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CONTRIBUTION A L'OPTIMISATION DES RESEAUX ELECTRIQUES DE DISTRIBUTION EN PRESENCE DES SOURCES ELECTRIQUES DE PRODUCTION DECENTRALISEE

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CONTRIBUTION TO THE OPTIMIZATION OF ELECTRICAL DISTRIBUTION NETWORKS IN THE PRESENCE OF DECENTRALIZED GENERATION SOURCES

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To my family and friends

ABSTRACT

This thesis offers an in-depth examination of optimization methods for contemporary electrical distribution networks, focusing on the heightened complexity introduced by distributed generations, network reconfiguration, and the incorporation of shunt capacitor banks. The study is organized into four main areas. An overview of distribution networks is presented, emphasizing the significant challenges in achieving efficient and reliable power delivery amid changing energy demands and the transition to smart grid technologies. A comprehensive analysis of network reconfiguration, capacitor bank placement, and distributed generation integration is conducted, highlighting the increasing significance of these methods when utilized in conjunction to enhance network performance. This has helped to situate our work within the existing literature and illustrate our contributions.

A careful study of metaheuristic optimization techniques for their efficacy in addressing the high-dimensional, multi-objective optimization challenges typical of electrical distribution networks has led to the creation of a brand-new multi-objective optimization method using the hybrid multi-population algorithm (HMPA) for optimal network reconfiguration while simultaneously allocating capacitor banks and distributed generations (ONRSACD). The proposed method incorporates fuzzy logic to reconcile conflicting objectives, achieving an optimal balance between substation energy costs and equipment investments while maintaining operational efficiency.

The methodology was validated through comprehensive experiments on 33-bus and 69-bus test systems, wherein the HMPA exhibited enhanced performance relative to other advanced optimization techniques. The thesis concludes by highlighting the potential of integrating advanced control systems, including flexible AC transmission systems (FACTS) and intelligent communication technologies, to improve network performance and support the transition to smart grids. Future research is suggested to investigate these avenues, as well as the effects of deregulation and real-time optimization in intricate, large-scale distribution networks.

Key words: HMPA, Fuzzy logic, Radial distribution network, Capacitor banks allocation, Distributed generations allocation, Radial distribution network reconfiguration.

RÉSUMÉ

Cette thèse propose un examen approfondi des méthodes d'optimisation pour les réseaux de distribution électrique contemporains, en mettant l'accent sur la complexité accrue introduite par les générations distribuées, la reconfiguration des réseaux et l'incorporation de banques de condensateurs shunt. L'étude est organisée en quatre domaines principaux. Un aperçu des réseaux de distribution est présenté, mettant en avant les défis importants pour atteindre une livraison d'énergie efficace et fiable face à l'évolution des demandes énergétiques et à la transition vers des technologies de réseau intelligent. Une analyse complète de la reconfiguration du réseau, du placement des banques de condensateurs et de l'intégration de la production distribuée est réalisée, mettant en évidence l'importance croissante de ces méthodes lorsqu'elles sont utilisées conjointement pour améliorer la performance du réseau. Cela a aidé à situer notre travail dans la littérature existante et à illustrer nos contributions.

Une étude approfondie des techniques d'optimisation métaheuristique pour leur efficacité à relever les défis d'optimisation multi-objectifs et de haute dimension typiques des réseaux de distribution électrique a conduit à la création d'une toute nouvelle méthode d'optimisation multi-objectifs utilisant l'algorithme hybride à multi-populations (HMPA) pour une reconfiguration optimale du réseau tout en allouant simultanément des banques de condensateurs et des générations distribuées. (ONRSACD). La méthode proposée intègre la logique floue pour concilier des objectifs conflictuels, atteignant un équilibre optimal entre les coûts énergétiques des sous-stations et les investissements en équipements tout en maintenant l'efficacité opérationnelle.

La méthodologie a été validée par des expériences approfondies sur des systèmes de test de 33 et 69 bus, où le HMPA a montré une performance améliorée par rapport à d'autres techniques d'optimisation avancées. La thèse se termine en soulignant le potentiel d'intégration de systèmes de contrôle avancés, y compris les systèmes de transmission AC flexibles (FACTS) et les technologies de communication intelligentes, pour améliorer la performance des réseaux et soutenir la transition vers des réseaux intelligents. Des recherches futures sont suggérées pour explorer ces pistes, ainsi que les effets de la déréglementation et de l'optimisation en temps réel dans des réseaux de distribution complexes et à grande échelle.

Mots-clés : HMPA, logique floue, réseau de distribution radial, allocation de banques de condensateurs, allocation de générations distribuées, reconfiguration du réseau de distribution radial.

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I would like to express my heartfelt gratitude to everyone who helped me complete my thesis. I am very grateful to my supervisor, Professor Ahmed Salhi, a full professor at the University of Biskra, for proposing the subject of my thesis and for his steadfast direction, insightful input, and ongoing support throughout this endeavor. I am equally thankful to my co-supervisor, Professor Naimi Djemai, a full professor at the University of Biskra, for his unwavering support, constructive criticism, and commitment to helping me refine my work.

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CONTENTS

LIST OF ABBREVIATION & SYMBOLS

HMPA	Hybrid Multi-Population Algorithm	**MOHMPA**	Multi-Objective Hybrid Multi-Population Algorithm
AEO	Artificial Ecosystem-based Optimization	**MOAEO**	Multi- Objective Artificial Ecosystem-based Optimization
HHO	Harris Hawks Optimization	**MOHHO**	Multi-Objective Harris Hawks Optimization
PSO	Particular Swarm Optimization	**MOPSO**	Multi-Objective Particular Swarm Optimization
MFO	Moth Flame Optimization	**MOMFO**	Multi-Objective Moth Flame Optimization
TPA	Thief and police algorithm	**NSGA II**	Non-dominated Sorting Genetic Algorithm
MBGWO	Modified Binary Gray Wolf Optimization	**QRSMA**	Quasi-Reflection Slime Would Algorithm
HS-PABC	Harmony Search Algorithm-Particle swarm Ant Bee Colony	**LSHADE-EpSin**	Success History-based parameter adaptation technique of Differential Evolution
BFO	Bacterial Foraging Optimization	**MOPSO-MCS**	MOPSO-Monte Carlo Simulation
ONRSACD	Optimal Network Reconfiguration Simultaneously with the allocation of Capacitor banks and Distributed generations	**DN**	Distribution Network

$\boldsymbol{CE_{sub}}$	The annual cost of active energy supplied by the substation ($/year)	$\boldsymbol{E_{loss}}$	Daily active energy losses (KWh)
$\boldsymbol{CE_{loss}}$	The annual cost of active energy losses ($/year)	$\boldsymbol{PW}$	Worth factor
$\boldsymbol{CE_{load}}$	The annual cost of active energy load demand ($/year)	$\boldsymbol{E_{load}}$	Daily active energy load demand (KWh)
$\boldsymbol{Nyr}$	Planning period (5 years)	$\boldsymbol{Nbr}$	Number of branches
$\boldsymbol{K_{Esub}}$	Price of energy market ($MWh) =49	$\boldsymbol{P_{loss}(n)}$	Active power losses at branch n.
$\boldsymbol{P_{load_j}}$	Active power demands at bus j	$\boldsymbol{C_{DG}}$	Annual DGs investment cost
$\boldsymbol{InfR}$	Inflation rate (%) = 9	$\boldsymbol{C_{TS}}$	Annual TS investment cost ($/year)
$\boldsymbol{IntR}$	Interest rate (%) = 12.5	$\boldsymbol{C_{ICB}}$	Total CBs investment cost
$\boldsymbol{CD}$	Annual devices investment cost	$\boldsymbol{Ncb}$	Number of CBs (5)
$\boldsymbol{C_{QCB}}$	The total annual Cost of CBs reactive power ($/year)	$\boldsymbol{K_{QCB}}$	Annual cost of injecting reactive power $(\$/KVAR/year) = 36$

Q_{CBi}	Reactive power of the ith CB	K_{IDG}	Installation cost of DGs ($/MWh) = 31800
C_{FCB}	Total fixed cost of CBs	P_{DGi}	Active power of ith DG.
K_{FCB}	Fixed cost of CB	K_{EDG}	Operation and maintenance cost of DGs ($/MWh) = 36
C_{IDG}	Total installation cost of DGs ($)	A^U	Annuity factor
N_{bus}	Number of buses	UDG	Useful lifetime of DGs (20 years)
Q_{CB_min}	Lower reactive power limit of CBs	UTS	Useful lifetime of TSs (15 years)
Q_{CB_max}	Upper reactive power limit of CBs	$URCS$	Useful lifetime of RCSs (35 year)
S	Integer number	Q_0	The smallest available size of CB (50 KVAR)
P_{DG_min}	Lower active power limit of DGs	P_{DG_max}	Upper active power limit of DGs
Ndg	Number of DGs (5)	C_{ITS}	Total installation cost of TSs
C_{IRCS}	Total installation cost of remote-controlled switches ($)	K_{MTS}	Operation and maintenance cost of TSs ($/Km/year) = 500
C_{MTSRCS}	The annual operation and maintenance cost of TS_s and RCS	K_{MRCS}	Operation and maintenance cost of RCSs ($/year) =150
Nts	Number of tie switches (5)	DS	Degree of satisfaction
L_{TSi}	Length of the ith TS (Km)	P_{sub}	Active power of substation
K_{TS}	Installation cost of TS ($=60K$/Km)	Q_{sub}	Reactive power of substation
$Q_{load}(j)$	Reactive power demands at bus j	$Q_{loss}(n)$	Reactive power losses at branch n.
V_j	Voltage magnitude of bus j.	I_n	Current in the nth branch
V_{min} and V_{max}	Lower and upper limits of the voltage magnitude, respectively	I_n^{max}	Maximum loading of the nth branch
MAQ	Maximum available reactive power of radial DN	OSi	The ith candidate open switch
PR	Penetration rate	MAP	Maximum available active power of radial DN.
LOC_{CBi}	Candidate bus location for the ith CB	Loc_{DGi}	Candidate bus location for the ith DG
$P_{loss}(j, j+1)$	Active power losses between bus j and $j+1$	$Q_{loss}(j, j+1)$	Reactive power losses between bus j and $j+1$
$P(j, j+1)$	Active power flow at line located between bus j and bus $j+1$	$Q(j, j+1)$	Reactive power flow at line located between bus j and bus j+1
$R(j, j+1)$	Resistance at line located between bus j and bus j+1	$X(j, j+1)$	Reactance at line located between bus j and bus j+1

PUBLICATIONS

Bouhanik A., Salhi, A., Imene, D., & Naimi, D. (2024). An efficient hybrid multi-population algorithm (HMPA) for enhancing techno-economic benefits. Soft Computing. https://doi.org/10.1007/s00500-024-09807-8

Bouhanik, A., Salhi, A., & Naimi, D. (2022). Optimal Capacitor Allocation Based on Hourly Load Variation Via New Optimization Algorithms. 2022 19th International Multi-Conference on Systems, Signals & Devices (SSD), 2035–2040. https://doi.org/10.1109/SSD54932.2022.9955910

Bouhanik, A., Salhi, A., Naimi, D., Zahraoui, Y., & Mekhilef, S. (2023). Distribution Network Reconfiguration Based on Hourly Load Variation Via New Optimization Algorithms. 2023 International Conference on Electrical Engineering and Advanced Technology (ICEEAT), 1–5. https://doi.org/10.1109/ICEEAT60471.2023.10426483

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Introduction

Electrical power systems worldwide differ in size, generation process, transmission structure, and load capacity. However, they exhibit the same construction and operating principles, with four primary components that are immediately noticeable, at first glance, generating units, transmission lines, transformers, and loads. The latter support four main functions, including energy generation, transmission, distribution, and consumption, organized according to different voltage levels. Substations serve as a link between them, transform power from one voltage to another as per guidelines, and perform operational and emergency switching and protection duties [1].

The distribution network (DN) is a vital part of the power system, connecting power production to end users. It provides reliable and efficient power to various users, including industrial facilities and residential homes. However, it is the most vulnerable element due to its geographical distribution, diverse load requirements, and susceptibility to environmental and operational difficulties. Distribution networks account for 60% to 70% of total energy losses in electrical power systems worldwide. These losses, including technical losses from conductors and transformers and non-technical losses like theft and metering errors, impose a significant economic burden and require improvement. Therefore, distribution network optimization is a major issue for electricity companies and scientists alike.

The effects of deregulation in the electrical industry have worsened the issues faced by distribution networks. Deregulation, which aims to foster competition and efficiency, has resulted in the separation of vertically integrated utilities, leading to a more intricate and competitive landscape. As a result, distribution network operators are now required to closely monitor their systems, frequently operating close to the network's technical limits. The change in regulations has limited planners' capacity to maintain network reliability and efficiency solely via conventional means. As a result, planners are increasingly using sophisticated methods, including network reconfiguration, the incorporation of capacitor banks (CBs), distributed generations (DGs), and flexible AC transmission systems (FACTS). These technologies have the potential to improve the performance and reliability of distribution networks. Reconfiguration enhances load balancing and minimizes losses, while capacitor banks provide reactive power assistance to sustain voltage levels. Distributed generation, especially from renewable sources, provides a decentralized method of supplying electricity, therefore decreasing the burden on central stations. FACTS devices, in contrast, provide the capacity to actively manage power flows and maintain voltage stability, facilitating a more adaptable and effective functioning of the network.

Recently, there has been an increasing interest in the concurrent use of network reconfiguration, capacitor placement, and distributed generation integration. Although each of these strategies has shown efficacy when used alone or in combination, their individual implementation often falls short of adequately addressing the whole range of issues encountered by contemporary DN. For example, reconfiguration on its own may improve load distribution, but it may not adequately address reactive power requirements or voltage stability. Similarly, the incorporation of DG units may decrease energy losses but may cause power quality problems if not accompanied by suitable reconfiguration or reactive power compensation. Strategic capacitor placement may improve voltage profiles, but it may not fully maximize the advantages of dispersed generation or network flexibility. Therefore, there is a growing perception that implementing all three methodologies simultaneously could lead to a more equitable and optimal result. By simultaneously achieving numerous goals, such as lowering energy expenses, improving voltage stability, and decreasing losses, this strategy enables the complete realization of the combined advantages of each method while also optimizing the investment in network infrastructure.

Changing the configuration of a network while also allocating DGs and CBs is a tough combinatorial problem that includes both discrete and continuous variables. The discrete factors include the status of sectionalizing and tie switches, as well as where to put CBs and DGs. The continuous variables include the sizes of DGs and CBs. Finding the most efficient network structure involves evaluating all possible radial topologies, a task that is both NP-hard and computationally demanding. The use of meta-heuristic methods to address intricate optimization problems would result in premature convergence and the emergence of local optima. This is a result of the primary challenge associated with meta-heuristics, which is the need for an insufficient balance between intensification and diversity during the problem-solving process. To improve solutions, it is necessary to use hybridized meta-heuristics that combine the complementary qualities of many optimization techniques.

In order to tackle these difficulties, this research suggests a multi-objective optimization approach that combines network reconfiguration, capacitor placement, and distributed generation deployment concurrently. The suggested technique aims to minimize two primary objectives: energy expenditure and capital investment in equipment. The aims mentioned are intrinsically contradictory, since the act of decreasing energy costs often necessitates substantial capital expenditure, while reducing investment costs may result in increased operating expenditures.

The following is a list of the most noteworthy contributions to this dissertation:

- This innovative study investigates the use, for the first time, of the hybrid multi-population algorithm (HMPA) to optimize the allocation of CBs and DGs while reconfiguring radial distribution networks (DNs). The purpose is to reduce the impact of conflicting goals, namely energy expenditure and capital investment in devices.
- The single objective HMPA algorithm is first applied to reduce energy cost and then to minimize investment cost. This process establishes the upper and lower bounds of the membership functions associated with each objective function.
- The fuzzy-based technique is then merged with the MOHMPA multi-objective method to determine the optimal compromise solution.
- Different consumer classes' hourly load profiles are employed to accommodate load variations.
- The hourly profile of the DGs' power production is considered to obtain a realistic simulation.
- The optimization problem is also solved using a variety of meta-heuristics, such as AEO and HHO, both of which are hybrids of the HMPA algorithm, PSO, the most well-known metaheuristic, and MFO recently developed optimizer. Each algorithm is built inside a single-objective framework and then re-implemented within a multi-objective framework to compare its performance to the HMPA technique.

The structure of this dissertation comprises four chapters. The first chapter offers a comprehensive examination of the electrical distribution network, emphasizing its significance, weaknesses, and the obstacles it encounters. The second chapter examines network reconfiguration, capacitor bank integration, and distributed generation methodologies, analyzing their separate and collective effects on network efficiency. The third chapter delves into optimization techniques applicable to distribution networks. It specifically highlights the use of metaheuristic approaches, which have been successful in handling intricate optimization problems involving many objectives. The fourth chapter demonstrates the implementation of the suggested optimization method and carefully analyzes the results to demonstrate its effectiveness in striking a good balance between energy costs and investment costs.

CHAPTER 1

Contemporary Distribution Networks: Challenges and Solutions

Contents

1.1. Introduction

The contemporary distribution network (DN) plays a vital role in providing dependable and effective electricity to users [2] . Technological improvements and population expansion have modified the typical operating dynamics of electrical networks, leading to a rise in worldwide power demand. This chapter presents an overview of the fundamental components and difficulties associated with electrical DNs at the present time. The chapter specifically explores the evolution of the electrical grid, the characteristics and types of loads it must handle, the effects of deregulation, and the integration of distributed generation and battery energy storage systems. The chapter also explores techniques designed to minimize energy losses in the distribution network, highlighting the significance of maximizing network performance to attain sustainability and reliability objectives.

1.2. Electrical grid evolution: implications for the distribution networks

The electrical grid, an essential component of the economy, is undergoing a revolution that is as significant as the introduction of electricity itself. It supports various production methods and facilitates the distribution of energy. In order to tackle these difficulties, it is imperative to incorporate enhanced intelligence into the grid by leveraging information and communication technology. This gives rise to the notion of the smart grid [3].

Contemporary electrical grids operate based on four main segments:

- Generation: mainly through strategically located and grid-connected large-scale power units.
- Transmission: refers to the process of transporting electricity to consumption locations via a sophisticated and centrally controlled network.
- Distribution: typically have radial layouts, with energy flowing in a single direction, serving as the intermediary between the transmission network and end customers.
- Consumers are inactive entities that do not participate in system management.

Despite their distinct institutions and defined roles, physical laws regulate these sectors to maintain a balance between production and consumption and adhere to technical limitations. The complete system, which aims to maximize quality and economic efficiency, is considered the most intricate structure ever constructed by humans. It spans millions of kilometers of lines and cables, includes countless connection points, operates at different voltage levels, and incorporates modern protection and supervision systems.

The architecture of electrical grids, which had remained mostly unaltered for almost a century, underwent significant changes in the late 20th century as a result of the deregulation of power markets. This transition resulted in an increase in the number of stakeholders, a division of duties, and a decrease in collaboration among parties. Regulators simultaneously implemented measures to promote the use of renewable energy, which resulted in the integration of certain energy sources into transmission networks and others into distribution networks or directly to end customers. This is known as distributed generation.

The inclusion of renewable energy sources has had a significant impact on the conventional functioning of transmission and distribution networks. Advanced technologies already equip transmission networks, which are essential for maintaining the equilibrium between production and consumption and guaranteeing system safety. However, distribution networks have been slow to embrace these technologies because of their widespread and decentralized structure. Traditionally, a centralized system largely constructed distribution networks to facilitate unidirectional energy transmission, focusing on maintaining a consistent supply and regulating voltage and current limitations, even during disruptions. For these reasons, their radial structure was economically efficient, but its initial design did not support significant distributed production units.

As the use of intermittent renewable energy sources, including solar and wind power, becomes more common, it requires specific management measures. The implementation of smart meters has had a significant impact on end users' roles. These instruments enable users to regulate their energy usage and aid in power system management by decreasing high-demand periods and offering other critical services. Consumers now have the ability to transform into energy producers or storage providers, allowing them to become active players in the energy system.

Despite the use of advanced prediction methods, the sporadic nature of renewable energy sources hinders precise power generation forecasting. Without sufficient backup production and storage solutions, the unregulated generation of renewable energy has the potential to disturb the equilibrium between production and consumption, posing a threat to the overall security of the electrical system.

The unpredictability and limited regulation of renewable energy generation are causing significant disruptions to the traditional functioning of electrical grids. These grids have traditionally relied on the precise control of conventional power sources to accommodate fluctuations in electricity consumption, resorting to load shedding only in rare and extreme circumstances. Conventional solutions are no longer sufficient with the increasing proportion of uncontrolled production, the unpredictable variations in consumption patterns across different locations and time periods, the rising number of electric and hybrid vehicles, and the urgent need for a reliable and efficient energy source.

Table 1.1 Current grid vs. Smart grid: some comparisons

Criteria for comparing	Current grid	Smart grid
Structure	Hierarchical, centralized	Network, decentralized
Communication technology	Simple, unidirectional	Advanced, bidirectional
Energy management	Responsive, relying on predictions	Real-time data-driven proactive
Dependability and resilience	Prone to regional power failures	Constant monitoring
Use of renewable energy	Restricted, mostly centralized	High, mostly decentralized
Consumption	Passive	Active, proactive
Energy efficiency	Significant losses	Minimized losses
Maintenance	Timed and manual	Conditionally and automatically
Flexibility	Limited, challenging to adapt	Rapid demand-supply adaptation
Safety and Security	Electromechanical	Digital
Costing	Fixed	Adaptable to real-time supply and demand
Environmental impact	Increased dependence on fossil fuels	Enhanced integration of renewable energy
Interoperability	Restricted	Seamless and effortless integration of diverse systems and technologies

This is particularly true in a financially limited setting that necessitates investment optimization. The intelligent distribution network concept aims to tackle several technical and socioeconomic difficulties. Technical aims are associated with advancements and resolutions for current problems, whereas socio-economic objectives concentrate on integrating engaged consumers into the energy system and creating business models for the shift to a more intelligent grid. Table 1.1. illustrates the prominent characteristics of the smart grid in contrast to the current system [4].

