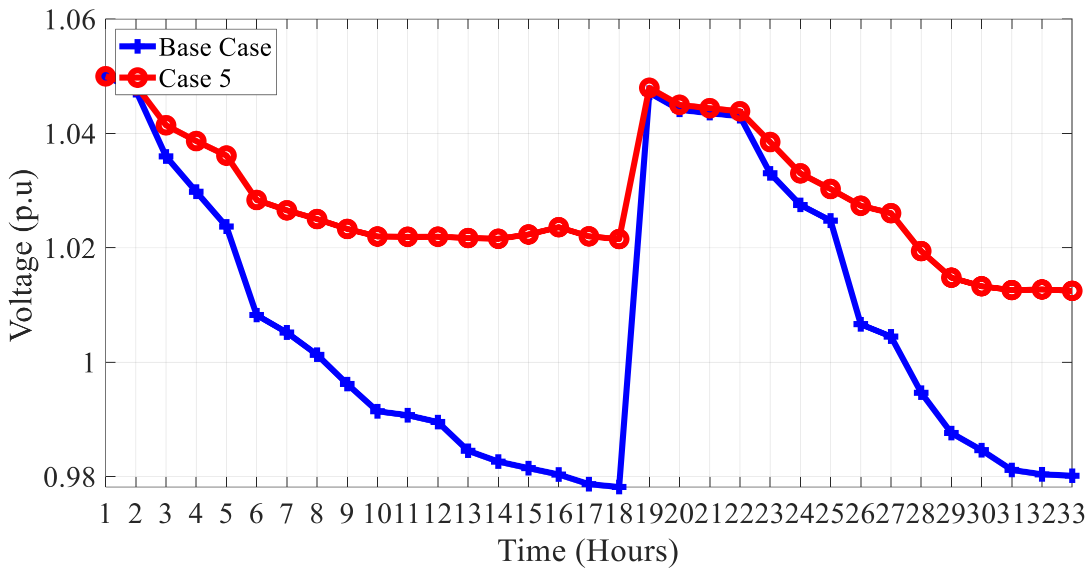

Fig. 4.18: Impact of DG and BESS (GA optimized) on voltage pattern

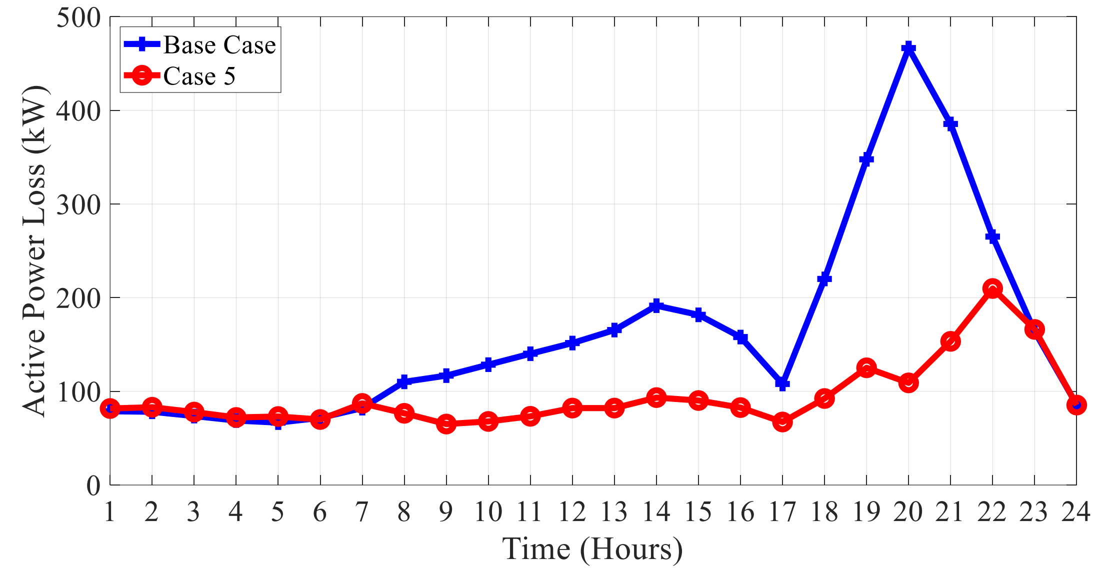

Fig 4.19: Impact of DG and BESS (GA optimized) on active power losses

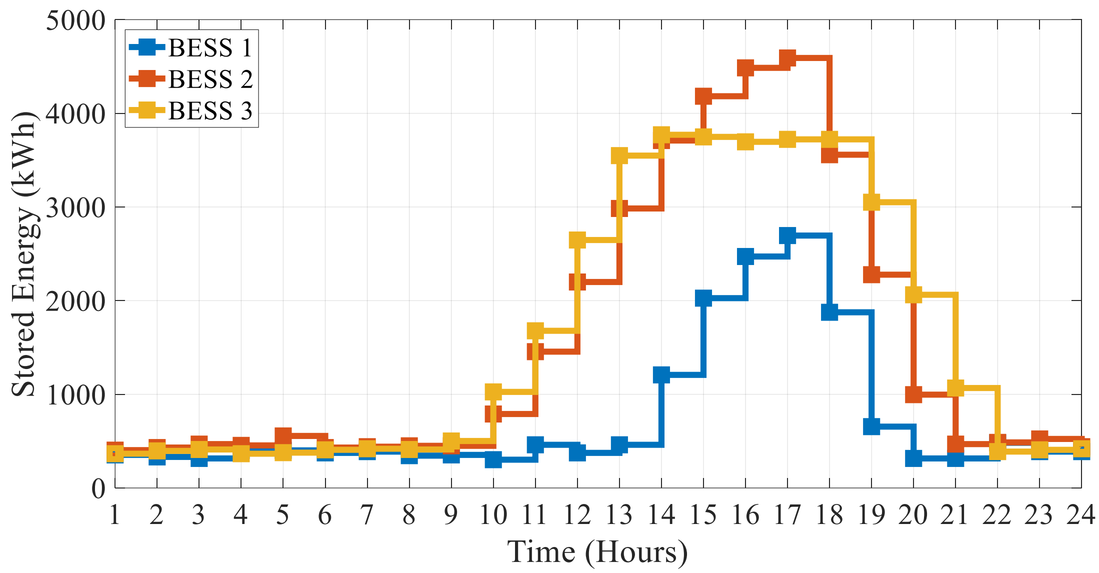

Fig 4.20: Impact of DG and BESS (GA optimized) on BESS energy storage

4.4.6 Case 6: DG, DR and BESS

In this scenario, the DR aggregator is coordinated with the BESS integrator to ensure the optimal allocation of DGs and BESS. It can be notice that size of BESS and DG are dependent on DR rate. Additionally, to improve the functionality of the DN, a higher DR rate results in a smaller BESS and DG due to the increased efficiency of the system. According to Table 4.3, the most significant decrease in yearly energy loss is accomplished by combining DG, BESS, and DR rates of 20%. This results in a savings of 46.77%. This study provides conclusive evidence that it is essential to incorporate an ideal rate of DR together with DGs and BESS in order to ensure the efficient operation of DS. The impact of a different DR rate in the synchronization of optimal DGs and

BESS allocation on demand pattern, voltage profile, active power losses, and BESS energy storage is shown in figure 4.21 to figure 4.28.