The following characteristics define the designated goals of distribution networks, which will impact their projected functioning.

- Accessible: All producers can use the connection.
- Economic: The concept of economics involves the effective use of infrastructure to reduce expenses.
- Adaptable: Enhanced resource redundancy to optimize current flow and efficiently handle interruptions.
- Dependable: A guarantee of consistent availability and excellence in quality.

Due to the high financial investment required for distribution infrastructure, the difficulties in building new lines, and the growing intricacy involved, it is crucial to include intelligence in the layout and operation of DNs. Projects like Smart Grid in Europe [5] and Intelligrid [6] in the USA are witnessing this phenomenon on a worldwide scale. The objective is to update the distribution infrastructure, which has been slower than transmission networks in embracing advanced technologies.

The objectives related to technical aspects include the following:

- Enable the seamless integration of renewable energy, electric vehicles, and energy storage on a wide scale, ensuring optimal economic, security, and quality conditions.
- Improve energy efficiency to optimize energy usage and increase the electrical system's overall efficiency.
- Active Consumer Integration: Involve consumers as active participants in managing the balance between supply and demand, decreasing high levels of consumption, and delivering vital services.
- Optimal System Management: Skillfully manage the growing complexity of incoming data.

- Interoperability: Guarantee smooth and efficient communication and collaboration among different entities, including transmission and distribution networks.
- Streamlined Management: Effectively manage the electrical system's increasing complexity.

In DNs, intelligence can be defined as the incorporation of intelligent devices into the network that manage measurement, analysis, decision-making, action, and communication. Additionally, it could entail the distribution of intelligence and the reevaluation of hierarchical structures or decision-making procedures. To accomplish these quality goals, substantial expenditures will be necessary to bridge the gap between the existing level of networks and the envisioned smart grid as illustrated in Figure 1.1.

Although the implementation of smart grids on a global scale is still mostly theoretical and an ongoing subject of study [7] , it is crucial to enhance the efficiency of current electrical distribution networks using the tools and technology that are already accessible. We are still in the early stages of developing fully operational smart grids, characterized by sophisticated automation, immediate data analysis, and seamless integration of dispersed energy sources. Therefore, it is imperative that we prioritize improving the efficiency and dependability of our

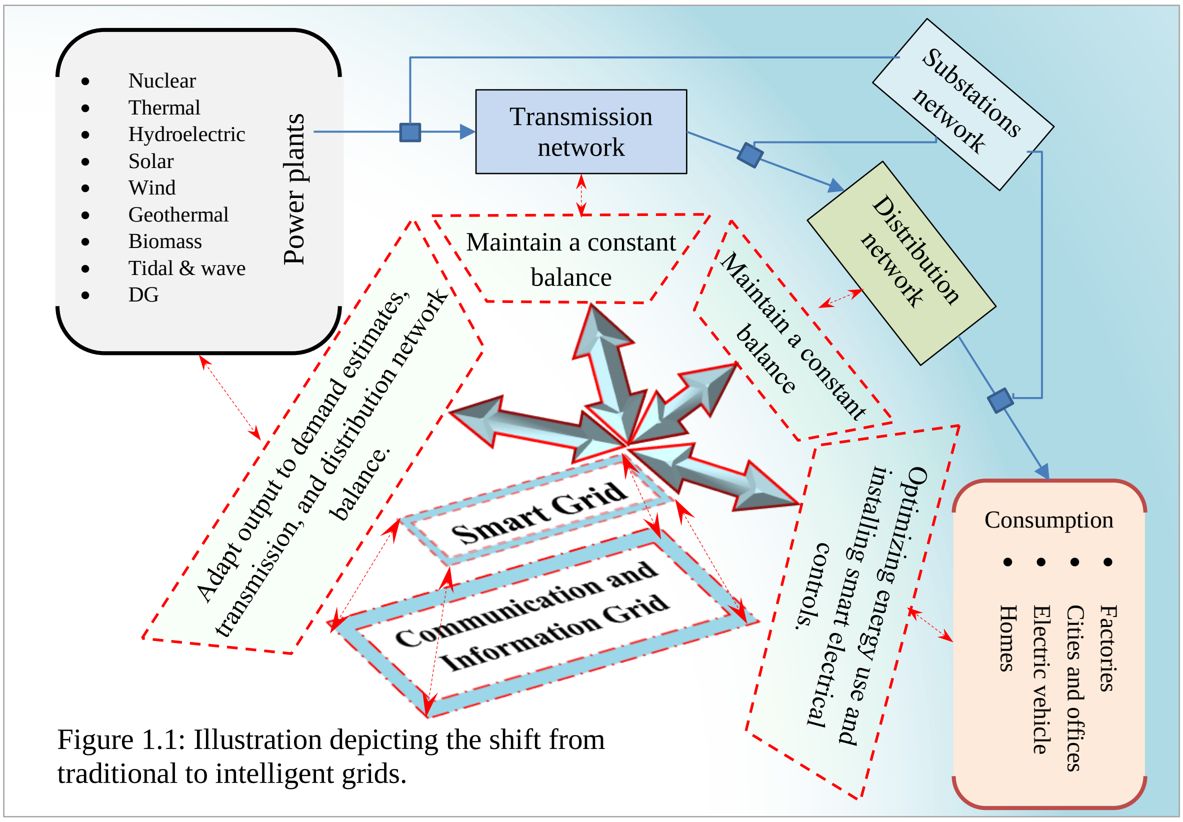

Figure 1.1: Illustration depicting the shift from traditional to intelligent grids.

existing networks, guaranteeing that they are better prepared to address modern issues and progressively evolve into more intelligent and robust grids in the future.

1.3. Electrical distribution networks: an overview

1.3.1. Distribution vs. transmission networks: analysis

Three main segments essentially categorize the electricity system: generation, transmission, and distribution [8]. The generation stage functions at voltage levels ranging from 11 kV to 25 kV. Step-up transformers raise these voltages to transmission levels between 220 kV and 765 kV to efficiently transport large amounts of electricity. Next, step-down transformers decrease the voltages to sub-transmission levels, specifically between 66 kV and 132 kV, before lowering to distribution levels below 33 kV. Distribution comprises two main systems: primary, which operates at voltages ranging from 4 kV to 33 kV, and secondary, which operates at 400 volts for three-phase systems and 230 volts for single-phase systems. Pictured in Figure 1.2.

Transmission networks improve dependability and stability by creating loops that allow electricity to flow via multiple paths. Even in unforeseen circumstances, the interconnection of the power supply system ensures uninterrupted electricity. Conversely, the radial design of distribution networks enables a simpler and more cost-effective design.

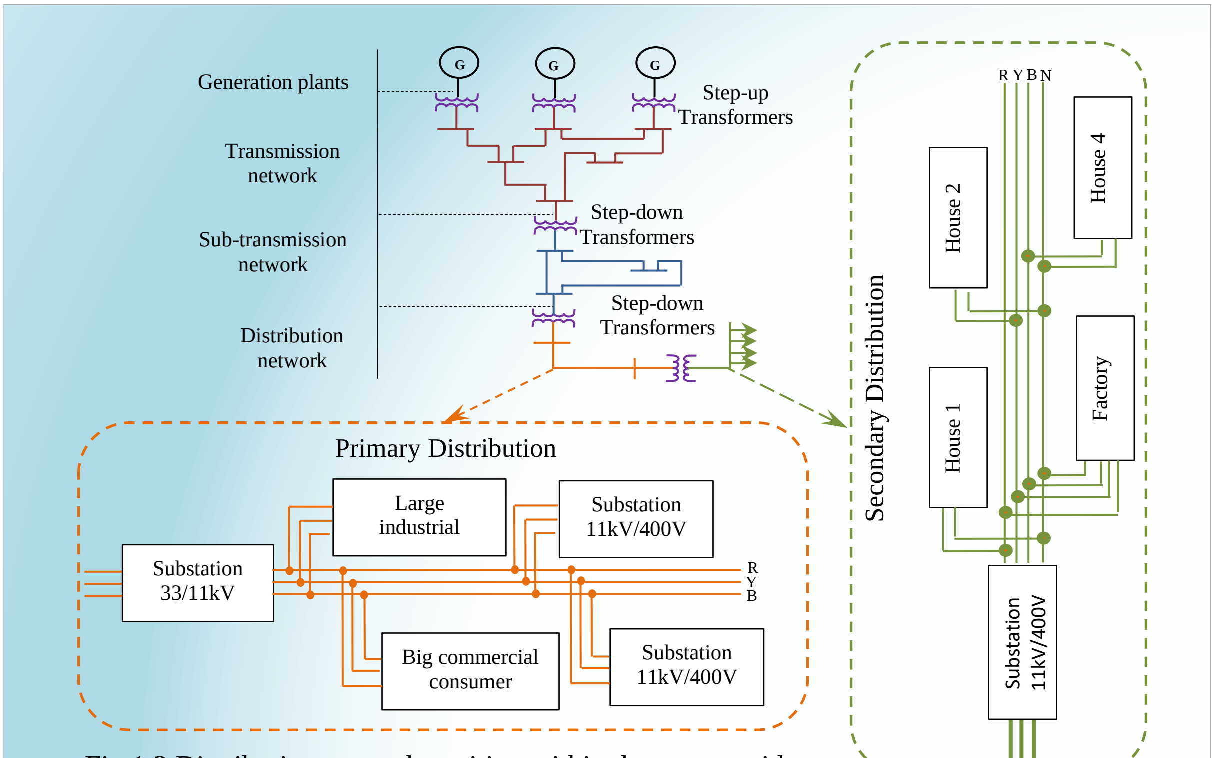

Fig 1.2 Distribution network position within the power grid

This design also makes it easier to secure the network, regulate voltage, locate faults, and manage power flow. The distribution system's goals include reducing losses, maintaining power quality without harmonics or voltage fluctuations, ensuring dependability, providing cost-effective power, and delivering secure power to consumers. The examination of the distribution network must take into account some important analytical factors necessary to understand its own weaknesses and functional characteristics.

Distribution networks are less complex than interconnected transmission systems due to their radial or poorly meshed configuration. This results in cost reduction and streamlines the implementation of protective and control measures. Distribution lines have untransposed configurations and loads often display imbalances, requiring specialized analytical methods to handle voltage dips and power quality concerns. Distribution systems have a high resistance to reactance ratio, affecting voltage management. Efficient voltage control requires considering load directionality and variability, often requiring active management and regulation.

Component complexity in DNs includes capacitors, regulators, distributed generating units, and storage systems, increasing modeling and analysis complexity. Fault analysis and protection are simplified due to the unidirectional flow of electricity, but the radial arrangement increases the likelihood of defects directly affecting service delivery. Modern analytical methods and real-time data processing are needed to optimize performance and dependability of smart grid elements, such as adjustable loads, decentralized storage, electric vehicles, and demand response technology.

Table 1.2 Analytical disparities between transmission and distribution networks.

Characteristic	Transmission system analysis	Distribution system analysis
Topology	Interconnected	Radial or weakly meshed
Line	Transposed	Untransposed
Load	Balanced, constant energy supply	Unbalanced, One-, two-, or three-phase configurations
Impedance ratio	$X/R \nearrow$	$R/X \nearrow$
Components	Reduced number of elements	Several components, like as capacitors, regulators, distributed generation, storage, and others.
Size	Reduced number of buses	High number of buses
Fault analysis	Symmetrical component analysis	Symmetrical component analysis increases inaccuracies.
Modeling of transformers	Single-phase equivalent of lines and transformers	Modeling of actual transformer connections: Y/Y, Y/Δ, Δ/Δ, etc.
Load voltage dependence	Generally, not regarded	Voltage dependency of various loads
Requirements for simulation	Steady-state analysis	Time series simulations
Smart grid elements	Generally, not regarded	Controllable loads, Distributed Storage, Electric vehicle, demand response, etc.

The table above illustrates how transmission and distribution networks differ in their unique system analysis.

1.3.2. Power flow and short-circuit analysis methods

Power flow analysis is an essential technique in power system design, operation, and optimization. It calculates the voltage magnitude, the phase angle, and the flow of actual and reactive power across transmission lines. This study enables engineers to evaluate the stable performance of the power system under various load levels and operating settings. Applications include operational decision-making, optimization during the design stage, control of voltage, reduction of power loss, placement of shunt capacitors, and distributed generation, as well as load balancing and reconfiguration. Load flow analysis has advanced by including renewable energy sources, dynamic load modeling, and machine learning approaches [9].

Short circuit analysis is essential for calculating the electric current passing through a power system when faults occur, assessing the thermal and mechanical strain on equipment, and configuring protection measures to ensure safety and dependability. It aids in identifying the suitable configurations for circuit breakers, relays, and fuses, guaranteeing that equipment can endure fault currents without sustaining any harm.

Table 1.3 Comparative table of load flow and short-circuit analysis techniques

Criteria	Power flow analysis	Short circuit analysis
Aim	Analyze network steady-state voltage, current, and power.	Calculate the electric current that occurs under abnormal situations and evaluate its effect on the system.
Pivotal interest	Power distribution, voltage regulation, loss mitigation	Magnitude and direction of fault current and protective device settings.
Application phase	during planning and steady-state operation	Mostly during design phase.
Optimization	Assists in optimizing the size of conductors and transformers, positioning of CBs, and integration of DGs.	Test the equipment's ability to withstand abnormal conditions and ensure the level of protection provided is adequate.
Results	Bus voltages, power flows, transformer tap settings, system losses.	Fault current levels, protective device settings, equipment stress levels.
Complexity	The use of iterative solutions and sensitivity analysis typically increases complexity.	Although less intricate, it is crucial for guaranteeing the synchronization of safety and protection.
DGs integration	Evaluates the influence of DGs integration on voltage stability and power quality.	Assesses the impact of DGs on the magnitude of fault currents and the effectiveness of protection systems.
Main use	Load balancing, voltage regulation, power loss reduction, network reconfiguration.	Detecting faults, configuring protective device parameters, and assuring the resilience of equipment.
Current tendencies	Combining dynamic load modeling, machine learning, and smart grid integration.	Highly advanced digital protection systems and fault current analysis with DGs

Fault current computation is essential for constructing protective systems, whereas system stability analysis evaluates the effects of faults on the stability of the system. Current advancements include the exploration of renewable energy sources and the use of digital protection systems, which necessitate more accurate and instantaneous short circuit diagnosis [10]. Table 1.3 provides a concise comparison of the two approaches, emphasizing their specific functions and uses in electrical distribution networks.

Our project aims to enhance the efficiency of electrical distribution networks by utilizing power flow analysis, also known as load flow analysis. This method is best suited to power system optimization problems, as shown in the table above. It is crucial for understanding the stable functioning of power networks, particularly in radial or poorly meshed topologies, as it helps calculate network voltage levels, power flows, and losses.

1.3.3. Power flow calculation techniques

Power flow analysis in electrical networks involves various techniques, each with its own advantages and limitations. Table 1.4 compares the most commonly used strategies in order to identify the best suited method to the context of this study [11].

The Gauss-Seidel and Newton-Raphson techniques have long been essential tools for analyzing and operating electrical networks. The Gauss-Seidel method, a recursive algorithm, is characterized by its straightforwardness and simplicity in application. The system functions by iteratively adjusting the voltage at each bus until it reaches a state of convergence. Although the approach is simple, it may exhibit sluggish convergence, particularly in large-scale systems with inadequate starting estimations. However, the Newton-Raphson approach is well-known for its strong resilience and rapid convergence characteristics. The use of a Jacobian matrix in an iterative manner to solve the non-linear power flow equations yields a solution that is both more precise and efficient in comparison to the Gauss-Seidel approach. Nevertheless, the computational intensity of creating and inverting the Jacobian matrix is quite high, especially for networks that are vast and extensively meshed. Although conventional approaches have played a crucial role in the historical progress of power flow analysis, their ability to handle current, dynamic distribution networks is limited. Therefore, it is necessary to investigate more sophisticated methodologies.

Novel methodologies have been devised to overcome the constraints of conventional approaches and cater to the requirements of contemporary electrical DNs. The methodologies mentioned are the Decoupled Load Flow (DLF) and Fast Decoupled Load Flow (FDLF) methods. These methods simplify the power flow equations by separating the calculations for real and reactive power. The FDLF approach, specifically, provides significant computational speed benefits and is highly suitable for large-scale networks with high R/X ratios [12]. Another sophisticated technique involves the use of probabilistic power flow (PPF) techniques. These approaches take into account the unpredictable characteristics of dispersed generation sources and fluctuations in demand, resulting in a more accurate evaluation of network performance in uncertain situations [13]. Furthermore, optimization-based methods, like the Optimal Power Flow (OPF) approach, enhance conventional power flow analysis by integrating economic and operational limitations. This allows for the efficient allocation of resources within the network [14]. Utilizing artificial intelligence (AI) and machine learning (ML) algorithms has improved power flow analysis, enabling the real-time monitoring and adaptive regulation of DNs [15]. These innovative procedures provide the essential means to handle the growing intricacy and variety of contemporary power systems, guaranteeing effective and dependable functioning.

The Backward/Forward Sweep (BFS) method is a commonly used approach for analyzing power flow in radial and poorly meshed DNs. Contrary to conventional techniques like Gauss-Seidel and Newton-Raphson, which are more appropriate for transmission networks, the BFS approach exploits the hierarchical arrangement of distribution systems. The technique consists of two primary stages: the backward sweep and the forward sweep. The backward sweep involves the calculation of currents, which begins at the end nodes (also known as leaf nodes) and proceeds towards the root node (substation). This calculation is based on the known loads at each node. During the forward sweep, the voltages are incrementally adjusted from the root node to the end nodes, using the previously computed currents. The iterative procedure continues until the answer reaches a certain degree of tolerance. The BFS algorithm is very efficient in dealing with the radial topology and unbalanced load situations that are often encountered in DNs. The simplicity, resilience, and computing efficiency of this method make it the ideal option for analyzing DNs. It allows for accurate and quick estimates of power flow, which are essential for real-time grid management and planning.

The BFS technique is an optimal option for doing power flow calculations in DNs, especially in networks that are radial or poorly meshed. Unlike conventional techniques like Gauss-Seidel and Newton-Raphson, BFS specifically adapts to the unique characteristics of DNs, resulting in faster and more efficient convergence. In these networks, the repeated process of backward and forward sweeps utilizes their radial structure to effectively manage imbalanced loads and changing network topologies. BFS's computational simplicity results in reduced computing strain and memory needs, making it well-suited for real-time applications and large-scale network research. Additionally, it can easily accommodate the incorporation of distributed generation and battery energy storage technologies, making it a very suitable option for effectively managing contemporary DNs [16].

Table 1.4 Power flow methods: comparative analysis

Criteria	Gauss Seidel	Newton-Raphson	BFS
Suitable type of network	Relevant but less effective in all networks	Appropriate for meshed transmission networks	Suitable for radial and poorly meshed distribution networks
Speed of convergence	Depending on the original estimate, slower convergence	Swift, particularly in meshed systems	Efficient and dependable for radial networks
Computing efficiency	Reduced processing requirements, but less effectiveness	Intensive computational demands	Extremely effective for expansive radial systems
Complexity of implementation	Easy, but time-consuming	Intricate, requires well-chosen starting values	Straightforward and user-friendly for radial networks
Management of DG	Restricted capacity	Exhibits efficient performance in interconnected networks	Efficiently incorporates distributed generation (DG) into radial networks
Robustness	Possible convergence concerns in huge systems	Unconditioned systems may cause problems	Robust, particularly when managing unbalanced and large-scale networks
Utilization in DN	Usable but not ideal	Not well-suited, especially for radial systems	Well-suited for radial DNs, particularly those with diverse load models and (DG).

1.3.4. Structural components

Several key structural components collectively comprise electrical DNs, ensuring the efficient delivery of electricity from transmission systems to end-users. Substations, which serve as critical nodes within the network, transform high-voltage electricity from transmission lines to lower voltages suitable for distribution. The DN usually begins at the substation (Fig 1.3), where various feeders, often numbering between 8 and 10, stretch to distribute electricity throughout the system. The primary essential element of any feeder is the circuit breaker, which functions as a safeguarding mechanism to disconnect the feeder in case of a problem. Installing a voltage regulator after the breaker is optional if the substation transformer has an on-load tap changer. The major purpose of the voltage regulator is to ensure that the distribution voltage remains within the specified limits, often within a range of 10% of the nominal value, as determined by industry standards [17]. The primary conduit of the DN, referred to as the 3-phase mainline, divides into several secondary lines, which may operate as single-phase, two-phase, or three-phase. Protective devices such as fuses, reclosers, and sectionalizers safeguard these lateral lines. Reclosers are notable for their distinction from conventional circuit breakers in their capacity to differentiate between temporary and permanent faults. After a temporary fault, they automatically attempt to restore service, but if the fault turns out to be permanent, they isolate the faulty section [18]. Sectionalizers work in tandem with reclosers to isolate the specific affected portion of the network, ensuring uninterrupted service in other regions.

Capacitor banks, whether fixed or switched, play a crucial role in providing reactive power support in the distribution network. Regardless of the load circumstances, the network continuously links fixed capacitors, while switched capacitors are only active during high demand and removed during lower load situations [19]. This technique enhances the network's voltage profile and minimizes losses. The presence of laterals, which may include overhead lines or subterranean cables, characterizes the distribution system. Additionally, tie switches link nearby feeders. When network reconfiguration is necessary, like during maintenance or outages, these tie switches, normally kept in an open state, may become closed. The incorporation of DGs such as solar photovoltaic systems, fuel-cell batteries, and wind energy is converting the conventional, inactive distribution network into an energetic one. This shift necessitates a reassessment of current protection strategies, as the existence of various generating sources brings about new intricacies in system functioning and protection. As a

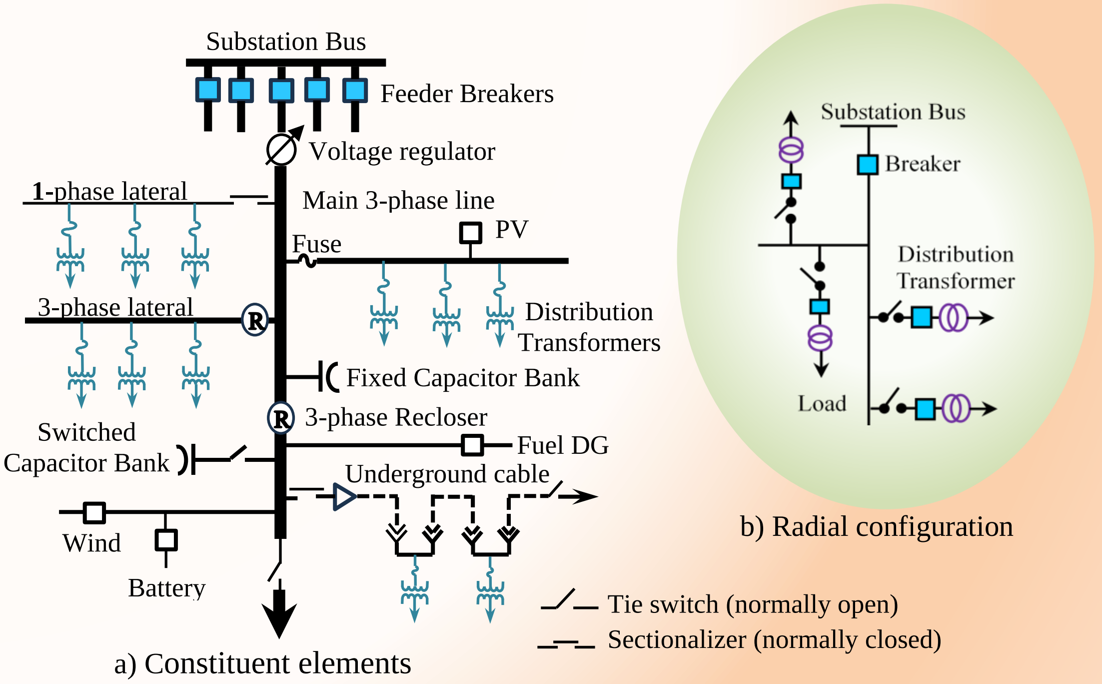

Fig 1.3 Structural diagram of the DN.

result, there is a growing need for sophisticated protection techniques and adjustable relay settings to guarantee the dependability and security of contemporary DNs [20].

The radial network is the prevailing architectural design for power distribution systems. Its tree-shaped topology allows for the transfer of power from one bus to another without creating closed loops.

However, it is important to locate the originating bus while tracing back. This network configuration, known as a tree structure, is the most basic and cost-effective for an electrical grid. However, if a fault occurs at a certain point in the network, all the lines downstream would experience a power outage. In a radial DN, the lateral line runs parallel to the root or main bus, the sub-lateral line branches out from the lateral line, and the network concludes with minor lines originating from the sub-lateral line. Power distribution systems often utilize radial network designs due to their inherent simplicity and cost-effectiveness. Typically, distribution transformers link the generators alone at the radial structure's beginning point (slack bus) to the load center. The nodes are numbered in ascending order, and uniquely numbered branches connect each pair of neighboring nodes. Figure 1.4 depicts a particular example of a radial DN [21].

A radial DN has intrinsic flexibility, making it a strong foundation for the advancement, experimentation, and verification of innovative configurations, devices, control mechanisms, communication protocols, and security attributes. The network derives its flexibility from its simple design, typically consisting of a single route connecting the power supply to each demand. This simplicity allows for the direct execution of modifications and advancements, as it makes it easier to see and manage the effects of alterations.

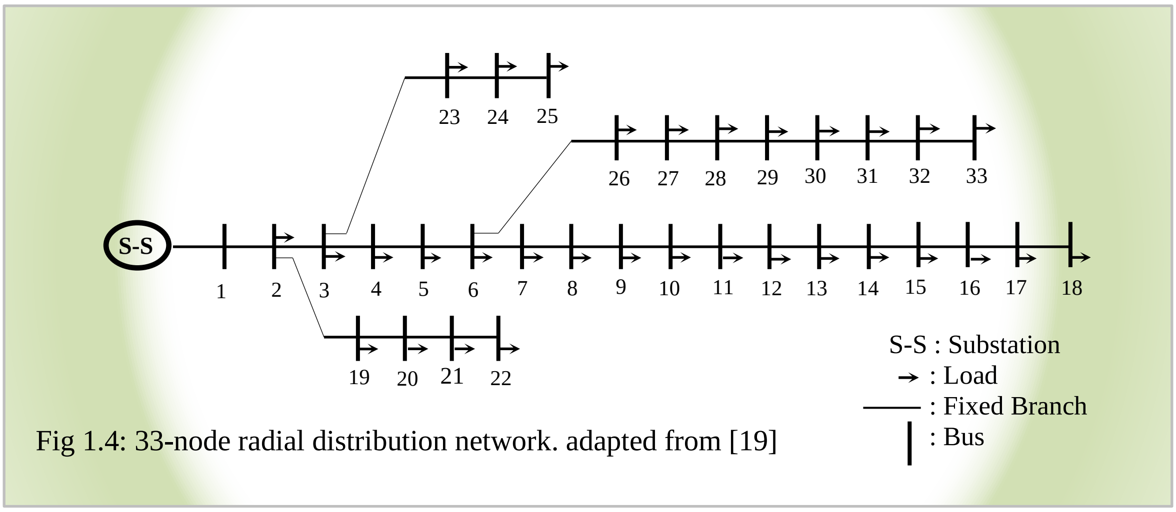

Fig 1.4: 33-node radial distribution network. adapted from [19]

Radial networks are characterized by their small times of inactivity, meaning that they can sustain a constant supply of power with minimum disruptions. This attribute increases the network's susceptibility to random elements, since the absence of extended periods of inactivity implies that even little variations or disruptions in the network may have quick and discernible impacts. The radial structure, which is characterized by a straight channel of power flow, may enhance the influence of these random fluctuations, thereby increasing the network's ability to adapt to changes in demand or generation. Distribution lines are of utmost importance when it comes to linking sources, loads, and energy storage devices. These lines function as pathways for the delivery of electricity from generating sources to consumers, and they also enable the incorporation of distributed energy resources, such as solar panels, wind turbines, and battery storage systems. The network's radial topology facilitates direct connections between these parts.

Table 1.5 The main differences between Radial and alternative configurations

	Network configuration		
Characteristic	Radial	Ring/loop	Grid
Cost	Affordable	Medium to expensive	Costly
Complexity of design	Straightforward	The design features a moderate level of complexity.	Intricate
Reliability	Unreliable	Moderately good.	Exceedingly high level
Safety	Basic	More intricate due to the existence of multiple pathways.	Highly intricate as a result of vast interdependencies
Failure consequences	High impact; failures can affect all downstream users	Constrained to a specific region; alternative routes serve to mitigate the impact.	Minimized by the use of numerous emergency routes.
Common applications	Rural and suburban regions lower dependability requirements.	Urban and suburban sites require greater reliability	Highly populated metropolitan regions and essential infrastructure necessitate optimal dependability.

In situations when uninterrupted service is crucial, the adoption of more intricate network designs and security techniques becomes necessary due to the dependability constraints of the radial topology, despite its cost-effectiveness and simplicity. Utilities may develop a more balanced strategy that fulfills both economic and reliability goals by using selected schemes, loop, ring, and grid networks, to overcome these restrictions. These arrangements, while more intricate and expensive, enhance dependability by offering numerous routes for power transmission and ensuring uninterrupted service even in the event of breakdowns [22]. The table above presents a concise comparison between the radial system and more sophisticated structures, highlighting the compromises between cost, complexity, and dependability.

1.3.5. Functional characteristics

Electrical DN play a vital role in the efficient and dependable delivery of high-quality electricity to end customers. Their functional components include operation dynamics, performance measurements, and balance-achieving strategies, as presented below.

A. Operational dynamics

The operational dynamics of DNs involve the immediate processes that regulate energy transmission from substations to consumers, including monitoring voltage levels, adjusting frequencies, and managing power flows. Voltage regulation, which maintains voltage levels within a specified range, ensures safe and efficient network and equipment operation using devices such as regulators, capacitor banks, and on-load tap changers. Power quality, including stability, harmonic distortion, and frequency fluctuation, is crucial for equipment safety and optimal functioning. Harmonic filters and uninterruptible power supply (UPS) help mitigate issues related to inadequate power quality [23].

B. Metrics of performance

Performance metrics permit to assess DNs efficiency and reliability. These metrics include the System Average Interruption Duration Index (SAIDI) and the System Average Interruption Frequency Index (SAIFI), which measure the mean length of power outages for each customer as well as the average number of times a client experiences a power interruption. The Customer Average Interruption Duration Index (CAIDI) provides a more detailed perspective on the process of restoring power to customers during outages. Energy Not Supplied (ENS) is a crucial performance indicator that quantifies the amount of energy unavailable due to interruptions, which is essential for understanding the economic consequences of power outages and strategizing network infrastructure investments [24].

C. Forecasting demand and managing load

DNs need to handle different levels of demand to function effectively. Accurate demand forecasting and load management are crucial for maintaining a balance between energy supplied and needed. Machine learning methods and time series analysis permit to forecast load patterns, leveraging past data, weather conditions, and economic indicators. These predictions help utility companies prepare for high demand periods and optimize resource distribution. Load management strategies involve modifying network loads to maintain supply and demand balance, avoiding system overload. Common techniques include demand response, which involves incentivizing users to decrease or shift their consumption during peak hours, and load shedding, which temporarily disconnects non-critical loads. Energy storage systems (ESS) are essential for maintaining load equilibrium, allowing surplus energy to be stored during low demand and released during high demand [25].

D. Control and supervision

The integration of Advanced Metering Infrastructure (AMI) and Supervisory Manage and Data Acquisition (SCADA) systems has significantly enhanced the monitoring, management, and automation of distribution networks. AMI uses intelligent meters to provide real-time power usage information, enabling more accurate invoicing, better energy demand prediction, and increased efficiency. It also enables remote monitoring and control, allowing utilities to promptly address power outages or anomalous circumstances. SCADA, on the other hand, provides centralized management by gathering data from distant devices, enabling instantaneous monitoring, fault identification, and remote control of network components, enhancing operational efficiency and dependability [26].

E. Adjustment to regulatory framework changes and technological advances.

DNs are constantly evolving to meet new demands, including the integration of renewable energy sources, adherence to emission reduction objectives, and cybersecurity in digitalized networks. Renewable energy sources like solar and wind often exhibit fluctuations and irregularities and require sophisticated prediction methods, storage technologies, and grid adaptability. Regulatory compliance involves ensuring reliability, electricity quality, and environmental impact, which drives the use of new technologies and infrastructure upgrades. Cybersecurity is a pressing issue as DNs adopt digital technologies like smart meters, IoT devices, and cloud-based management systems. Safeguarding data and thwarting cyberattack are essential for the secure functioning of DNs [27].

1.4. Load characteristics and types.

The main goal of an electrical distribution system is to provide energy to users at their individual locations, guaranteeing a dependable and effective power supply. Consumer loads pertain to the electrical appliances and gadgets that are linked to and extract electricity from the distribution system. The combined loads, when added together for a community or a particular set of consumers, make up the total load that is linked to the DN [28].

1.4.1. Categories of consumers

Electrical DNs often categorize users based on their power usage characteristics, consumption patterns, and demand magnitude. Comprehending these distinct categories of users is crucial for efficient system design, load prediction, and energy management [29] . A detailed overview of consumer classes follows (Fig 1.5):

A. Residential consumers

- Load profile

Residential or domestic consumers are defined as households or single dwelling units. These users' load profile is defined by very modest power requirements, which fluctuate based on the household's size, the number of active electrical devices, and lifestyle choices. Typical domestic loads include lights, heating, cooling, kitchen appliances, entertainment devices, and small household electronic gadgets.

- Peak demand

Residential users frequently experience the highest demand for electricity during the evening hours, when residents come home and use numerous appliances concurrently. During this time, there is typically a simultaneous need for lighting, heating or cooling, and cooking, resulting in a substantial surge in power use.

- Implications for DN

Residential users contribute to the distribution network's nighttime peak load, which requires careful control to ensure a reliable power supply. The presence of a diverse range of loads in residential areas often leads to a more equitable and predictable pattern of demand, which may have positive effects on the system's stability.

B. Industrial consumers

- Load profile

Industrial consumers include manufacturing facilities, factories, and other extensive industrial enterprises. These customers exhibit significant power requirements, often ranging from several hundred kilowatts to several megawatts. Industrial customers' load profile is primarily characterized by the prevalence of heavy equipment, motors, assembly lines, and other energy-intensive operations. Industrial loads exhibit significant variability, which is influenced by production schedules, shifts, and the industry's unique characteristics.

- Peak demand

Industrial customers often encounter high demand during regular working hours, especially in the morning when activities begin and in the afternoon. Certain industrial customers may have two different peaks in their load curve. Moreover, some sectors, such as steel production or chemical processing, may need continuous operation, resulting in a consistently steady demand pattern.

- Implications for DN

Industrial users make a substantial contribution to the total load on the distribution network and need strong infrastructure to accommodate their high demand. Because industrial loads are diverse and extensive, it is critical to accurately predict and regulate the load in order to avoid voltage fluctuations and maintain a steady power supply.

C. Commercial consumers

- Load profile

Commercial customers include several types of enterprises, including office buildings, retail establishments, shopping centers, hotels, and restaurants. The load profile for business users often lies between that of residential and industrial consumers, with power needs ranging from tens to hundreds of kilowatts. Primary energy demands in business environments include lighting, heating, ventilation, air conditioning (HVAC) systems, computers, lifts, and many other office equipment.

- Peak demand

Commercial customers often experience their highest demand during business hours, which typically fall between late morning and early afternoon. During this time, there is a significant increase in activity levels in business facilities, with several systems and devices operating concurrently.

- Implications for DN

Commercial users significantly contribute to the peak demand on the distribution network during the daytime, especially in metropolitan and commercial areas.

Commercial users often exhibit a more regular load pattern, which facilitates load control and energy-saving efforts.

D. Agricultural consumers

- Load profile

Agricultural users mostly consist of farms and other agricultural activities that utilize electricity for the purpose of irrigation, pumping, and processing equipment. Agricultural consumers exhibit a highly fluctuating load profile, which is determined by seasonal patterns, weather conditions, and the need for crop irrigation.

- Peak demand

Agricultural loads see their highest demand during certain time periods, such as early morning or late evening, when irrigation systems are often in use. The demand may also reach its maximum during certain seasons, when irrigation or harvesting activities are at their peak.

- Implications for DN

Agricultural loads may lead to substantial variations in the distribution network, especially in rural regions where these loads are concentrated. Dynamic load control solutions are necessary to provide a dependable power supply and prevent system overload due to seasonal and daily fluctuations in agricultural demand.

E. Municipality Consumers

- Load profile

Municipality customers include the public services administered by local governments, including street lighting, water pumping stations, sewage treatment facilities, and public transit networks. These loads are generally consistent but may fluctuate in magnitude based on the size of the municipality and the particular services offered.

- Peak demand

Municipal loads often reach their highest levels during non-peak hours compared to the rest of the power system. Street illumination reaches its peak at night, while water pumping occurs when there is little overall demand. Certain municipal services, such as sewage treatment, function without interruption, resulting in a consistent load profile.

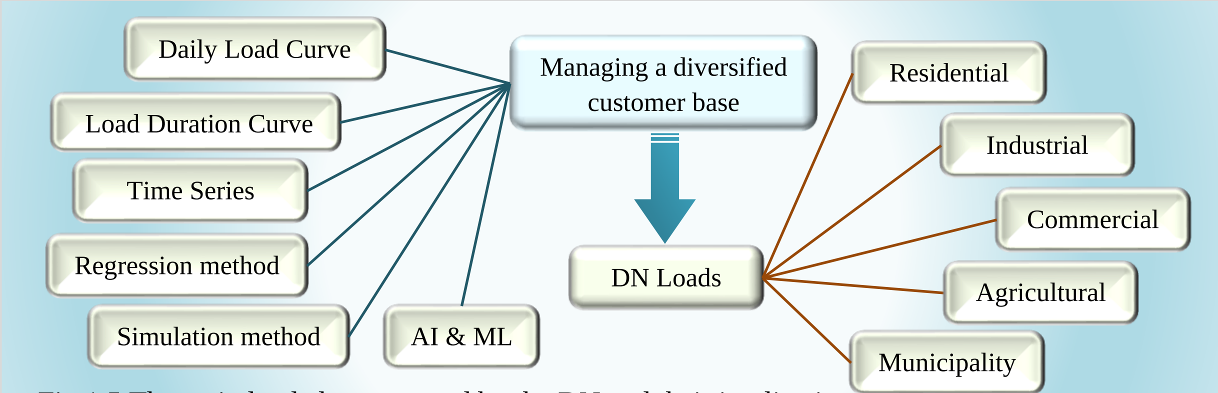

Fig 1.5 The main load classes served by the DN and their implications

- Implications for DN

Municipality customers have a vital role in upholding key services, and it is important to prioritize their loads to ensure dependability. The consistent and unchanging character of municipal loads may assist in stabilizing the total demand on the distribution network, especially during periods of low demand.

The expansion of the customer base within an electrical DN has a significant impact on network optimization. Consumers' diversification across multiple categories leads to variable load characteristics and peak demand periods. This makes load forecasting and resource allocation more complex. To attain optimal network performance, operators must deftly manage and prioritize these varied needs. This involves adopting techniques that consider the distinct consumption patterns and requirements of each consumer group. Therefore, it is essential to have advanced analytical tools and adaptable infrastructure that can accommodate the constantly changing needs.

1.4.2. Load Variability and Analysis

The inherent fluctuation of electrical loads is a key attribute of DN [17]. This unpredictability stems from several causes, such as changeable consumer behavior, changing weather conditions, and operating schedules. These oscillations are particularly noticeable at the consumer level, where individual consumption habits result in substantial differences in demand. The substation transformer aggregates these loads to reduce the impact of individual variations, resulting in a more stable load profile [30].

A. Fundamental Concepts in Load Analysis

- Connected load

The connected load refers to the sum of the continuous ratings of all electrical devices linked to the DN. This term refers to the hypothetical maximum level of demand that would occur if all devices were to function concurrently at their utmost capacity. Nevertheless, this situation is seldom achieved in real-world situations because of the sporadic and diverse use of electrical devices.

- Maximum demand

Maximum demand is the greatest documented level of electrical demand within a certain time period, such as daily, weekly, monthly, or annual intervals. Typically, the connected load exceeds the highest demand, suggesting that not all devices operate simultaneously or to their full capacity. Maximum demand is a critical measure for system design and operational efficiency because it establishes the highest level of load that the system needs to handle.

- Demand factor

The demand factor refers to the proportion of the highest level of demand in relation to the total connected load. The value of this component usually falls between the range of 0.5 and 0.8. A lower demand factor signifies a better level of redundancy in the system, indicating that the infrastructure can handle extra loads without substantial danger. On the other hand, a larger demand factor indicates that the system is functioning at a greater proportion of its maximum capacity, necessitating careful management to prevent overloading.

B. Load behavior analysis methods

Examining load behavior in electrical DN is critical for understanding power demand fluctuations over time and across various customer categories [31]. There are numerous methods for simulating, forecasting, and regulating load behavior that ensure efficient and reliable distribution network operation [32]. Here are a handful of often-used techniques.

- Daily load curve

A daily load curve is a visual depiction of the fluctuation in electrical demand over a 24-hour period, which helps to determine the times of highest and lowest demand. It assists in managing load distribution, such as time-of-use pricing, and in designing infrastructure to ensure that the distribution system can accommodate peak loads without excessive construction. Figure 1.6 displays one example [33].

- Load duration curve

This analysis method provides a thorough examination of load patterns over a long period of time, such as a year, which aids in capacity planning and reliability evaluation. It ensures effective network support and meets demand even during peak times.

- Time series

Time series analysis is a statistical method used to forecast future load behavior based on historical data, considering factors like economic growth, weather patterns, and consumer behavior. It aids in predicting demand and preparing networks for peak load periods.

- Regression method

Regression analysis is a statistical technique that examines the connection between a dependent variable, such as load, and independent variables like temperature, time, or economic indicators. It is helpful in forecasting consumer behavior and external influences, which in turn aids in demand response programs and environmental impact assessment.

- Simulation method

Distribution networks use simulation models like Monte Carlo and agent-based models to forecast their load behavior. They facilitate scenario planning and risk assessment, enabling utilities to examine possible vulnerabilities and explore hypothetical situations.