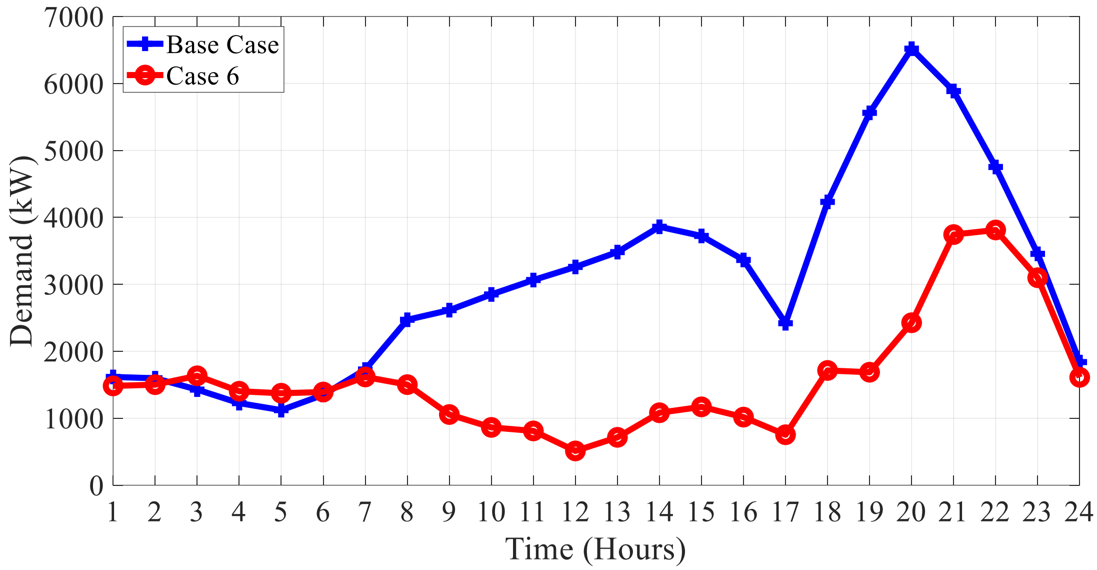

Fig. 4.21: Impact of DG, BESS and,10% DR rate (GA optimized) on demand pattern

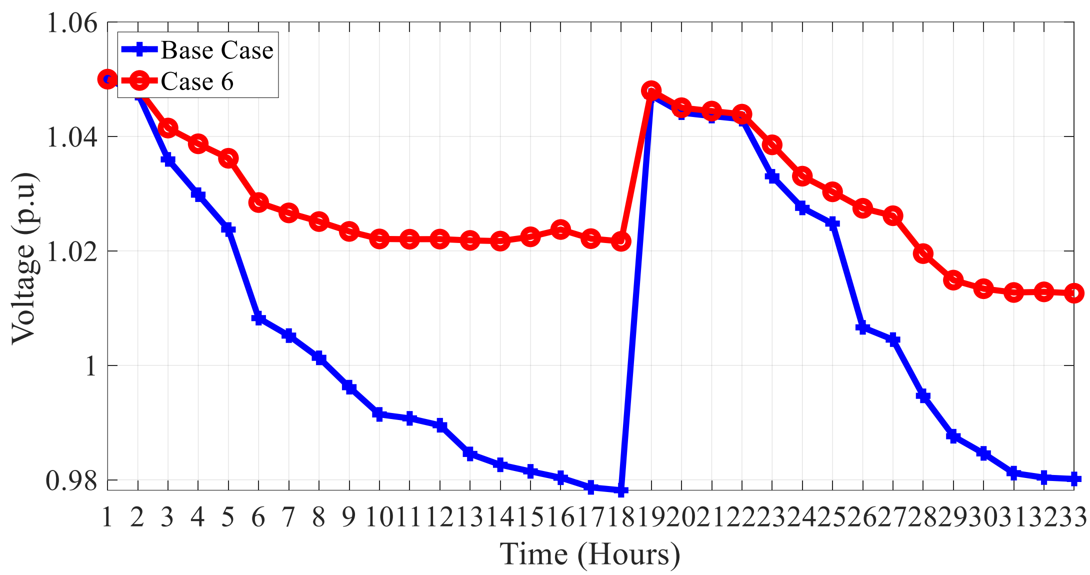

Fig. 4.22: Impact of DG, BESS and,10% DR rate (GA optimized) on voltage pattern

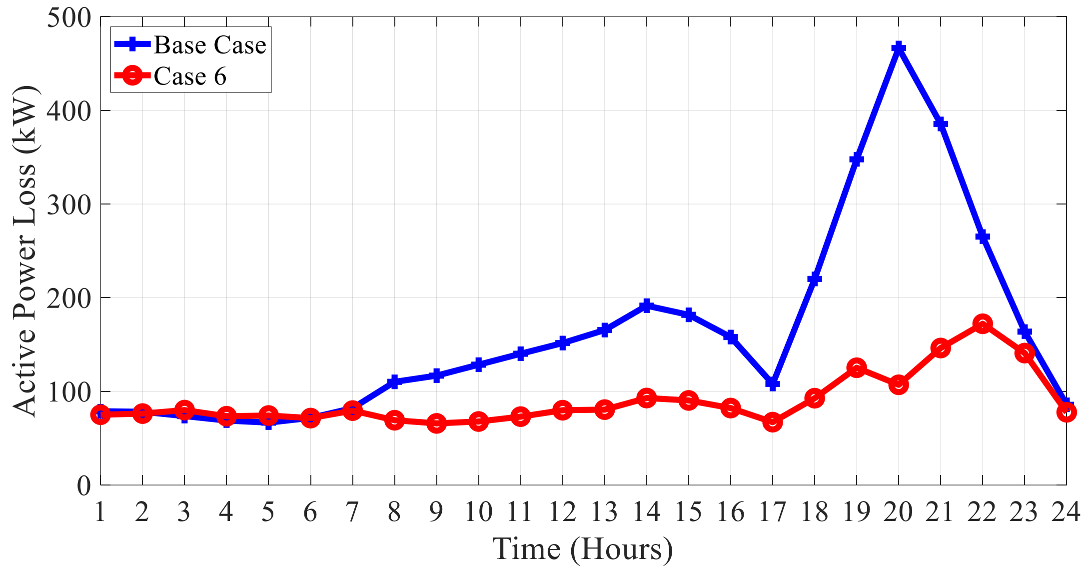

Fig. 4.23: Impact of DG, BESS and,10% DR rate (GA optimized) on active power losses