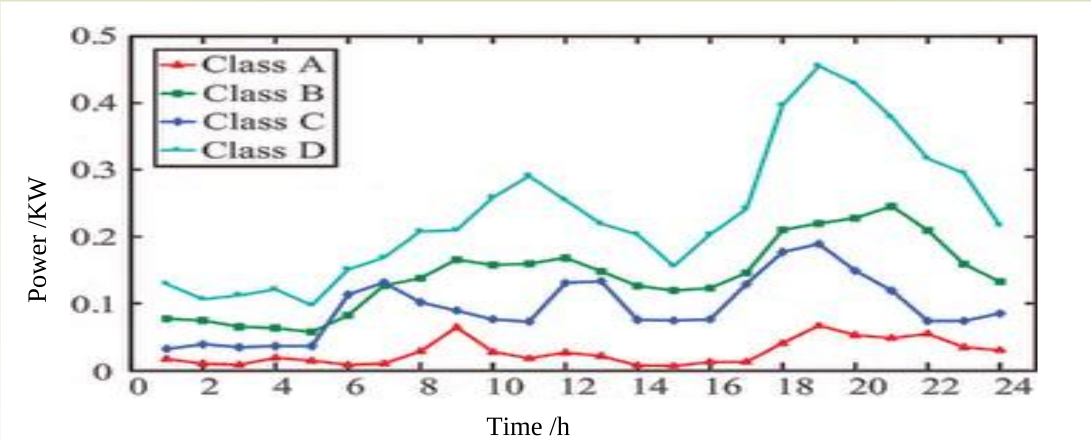

Fig 1.6 Daily load curve of four household user classes [31]

- Artificial intelligence and machine learning techniques

Artificial intelligence (AI) and machine learning (ML) methods are becoming more prevalent in the study of load behavior in smart grids and big data analysis. These approaches allow for real-time load forecasting and anomaly identification, empowering operators to promptly address shifts in demand.

Analyzing load behavior using the aforementioned methods aids in handling intricacies in contemporary electrical DNs, allowing utilities to predict demand, improve efficiency, and guarantee dependable service.

1.5. Impact of deregulation

The deregulation of the energy industry, also known as the liberalization of electricity markets, arose in the latter part of the 20th century as a reaction to the monopolistic control exerted by vertically integrated utilities. The motivation for this transition stemmed from the conviction that the introduction of competition into the electrical market would stimulate innovation, improve operational efficiency, and lower prices for customers. The deregulation process included the separation of energy production, transmission, and distribution, enabling independent firms to participate in the market and compete in power generation and retail supply [34].

The legislative reforms have significantly transformed the structure of electrical distribution networks, creating both difficulties and possibilities for those involved. A significant consequence of deregulation has been the implementation of competitive forces, which have compelled utilities to enhance operational efficiency and embrace cost-effective management strategies. The emergence of independent power producers and competitive retail providers has increased the variety of power sources and contractual arrangements that distribution network operators are responsible for overseeing. The expansion of different sectors has led to the development of complicated grid management techniques and the use of modern information and communication technologies to effectively manage the system's growing complexity.

Furthermore, deregulation has caused a change in utility operations, moving away from a primary concentration on dependability to one that also prioritizes economic efficiency. Performance-based regulation and other incentive systems have accompanied the transition, aiming to align utility performance with consumer and regulator expectations. Investment plans have advanced, placing more importance on optimizing assets and using smart grid technologies that improve monitoring, control, and automation capabilities. Deregulation has fundamentally transformed the operation and management of distribution networks. This has created a need for continuous adaptation and innovation in order to satisfy the ever-changing needs of a competitive market [35].

1.6. Integration of distributed generation and battery energy storage

1.6.1. Distributed generation

The process of generating power from sources spread out over the electrical grid, closer to its use, is known as distributed generation (DG). DG comprises a range of technologies, such as solar photovoltaic (PV) systems, wind turbines, microturbines, and small-scale hydropower generators. These systems have several advantages, including the reduction of transmission losses, improvement of energy security, and more flexibility in fulfilling local demand. In addition, DG may aid in the decarbonization of the energy sector by incorporating renewable energy sources, therefore reducing dependence on fossil fuels and mitigating greenhouse gas emissions. Despite this, adding DG to existing distribution networks comes with a number of challenges. For instance, complex grid management is necessary to manage the intermittent and changing nature of renewable energy sources, maintain stable voltage, and control power flow in both directions. Adding DG efficiently necessitates large investments in smart grid technology, improved grid infrastructure, and revised regulations to ensure DG's smooth functioning within current networks [36].

1.6.2. Battery storage energy system

Battery Energy Storage Systems (BESS) play a crucial role in the modernization and stabilization of electrical distribution networks. BESS has the capability to store surplus energy produced during times of low demand and distribute it during periods of high demand, hence improving the reliability and efficiency of the power grid. These systems are especially beneficial for mitigating the sporadic characteristics of renewable energy sources like solar and wind. BESS technologies, such as lithium-ion, flow batteries, and advanced lead-acid batteries, differ in terms of their energy density, discharge rates, and lifespan costs. Integrating Battery Energy Storage Systems (BESS) into distribution networks has several benefits. It may effectively reduce power fluctuations, improve power quality, and serve as a reliable backup power source during outages. In addition, BESS has the capability to provide grid ancillary services, such as frequency regulation and voltage control. Although BESS offers advantages, its implementation encounters obstacles such as expensive initial investments, safety considerations, and the need for well-developed regulatory and commercial frameworks that encourage the use of storage systems and guarantee seamless connection with the current grid infrastructure [37].

1.6.3. Joint impact on the distribution network

The integration of DG and BESS into electrical distribution networks brings a new way of operating and managing these networks. Collectively, these technologies have the potential to greatly improve the flexibility, dependability, and sustainability of the power system. When combined with BESS, DG, especially those derived from renewable sources, may mitigate the fluctuations in power production, ensuring more consistent and uninterrupted power provision. This synergy may also diminish the need for substantial infrastructure expenditures by maximizing the current grid capacity and postponing the requirement for new transmission and distribution lines. Even so, using both DG and BESS requires advanced grid management systems to keep voltage levels stable, handle complex power flows, and make sure everything works together safely. To effectively address concerns about tariff structures, grid connectivity requirements, and incentives for distributed energy resources, it is also necessary to implement updated regulatory frameworks. The effect of DG and BESS working together is revolutionary. It makes it possible for a distribution network that is more stable and adaptable, able to handle the changing needs of today's decentralized energy environment [38]

1.7. Distribution network problems

DNs, crucial for delivering energy from power plants to customers, face numerous challenges including technological, economic, and regulatory issues, each requiring comprehensive mitigation measures [39].

1.7.1. Technical challenges

- Infrastructure deterioration

In many countries, a significant proportion of the electrical distribution infrastructure is antiquated and decaying. The aged equipment is susceptible to malfunctions, resulting in frequent power outages and escalated maintenance expenses. The incorporation of contemporary technologies, such as smart grids, is imperative to augment the resilience and dependability of these systems [40], [41].

- Power quality problems

Fluctuations in voltage, frequency, and waveform distortions can have an impact on the operation of electrical equipment. The growing presence of renewable energy sources in the grid exacerbates power quality concerns by introducing variable and intermittent behavior. Advanced power electronics and real-time monitoring systems are essential for tackling these difficulties [42].

- Load management:

The increasing need for power, fueled by population expansion and the widespread use of electric cars and technological gadgets, puts pressure on distribution networks. Efficient load management measures [43], such as demand response programs and energy storage systems, are essential for maintaining a balance between supply and demand and avoiding network overload.

1.7.2. Economic challenges

- Financing and capital investment

Enhancing and expanding distribution networks need significant financial capital. Obtaining funding for infrastructure projects is a major obstacle, especially in areas with limited financial resources. Public-private partnerships and new finance methods provide viable strategies for overcoming the financial deficit [44].

- Cost of energy losses

The presence of resistive losses in conductors and transformers in distribution networks leads to substantial economic expenditures. These losses may represent a significant proportion of the overall power produced. By using energy-efficient technology and enhancing network architecture, it is possible to mitigate these losses [45].

- Structure of tariffs

Designing fair and sustainable tariff structures that accurately reflect the actual cost of electricity distribution while ensuring an affordable price for consumers is a challenging task. The regulatory frameworks must strike a balance between the need to generate revenue and the objective of providing reliable and affordable electricity to all consumers [46].

1.7.3. Regulatory challenges

- Government policies and regulations

The regulatory framework significantly influences the growth and functioning of electricity distribution networks. Fluctuating regulations and a lack of regulatory clarity may impede investment and inhibit the development of new ideas and technologies. It is crucial to have well-defined and consistent regulatory frameworks that foster competition and incentivize investment in contemporary technology [47].

- Standards for network Modernization

It is crucial to establish and enforce standards for grid modernization, which includes integrating smart grid technology and implementing cybersecurity measures. This is necessary to guarantee the resilience and security of distribution networks. It is essential for governments, regulatory organizations, and industry players to work together in order to create and enforce these standards [48].

- Ecological Factors

To achieve sustainable energy systems, renewable energy sources must be included in the distribution network. Regulatory frameworks should facilitate this shift by encouraging the use of distributed energy resources, such as rooftop solar panels and community wind projects, while also guaranteeing the stability and dependability of the power grid [49].

1.8. Energy loss reduction techniques

There are a number of strategies used to lessen the financial burden of energy loss in electrical DNs. Smart grid technologies like automation and sensors are part of the package. It also includes network architecture optimization, segmentation and redundancy, equipment performance enhancement via low-resistance conductors and high-efficiency transformers, and energy management systems (EMS).

Smart meters and other advanced monitoring and control systems aid in the detection and mitigation of nontechnical losses. Enhanced security measures prevent theft and illegal meter manipulation. Dynamic pricing and demand response programs are two forms of demand management that aim to balance the load and minimize losses by encouraging customers to modify their usage during peak hours.

Limiting transmission lengths is another way that renewable and distributed energy sources, including wind turbines in the area and solar panels on rooftops, may help decrease losses. More localized energy distribution is possible with microgrids, which may function autonomously or in conjunction with the main grid; this further decrease transmission losses.

Contemporary techniques, including network reconfiguration, CB and DG allocation, and the use of flexible AC transmission systems (FACTS). While other methods address energy loss at a systemic level, these strategies offer precision and adaptability, leading to a direct increase in network reliability and efficiency but also providing specific means to improve energy flow, reduce operating costs, and improve voltage profiles in more complex power distribution contexts.

1.8.1. Capacitor banks integration

CBs play a crucial role in improving power factor and reducing reactive power losses in distribution networks [50]. By compensating for reactive power, CBs reduce total losses, thereby minimizing the amount of reactive power required for network transmission. CBs play a vital role in regulating voltage levels to ensure the optimal operation of electrical equipment. By stabilizing the voltage, they lower the chance of undervoltage situations, which could lead to high current flow and the losses that come with it. Using capacitors to improve the power factor lowers the phase difference between voltage and current. This reduces the total current going through the network, which in turn minimizes resistive losses. CBs are most efficient when strategically positioned in areas with substantial demand for reactive power, particularly in close proximity to inductive loads. This specific kind of compensation alleviates the strain on the overall network.

1.8.2. Distributed generation integration

The integration of small-scale energy sources near the energy consumption point reduces transmission and distribution losses by producing power in close proximity to the load centers. DG supplies electricity locally during blackouts or periods of high demand, provides redundancy and therefore enhances the grid's reliability. The incorporation of renewable energy sources, such as photovoltaic panels and wind turbines, not only aids in minimizing energy loss but also promotes the achievement of sustainability objectives [51].

1.8.3. Network reconfiguration

Network reconfiguration is the process of modifying the distribution network's topology, either manually or using automated methods, in order to optimize the flow of electricity and reduce losses [52]. Network reconfiguration may improve load distribution, mitigate overcrowding, and reduce losses in specific network segments. Advanced algorithms have the ability to determine the best possible setups in real-time by taking into account the current load circumstances and network factors. Automated switching devices provide rapid reconfiguration in response to fluctuating load patterns, enhancing network efficiency and reducing losses.

1.8.4. Flexible AC Transmission Systems (FACTS)

FACTS solutions improve the manageability and stability of AC transmission systems, resulting in reduced losses and enhanced power quality. Essential elements include static VAR compensators (SVCs), unified power flow controllers (UPFCs), and dynamic line rating (DLR). SVCs are capable of providing instantaneous adjustment of reactive power, while UPFCs allow for real-time manipulation of power flow. The DLR system has the capability to adapt the current-carrying capacity of transmission lines in response to real-time environmental circumstances. This feature improves efficiency and minimizes thermal losses [53].

1.9. Conclusion

To summarize, this chapter has presented a thorough analysis of electrical DNs, exploring their organization, operation, related difficulties, and possible remedies. By comprehending the intricacies and challenges inherent in these systems, we provide the foundation for investigating sophisticated optimization strategies. The next chapter explores precise techniques like network reconfiguration, capacitor bank allocation, and the incorporation of distributed generation, focusing on their contribution to enhancing the operation of electrical DNs.

CHAPTER 2

Current Advances in the Reconfiguration and Optimal Allocation of Capacitor Banks and Distributed Generation in Distribution Networks

Contents

2.1 Introduction

DN losses account for a significant portion of energy consumption in power systems. Sharp increases in power consumption often lead to congestion in these networks, further complicated by competitive energy markets and strict environmental restrictions. As a result, managing losses in DNs has become a critical concern. In order to maximize economic results, it is critical to improve power quality and streamline operational efficiency. Such enhancements will provide a favorable atmosphere for executing loss-reduction efforts and embracing cutting-edge operational processes. The DN obtains a comprehensive power supply that is equivalent to its output minus any losses incurred during transmission. Within this particular framework, the main approach to improving the efficiency of DNs is to minimize power losses.

The research community has progressively focused its attention on techniques to minimize losses and guarantee voltage stability in DNs in recent decades. The literature documents numerous approaches for minimizing losses in DNs. Some important strategies are the allocation of capacitors, which works best in high-voltage systems; network reconfiguration, which is particularly effective in low-voltage systems; and the allocation of distributed generation (DG), which is crucial for adding small-scale power plants like solar panels or wind farms to the DN. Combining these methods synergistically can further optimize the desired advantages.

2.2. Network reconfiguration

Network reconfiguration is a vital technique for improving power quality, operational efficiency, and reliability. It has become an economic necessity due to the increased complexity of DN, which is the result of a combination of factors such as demand for dependable power, the advent of smart grids, and the integration of DG. By manipulating and tying switches to modify the network design, utilities can achieve substantial improvements in network performance.

2.2.1. Definition

Network reconfiguration refers to the process of altering the overall structure of an electrical distribution network by manipulating switches, with the aim of maximizing certain operational characteristics. The primary objectives include the reduction of power losses, the equitable distribution of feeder loads, the enhancement of voltage profiles, and the overall improvement of network dependability. Modern control systems frequently carry out reconfiguration either statically, during off-peak hours, or dynamically in response to real-time operating situations.

Sectionalizing and tie switches are key elements of The DN. Switches in a closed position, known as sectionalizing, divide the network into distinct sections. These switches allow for the isolation of specific areas during problem situations. Tie switches, often in the open position, link separate feeders together. They serve the purpose of providing alternate channels for the flow of electricity.

2.2.2. Progress in Network Reconfiguration Techniques

2.2.2.1. Historical foundations

The concept of network reconfiguration in distribution systems originated in 1975 with Merlin and Back's introduction of the "branch exchange" method [54]. This method entailed transforming the network into a meshed configuration and then gradually opening switches to revert back to a radial configuration that minimized losses. Despite being innovative, this system had drawbacks, namely its disregard for voltage angles and emphasis on only active loads represented by current sources. In 1988, authors in [55] improved the approach by introducing a formula that calculates changes in loss caused by load movement across feeders. Their approach, which allowed for efficient load balancing, proved complex in terms of recalculating the power flow for each possible arrangement. In 1989, the authors of [56] devised a more reliable technique for enhancing network reconfiguration. This method overcomes the drawbacks of prior techniques by integrating operational restrictions. This study laid the groundwork for future research, emphasizing the importance of incorporating restrictions like voltage limitations, which compensators can adjust. In the 1990s and early 2000s, several researchers suggested new methods to address the reconfiguration problem, including authors in [57] who introduced genetic algorithms as a solution to deal with the combinatorial aspect of the problem. This represented a notable transition towards heuristic and metaheuristic techniques, which would become the predominant focus of research in the subsequent decades [58].

2.2.2.2. Recent advancements

Between 2019 and 2024, there was a significant increase in the advancement of hybrid and multi-objective optimization approaches. Researchers are increasingly concentrating on combining several metaheuristic techniques to overcome the limits of using just one method. Artificial intelligence (AI) and real-time optimization approaches have propelled the latest progress in network reconfiguration [59].

For instance, authors in [60] introduced a reconfiguration technique that utilizes genetic algorithms grounded in graph theory. Their approach integrated various objectives, including the minimization of voltage deviation, the reduction of losses, and the guarantee of topological stability. They showcased the efficacy of their approach on a typical 10-node distribution network, emphasizing its efficiency and potential for real-world implementation. In a similar timeframe, authors in [61] employed an analytical approach to restructure the medium-voltage network in Bagan Siapiapi. This resulted in notable reductions in power losses and enhancements in voltage profiles through the establishment of an extra substation and the redistribution of loads. Reference [62] hybridizes Genetic Algorithm (GA) with Particle Swarm optimization (PSO) and Teaching and Learning Based Optimization (TLBO) methods, within the DN reconfiguration process to reduce power loss during faults. The suggested approach in [63] is based on an adaptively adjustable fuzzy logic controller, where the membership functions vary based on inputs. This approach allows for a unique determination of the restoration sequence of loads and generators. The IEEE 118-bus system evaluates the suggested network reconfiguration algorithm, revealing its efficiency and practicality. Reference [64] presents a model of DN reconfiguration for new energy and electric vehicles (EVs), where the decision variables include the position of bus tie switches and the range of reactive power regulation. It employs a novel decision-making method called the Prevalence Effect Method

(PEM), as well as a multi-objective evolutionary algorithm that considers line loss and voltage deviation as objective functions. Authors in [65] introduce a new real-time autonomous dynamic reconfiguration (ADR) approach that uses a deep learning (DL) algorithm to minimize power loss and switch action in DNs. The suggested ADR approach involves making decisions based on both the historical control dataset and the current system state. The study in [66] introduces a novel approach to examine and clarify decisions obtained via reinforcement learning in the reconfiguration of distribution networks. The suggested methodology involves the deployment of a reinforcement learning agent to train an explanatory neural network. This innovative technique is effective in both the 33- and 136-bus test systems.

The progression of network reconfiguration strategies from the early "branch exchange" method to the advanced AI-driven systems of today, which reflects the growing complexity and requirements of current DNs. Recent developments have concentrated on hybrid approaches, multi-objective optimization, and the integration of real-time artificial intelligence technology, allowing for more adaptable, efficient, and dependable power distribution systems.

2.2.3. Taxonomy of methodologies

A broad range of strategies exist for network reconfiguration, including both conventional optimization techniques and sophisticated metaheuristic and artificial intelligence-based approaches. The choice of technique is contingent upon characteristics such as the size of the network, its complexity, and the specific goals of the reconfiguration procedure [52], [59]. Figure 2.1 illustrates different methods used in DN reconfiguration.

2.2.3.1. Conventional methods

DN reconfiguration is a very challenging Mixed Integer Nonlinear Programming (MINLP) issue to answer strictly mathematically. Within traditional methods, the issue of reconfiguration transforms into either a mixed integer linear programming problem (MILP) or a mixed integer quadratic programming (MIQP) problem. These methods significantly reduce computation time. However, the approximations of objective functions and restrictions may lead to discrepancies between the approximate network configuration and the optimal configuration in real networks.

2.2.3.2. Heuristic methods

The branch exchange approach entails assessing pairs of branches to permit or prohibit their operation depending on their effect on the target function, usually aiming to minimize power losses. Although it continuously maintains a radial arrangement, it is very responsive to the original arrangement and may need significant processing resources. Recent research has expanded the branch exchange approach to maximize power quality goals such as harmonic distortion and voltage imbalance. Conversely, a network load flow analysis using the optimum flow pattern approach entails closing all switches and focusing just on the resistance of lines, disregarding their reactance. It first identifies the branch with the lowest current, opens it, and recalculates the load flow to accommodate the new topology. The iterative approach continues until attaining a radial topology with the lowest possible losses. The original setup does not affect the final configuration of this approach, but the mutual influences among the loops may prevent it from ultimately providing the global optimum. Various improvements, such as addressing individual loops or utilizing global optimization techniques, can enhance the performance of this approach. Some other heuristic methods use optimal power flow techniques, such as convex relaxation and branch-and-bound solutions, to investigate the search space more thoroughly and improve the reconfiguration process.

2.2.3.3. Metaheuristic techniques

Independent of specific issue characteristics, metaheuristic techniques are iterative algorithms that explore and exploit search areas to identify optimum or nearly optimal solutions. Unlike knowledge-based approaches, metaheuristics are versatile and can adapt to various optimization situations through parameter calibration. Often, we can parallelize these approaches and integrate them with other techniques like heuristics. Furthermore, these approaches are sometimes referred to as derivative-free optimization methods because they do not rely on derivatives. We widely use metaheuristics to address static reconfiguration difficulties. Certain uses of methods like discrete particle swarm optimization (DPSO), genetic algorithms (GA), and bat algorithms (BA) have been shown to reduce power losses and improve reliability metrics. Recent research has expanded the application of these techniques to dynamic reconfiguration challenges. This includes the integration of stochastic model predictive control and enhanced genetic algorithms to effectively manage dynamic scenarios that involve plug-in hybrid electric cars and renewable energy sources.

2.2.3.4. Hybrid techniques

Hybrid techniques combine several algorithms to improve performance and overcome the limitations of individual techniques, such as the trapping of local optima, sluggish convergence, and insufficient search space exploration. Hybrid metaheuristics methods combine, for example, Particle Swarm Optimization (PSO) with Shuffled Frog Leaping Algorithm (SFLA) to efficiently optimize static DN reconfiguration objectives such as reducing power loss and maintaining voltage stability. In a similar vein, hybrids based on heuristic rules, such as the combination of the successive branch-exchange algorithm with genetic algorithms (GA), provide rapid convergence and almost optimum solutions in large networks. In the context of dynamic reconfiguration, the integration of linearization approaches with other methodologies, such as the conversion of nonlinear problems into mixed-integer second-order cone programming (MISOCP) models solved by binary PSO and CPLEX, effectively addresses intricate reconfiguration problems while simultaneously decreasing computational complexity by utilizing clustering techniques like fuzzy c-means (FCM).

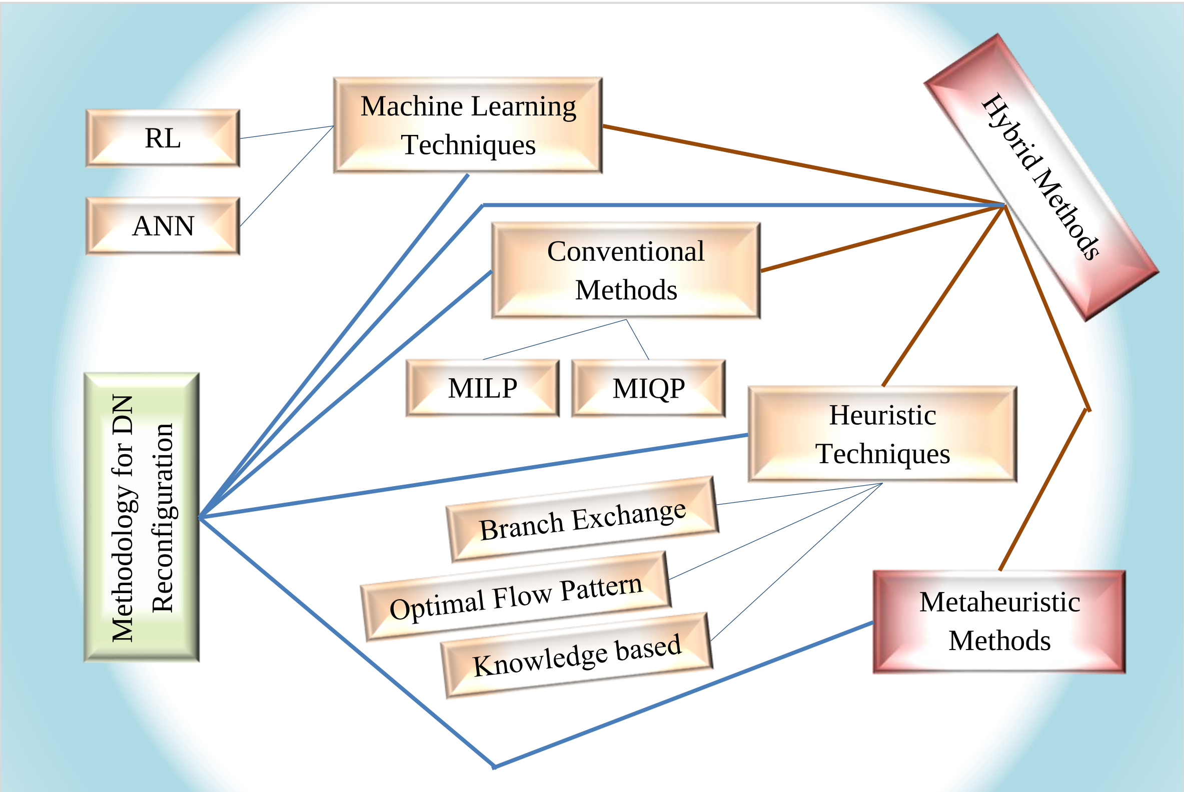

Fig 2.1: Taxonomy of DN reconfiguration approaches

2.2.3.5. Machine learning techniques

Machine learning techniques, which are a subset of artificial intelligence, enable computers to independently acquire knowledge and form judgments with few processing resources, making them well-suited for dynamic reconfiguration challenges. We can broadly classify the approaches into two main categories: artificial neural networks (ANN) and reinforcement learning (RL). Artificial neural network (ANN) techniques use linked neurons to learn from data and quickly create the best network configurations in real time, adapting to different load patterns. These techniques are based on the structure of the human brain. In contrast, reinforcement learning (RL) approaches include an agent that acquires optimum decision-making skills by engaging with an environment and obtaining feedback. Reinforcement learning (RL) is very efficient for online reconfiguration due to its ability to react to dynamic settings, consistently improve tactics, and function with little computing burden, making it optimal for quick, real-time network modifications.

To conclude, the goal of the static reconfiguration problem is to determine the most efficient network configuration for an extended duration while keeping the load and generation data constant. It is more important to be accurate than to be quick at computing. This implies that metaheuristic and hybrid metaheuristic approaches outperform classical or heuristic techniques, susceptible to approximations and local optima. Dynamic reconfiguration, on the other hand, necessitates immediate modifications, with an emphasis on speed and minimal computing resource use. The effectiveness of classical, hybrid, and machine learning approaches makes them preferred for dynamic situational analysis. Although machine learning methods need extensive offline training, they excel in rapidly generating optimum configurations during online reconfiguration, even in the face of huge and complicated network training issues.

2.3. Capacitor banks allocation

The allocation of capacitors is essential for optimizing the performance of high-voltage DNs. Effective regulation of reactive power results in reduced power and energy losses, enhanced voltage stability, and a more favorable voltage profile across the network. In addition, capacitors augment power factor correction, therefore enhancing the overall efficiency and reliability of the system.

2.3.1. Capacitor allocation techniques: Historical evolution

Voltage control and loss reduction using capacitors have been a well-established idea since the 1940s. Initially, substations housed capacitors. Nevertheless, starting in the 1950s, there was a change in the prevailing pattern towards positioning capacitors in closer proximity to the loads on primary distribution feeders. The goal of this change was to improve capacitors' efficiency in reducing losses. The main contributions are as follows: In 1956, Neagle and Samson proposed a rule-of-thumb method for allocating capacitor storage [67]. In 1965, Schmill expanded the rule-of-thumb method by accounting for both switching and fixed capacitors in main distribution feeders characterized by changing load distributions [68]. In 1968, Dura devised a quantitative approach to determine the economic justification of capacitor installation [69]. In 1978, Bae introduced an analytical approach to determining the most effective and optimal amount of reactive compensation in order to achieve the greatest possible annual decrease in losses [70].

Historical approaches to capacitor allocation encountered several obstacles, including the assumption of restricted or simplified distribution of reactive loads, which frequently did not correspond to actual circumstances, and the dependence on consistent feeder wire widths, which resulted in errors in estimating losses. Voltage management challenges and limitations imposed by the maximum number of capacitors analyzed concurrently diminished the efficacy of these approaches. Furthermore, some approaches lacked the necessary flexibility to adapt to various network setups, and the solutions derived from assumptions that were not necessarily applicable in real-life situations.

2.3.2. Recent developments

The constraints of previous methodologies prompted the emergence of more advanced techniques. The authors in [71] rectified the impractical assumptions of earlier methodologies and devised a more flexible technique that could adjust to the specific circumstances of the system. Furthermore, they presented the notion of managing many segments of a radial feeder that had varying wire diameters and distributions of reactive loads. Reference [72] devised a control approach and algorithm to enhance voltage regulation and remediate reactive power at both the substation and feeder levels. This study made a significant contribution to the advancement of integrated distribution control systems. The writers of [73] came up with a continuously controlled capacitive compensation method for primary feeders that makes reactive power regulation in distributed automated systems (DAS) better.

Notwithstanding these improvements, previous approaches failed to address specific concerns, such as the benefits of capacity release, the consequences of load increase, higher voltage during off-peak hours, and fluctuations in energy expenses. Furthermore, the techniques often overlook the optimum number of capacitors, their specific type (fixed or switched), and their typical standard size. These gaps have prompted the development of numerous analytical, heuristic, and evolutionary methods that consistently improve capacitor allocation methodology.

The algorithm for allocating capacitors has significantly advanced from basic rule-of-thumb techniques to more sophisticated and flexible solutions. Although early techniques established the fundamental principles, contemporary methods integrate sophisticated algorithms to overcome the constraints of previous methods.

2.4. Distributed generation allocation

In recent years, the generation and distribution of electricity have seen a notable transformation, mostly attributed to the growing incorporation of DG into DNs. DG typically consists of smaller power-generating units strategically positioned near electricity consumption locations, either on the demand side (near load points) or the supply side (utility side of the meter). Renewable energy sources like solar, wind, or biomass often construct these units, gaining prominence as the demand for cleaner, decentralized energy systems intensifies.

2.4.1. DG definition, impact, and challenges

A variety of definitions of DG exist in the literature, with its specific meaning varying based on aspects such as purpose (e.g. loss minimization, renewable energy integration, etc.), technology, location, rating, power delivery area, environmental effect, operating mode (e.g. off grid or grid-connected), ownership, and penetration. DG refers to the electric power generated from smaller demand and supply-side resources, capable of being deployed throughout the DN to meet the energy demands of customers. The growing use of DG is causing a transition of the power grid from a centralized to a decentralized structure. The need to incorporate renewable energy, enhance energy security, and achieve lower transmission losses motivates this movement. Although DG provides substantial environmental benefits by reducing greenhouse gas emissions and economic advantages via cost savings and decreased infrastructure requirements, it also presents technical challenges such as voltage control and power quality issues. As a result, it is critical to determine the optimal size and placement of DG units in order to maximize benefits while maintaining satisfactory grid performance. To ensure the safe and dependable integration of DG into current distribution networks, strict adherence to standards such as IEEE 1547 is required [74].

2.4.2. Methodologies

The evolution of the conventional energy industry into a competitive and dynamic environment has had a profound effect on DNs, which were formerly passive elements of the electrical grid [75]. Given the exponential expansion in population and industrial activity, these networks are currently under heightened strain as a result of the expanding disparity between electricity production and consumption. Implementing DG at the distribution level is an essential approach to tackling this problem, as it improves the capacity and dependability of the network when carried out with careful planning. The integration of DGs into DNs transforms them from passive to active, bringing new economic and technological challenges that require rigorous management. The appropriate placement of DG within DN not only facilitates environmental objectives, but also provides economic benefits to both utilities and customers, necessitating sophisticated approaches for optimizing power flow and preserving stability and efficiency in modern distribution networks.

The allocation process commonly uses optimization methods [76] to minimize power losses, boost voltage profiles, improve system stability, and reduce operating expenses. These techniques encompass metaheuristic algorithms which are particularly suitable for managing the nonlinear and intricate characteristics of DG integration in DNs. In addition, several techniques include multi-objective strategies to reconcile trade-offs between conflicting objectives, such as reducing costs and minimizing environmental effects. It is important to take into account factors such as load demand patterns, network structure, and the intermittent nature of renewable energy sources when allocating resources to ensure they are resilient and efficient. The use of accurate modelling and simulation techniques in these methods helps to develop strong, efficient, and eco-friendly power distribution systems that can handle the growing use of DG.

DG installations significantly change power network characteristics, calling for a range of DG allocation strategies to meet operational goals and limitations. These approaches' optimization algorithms are a common way to classify them. Analytical approaches, when coupled with basic or comprehensive searches, may provide accurate results; nevertheless, they are not feasible for large-scale networks. Given the limitations of individual metaheuristic optimization algorithms, multi-objective and hybrid optimization methods are becoming more appropriate for DG allocation, particularly when renewable energy sources are involved.

2.5. Impacts of reconfiguration, capacitor banks, and distributed generation on distribution network performance

Effective use of reconfiguration techniques, CBs, and DG in electrical DNs is essential for improving system performances. The influence of each of these elements extends to many facets of the network, including power losses, voltage profiles, system dependability, and environmental sustainability, etc. A thorough understanding of the distinct contributions and difficulties associated with each strategy is critical for maximizing the efficiency of contemporary distribution networks' design and functioning.

Table 2.1. How DN performance is impacted by reconfiguration, CBs, and DGs.

Performance criterion	Network reconfiguration	CBs allocation	DGs allocation
Loss minimization	By optimizing the network topology.	Reduces reactive and overall power losses	By producing electricity in close proximity to the load.
Voltage profile improvement	By minimizing voltage dips	By offering active power assistance	Substantial enhancement in local voltage profiles, albeit may need the use of voltage control devices.
Reliability enhancement	By offering other power routes	By voltage stabilization during periods of high demand	Potentially by lowering dependence on centralized generation
Loadability enhancement	By distributing load evenly across feeders	By correcting power factor	By providing supplementary electricity locally
Environmental impact	based on configuration objectives (neutral)	Minimizes the need for spare production, therefore decreasing emissions	decreases dependence on fossil fuels.
Economic impact	Minimizes operating expenses.	Contributes to energy cost reduction by minimizing losses.	Enables economic advantages by energy savings and potential profit from surplus power.
Power quality improvement	By load balancing	By decreasing voltage fluctuations	May result in power quality problems such as harmonics.
Grid flexibility enhancement	Through dynamic reconfiguration	Modest contribution	By offering local generation alternatives
Complexity of implementation	Moderate to high, depending on network size and complexity	Low to moderate, depends on location strategy	Elevated, owing to integration difficulties and the need for control
Safety enhancement	Potentially, by decreasing local overloads	By regulating voltage stability	May provide safety hazards, especially when dealing with the occurrence of islanding
Resilience improvement	by offering alternative power paths during outages	Mainly by voltage stabilization	by energy sources diversification.

Table 2.1 provides a comprehensive analysis of these effects across many parameters, offering valuable insights into how these technologies collectively enhance the efficiency and adaptability of the electricity grid. Each of the three methods discussed here, regardless whether it pertains to network reconfiguration, capacitor installation, or DG integration, contributes in its own special way to improving DN performance. The following section examines the most recent developments in approaches that tackle the simultaneous optimization of various components, which is a challenging task because of their interdependencies. Efficient network reconfiguration shortens power flow routes, resulting in decreased losses and enhanced voltage stability. The provision of reactive power support by CBs is critical, as it improves the voltage profile and decreases the grid's reactive power demand. Meanwhile, DG units provide both loss reduction and voltage support by producing power in close proximity to load centers.

Optimizing these components together enables the DN to attain exceptional performance, such as enhanced loadability, decreased ecological impact, and heightened operational adaptability. This sophisticated methodology has attracted considerable interest from both scholars and distribution network operators due to its capacity to provide major techno-economic advantages by skillfully managing the trade-offs between investment costs, operational efficiency, and network reliability.

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2.6. Simultaneous network reconfiguration, capacitor, and distributed generation allocation

This section looks first at the impacts of these techniques when used in pairs, illustrating how their combined application can cause synergistic enhancements in network performance. We then scrutinize their concurrent application to identify the most noteworthy benefits related to power flow optimization, loss reduction, and voltage stability enhancement across the DN. Figure 2.2 illustrates the concept of the integrated use of these techniques, which, when combined, provide the highest potential for optimal benefits.

2.6.1. Network reconfiguration simultaneously with DG allocation

Optimizing reconfiguration simultaneously with DG allocation coordinates the strategic placement of DG units with the network topology, thereby greatly increasing the benefits of DNs. This method ensures the delivery of power through the most efficient pathways, thereby reducing losses, improving voltage stability, and enhancing system reliability. Furthermore, by addressing changing load patterns and incorporating renewable energy, it enhances adaptability, enabling the grid to adapt to current requirements. Still, this approach presents difficulties, such as the intricacy of resolving a multi-objective optimization problem and the urgency for accurate synchronization between reconfiguration and DG placement, necessitating sophisticated algorithms and meticulous real-time control. Notwithstanding these difficulties, when executed with effectiveness, this integrated strategy is essential for maximizing the performance, efficiency, and resilience of contemporary distribution networks.

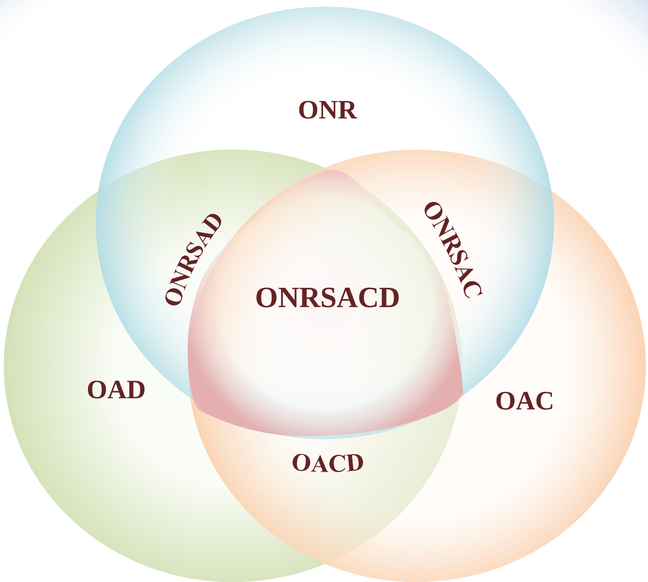
2.6.2. Network reconfiguration simultaneously with CBs allocation

The simultaneous reconfiguration and allocation of capacitors in DNs is a potent strategy that exploits the advantages of both approaches to enhance system performance. Network reconfiguration is the modification of the network topology by adjusting the status of switches in order to minimize power losses, achieve load distribution balance, and enhance voltage profiles. Capacitor allocation, on the other hand, refers to the strategic placement of CBs to enable reactive power support, minimize power losses, and improve voltage stability. By optimizing these two approaches in conjunction, the network can achieve even more significant reductions in power losses by incorporating the capacitors' reactive power compensation into the reconfiguration algorithm. This synergy not only enhances the efficiency of power delivery but also optimizes voltage regulation throughout the network, minimizing the requirement for supplementary voltage control devices. Furthermore, the implementation of simultaneous optimization can improve network loadability by efficiently managing the distribution of active and reactive power flows, boosting the system's overall dependability. Nevertheless, the integration of these two methods introduces complexity to the optimization procedure because it necessitates sophisticated algorithms to effectively handle both the binary nature of reconfiguration and the continuous nature (size) of capacitor allocation. Even though it's hard, the strategy of concurrent reconfiguration and capacitor allocation must be used together to make the distribution network more reliable, stable, and efficient.

2.6.3. Simultaneous allocation of CBs and DG

The concurrent allocation of capacitors and DG in DNs is a sophisticated optimization technique useful to improve the efficiency and stability of the power system.

Reactive power support is a common application of capacitors, as they effectively mitigate power losses and enhance voltage regulation by rectifying power factor fluctuations. DG units, such as solar panels or wind turbines, produce active electricity in close proximity to the electrical load centers, alleviating the strain on the transmission network and further reducing power losses. By optimizing these two components in conjunction, the network gains a more balanced and efficient power flow since the reactive power compensation of the capacitors is synchronized with the active power generation of the distribution generator units.



O: optimal, N: network, R: reconfiguration, S: simultaneously with, A: allocation, C: capacitor, D: distributed generation.

Fig 2.2. The deployment of reconfiguration, CBs and DGs, individually and in combination, within a DN.

Implementing this integrated strategy not only reduces total power losses but also greatly enhances voltage profiles, increasing the network's resistance to voltage variations and improving power quality. Furthermore, the strategic positioning of capacitors and DGs can help alleviate possible problems like voltage increase or instability that may occur when DG units are integrated without adequate reactive power support. However, this simultaneous allocation necessitates advanced optimization methods, as it entails the management of the interaction between active and reactive power flows while taking into account distinct operational limitations. The effective allocation of capacitors and DG units is crucial for establishing a resilient, efficient, and environmentally-friendly DN, particularly in light of the increasing integration of renewable energy sources.

2.6.4. Network reconfiguration simultaneously with allocation of CBs and DG

A unified strategy for improving the performance of DNs is the simultaneous optimization of network reconfiguration with the allocation of CBs and DG. By aligning the reconfiguration process with the positions of CBs and DG units, this integrated approach enables the network to optimize power flows, resulting in more efficient loss reduction, increased voltage stability, and enhanced loadability. The simultaneous use of CBs and distributed generators manages both voltage regulation and power factor correction, essential for ensuring a stable and efficient network, particularly in the face of fluctuating load conditions. This concurrent optimization improves the system's adaptability and robustness by enabling it to more effectively handle variations in demand and supply, especially from sporadic renewable energy sources. Nevertheless, the intricacy of this method is remarkable, since it entails resolving a multi-objective optimization issue that necessitates sophisticated algorithms capable of managing the interconnections among reconfiguration, capacitor placement, and distributed generation allocation.

Throughout this section, we have described the techniques of network reconfiguration, CBs, and DG allocation both separately and in conjunction, emphasizing their importance and effectiveness in improving the efficiency of DNs. The primary objective of our study has been to illustrate the positive impact of each technique, together with their combined implementation, on enhancing different dimensions of network performance. The subsequent section provides an overview of recent developments and methodologies.