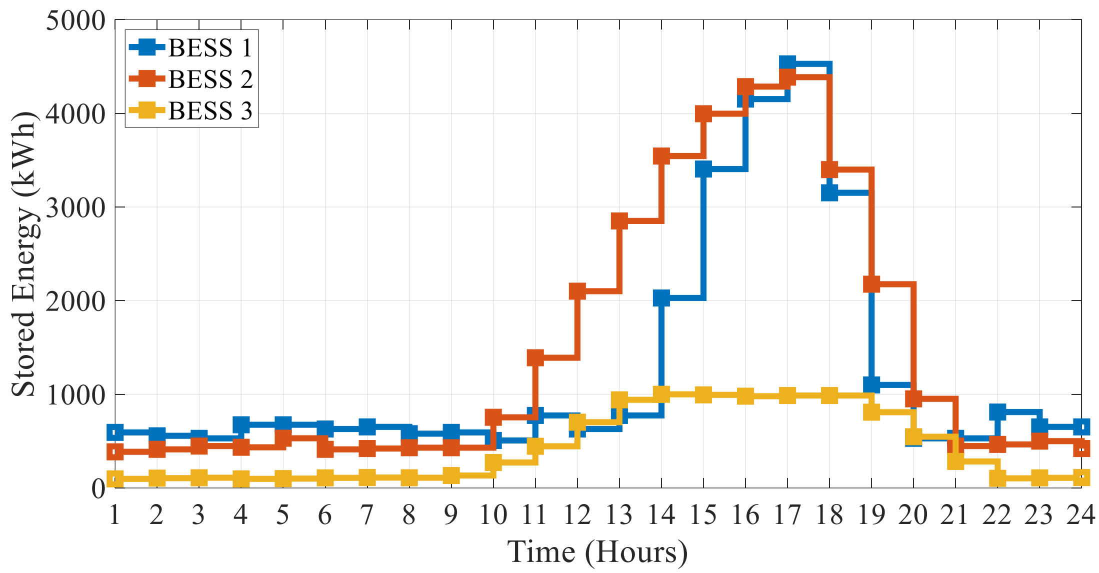

Fig. 4.24: Impact of DG, BESS and,10% DR rate (GA optimized) on BESS energy storage