2.7. Extant literature and the proposed study

The crucial importance of these techniques in enhancing the operational capabilities of distribution networks has led to a significant focus on cost-effective methods for reconfiguring networks, allocating capacitor banks, and integrating distributed generations. Researchers have initiated a significant amount of research, introducing a variety of methodologies with distinct objectives to address these challenges. Certain research concentrates on individual tactics, as outlined in references [77] [78] [79] [80], while others investigate the integration of various approaches in pairs, as shown in references [81] [82]. Furthermore, there is an increasing focus on the simultaneous use of different techniques to optimize advantages. Utilized tactics include heuristic algorithms, mathematical programming, and machine learning approaches to achieve objectives such as improving reliability and voltage stability, decreasing power losses, and minimizing costs. A comprehensive analysis of existing research, as presented by the authors in [83] [84], highlights the exceptional results obtained by integrating various methods. Nevertheless, there is a scarcity of researchers that have explicitly examined and evaluated many techniques for optimal network reconfiguration simultaneously with the allocation of capacitor banks, and distributed generations (ONRSACD). Ref [85] presents a hybrid HS-PABC method for optimum distribution network design. The approach demonstrates promising outcomes in reducing power loss and improving the bus voltage profile under different load scenarios. The work described in reference [86] presents a stochastic multi-objective model that integrates NSGA-II with fuzzy set theory to effectively tackle technical, economic, and environmental goals. The paper in reference [87] presents a multi-objective approach based on fuzzy-BFO (Block Forest Optimization) that aims to reduce power loss, enhance voltage deviation, and balance feeder loads in distribution systems. For the purpose of minimizing actual power loss, the work in [88] suggests the use of the LSHAD-EpSin algorithm. An MOPSO-MCS-based multi-objective planning model is introduced in reference [89] to optimize the positioning of distributed generators and capacitors in imbalanced DNs. The model takes into account reconfiguration and aims to minimize energy loss, energy not supplied, and current imbalances. The MBGWO algorithm, as described in reference [90], exhibits substantial energy conservation and a decrease in peak demand for both balanced and unbalanced distribution systems. Furthermore, the TPA algorithm introduced in reference [91] aims to reduce power loss and operating expenses while improving the network's voltage stability. The paper in reference [92] presents the QRSMA algorithm for determining the most efficient positioning of DGs and CBs during the restructuring of a radial distribution system. This algorithm takes into account line losses, cumulative bus voltage deviation, reliability index, and total system cost, considering both fixed and variable loading scenarios. Optimal integration of renewable distributed generators and shunt capacitors is proposed in [93] using the SHADE optimization algorithm in conjunction with the SOE reconfiguration technique. This approach considers uncertainty in demand load and DG output power. The aims of this study are to strengthen the voltage profile, increase the probabilistic hosting capacity, and decrease power losses. The hybrid HSA-PABC strategy is introduced in reference [94] as a resolution to the planning difficulties encountered in radial power DN.

According to the literature, it is becoming clear that the current technical trend is to simultaneously consider grid reconfiguration, CBs, and DGs to improve DNs operation. This holistic approach aims to combine the individual benefits of each technique to effectively address the complex issues associated with today's distribution grids, such as efficiency, reliability, and the incorporation of renewable energy sources.

The tendency in optimization methodologies is clearly to hybridize metaheuristics and implement multi-objective optimization techniques. Various sophisticated methods exploit the advantages of different algorithms to efficiently study complex solution spaces while taking into account competing objectives such as cost, loss reduction, and voltage stability. This dual trend, which is part of the ongoing development of more robust and efficient DNs, emphasizes the growing importance of technical and methodological innovation.

Table 2.2. Comparison of the published studies to the intended

Reference	Publishing year	Solving algorithm	Optimization problem		DN uncertainty			Objective function		
			O_1	O_2	U_1	U_2	U_3	C_1	C_2	C_3
[83]	2016	HS-PABC		✓						
[84]	2017	NSGAII		✓						
[85]	2017	BFO		✓						
[86]	2018	LSHADE-EpSin	✓							
[87]	2019	MOPSO-MCS		✓						
[88]	2020	TPA		✓						
[89]	2020	MBGWO	✓			✓	✓		✓	
[90]	2021	QRSMA		✓					✓	
[91]	2022	SHADE		✓						
[92]	2022	HAS-PABC	✓							
Suggested study	2023	HMPA	✓	✓	✓	✓	✓	✓	✓	✓

O_1: Single-objective, O_2: Multi-objective, U_1: Multiple load models, U_2: Hourly load variation, U_3: Hourly DG output variation, C_1: Annual devices investment cost minimization, C_2: Annual cost of energy losses minimization, C_3: Annual cost of energy load demand minimization.

As a result, this study proposes a multi-objective optimization approach that uses the hybrid multi-population algorithm (HMPA) to address the optimal network reconfiguration simultaneously with the allocation of CBs and DGs (ONRSACD) problem. Table 2.2 describes the characteristics of this approach and sets it apart from previous research, emphasizing the unique contributions of this thesis.

2.8. Conclusion

A wide range of strategies, including both single and multi-objective approaches with different constraints, have addressed the loss reduction issue. An analysis of the methods investigated in the literature to reduce losses in DNs yields numerous important findings. First and foremost, we acknowledge network reconfiguration as the most economically efficient approach for low-voltage DNs. Nevertheless, it requires an intricate control design and encompasses a multitude of switching possibilities, therefore presenting a formidable optimization issue. Notwithstanding its effectiveness, this approach provides restricted financial gains. Furthermore, by virtue of its simplicity and dependability, capacitors allocation arises as the most appropriate strategy for high-voltage DNs. However, this approach primarily focuses on reducing losses, offering minimal additional benefits. Furthermore, the allocation of DGs places a particular emphasis on the integration of pre-existing small-scale generating sources, such as standalone solar projects or wind farms, into the distribution system. Despite its outstanding efficiency, this approach requires advanced implementation skills and is the least dependable in terms of installation. Among the approaches examined in the literature, the concurrent implementation of these methods seems to be the most efficient strategy for improving system performance, capitalizing on the unique benefits of each approach.

The subsequent Chapter looks into metaheuristic optimization techniques and their ability to tackle the intricate, multi-objective problems found in contemporary DNs. These algorithms can enhance various network features, notably the simultaneous optimization of network reconfiguration, and the allocation of CBs and DGs. Furthermore, it describes the hybrid multi-population algorithm (HMPA) chosen for this study.

CHAPTER 3

Metaheuristic Optimization Methods for Distribution Networks

Contents

3.1 Introduction

Optimization is a crucial element in the management and improvement of DNs, which face growing constraints from increasing electricity demand and the incorporation of distributed energy resources. In this particular setting, the traditional approach to optimization was to minimize power losses and guarantee voltage stability by using deterministic techniques that offered unambiguous solutions to rather straightforward problems. However, as DNs become increasingly complex and large due to technological advancements and the need for increased efficiency and reliability, these traditional methods have proven to be insufficient. The evolution has resulted in the introduction of advanced optimization methods, namely metaheuristic algorithms, which provide greater adaptability in managing contemporary power systems' non-linear, high-dimensional, and stochastic characteristics. Hybridizing these algorithms has made them much more useful by letting them combine the best parts of different approaches to solve the wide range of problems that DNs face. Furthermore, multi-objective optimization has become a crucial method for reconciling the frequently contradictory objectives of technical efficiency, economic feasibility, and environmental sustainability. The objective of this chapter is to offer a thorough examination of these sophisticated optimization techniques, emphasizing their theoretical foundations, practical implementations, and notable benefits compared to conventional approaches.

3.2 Traditional vs Metaheuristic optimization methods

Optimization is a fundamental field in mathematics and computer science that aims to devise mechanisms for identifying optimal solutions to intricate problems by minimizing or maximizing one or more objective functions using dependent variables, which may be integers or real values [95]. Diverse domains such as engineering, economics, logistics, and medicine extensively use these optimization methods to facilitate efficient decision-making.

Conventional optimization techniques, such as linear programming, nonlinear programming, and dynamic programming [96], are widely effective in solving various optimization problems. These methods provide benefits such as efficient use of time and assured convergence to local optima. However, these methods often have major flaws, like not being able to get past local optima, the chance of divergence, the need to deal with complicated constraints, and the fact that it's challenging to compute first- or second-order derivatives.

On the other hand, metaheuristic algorithms specifically address these optimization problems by reducing the number of challenges that conventional approaches face. These algorithms are often modeled on natural phenomena or on the functions of living organisms, making them adaptable and capable of customization, integration, or alteration to address specific optimization problems. These methods are especially efficient in stochastically exploring high-dimensional, nonlinear search spaces, providing robustness and global search capabilities. However, their stochastic nature does not always ensure the selection of an optimal solution [97]. The table 3.1 shows a comparison between traditional and metaheuristic optimization techniques.

3.3 Metaheuristic algorithms

The optimization procedure entails determining the most efficient approach to optimize the use of current resources while considering any preexisting limitations. The procedure has many stages: development of a mathematical model of the system, identification of variables and restrictions, establishment of an objective function, and exploration for states that maximize or minimize this function. Numerical optimization issues may be addressed using a range of tactics, including quantum-based techniques, metaheuristic approaches, and multi-objective methods [98]. The fundamental objective of addressing intricate optimization problems is to identify a feasible solution, which may then be enhanced and corrected utilizing various methodologies. This concept is the foundation of metaheuristic optimization algorithms, which are sophisticated techniques that integrate fundamental heuristic concepts to improve the exploration and exploitation of the search space [99]. This space includes all possible solutions within the physical constraints of the system. Metaheuristics, are methods that direct and optimize activities via iterative processes, often by balancing global and local search strategies with adaptive coefficients. These algorithms are abstract and generalizable, since they do not depend on gradients or Hessian matrices. This characteristic makes them non-deterministic and capable of generating solutions that are close to optimum. Furthermore, they integrate the memory from prior searches to direct ongoing operations, require the customization of parameters to suit the particular task, and contain techniques to prevent being stuck in local optima, therefore enhancing overall performance. Recent research has included artificial intelligence elements into these algorithms to further augment their efficacy [100].

3.4 Metaheuristic algorithms classification

Various factors can classify metaheuristic algorithms. An alternative categorization differentiates between those that draw inspiration from natural processes and those that do not.

Table 3.1 Traditional and metaheuristic optimization techniques

Criteria	Conventional methods	Metaheuristic methods
Methodology	Deterministic, based on mathematical models and exact algorithms.	Stochastic, inspired by nature or biology
Search domain	Generally restricted to local search; depends on gradient data	Capable of investigating extensive, non-linear, and high-dimensional problem domains
Solution assurance	ensures convergence to a local or global optimum according to the specific problem.	Seeking a "good enough" answer without any assurance of identifying the global optimum.
Treatment of constraints	Complex managing of restrictions, requires precise mathematical formulations.	Modular management of constraints; may integrate many types of constraints.
Robustness	Susceptible to prior conditions; prone to become trapped in local optima	Enhanced robustness; more adept in circumventing local optima via diversification practices
Complexity	Costly to compute for large-scale or nonlinear problems.	Large-scale problems are typically less computationally arduous.
Flexibility	Limited; intended for specific problems	Versatile; adaptable, combinable, and modifiable for diverse issues
Application	Ideal for well-defined, mathematically tractable problems	Appropriate for intricate, ambiguous, or highly non-linear issues.
Velocity of convergence	May be rapid for straightforward, convex issues but sluggish for intricate, non-convex problems.	Characterized by a generally slower convergence, however capable of exploring a wider spectrum of solutions.
Variability of Solutions	Frequently converges to a single solution	Capable of producing a wide range of solutions, beneficial for multi-objective optimization.
Implementation	Demands profound mathematical expertise and formulation tailored to the issue.	Greater ease of implementation across a range of challenges owing to its heuristic character.

One further classification distinguishes between algorithms that function on a single solution and those that operate on a population of solutions. Moreover, we can categorize metaheuristics as either deterministic or stochastic, based on their use of deterministic processes or randomization to generate novel answers. Furthermore, we can categorize these methods based on their focus on enhancing a single solution (trajectory-based) or exploring multiple options simultaneously (population-based). Finally, we often classify metaheuristics based on their search strategy, which can either prioritize local search, focusing on the immediate area of the existing solution, or global search, exploring the entire solution space. In contrast to conventional optimization methods that rely on mathematical models and assumptions, metaheuristics are independent of specific situations and may be adjusted to other problems with negligible adjustments. Metaheuristics are characterized by their ability to balance exploration and exploitation, the use of stochastic search to avoid local optima, iterative enhancement of solution quality, the demonstration of robustness in handling noisy and uncertain problems, the provision of flexibility through customization, and the facilitation of parallelism to expedite the search process and effectively solve large-scale problems. Figure 3.1 shows metaheuristics classification according to the variety of solutions and the inspiration origin.

Diverse origins, such as natural evolution, physics, swarm intelligence, and human interaction, motivate metaheuristic algorithms to be classified into several distinct categories [97]. Evolutionary algorithms, which draw inspiration from natural evolution, use concepts such as survival of the fittest, reproduction, and mutation to systematically enhance a population of candidate solutions. These include techniques such as genetic algorithms (GA), evolutionary programming (EP), evolution strategies (ES), and differential evolution (DE), which have extensive applications in several research domains. Physics-based metaheuristics are computer algorithms that use principles from physical laws such as gravitational forces, electromagnetic fields, and quantum mechanics to inform the search for optimum solutions. Notable examples include the gravitational search algorithm (GSA), electromagnetic field optimization (EMO), and evolutionary algorithms informed by quantum principles (QEA). Swarm-based algorithms, which draw inspiration from the collective behavior of social creatures like ants, bees, and birds, function by means of decentralized, self-organized systems in which individual agents engage in local interactions to accomplish a shared objective. Prominent algorithms under this classification include ant colony optimization (ACO), particle swarm optimization (PSO), and bee colony optimization (BCO). Furthermore, human-based algorithms integrate human intellect, expertise, and input directly into the optimization process, thereby increasing the algorithm's capacity to effectively identify solutions of superior quality. These include approaches like the expert-guided evolutionary algorithm (EEA), human-guided search (HGS), interactive evolutionary computation (IEC), and human-in-the-loop optimization (HILO). Studies successfully used each type of metaheuristics to solve a wide range of difficult optimization problems, from engineering design to computational biology. Each type of metaheuristics had its own benefits.

3.5 Comparing Metaheuristic Methods

A comparative study of metaheuristics identifies their unique strengths and limitations in addressing DN optimization problems [101]. These methods, ranging from focusing on individual answers to concurrently investigating several alternatives, underscore the need to meticulously align the algorithm with the specific attributes of the issue under consideration. Certain metaheuristics have exceptional local search performance, quickly approaching solutions close to the original estimate. On the other hand, some metaheuristics excel in global search, thoroughly exploring the entire solution space to avoid becoming trapped in local optima. Although deterministic algorithms may provide quicker convergence in clearly defined problems, they may encounter difficulties in complicated, stochastic settings where the adaptability and flexibility of stochastic approaches prove more advantageous. Furthermore, population-based algorithms tend to provide a broader exploration of the search space, thereby increasing the probability of discovering a global optimum.

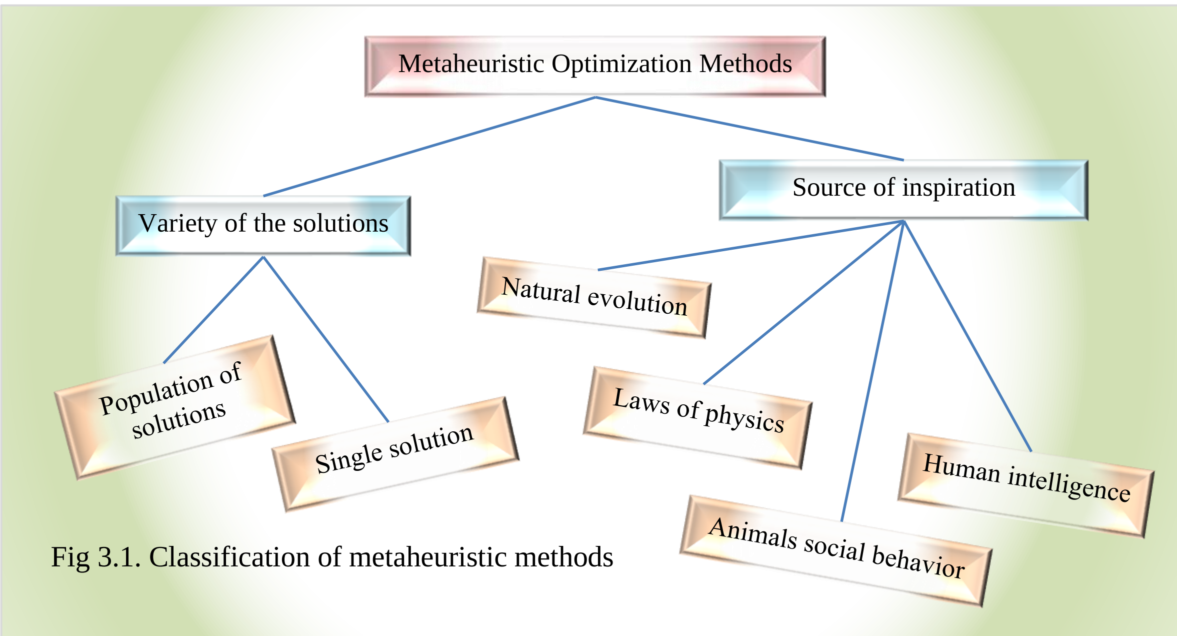


Fig 3.1. Classification of metaheuristic methods

On the other hand, methods that focus on a single solution are often more effective at improving a solution if it falls inside a promising area of the search space. The choice of a metaheuristic must also take into account computing efficiency, since some algorithms are more resource-intensive and may require higher processing capabilities, particularly when addressing large-scale issues. The ultimate success of a metaheuristic in optimizing a DN depends on its ability to successfully balance exploration and exploitation, adapt to the unique issue structure, and achieve high-quality solutions within an acceptable timeframe. Understanding the relative benefits of various metaheuristics allows them to make well-informed choices about which methods are most appropriate for their optimization endeavors, leading to more effective and reliable results in DN management. Table 3.2 compares metaheuristics with reference to search strategy, solution exploration, scope of optimization, computational efficiency, and adaptability.

3.6 Metaheuristics hybridization

3.6.1 The principle of Hybrid metaheuristics

Hybrid metaheuristics are a sophisticated optimization method that integrates the advantages of multiple metaheuristic algorithms to overcome challenges encountered when using them independently [102]. The goal of hybrid metaheuristics is to use the complimentary benefits of various algorithms by combining the exploration capabilities of global search algorithms with the refining strengths of local search methods. When compared to traditional metaheuristics alone, this synergistic strategy makes the optimization process more resilient and flexible, and it can quickly move through complex, high-dimensional search spaces. The hybridization process can manifest itself in a variety of ways, such as mixing different algorithmic parts, using different approaches one after the other, or fluid switching between approaches as the needs of the problem change. The need to tackle more intricate optimization issues that individual algorithms find difficult to handle effectively motivates the advancement of hybrid metaheuristics, particularly in the realm of multi-objective problems where many contradictory criteria require concurrent optimization. As a result, hybrid metaheuristics has become a powerful tool for solving real-world optimization problems, offering higher efficiency, greater flexibility, and better convergence towards better solutions.

3.6.2 Hybridization techniques

The wide range of hybrid metaheuristics design and implementation reflects the various ways to integrate different optimization approaches to enhance performance. We can broadly classify

Table 3.2 Comparison of metaheuristics

Criteria	Metaheuristic	Strengths	Limitations	Most suitable for
Search strategy	Trajectory -based	Proficient in localized solution refinement	May get ensnared in local optima	Problems requiring exact local optimization
	Population-based	Navigates a broader search domain, circumventing local optima	Severe computational cost, sluggish convergence	Problems requiring an exhaustive, global exploration of all potential solutions.
Investigation of solutions	Deterministic	Rapid convergence predictable results	Difficulties in navigating non-linear and intricate areas	Problems with a clearly delineated, simple settings
	Stochastic	Modularity, circumvents local optima, flexible to variations	Necessitates meticulous adjustment of settings, may exhibit limited speed	Non-linearity, noise, or dynamic environmental conditions.
Scope of optimization	Local search	Ability to fine-tune a specific search area	Starting point may miss global optima.	Problems requiring rigorous search in a decent area
	Global search	Explores full search space, resists local optima	Computationally intensive, sluggish start	Applications where determining the global optimum is of utmost importance
Computational Efficiency	Lightness	Fast, low resource consumption	restricted capacity for exploration	Small, low-complexity issues
	Significant needs for resources	In-depth investigation reveals near- optimal solutions	High computational cost, resource-intensive	Large, difficult issues requiring significant investigation
Adaptability	Problem-specific	Customized to solve specific types of problems, highly effective	Constrained applicability, may need tailoring	Problems with precise and well-defined attributes
	Adaptable	Applicable to a diverse array of problems	May lack optimal efficiency for specialized problems	Varieties of problem sets, settings with unpredictable dynamics

these methodologies into three primary categories: sequential, parallel, and adaptive hybridization. Sequential hybridization is the sequential use of algorithms in a predetermined order, with each algorithm addressing a particular stage of the optimization process. Initially, we may use a global search method like a genetic algorithm to extensively explore the solution space. Later on, we may refine the solutions using a local search technique, such as simulated annealing. Conversely, parallel hybridization refers to the concurrent execution of many algorithms, enabling them to exchange information and cooperate throughout the optimization process. This approach, by harnessing the complementary qualities of many algorithms simultaneously, may improve search efficiency and increase the likelihood of discovering a globally optimized solution. Adaptive hybridization is a flexible strategy in which the optimization process may alternate between many methods depending on the changing features of the problem. Under this approach, the system dynamically adjusts in real-time, fine-tuning the equilibrium between exploration and exploitation as the search advances. This hybridization method works particularly well for complicated, multi-objective optimization problems with a changing issue landscape or different strategies needed at different stages of the optimization process. Each of these hybridization schemes has distinct benefits and can be customized to accommodate specific problem domains, making hybrid metaheuristics a flexible and potent instrument in complex system optimization.

Many practical domains, such as engineering design, neural network training, and multi-objective optimization, have demonstrated the efficacy of hybrid metaheuristics. This hybrid methodology integrates many algorithms to exploit their respective advantages, leading to enhanced convergence rate, solution quality, and flexibility in handling complex problems. Notwithstanding their achievements, some obstacles persist, such as the intricacy of incorporating several algorithms, heightened processing requirements, and possible problems with scalability and overfitting. Potential future paths in hybrid metaheuristics include the advancement of adaptive and self-tuning systems, the integration of machine learning for autonomous strategy modifications, and the investigation of quantum computing integration to address increasingly intricate optimization difficulties. The objective of these developments is to improve the effectiveness and availability of hybrid metaheuristics for a wider range of applications [103].