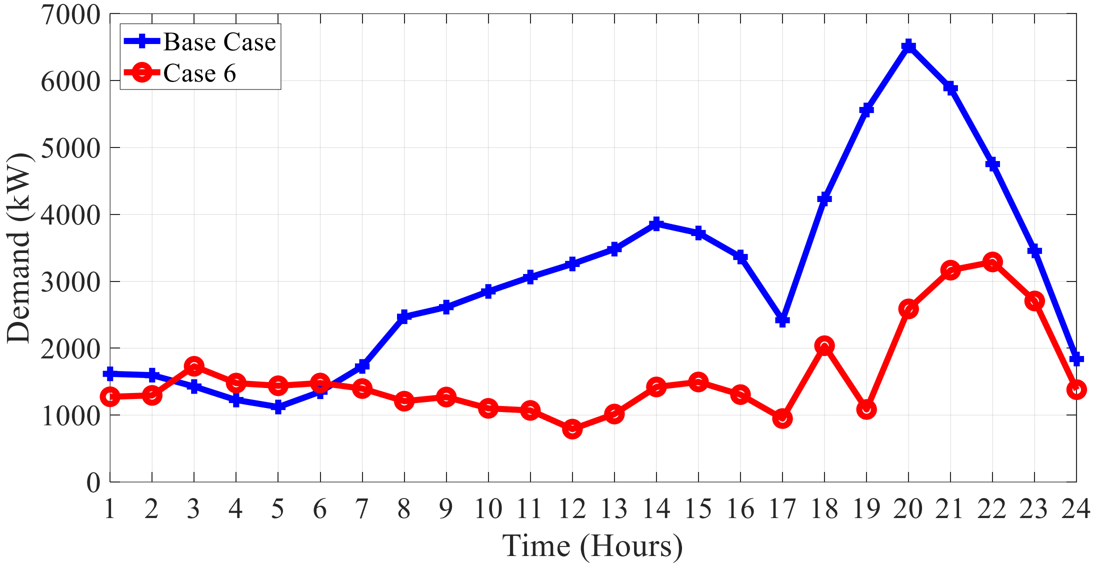

Fig 4.25: Impact of DG, BESS, and 20% DR rate (GA optimized) on demand pattern

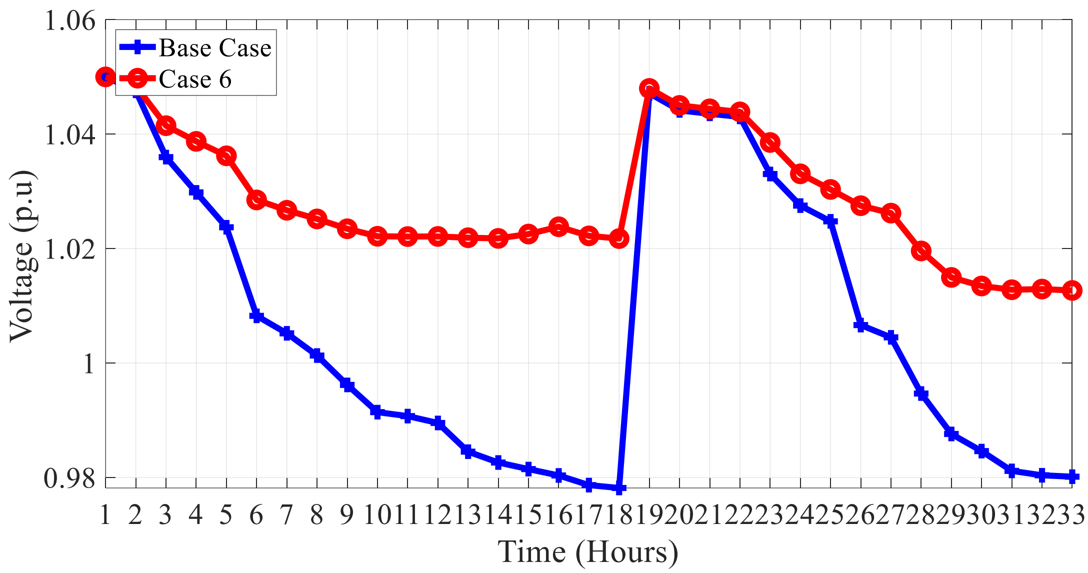

Fig 4.26: Impact of DG, BESS, and 20% DR rate (GA optimized) on voltage pattern

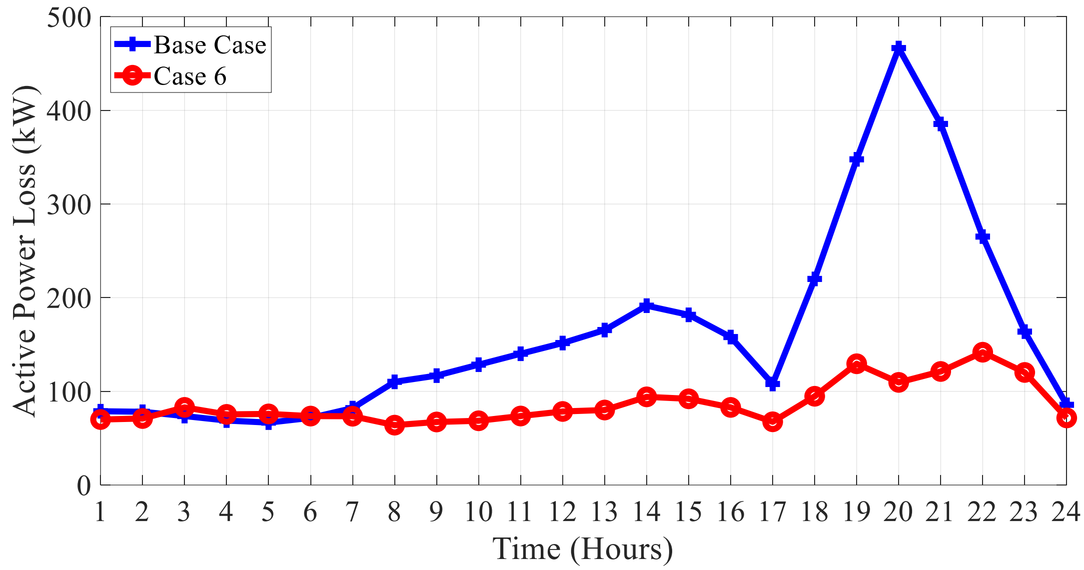

Fig. 4.27: Impact of DG, BESS and,20% DR rate (GA optimized) on active power losses

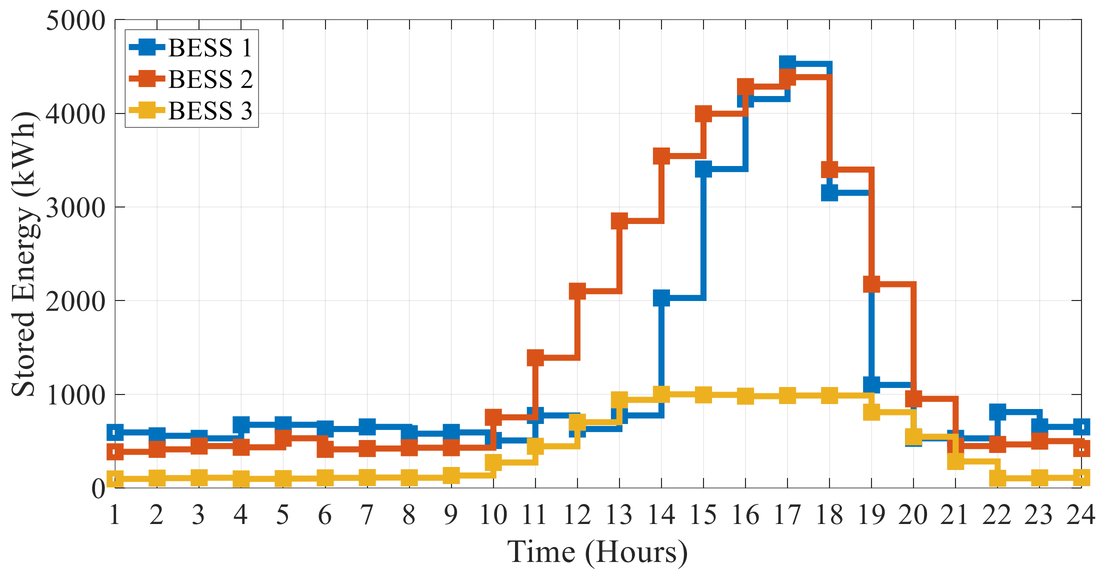

Fig. 4.28: Impact of DG, BESS and,20% DR rate (GA optimized) on BESS energy storage

4.5 Conclusions

The significant integral parts of futuristic DN are renewable energy utilization, DR planning, and the energy storage system. The optimized planning and coordination of these parameters maximize the benefits of DN in terms of its technical, financial, and environmental factors. The present article proposes an efficient multilevel optimization methodology for the planning and execution of upgraded DN. Such a system exhibited optimized coordination for dispatch of PV penetration, scheduling of DR, and BESS allocation. The optimal sizes and locations of DGs and BESS are determined at level-1 subjected to various constraints. The DR program is carried out at level 2 with the coordination of level 1 outcomes and the dispatching of BESS subject to the system's balance of renewable energy generation and load demand. The suggested technique was implemented on IEEE 33 test system, and the harmony of DGs, BESS, and DR was explored for the purpose of achieving the highest possible level of DN performance. It has been discovered that the performance of DN is considerably impacted when different rates of DR are coordinated with one another. The most significant takeaways from this research may be summed up as follows:

i. From a performance standpoint, the DGs are largely successful in reducing yearly energy loss. However, the flattening of the load profile is either negatively affected or unaffected by the DGs. A greater penetration of DGs may have a negative impact on the DS due to a sudden increase in voltage level and may facilitate reverse power flow to the grid system. This highlights the limit of DG penetration into the DN.

ii. In addition to levelling the load profile and enhancing the voltage profile, and minimizing the energy losses, the BESS effectively makes it possible for a larger penetration of DG.

iii. The inclusion of DR is successfully leveling the load profile and reduce the difference between maximum and minimum load demand, thus relieving stress on the system and providing subsequent advantages, such as a reduction in the need for BESS. When there is a smaller deployment of BESS, there is a correspondingly lower penetration of DG. To put it another way, if the probable penetration of PV and BESS is lower, then higher DR rate offers an efficient way to increase the efficiency of DN.

iv. It can be concluded that the higher the value of the DR rate in comparison to optimal results, the lower the penetration of DGs. The lower power dispatch from DGs facilitates the lower minimization of energy losses, and the high value of DR may adversely affect the system. Therefore, a coordinated approach is essential among the DGs, BESS, and DR in the DN.

Chapter- V

Investigating the Impact of DG on Distribution System Protection and Voltage Regulation

5.1 Introduction

The integration of Distributed Generation (DG) stands as a transformative strategy, surpassing conventional methods, to revolutionize the conventional power paradigm. DG not only optimizes the utilization of renewable energy sources but also exhibits advantages in terms of economic viability and enhanced power quality. However, given the intermittent nature of renewable sources, the widespread adoption of DG technology introduces a spectrum of challenges including optimal allocation, protection mechanisms, and other pertinent issues. In response to these multifaceted challenges, this study embarks on a meticulous exploration of the emergent complexities arising from the seamless assimilation of DG into centralized electrical grids. By delving into the intricate dynamics of this integration, this research aims to unearth valuable insights, identify potential hurdles, and propose adaptive strategies to ensure the harmonious coexistence of DG with existing grid infrastructure. Key facets of examination encompass the allocation strategies of DG units, which necessitate a robust framework capable of adapting to the intermittent availability of renewable energy. Additionally, the study scrutinizes the existing protection mechanisms to ascertain their efficacy in safeguarding the integrity of the grid amidst dynamic and bidirectional power flows introduced by DG sources. Moreover, power quality considerations are investigated to ascertain the stability and reliability of the grid under varying DG operational scenarios. This chapter endeavors to present a comprehensive overview of the complexities and intricacies surrounding DG integration within centralized power systems. By providing a systematic analysis of these challenges, we seek to contribute to the body of knowledge surrounding the seamless amalgamation of DG technologies in the existing power infrastructure. The findings of this study hold the potential to inform and guide future strategies in reshaping the power landscape towards a more sustainable and efficient future.

5.2 Protection System

The conventional protection system for energy generation is relatively straightforward, utilizing re-closers, relays, and fuses. This simplicity arises from the radial configuration of the distribution system. However, the integration of DG technology introduces the possibility of delayed synchronization in the protection system. In light of this, the authors propose a method to ensure the security of the distribution system when DG is present. This method is founded on a zone-wise classification of the power network, coupled with a corresponding risk analysis. Moreover, both offline and online data are imperative. Once the location of a fault is identified, a restoration signal is dispatched to initiate load shedding [209]. The integration of DG into the distribution network poses novel challenges to the protection system. Addressing these challenges requires the amalgamation of advanced protection technologies with the existing protection infrastructure. To enhance over-current protection within the distribution network, the authors suggest a hybrid protection strategy that synergistically combines conventional and modern protection techniques. This strategy incorporates limit grading and wavelet energy as key components in processing the instantaneous signal. The research results exhibit significant potential for reducing relay operation time and preventing hazardous situations [210]. In a distribution system incorporating DG, active network management and islanded operation serve as valuable tools for the protection strategy. This safety system leads to a reduction in both the magnitude and direction of fault currents. A novel overcurrent protection technique is introduced in [211], which automatically triggers all circuit breakers in abnormal conditions. A comparison between the traditional and proposed methods reveals a decrease in spurious signals and relay operation time. This advancement signifies improved efficiency and accuracy in fault detection and isolation. Before incorporating DG into the electrical power system, it is imperative to meticulously configure the protection system to guarantee seamless coordination. In this context, the authors propose a method for the judicious selection of relay protection parameters prior to DG integration. This method leverages the simplex method as the cornerstone of its optimization strategy, specifically tailored for addressing issues with linear programming formulations. The efficacy of this strategy is evaluated on the radial distribution systems of the IEEE 13 and IEEE 14 bus systems, exhibiting markedly superior results compared to previous methodologies. To mitigate the impact of DG penetration on the protective system, the conclusion underscores the urgency of prompt adjustments in relay settings [212]. Within the protection unit, establishing effective communication is imperative for mitigating the influence of DG. Furthermore, the implementation of a multi-agent-based technology, executed on the Java representative platform, is recommended to ensure the proper functioning of the protection unit in the distribution network subsequent to the integration of DG. Autonomous decision-making computers continuously engage with physical parameters, concurrently establishing a protocol for system modifications. This approach hinges on specific methodologies, relay parameters, and operational timelines, contingent on successful coordination with each agent and the entire relay family [213]. Following the integration of DG, the authors advocate for and model an adaptive fortification-based technique aimed at enhancing the performance of overcurrent relays. Initially, the reach of the relay is established, followed by an assessment of DG performance during fault conditions. Subsequently, this proposed methodology is employed to define the optimal operating state of a centralized power system incorporating DG, taking into consideration the fault current magnitude. The obtained results provide assurance that the system will operate effectively under these circumstances [214]. After connecting DG to the electricity grid, it becomes imperative for the protection system to promptly detect any alterations in the system. The authors present a protection module employing Fourier transform-dependent fuzzy logic, substantiated by several case studies. This module is thoroughly examined using the IEEE 34 bus test system. The proposed approach yields a precise estimation of the fault current, subsequently employing fuzzy logic to determine the relay's setup parameters. The technique is thoroughly scrutinized under various scenarios, encompassing grid presence, DG power augmentation, DG absence, and different levels of power generation during islanding [215].

The authors advocate for an adaptive approximation technique for selecting the optimal configuration parameters of the protection system. This selection is based on locally available pertinent observations. The suggested method entails determining the parameters of Thevenin's equivalent circuit. This is essential to ensure a secure and reliable operation, especially with the implementation of a two-layer relay protection system [216]. For mitigating voltage distortion arising from upper-level harmonics without necessitating an additional filtration device, the authors strongly endorse the utilization of three-phase converters. The outcomes are assessed in the context of DG powered by renewable energy sources [217].

Table 5.1 provides a comprehensive listing of the impact assessment of DG on the protection system of the distribution network.

5.3 Voltage Regulation

The integration of DG systems into the distribution network can introduce a range of disturbances, presenting challenges for effective system operation. While power flow is typically unidirectional under heavy load, it may become bidirectional during light load conditions due to reverse power flow to the grid. This surplus power generation from DG sources has the potential to cause significant voltage fluctuations and compromise voltage regulation. This section provides a comprehensive analysis of the issues and potential remedies arising from voltage limit violations. Ineffective voltage regulation hinders the efficient utilization of DG resources. Several factors may impact the distribution network in the presence of DG:

- The magnitude of the voltage.
- The type of distribution network.
- The level of power consumption.
- The capacity of the DG.

5.3.1 Grid Power Cutbacks

In the absence of a suitable voltage control method, the grid operator may disconnect all DG sources from the distribution network. While this may reduce poor voltage control, it comes at the cost of forfeiting the benefits of DG and renewable energy. As an alternative, the authors have proposed a voltage droop methodology involving the control of wind turbine generator pitch angles during periods of suboptimal voltage regulation. This approach has been successfully implemented in small-scale wind turbines in North America, yielding significant improvements [218].

Additionally, in rooftop photovoltaic arrays integrated into low voltage distribution networks, active power curtailment offers a practical solution for charging electric vehicles during periods of high-power generation or light load. In the presence of solar energy-based DG, the authors have suggested a mutually agreeable approach to managing reverse power flow, resulting in enhanced voltage regulation during light load hours [219].