3.7 Multi-objective optimization

DN multi-objective optimization is an essential component of contemporary power system management, especially considering the growing intricacy and requirements imposed on these networks. With the increasing integration of renewable energy sources, the handling of larger loads, and the imposition of more stringent regulatory requirements, the necessity to optimize many competing goals concurrently has become vital for DNs. Multi-objective optimization differs from single-objective optimization in that it aims to achieve a balance among several objectives, including minimizing power losses, enhancing voltage stability, decreasing operational costs, and minimizing environmental impact. This section examines the concept, techniques, and practical applications of multi-objective optimization in DNs.

3.7.1 Principle of multi-objective optimization

Multi-objective optimization is the simultaneous optimization of two or more competing goals. Divergent from conventional optimization approaches that prioritize a single criterion, multi-objective optimization aims to discover a collection of optimum solutions, referred to as the Pareto front, where no one solution is better in all goals [104]. Each solution on the Pareto front entails a compromise between the goals, enabling decision-makers to choose the best suitable option according to particular priorities or operational limitations. Within DNs, the primary goals are to minimize power losses, optimize voltage stability, decrease greenhouse gas emissions, and minimize total costs. The task of balancing these goals is complex and requires sophisticated optimization methods that can effectively traverse vast, non-linear, and sometimes contradictory search spaces.

3.7.2 Methods for Multi-Objective Optimization

Several methodologies have emerged to address the challenges of multi-objective optimization in DNs. Non-dominated sorting genetic algorithm II (NSGA-II), multi-objective particle swarm optimization (MOPSO), and strength pareto evolutionary algorithm (SPEA) are three of the most notable algorithms. NSGA-II [105] is a very popular technique, renowned for its effectiveness in preserving variety in the solution set and its ability to converge towards the Pareto front. The algorithm organizes solutions according to non-domination levels, ensuring a well-proportioned collection of optimal solutions. Instead, MOPSO [106] builds on the usual particle swarm optimization method by adding techniques that keep mechanisms interesting and prevent them from settling too quickly on a single solution. This lets you calculate more than one goal. SPEA [107] uses a fitness assignment algorithm based on Pareto dominance to make sure that the solutions it comes up with move closer to the Pareto front while still being different. The multi-objective evolutionary algorithm based on decomposition (MOEA/D) [108] and the pareto archived evolution strategy (PAES) [109] are important ways to solve multi-objective optimization problems in DNs. Each approach has distinct advantages, making it appropriate for a wide range of challenges and operational situations.

Increasingly, fuzzy logic has become a crucial tool in multi-objective optimization, especially for dealing with the uncertainties and ambiguities that are inherent in complicated real-world issues, such as those encountered in power DNs [110]. Fuzzy logic combines fuzzy sets and inference protocols to make it easier to weigh the pros and cons of different goals. This helps in the decision-making process with fuzzy data and unclear goals. This strategy is especially beneficial in applications where conventional optimization techniques face difficulties, since it provides the capability to dynamically assign weights to goals and adjust to evolving circumstances. Different optimization techniques, such as genetic algorithms and particle swarm optimization, often combine with fuzzy logic to accelerate the search process, circumvent local optima, and enhance accuracy. Hybrid approaches have proven to be highly effective in applications such as distributed generation placement, power flow optimization, and scheduling, where it is necessary to balance many opposing requirements [111]. The use of fuzzy logic in multi-objective optimization improves the solutions' resilience and adaptability while also enabling more effective decision-making through techniques such as fuzzy Pareto fronts and fuzzy-based decision support schemes. The use of fuzzy logic has resulted in notable progress in the optimization of intricate systems, thus establishing it as an essential element in the development of multi-objective optimization theories.

3.8 Distribution networks optimization: challenges and prospects

DNs optimization encompasses several strategies, such as reconfiguring tie and sectionalizing switches, building new substations, updating conductors, and installing automated reclosers, capacitors, and DG units. Nevertheless, contemporary research typically overlooks the intrinsic uncertainties of the system, including changes in demand, non-dispatchable DG units, and variable energy prices, which are essential for developing accurate models. Furthermore, the construction of new substations has become more unfeasible due to environmental and economic constraints. This has resulted in a heightened focus on the integration of capacitors and DGs, an aspect often overlooked in favor of straightforward reconfiguration. Additionally, existing models often disregard contemporary factors such as deregulation and demand-side management. These models mostly rely on small-scale test systems, which restricts the relevance of the results to real-world, large-scale networks. Moreover, omitting crucial system restrictions like voltage levels, radiality, and connectivity diminishes the practical usefulness of many optimization solutions. In addition, it is critical to have a comprehensive strategy that effectively tackles technological, economic, and environmental goals in a unified manner. The increasing influence of plug-in cars as substantial additional traffic sources significantly complicates network performance, although their impacts are mostly uncharted. Despite the use of numerous optimization algorithms, it is critical to develop more efficient approaches that can overcome local optima and achieve near-global solutions. This should, in particular, focus on improving the variety of metaheuristics. While fine-tuning metaheuristic control settings is critical for achieving maximum performance, it remains a relatively unexplored field of research. Although distribution system planning has made large progress, many utilities in developing countries still depend on experience-based techniques.

In summary, the complexity and changing demands of modern DNs require a holistic approach to optimization that addresses both existing gaps and emerging challenges. The current body of research reveals gaps, highlighting the need for more robust, scalable, and integrated solutions that can effectively apply to real-world systems. As we progress, we place emphasis on the methodologies employed in this work. Hybrid metaheuristics are becoming increasingly popular as a powerful way of circumventing the problems of traditional optimization methods. We now look at the hybrid multi-population algorithm (HMPA), a brand-new tool for optimizing DNs.

3.9 Hybrid multi-population algorithm

The HMPA algorithm was first introduced in 2020 by [112] as a compilation of the Artificial Ecosystem-based Optimization (AEO) and Harris Hawks Optimization (HHO) algorithms. Hence, it achieves optimal efficiency by including the most advantageous features of both algorithms, such as the levy-fight strategy, local search mechanism, quasi-oppositional learning, and chaos theory.

3.9.1 Artificial Ecosystem-based Optimization algorithm

AEO is a population-based algorithm that draws inspiration from the energy flow seen in natural ecosystems [113]. It has three primary operators: production, consumption, and decomposition. We provide an overview of the equations for each operator below. Figure 3.2 displays the flowchart of the AEO.

3.9.1.1 Production

This operator creates a new individual by applying Equation (3.1) to the match between the best individual in the current population and a randomly selected individual.

$$NewX_1^{It+1} = (1-a) \cdot BestX + a \cdot X_r^{It} \tag{3.1}$$

$$a = \left(1 - \frac{It}{Max\_It}\right) \cdot r_1 \tag{3.2}$$

$$X_r^{It} = Lb + r \cdot (Ub - Lb) \tag{3.3}$$

Where $BestX$ is the best individual detected yet, It is the current iteration; r and r_1 are random number vectors within the range $(0,1)$ with dimensions Dim and one, respectively. Moreover, Dim is the problem's dimension, while Lb and Ub are the lower and upper limits of the problem space, respectively. The a is a linearly decreasing coefficient that describes the exploration or exploitation of $NewX_1^{It+1}$.

3.9.1.2 Consumption

Equations (3.4) – (3.6) correspondingly update the consumer individuals for herbivores, carnivores, and omnivores.

$$NewX_i^{It+1} = X_i^{It} + C \cdot (X_i^{It} - newX_1^{It+1}) \tag{3.4}$$

$$NewX_i^{It+1} = X_i^{It} + C \cdot \left(X_i^{It} - X_j^{It}\right) \tag{3.5}$$

$$NewX_i^{It+1} = X_i^{It} + C \cdot r_2 \cdot (X_i^{It} - NewX_1^{It+1}) + (1 - r_2)\left(X_i^{It} - X_j^{It}\right) \tag{3.6}$$

Where r_2 is a random number in range $(0,1)$, X_j is a randomly selected solution from the current population, and C can be calculated as follows:

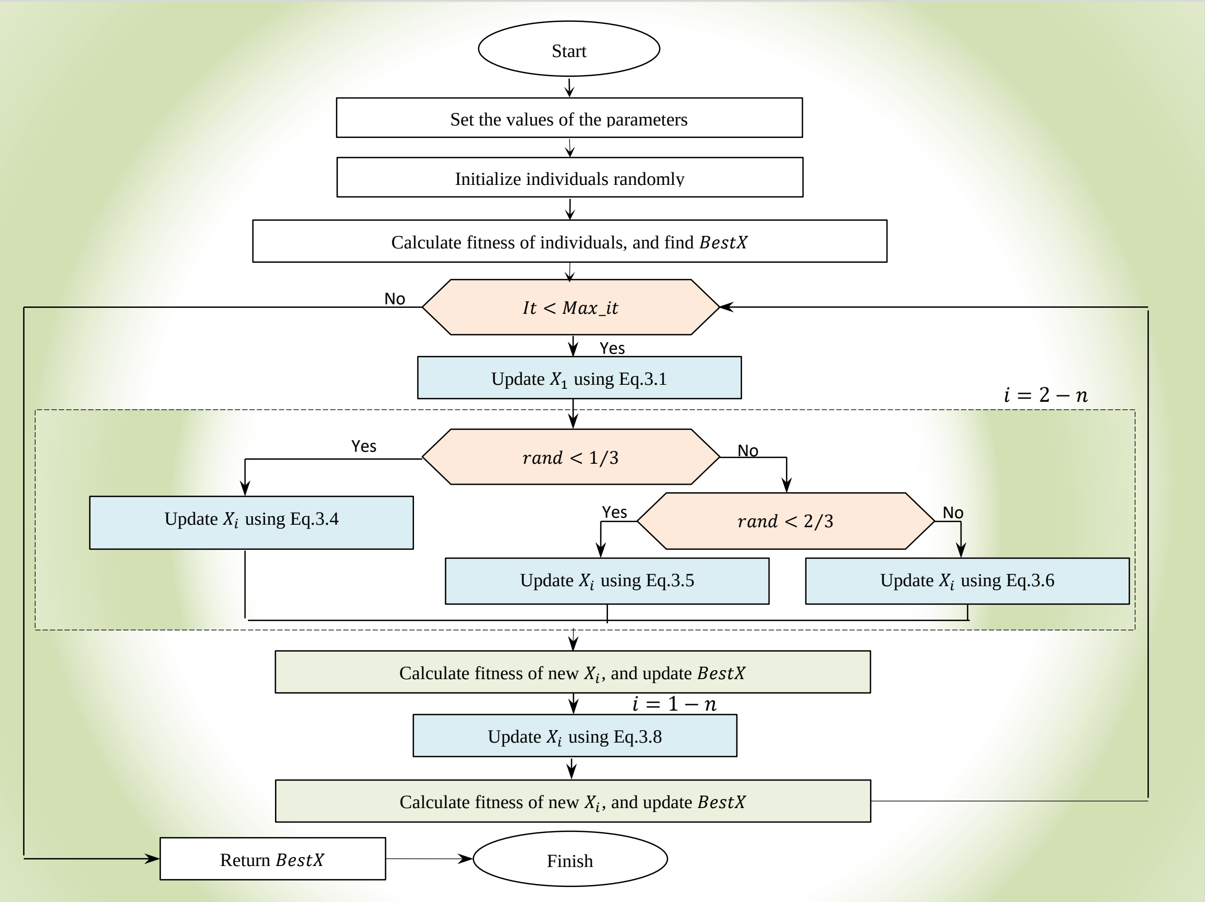


Fig.3.2: Flowchart of the basic AEO

$$C = \frac{1}{2} \cdot \frac{u}{v} \tag{3.7}$$

Where u and v are random numbers with a normal distribution. It is noteworthy that the second-best individual belongs to the Herbivore group.

3.9.1.3 Decomposition

The present operator serves to model the process of decomposition within ecosystems. We use equation (3.8) to update individuals.

$$NewX_i^{It+1} = X_N^{It} + D \cdot (e \cdot X_N^{It} - h \cdot X_i^{It}) \tag{3.8}$$

Where X_N^{It} is the best individual in the current iteration, D, e, and h are calculated using equations $(3.9) - (3.11)$.

$$D = 3u \tag{3.9}$$

$$e = r_3 \cdot randi([12]) - 1 \tag{3.10}$$

$$h = 2 \cdot r_3 - 1 \tag{3.11}$$

Where u is a normally distributed random numbers, and r_3 is a random number in $(0,1)$.

3.9.2 Harris Hawks optimization algorithm

The HHO technique is a robust population-based meta-heuristic algorithm that draws inspiration from the intrinsic behavior of Harris' hawks [114]. The HHO model mathematically replicates the cognitive abilities, team composition, and hunting strategies of Harris hawks. The HHO algorithm has two stages: exploration and exploitation, selected according to the value E specified in Eq. (3.12).

$$E = 2E_0 \left(1 - \frac{It}{Max\_It}\right) \tag{3.12}$$

Where E_0 is the initial energy of the prey, It and Max_it represent the current and maximum number of iterations, respectively. When $|E| \geq 1$, the exploration phase is chosen, and whenever$|E| < 1$, the exploitation phase is selected.

3.9.2.1 Exploration stage

The exploratory mode of HHO emulates the perching behavior shown by Harris hawks. Presented below is the updating equation.

$$NewX_i^{It+1} = \begin{cases} X_r^{It} - r_1 \left| X_r^{It} - 2r_2 X_i^{It} \right| & q \geq 0.5 \\ (BestX - X_m^{It}) - r_3\big(Lb + r_4(Ub - Lb)\big) & q < 0.5 \end{cases} \tag{3.13}$$

Where, X_i^{It} is the current position of the ith solution in iteration It, $NewX_i^{It+1}$ is the updated position of ith, X_r^{It} is a randomly chosen solution from the population, r_1, r_2, r_3, r_4 and q are random numbers in $(0,1)$, $BestX$ is the best solution found so far, Lb and Ub are the lower and upper bounds of problem space, and X_m^{It} is the average of the solutions in the current population, and can be determined using Eq. (3.14).

$$X_m^{It} = \frac{1}{N} \sum_{i=1}^{N} X_i^{It} \tag{3.14}$$

N is the number of solutions in the population.

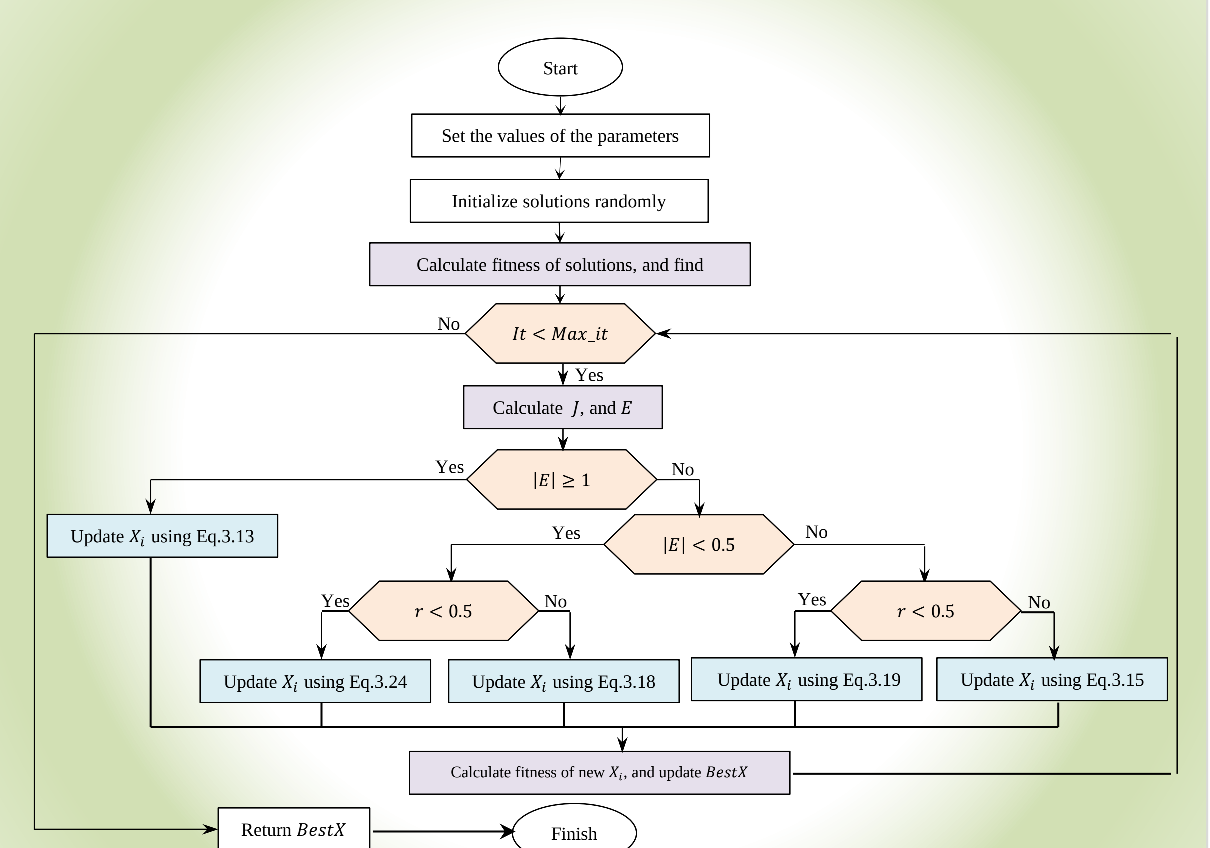


Fig.3.3 Flowchart of the basic HHO

3.9.2.2 Exploitation stage

This stage exemplifies the rapid and unexpected activity of Harris Hawks as they launch their attack. While hunting, Harris hawks use a range of pursuit strategies that exploit the inherent inclination of their prey to escape from danger. In this context, the approaches of soft besiege, hard besiege, soft besiege with progressive quick dives, and hard besiege with progressive rapid dives are viable methods for modelling aggressive behaviors.

In HHO, two factors are used to settle on one of these four tactics. First parameter is r, which is an unspecified random number inside $(0,1)$, and the second one is E, which is determined by Eq. (3.12).

- **Soft besiege**

When $r \geq 0.5$, and $|E| \geq 0.5$, the soft besiege is selected, and the solution is updated by Eq. (3.15).

$$X_i^{It+1} = \Delta X^{It} - E\left|J \cdot BestX - X_i^{It}\right| \tag{3.15}$$

$$\Delta X^{It} = BestX - X_i^{It} \tag{3.16}$$

$$J = 2(1 - r_5) \tag{3.17}$$

Where r_5 is a random number within $[0,1]$.

- **Hard besiege**

When $r \geq 0.5$ and $|E| < 0.5$, the hard besiege phase is used, and the solution is updated by Eq. (3.18).

$$X_i^{It+1} = BestX - E|\Delta X^{It}| \tag{3.18}$$

- **Soft besiege with progressive rapid dives**

When $r < 0.5$ and $|E| \geq 0.5$, the third strategy is selected, and the solution is updated using Eq. (3.19).

$$X_i^{It+1} = \begin{cases} Y \; F(Y) < F(X_i^{It}) \\ Z \; F(Z) < F(X_i^{It}) \end{cases} \tag{3.19}$$

$$Y = BestX - E\left|J \cdot BestX - X_i^{It}\right| \tag{3.20}$$

$$Z = Y + S \times L \tag{3.21}$$

$$LF(x) = 0.01 \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}} \tag{3.22}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2\left(\frac{\beta-1}{2}\right)} \right)^{\frac{1}{\beta}} \tag{3.23}$$

Where F is the fitness of the given solution, S is a random vector, L is the levy-flight function, u and v are random values in $(0,1)$, and β is a constant value of 1.5.

- **Hard besiege with progressive rapid dives**

When $r < 0.5$ and $|E| < 0.5$, the solution is updated using the last phase, which is modeled by Eq. (3.24).

$$X_i^{It+1} = \begin{cases} Y\ F(Y) < F(X_i^{It}) \\ Z\ F(Z) < F(X_i^{It}) \end{cases} \tag{3.24}$$

$$Y = BestX - E|J \cdot BestX - X_m^{It}| \tag{3.25}$$

$$Z = Y + S \times L \tag{3.26}$$

Where X_m^{It}, and L are calculated using equations (3.14) and (3.22), respectively. The flowchart of the HHO algorithm is represented in Fig.3.3.

3.9.3 Hybrid Multi-Population Algorithm

The main challenge of meta-heuristic algorithms is to enhance and balance their exploration and exploitation capabilities while also devising a strategy to avoid local optima. The suggested HMPA addresses these issues and provides solutions for each of them. Figure 3.4 demonstrates a simplified representation of the HMPA.

3.9.3.1 Multi-population technique

The algorithm uses a novel multi-population technique to encourage a diverse array of answers. This technique facilitates the dispersion of solutions, exploration for sufficient space inside the issue, and dynamic exchange of solutions, taking into account three sub-populations. The first sub-population independently investigates the entire issue space, which initially comprises 60% of the available alternatives. This technique greatly enhances the process of exploration. Equation (3.27) updates the spatial positions of the solutions in the first sub-population. This equation finds equal utility throughout the solution's initialization phase.

$$newX_i^{It} = Lb + rand(0,1) \times (Ub - Lb) \tag{3.27}$$

In order to optimize the effectiveness of this random search procedure, the new solution produced will replace the previous one only if it includes a greater level of fitness .