5.3.2 Reframing of Distribution Network

Reframing the distribution network can be achieved by regulating the operating times of circuit breakers between feeders to enable loop operation. This reconfiguration brings benefits such as improved voltage profiles, reduced power losses, and maximized resource utilization. The authors have demonstrated how to reframe a distribution network in the presence of DG, with a focus on optimizing cost and voltage levels. The methodology, incorporating multiple regulators and VAR

Table 5.1 Assessment of protection system impact caused by DG

Ref.	Complication	Remedial Methodology	Encounters
[209]	Integration of DG in distribution systems leads to the need for adaptive overcurrent protection	Division of the distribution system into multiple independent operating zones	Identification of fault zones and categories while operating with DG
[210]	Overcurrent protection in the presence of DG requires real-time signal analysis	Real-time signal segmentation into limit grading and wavelet energy components to identify fault initiation time	Reduction in the operating time of overcurrent relays during DG operation in the distribution network
[211]	Integration of DG in distribution systems necessitates an adaptable overcurrent protection approach	Automatic operation of all circuit breakers by applying optimized real parameters directly	Reduction in the number of false operating actions and a decrease in the average operating time of protection relays
[212]	Coordination of directional overcurrent relays in DG-integrated systems	Utilization of the simplex technique to solve linear programmed problems	Procurement of a set of relay setting parameters for all types of DG scenarios
[213]	Optimization of overcurrent relay coordination in distribution networks with DG	Implementation of multiagent-based technology on the Java platform	Coordinated protection through communication arrangements to facilitate the exchange of necessary information
[214]	Overcurrent relay protection in DG-integrated power systems	Adoption of an adaptive fortification-based approach to optimize relay performance post DG integration	Reduction in the reach or line protection covered by distance relays
[215]	Protection of DG-based distribution networks	Utilization of a Fourier transform-dependent fuzzy logic-based protection module	Understanding various network procedures and methodologies
[216]	Adaptive overcurrent protection with multi-level definite time in DG-	Calculation of optimized parameters of Thevenin's	Line-interacted measurement of fault current for various relevant cases

	incorporated distribution networks	equivalent circuit based on local parameters	

compensators, was applied to the IEEE 33 and IEEE 392 test systems. Both continuous and discrete voltage regulation approaches produced remarkably positive results. The reconfiguration of the network also led to a reduction in the cost of energy production [220]. To mitigate voltage limit violations, the three-phase power generation model is transformed into a mixed-integer second-order cone programming model using various techniques. The results demonstrate significant improvements compared to other methodologies [221].

5.3.3 On Load Tap Changer (OLTC)

Voltage regulation is a critical aspect of power system operation, especially in the presence of DG. One commonly employed tool for achieving effective voltage regulation is the OLTC. It operates by adjusting the phase angle and balancing the voltage magnitude, working in conjunction with other control and regulation equipment.

In scenarios where power generation is predominantly single-phase, voltage variations become more pronounced due to uneven distribution. To address this, the authors have developed a coordinated OLTC system integrated with solar cells. This innovation has been successfully implemented in a Danish low voltage system. The methodology involves specific procedures including OLTC framing, load framing, active PV power generation, and control of VAR [222].

In cases where OLTC alone may not suffice to manage a specific voltage fluctuation, enhancements can be made to ensure that voltage fluctuations remain within specified limits. An advanced multi-stage optimization approach, reliant on data acquisition and working in tandem with OLTC, is presented [223].

5.3.4 Static Synchronous Compensator (STATCOM)

Reactive power compensation offers an effective means of controlling voltage levels in distribution networks, particularly when integrating DG sources. This is achieved through the utilization of solid-state devices like the Static STATCOM within the realm of flexible AC transmission systems. The procedure of reactive volt-ampere compensation stands out as a reliable corrective measure for voltage level optimization. In order to mitigate voltage fluctuations, the authors propose the deployment of distributed reactive power compensators. In this scenario, both positive sequence admittance and negative sequence conductance need to function concurrently. These sequences are dynamically adjusted to optimize voltage levels through a proportional resonator. Acting as a regulator, the current resonator efficiently mitigates harmonic distortion and safeguards the crucial current component [224].

5.3.5 Inverter Controlled DG

Inverter-based DG units provide an effective means of regulating voltage fluctuations by supplying or absorbing reactive electricity to/from the electric grid. During islanded grid operation in hybrid mode, a photovoltaic system serves as a VAR correction component. The test module consists of a wind-powered generator, a diesel engine, and a solar inverter unit. Through simulation using a fuzzy-based proportional integral controller, optimal configurations for the integrated units are determined. The study extensively evaluates the benefits of a self-tuned distribution network coupled with renewable DG, comparing the findings with existing optimization methods [225].

The authors strongly advocate for the use of three-phase converters to mitigate voltage waveform distortion, effectively eliminating the adverse effects of upper-level harmonics without the need for additional filtration devices. Results are evaluated in the context of DG powered by renewable energy [226].

5.3.6 Energy Demand Management (EDM)

The evolution of modern power systems is being steered by the advent of the smart grid, which revolves around the concept of demand management of energy. This initiative is driven by distribution corporations and end-users, relying on mutual agreements for load shifting and curtailment. To ensure the efficacy of EDM, the authors emphasize key parameters that can be fine-tuned [183].

- Political support is pivotal in attracting participants, spanning from low-level to high-level energy users, to engage in energy management.
- A clear policy plan is indispensable in steering the process in the right direction within the allotted timeframe. The effectiveness of the approach is contingent on EDM rules.
- EDM necessitates a precise list of objectives to monitor progress and achieve goals. This list may be based on prior experiences and input from relevant stakeholders.
- Financial stability is crucial for establishing a self-sustaining system under various conditions, whether favorable or unfavorable.
- User engagement is paramount to the operation of EDM, as it hinges on human intelligence.

Voltage regulation is a proactive concern addressed by EDM. The authors introduce a method for regulating voltage variations wherein ice thermal storage is converted into an electrical load. The integration of DGs into the concept of a smart building is highlighted to showcase the impact of EDM. The adaptability of the thermal load further mitigates the intermittent nature of renewable energy sources [227].

5.3.7 Battery Storage

The variable generation patterns of renewable energy sources, influenced by specific local climatic and atmospheric conditions, present a challenge to their seamless integration. Battery storage plays a pivotal role in mitigating this intermittent nature by either supplying or absorbing electrical energy to and from the grid. Through real-time power management, a system can attain an optimal level of voltage regulation. During periods of heightened energy generation or low demand, the energy storage system undergoes a charging process. Subsequently, it will feed energy into the grid during intervals of low energy generation or high demand. A recommended approach involves the

Table 5.2 Assessment of voltage regulation impact caused by DG

Ref.	Problem	Solution
[218]	Regulation of voltage levels in a distribution grid employing wind energy-driven DG.	Optimizing the pitch angle of a wind turbine to align with the real-time power demand.
[219]	Limiting the voltage of rooftop solar-powered DG systems during periods of high load demand and low energy production.	Decreasing the actual solar power output and proficiently managing energy storage in electric vehicles.
[220]	Voltage variation management in unbalanced distribution networks with DG	Optimization of setting parameters for various voltage regulating devices.
[221]	Voltage fluctuations in the distribution network due to intermittent DG power output during varying load conditions	Integration of reactive volt-ampere compensation in the reconfigured distribution network.
[222]	Minimizing voltage infractions resulting from SPV systems and uneven distribution of single-phase supply.	Utilization of OLTC transformers to control reactive power and enhance voltage regulation, thereby maximizing the benefits of DG in the distribution network.
[223]	Poor voltage regulation due to extensive deployment of distributed energy sources.	Effective communication and coordination among essential components of the generation and protection systems.
[224]	Maintenance of voltage magnitude in renewable DG-based distribution networks	Deployment of a static reactive power compensator with continuous current regulation.
[225]	Distribution grids incorporating voltage regulation for DG derived from both renewable and non-renewable sources.	Control of reactive power through solid-state inverter-based DG systems.
[227]	Control of voltage and intermittency in renewable energy-based DG within the distribution network	Ice thermal storage is transformed into an electrical load in order to regulate voltage fluctuations.
[228]	Addressing voltage rise challenges in low voltage solar photovoltaic systems	Utilization of battery storage for state of charge control and voltage management.

implementation of a coordinated consensus strategy to maintain the voltage magnitude within predefined thresholds. This method is put into practice within a low voltage distribution system, where local control devices oversee the state of charge. To interconnect end users, battery storage, and solar systems within a DC link, bidirectional converters and a voltage booster are employed. The methodology is subjected to simulations to account for variations in daily load patterns [228]. For a comprehensive assessment of the impact of DG on voltage regulation within the distribution network, Table 5.2 provides an exhaustive list of evaluations.

5.4 Conclusion

The integration of DGs in electrical power networks brings forth a host of benefits encompassing technical advancements, improved financial viability, and noteworthy environmental gains. Nevertheless, this integration also gives rise to certain challenges, primarily in the domains of protection systems and voltage regulation, which could potentially impede the widespread adoption of DG technologies. As the global reserves of fossil fuels continue to dwindle, the future of energy generation hinges significantly on the utilization of DG and renewable energy sources. This report offers an in-depth exploration of the intricate interactions that arise from the amalgamation of DG with distribution networks.

In order to forge a more robust, reliable, and proficient electrical power system underpinned by DG and high levels of renewable energy integration, it is imperative to conduct a comprehensive examination of the hurdles, concerns, and corresponding remedial measures. This report has specifically addressed two pivotal challenges: variations in the peak values and directions of fault currents, as well as violations of voltage limits.

To mitigate the issues pertaining to fault currents, alternative approaches and recommended relay settings have been introduced. These measures effectively circumvent fault current problems, bolstering the overall stability and resilience of the system. Additionally, strategies have been proposed to rectify instances of poor voltage regulation, further enhancing the operational efficacy of the system.

In summation, the successful integration of DG into distribution networks not only augments the overall efficiency and sustainability of the power grid but also necessitates a nuanced understanding of the associated challenges. By meticulously investigating and proactively addressing issues concerning fault currents and voltage regulation, we pave the way for a more robust and adaptive electrical power system, poised to accommodate the escalating demands of a dynamic energy landscape.

Chapter- VI
Main Conclusion and Future Scope

6.1 Main Conclusion

The integration of Distributed Generation (DG) within distribution systems presents a transformative opportunity for enhancing power networks across various dimensions. Through a comprehensive exploration of optimization techniques, this thesis has illuminated the path toward effective DG allocation while adhering to specific constraints. This endeavor not only fortifies the stability, reliability, and consistency of distribution networks but also serves as a pivotal tool for dissecting the intricacies of optimization algorithms.

The comparative analysis of conventional, modern mathematical, and hybrid optimization methods has shed light on their respective strengths and trade-offs. While conventional approaches offer simplicity, precision, and ease of execution, their single-objective focus may lead to slower convergence. In contrast, modern mathematical techniques excel in solving multi-objective complex problems, though they introduce challenges such as increased coding complexity and diverse settling parameters. Hybrid optimization approaches, though capable of handling intricate problems with swifter convergence, may entail greater complexity and possess a smaller existing body of literature.

Furthermore, the amalgamation of renewable energy sources with DG has emerged as a powerful catalyst for amplifying the benefits of DG planning within distribution networks. However, this integration has underscored the imperative need for a reliable assessment tool for renewable energy. Addressing the intermittent nature of renewable sources necessitates effective energy storage solutions, potentially mitigating the challenges posed by intermittency.

Demand Response (DR) emerges as a linchpin in the development of smart distribution systems, offering a vital solution, especially in light of the high costs associated with energy storage systems. There lies a promising opportunity to develop a comprehensive system that encompasses the planning and optimal dispatch of renewable DG, coupled with energy storage and demand response mechanisms.

However, as DG penetration escalates, potential challenges come to the fore, including voltage level rise and reverse power flow into the grid. These limitations accentuate the need for a nuanced approach to DG integration within the distribution network. Incorporating DR emerges as a pivotal strategy, balancing the load profile, minimizing disparities between peak and off-peak load demands, and alleviating strain on the system. A higher DR rate offers a promising avenue for improving demand normalization efficiency.

In conclusion, the impact assessment of DR on the optimal placement of Solar Photovoltaic (SPV) systems within the distribution network presents substantial promise in enhancing the efficiency and effectiveness of renewable energy integration. Through rigorous simulation studies and empirical analyses, it has been demonstrated that the integration of demand response mechanisms leads to improved power quality parameters and increased penetration levels of renewable energy sources. This research offers invaluable insights for policymakers, utilities, and stakeholders involved in the planning and management of distribution networks.

As the energy landscape evolves, the integration of DR into energy systems planning and design emerges as an indispensable component for meeting future energy needs sustainably. This thesis underscores the importance of adopting a holistic approach to energy systems planning, considering the intricate interplay between different components of the energy system and the potential for innovative solutions to address complex challenges.

The essential components of a futuristic distribution network encompass renewable energy utilization, DR planning, and energy storage systems. The optimized planning and coordination of these parameters maximize the benefits of distribution networks in terms of technical, financial, and environmental factors. The proposed multilevel optimization methodology exhibited optimized coordination for the dispatch of Photovoltaic (PV) penetration, scheduling of DR, and Battery Energy Storage System (BESS) allocation. The findings underscore the importance of a coordinated approach among DGs, BESS, and DR in distribution systems.

The integration of DGs into electrical power networks ushers in a host of benefits, ranging from technical advancements to improved financial viability and noteworthy environmental gains. Nevertheless, this integration also gives rise to certain challenges, particularly in the realms of protection systems and voltage regulation, which could potentially impede the widespread adoption of DG technologies. As global reserves of fossil fuels continue to dwindle, the future of energy generation hinges significantly on the utilization of DG and renewable energy sources. This thesis offers an in-depth exploration of the intricate interactions that arise from the amalgamation of DG with distribution networks.

To build a more robust, reliable, and efficient electrical power system underpinned by DG and high levels of renewable energy integration, a comprehensive examination of hurdles, concerns, and corresponding remedial measures is imperative. This thesis has specifically addressed two pivotal challenges: variations in the peak values and directions of fault currents, as well as violations of voltage limits.

To mitigate the issues pertaining to fault currents, alternative approaches and recommended relay settings have been introduced. These measures effectively circumvent fault current problems, bolstering the overall stability and resilience of the system. Additionally, strategies have been proposed to rectify instances of poor voltage regulation, further enhancing the operational efficacy of the system.

In summation, the successful integration of DG into distribution networks not only augments the overall efficiency and sustainability of the power grid but also necessitates a nuanced understanding of the associated challenges. By meticulously investigating and proactively addressing issues concerning fault currents and voltage regulation, we pave the way for a more robust and adaptive electrical power system, poised to accommodate the escalating demands of a dynamic energy landscape. This thesis endeavors to contribute to the evolving discourse on

Distributed Generation Planning in Distribution Systems, with the hope of propelling our energy systems into a more sustainable and resilient future.

6.2 Future Scope

The research conducted in this thesis opens up avenues for further exploration and development in the field of Distributed Generation (DG) planning within distribution systems. Several areas of future research are identified based on the findings and implications of this study:

- *Advanced Optimization Techniques*:

Future studies could delve deeper into the development and application of advanced optimization techniques, including machine learning algorithms and artificial intelligence, to enhance the accuracy and efficiency of DG allocation and planning.

- *Integration of Energy Storage Systems:*

Given the critical role of energy storage in mitigating the intermittent nature of renewable energy sources, further research can focus on optimizing the integration of energy storage systems with DG and their impact on the overall performance of distribution networks.

- *Dynamic Demand Response Strategies:*

Investigating dynamic demand response strategies that adapt to real-time changes in energy demand patterns can further enhance the efficiency and effectiveness of distribution networks, especially in the context of high DG penetration.

- *Cybersecurity and Resilience:*

With the increasing reliance on digital technologies for monitoring and control of distribution systems, future research should address the cybersecurity aspects to ensure the resilience and security of the integrated DG networks.

- *Microgrid Development:*

Exploring the potential for microgrid development within distribution networks, incorporating DG, energy storage, and demand response, could lead to more localized and resilient energy systems.

- *Grid-Interactive Buildings:*

Investigating the role of grid-interactive buildings, equipped with technologies for demand response and integration of DG, in enhancing the overall efficiency and stability of distribution networks.

- *Multi-Objective Optimization:*

Future studies could focus on multi-objective optimization techniques that balance technical, financial, and environmental considerations to achieve more comprehensive and sustainable DG planning outcomes.

- *Real-World Case Studies:*

Conducting extensive real-world case studies and field trials to validate and refine the methodologies proposed in this thesis, taking into account specific regional and contextual factors.

- *Policy and Regulatory Frameworks:*

Research on policy and regulatory frameworks that incentivize and facilitate the integration of DG into distribution networks, including mechanisms for grid interconnection and market participation.

- *Economic Viability Analysis:*

Further studies can delve into the economic viability of DG projects, considering factors such as return on investment, cost-benefit analysis, and financial models for different stakeholders.

- *Environmental Impact Assessment:*

Conducting detailed environmental impact assessments to quantify the reduction in greenhouse gas emissions and other environmental benefits associated with the integration of DG.

- *Smart Grid Technologies:*

Investigating the incorporation of advanced smart grid technologies, including advanced metering infrastructure, grid automation, and real-time monitoring, to enhance the performance and capabilities of distribution networks.

By addressing these future research areas, the field of DG planning in distribution systems can continue to evolve and contribute to the development of more sustainable, efficient, and resilient energy networks. The ongoing pursuit of these research directions will play a crucial role in shaping the future of distributed energy systems and their integration into the broader energy landscape.

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List of Publications

Details of Publications in SCI/SCIE/ESCI Journals

[1] Saxena, V., Kumar, N., & Nangia, U. (2023). Impact analysis of demand response on the optimal placement of solar PV systems in the distribution network. BRAZILIAN ARCHIVES. (accepted)

[2] Saxena, V., Kumar, N., & Nangia, U. (2023). Computation and optimization of BESS in the modeling of Renewable Energy based framework. Arch Computat Methods. (accepted)

[3] Saxena, V., Kumar, N., & Nangia, U. (2023). An Extensive Data-Based Assessment of Optimization Techniques for Distributed Generation Allocation: Conventional to Modern. Arch Computat Methods Eng, 30, 675–701. https://doi.org/10.1007/s11831-022-09812-w

[4] Saxena, V., Kumar, N., & Nangia, U. (2022). Recent Trends in the Optimization of Renewable Distributed Generation: A Review. Ingeniería e Investigación, 42(3), e97702. https://doi.org/10.15446/ing.investig.97702

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Details of Publications in International Conferences:

[1] Saxena, V., Kumar, N., & Nangia, U. (2022). An Impact Assessment of Distributed Generation in Distribution Network. In M. Pandit, M. K. Gaur, P. S. Rana, & A. Tiwari (Eds.), Artificial Intelligence and Sustainable Computing. Algorithms for Intelligent Systems. Springer. https://doi.org/10.1007/978-981-19-1653-3_26

[2] Saxena, V., Kumar, N., Nangia, U. (2021). Analysis of Smart Electricity Grid Framework Unified with Renewably Distributed Generation. In R. Agrawal, C. Kishore Singh, & A. Goyal (Eds.), Advances in Smart Communication and Imaging Systems (Vol. 721, Lecture Notes in Electrical Engineering). Springer. https://doi.org/10.1007/978-981-15-9938-5_68

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Appendix A

Table A.1 Line data and Load of System IEEE 33 bus

Branch No.	From bus	To bus	R (Ω)	X (Ω)	Load at to bus	
					P (kW)	Q (kW)
1	1	2	0.0922	0.0477	0	0
2	2	3	0.4930	0.2511	100	60
3	3	4	0.3660	0.1864	90	40
4	4	5	0.3811	0.1941	120	80
5	5	6	0.8190	0.7070	60	30
6	6	7	0.1872	0.6188	60	20
7	7	8	1.7114	1.2351	200	100
8	8	9	1.0300	0.7400	200	100
9	9	10	1.0400	0.7400	60	20
10	10	11	0.1966	0.0650	60	20
11	11	12	0.3744	0.1238	45	30
12	12	13	1.4680	1.1550	60	35
13	13	14	0.5416	0.7129	60	35
14	14	15	0.5910	0.5260	120	80
15	15	16	0.7463	0.5450	60	10
16	16	17	1.2890	1.7210	60	20
17	17	18	0.7320	0.5740	60	20
18	2	19	0.1640	0.1565	90	40
19	19	20	1.5042	1.3554	90	40
20	20	21	0.4095	0.4784	90	40
21	21	22	0.7089	0.9373	90	40
22	3	23	0.4512	0.3083	90	40

23	23	24	0.8980	0.7091	90	50
24	24	25	0.8960	0.7011	420	200
25	6	26	0.2030	0.1034	420	200
26	26	27	0.2842	0.1447	60	25
27	27	28	1.0590	0.9337	60	25
28	28	29	0.8042	0.7006	60	20
29	29	30	0.5075	0.2585	120	70
30	30	31	0.9744	0.9630	200	600
31	31	32	0.3105	0.3619	150	70
32	32	33	0.3410	0.5302	210	100

*R: resistance *X: reactance