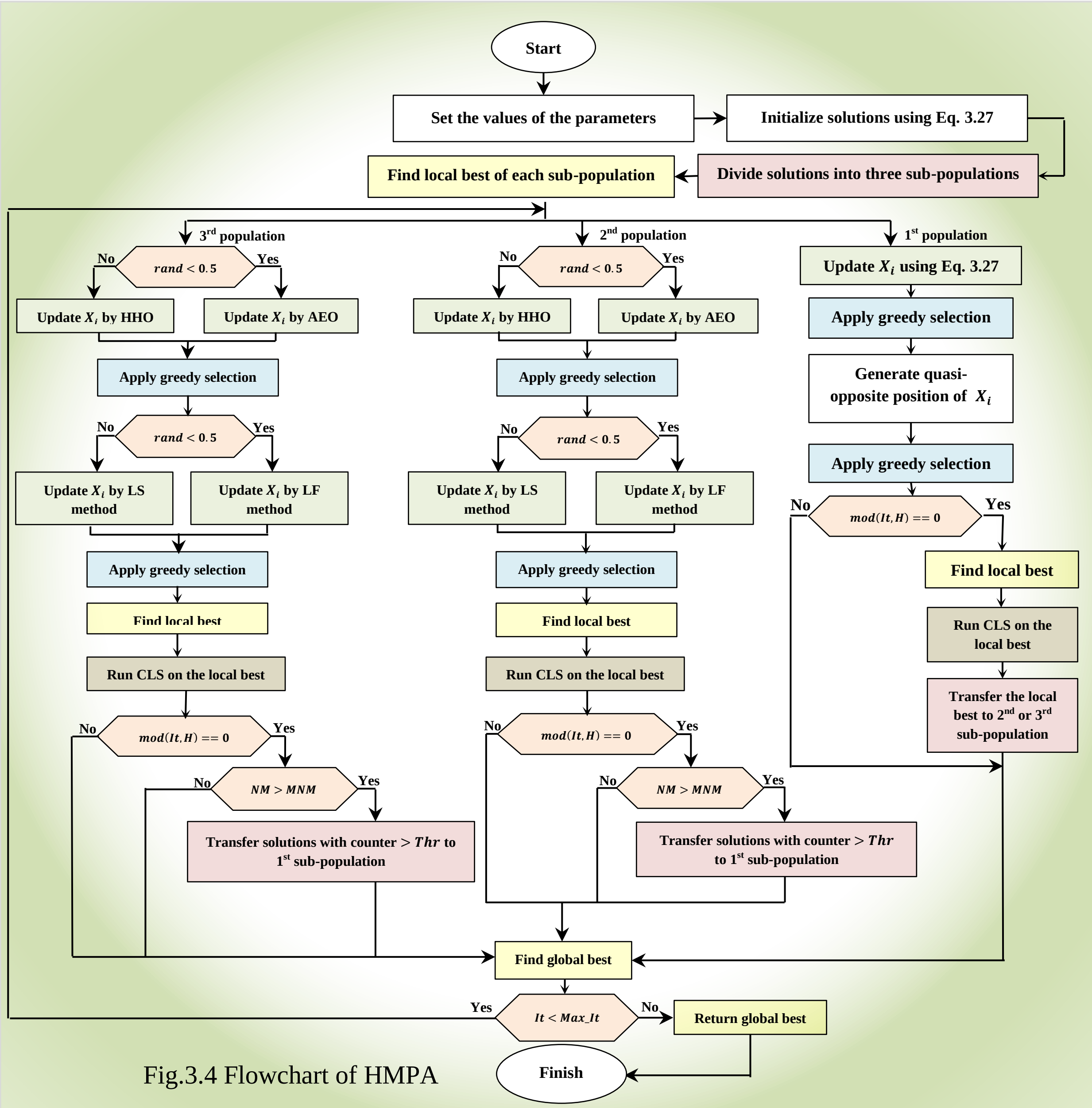


Fig.3.4 Flowchart of HMPA

The technique of greedy selection significantly enhances efficiency. The HMPA model employs this method, and its pseudo-code is shown in figure 3.5. Moreover, the optimal solution from the first sub-population is selected per H iterations and allocated to either the second or third sub-populations. Consequently, the quantity of solutions in the first sub-population declines while simultaneously rising in the second and third sub-populations. This phenomenon enhances the algorithm's exploration in the first iterations and its utilization in the latter iterations. However, the remaining 40% of the initial solutions are divided between two sub-populations. Its relative positions vary depending on the local optimal solution of the sub-population and other solutions of the corresponding sub-population.

Consequently, the obtained solutions exhibit convergence on two separate areas instead of a singular point. Furthermore, the solutions of the second and third sub-populations include a counter that tally the cumulative count of unsuccessful solution updates. This parameter facilitates the identification of solutions that are trapped at optimal local positions.
As a result, the solution is sent to the first sub-population to be reinitialized in each of the H iterations if the counter of the solution exceeds a specific threshold (Thr) and the members of the sub-population (NM) are more than the given minimum numbers (MNM). Adhering to a limited number of solutions in sub-populations is essential for the ongoing survival of such sub-populations. The sub-populations may engage in interactions based on the exchange mechanism shown in Figure 3.6. The AEO or HHO approach is used to update the solutions for the second and third sub-populations, and their size changes dynamically.

3.9.3.2 Quasi-oppositional learning

To enhance its search capabilities, the HMPA employs the QOPP, or quasi-oppositional position technique.

$if\ fitness(newX_i^{It}) < fitness(X_i^{It})$
    $X_i^{It} = newX_i^{It}$
    $Counter(i) = 0$
$else$
    % only for solutions of 1^{st}, 2^{nd} sub-populations
    $Counter(i) = Counter(i) + 1$
$end\ if$

Fig.3.5 Greedy selection Pseudo-code

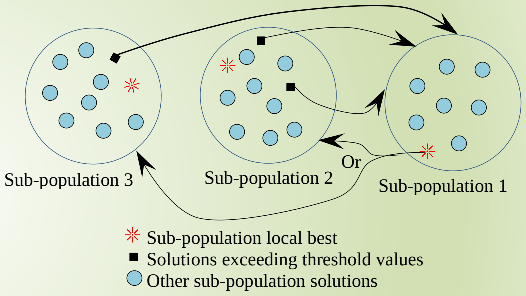


Fig.3.6 Sub-populations: Solution Exchange Process

$for\ j = 1\ to\ D$

$\quad OpX_{i,j}^{It} = Lb + Ub - X_{i,j}^{It}$

$\quad C_j = (Lb_j + Ub_j)/2$

$\quad if\ X_{i,j}^{It} < C_j$

$\quad\quad QOpX_{i,j}^{It} = C_j + (OpX_{i,j}^{It} - C_j) \times rand(0,1)$

$\quad else$

$\quad\quad QOpX_{i,j}^{It} = 0pX_{i,j}^{It} + (C_j - OpX_{i,j}^{It}) \times rand(0,1)$

$\quad end\ if$

$end\ for$

D : Problem dimension ; $QOpX_i^{It}$: X_i^{It}Quasi-opposite position

Fig.3.7 QOPP's pseudo-code

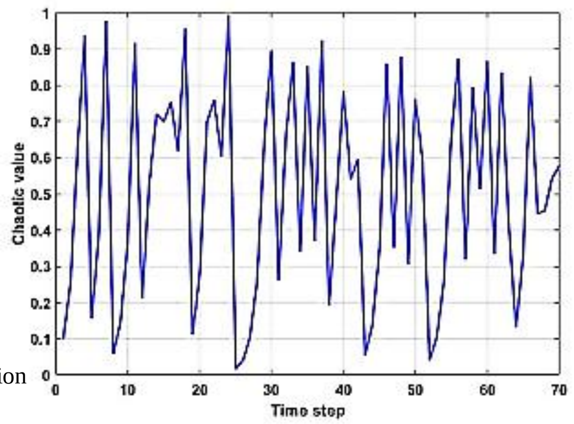


Fig.3.8 The piecewise distribution map

The QOPP utilizes a learning-based methodology to enhance its search capabilities by generating a symmetrical solution location. Only the first sub-population autonomous solutions in HMPA have utilized the QOPP. Figure 3.7 shows the pseudo-code of the QOPP.

3.9.3.3 Chaotic local search strategy

The chaotic local search (CLS) method investigates the vicinity of a solution in order to identify potential regions suitable for exploration. Therefore, this approach enhances the potential for exploitation. Furthermore, incorporating chaos theory improves the technique's efficacy. The HMPA framework only applies the CLS approach to the local best sub-populations, examining the immediate vicinity of the optimal solutions, thereby reducing the overall execution time. The CLS process uses Equation 3.28 to calculate a novel local best solution.

$$new\ BestX = BestX + (CV^{k+1} - 0.5) \times (X_{r1}^{It} - X_{r2}^{It}) \tag{3.28}$$

X_{r1}^{It} and X_{r2}^{It} are solutions chosen randomly from the associated sub-population, while CV^{k+1} is the chaotic value that the chaotic map produces. The HMPA uses the piecewise map shown in figure 3.8, a conventional chaotic map that generates random values in the range of (0,1). Figure 3.9 depicts the CLS approach's pseudo-code. The suggested CLS technique generates a new local best, after which the greedy selection mechanism maximizes efficiency. Below is a mathematical representation of the piecewise chaotic map.

$$CV^{k+1} = \begin{cases} \frac{CV^k}{P} & 0 \le CV^k \le P \\ \frac{CV^k - P}{0.5 - P} & P \le CV^k \le 0.5 \\ \frac{1 - P - CV^k}{0.5 - P} & 0.5 \le CV^k \le 1 - P \\ \frac{1 - CV^k}{P} & 1 - P \le CV^k \le 1 \end{cases} \quad ; P = 0.4 \tag{3.29}$$

3.9.3.4 Levy flight function

The levy-fight (LF) random walk function is initially introduced by the HHO algorithm to enhance the algorithm's performance by optimizing exploitation. This concept has been employed in numerous advanced algorithms and is utilized in an innovative manner in the HMPA, as illustrated in Figure 3.10. While the second command increases the probability of exploitation, the first one accelerates convergence in the LFF. Moreover, LF is the solution to Equation (3.22).

3.9.3.5 Local search strategy

The LS local search mechanism efficiently explores the space between sub-population solutions to provide more precise identification of superior ones and enhance the quality of the HMPA search. Equation 3.30 below describes the LS approach.

$$X_i^{It+1} = \begin{cases} X_i^{It} + \mu \cdot \left(X_i^{It} - X_j^{It}\right) & \delta < CP2 \\ X_i^{It} + \mu \cdot (BestX - NX) & Otherwise \end{cases} \quad ; \quad CP2 = 0.5 \tag{3.30}$$

Where $CP2$ is a control parameter with a value of 0.5 and NX is a solution vector generated by Eq. (3.27), where μ is a coefficient between $(-L, L)$, L and δ are random numbers in (0, 1), and X is a randomly selected solution from the sub-population. Figure 3.11 displays the LS pseudo-code of the HMPA.

$for\ \ k = 1\ to\ K$
    Update CV using Eq.71
    Select X_{r1}^{It} and X_{r2}^{It} randomly from the sub-population
    Generate new local best using Eq. 70
    Apply the greedy selection mechanism
$end\ for.$

Fig. 3.9 Chaotic local search (CLS) method

$if\ CP1 < \rho$
    $X_i^{It+1} = X_i^{It} \times LF$
$else$
    $X_i^{It+1} = X_i^{It} + LF$
$end\ if.$

Fig. 3.10 Levy-flight (LF) mechanism

$for\ \ i = 1 : N$
    Update X_i^{It} using Eq. 72
    Apply greedy selection mechanism
$end.$

Fig. 3.11 Local search (LS) strategy

3.10 Conclusion

This chapter has undertaken a general analysis of the evolution and application of metaheuristic optimization techniques in the specific domain of DNs. Initially, the analysis has focused on the significant advantages of metaheuristics in effectively addressing the complex and non-linear nature of contemporary optimization problems. The categorization and comparison of different metaheuristic algorithms provided valuable insights into their individual advantages and constraints, highlighting the possibility of hybrid approaches to improve performance and robustness. The exploration of multi-objective optimization has highlighted the adaptability of metaheuristics to reconcile competing objectives, which is necessary in the dynamic setting of DNs. Finally, the difficulties and potential advantages of using these techniques in DNs were described, leading to the proposal of the hybrid multi-population algorithm (HMPA) as a very promising approach for efficiently optimizing these networks.

Building on the insights gained from exploring metaheuristic optimization methods, the next chapter focuses on a more specific application: optimal network reconfiguration simultaneously with the allocation of CBs and DGs (ONRSACD), aiming to maximize techno-economic benefits by improving system reliability, reducing losses and optimizing investment costs. Integrating advanced optimization techniques with practical network management strategies, this holistic approach can significantly improve the operational efficiency and economic viability of distribution systems.

CHAPTER 4

Optimal Network Reconfiguration Simultaneously with the Allocation of Capacitor Banks and Distributed Generations in a radial distribution network

Contents

4.1 Introduction

This chapter explores sophisticated techniques and practical research to enhance the efficiency of radial distribution networks by reconfiguring the network simultaneously with strategically allocating CBs and DG units. The chapter is organized into two separate yet cohesive parts.

In the first section, we present and discuss our research contributions on new optimization techniques for determining the optimal location and sizing of CBs and network reconfiguration under varying load conditions throughout the day, highlighting the importance of adapting optimization strategies to hourly load variations to improve the operational performance of distribution systems.

The second part of this chapter introduces the fundamental technique of the strategy we propose, namely the multi-objective optimization framework based on the hybrid multi-population algorithm (HMPA). The first step is to provide a comprehensive description of the optimization problem, including all the objectives and constraints arising from the complex interaction of the placement of DGs resources, the allocation of CBs, and the reconfiguration of the network. A detailed analysis of the results follows this step, demonstrating how HMPA effectively optimizes the DN in a balanced manner, thereby enhancing its technical and economic performance.

4.2 Optimal capacitor allocation based on hourly load variation.

In order to tackle the difficult task of determining the optimal placement and size of shunt CBs in a radial distribution system, this application presents the use of three newly developed optimization techniques: Equilibrium Optimizer (EO) [115], Gorilla Troops Optimization (GTO) [116], and African Vultures Optimization Algorithm (AVOA) [117]. The main goal is to enhance the DN efficiency by catering to hourly demand fluctuations while obeying specified cost limitations, as well as equality and inequality restrictions. IEEE 33-bus and 69-bus standard radial distribution networks are used as benchmark test systems to evaluate the efficiency of these optimization techniques.

The experimental process starts by selecting the most appropriate candidate buses for capacitor installation, a step informed by the study of the voltage profile of the test networks. By prioritizing these crucial nodes, the research guarantees that the optimization efforts are targeted in areas where they are most likely to result in substantial improvements in system performance. Following this, the algorithms EO, AVOA, and GTO are implemented on the selected candidate buses in order to ascertain the most efficient allocation of shunt capacitors.

The outcomes derived from these optimization techniques are then submitted to a comparison study, in which the algorithms' performance is assessed using important criteria such as solution quality and convergence properties. This comparison method allows for the determination of the most efficient optimization tool among the three, therefore offering significant insights into their individual advantages and constraints [118].

4.2.1 Problem formulation

4.2.1.1 Objective function

For load flow calculation, backward/forward sweep method is used [119]. The objective function is to minimize total annual cost and is defined by:

$$min\ C_{Tot} = C_{energy} \times \left(\sum_{t=1}^{24} \sum_{i=1}^{nbr} Re\left\{ \left({I_{br}}_{t}^{i} \right)^2 \times Z^i \right\} \right) \times N_{day} + C_{cb} \times \sum_{k=1}^{ncb} Q_{cb,k} \tag{4.1}$$

Where, C_{tot} is the total annual cost ($/year), C_{cb} is the purchase cost ($/KVAR), t is the hour in a day, $I_{br}{}_{t}^{i}$ is the current flowing through the branch i at time t (h), $Q_{cb,K}$ is the reactive power of the capacitor bank k, C_{energy} is the average energy cost ($/KWh), nbr is the network number of branches, ncb is the number of capacitor banks, $N_{day} = 365.$

The purpose is to minimize the total annual cost while upholding equality and inequality constraints.

4.2.1.2 Equality Constraints

The power balance equations describe these constraints as follows:

$$P_{sub} = \sum_{i=1}^{nbr} P_{loss,i} + \sum_{j=1}^{Nb} P_{load,j} \tag{4.2}$$

$$Q_{sub} + \sum_{k=1}^{ncb} Q_{cb,k} = \sum_{i=1}^{nbr} Q_{loss,i} + \sum_{j=1}^{Nb} Q_{load,j} \tag{4.3}$$

Where P_{sub} and Q_{sub} are real and reactive substation power respectively, $P_{load,j}$ and $Q_{load,j}$ are real and reactive load demands at bus j respectively, N_b is the number of buses.

4.2.1.3 Inequality Constraints

3. Bus voltage limits

$$V_{min} \leq V_i \leq V_{max} \tag{4.4}$$

4. Reactive power limits

$$Q_{cb,min} \leq Q_{cb,\ k} \leq Q_{cb,max} \tag{4.5}$$

5. Total compensation

$$\textstyle\sum_{k=1}^{ncb} Q_{cb,k} \leq \sum_{j=1}^{Nb} Q_{load,j} \tag{4.6}$$

6. Line capacity limits

$$I_{n,i} \leq I_{max,i} \quad ; \quad i = 1, \dots, nbr \tag{4.7}$$

4.2.2 Tests and results

This method looks into the problem of optimal allocation of shunt CBs by using the MATLAB programming language to run the EO, AVOA, and GTO algorithms and find the best spot and size for CBs in a radial DN. The method employs IEEE 33-node (Figure 4.1) and 69-node

(Figure 4.5) test systems to assess the effectiveness of these optimization tools. For a detailed account of their specifications, see [120].

An objective function directs the optimization process, aiming to minimize the overall cost associated with the installation of CBs. To accomplish this, we solely assess designated candidate buses for capacitor placement, selecting them based on the system's voltage profile. This analysis reveals that buses with low voltage magnitudes are the most prominent areas for intervention. To faithfully replicate the dynamics of actual distribution systems, the study includes a 24-hour load profile for each test system. By including hourly fluctuations in load demand into the optimization algorithms, this method guarantees the generation of more realistic and efficient solutions for the allocation of CBs.

The following values are applied:

$C_{cb} = 3\$/KVAR$, $C_{energy} = 0.06\$/KWh$, $Q_{cb,min} = 0$, $Q_{cb,max} = 150\ KVAR$,
$V_{min} = 0.95\ p.u$, $V_{max} = 1.05\ p.u$, $V_{sub} = 12.66\ KV$

Results obtained for each test system are shown and reviewed below.

4.2.2.1 Results for the 33-node test feeder

This study carried out the optimization procedure with a defined maximum iteration count of (T = 100) and a constant population size of 100. Nine buses specifically identified as voltage-sensitive were considered for shunt capacitor installation.

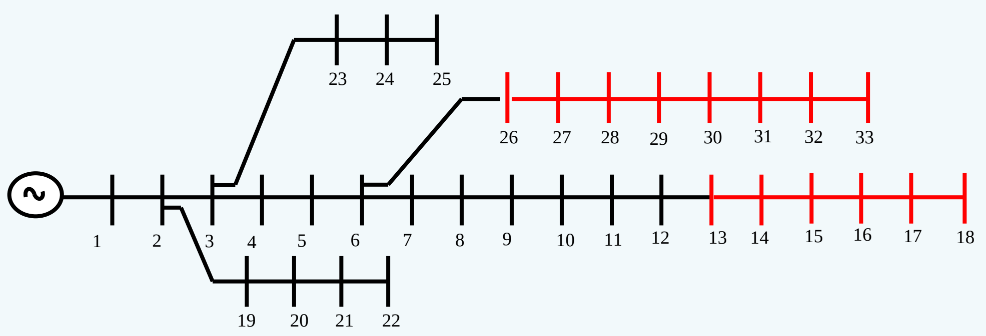


Fig.4.1. The 33-node radial distribution network with voltage-sensitive buses in red

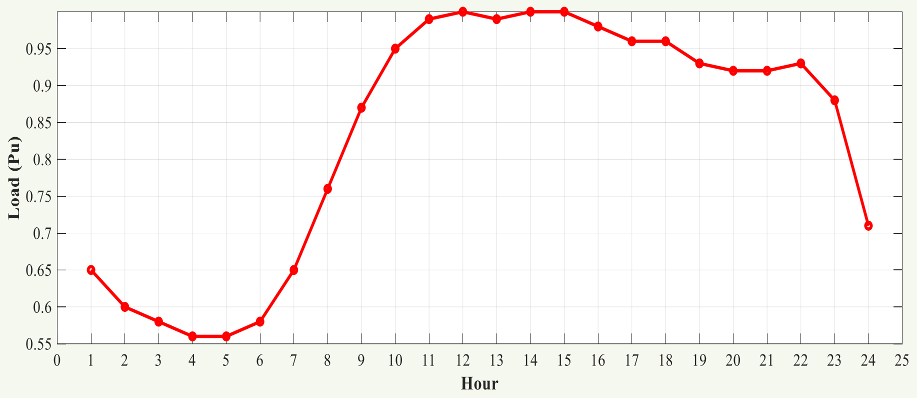


Fig 4.2. Annual daily average load variation for IEEE 33-node system

These buses are highlighted in red on the schematic shown in Figure 4.1. Figure 4.2 displays the load fluctuation over a 24-hour period, providing a comprehensive understanding of the changing demand within the network.

As a means of demonstrating the effects of these fluctuations, Figure 4.3 displays the voltage profiles for each hour, using 24 different colors to differentiate the hourly changes. The presented visualization effectively illustrates the fluctuations in voltage profiles resulting from the dynamic load conditions experienced throughout a day.

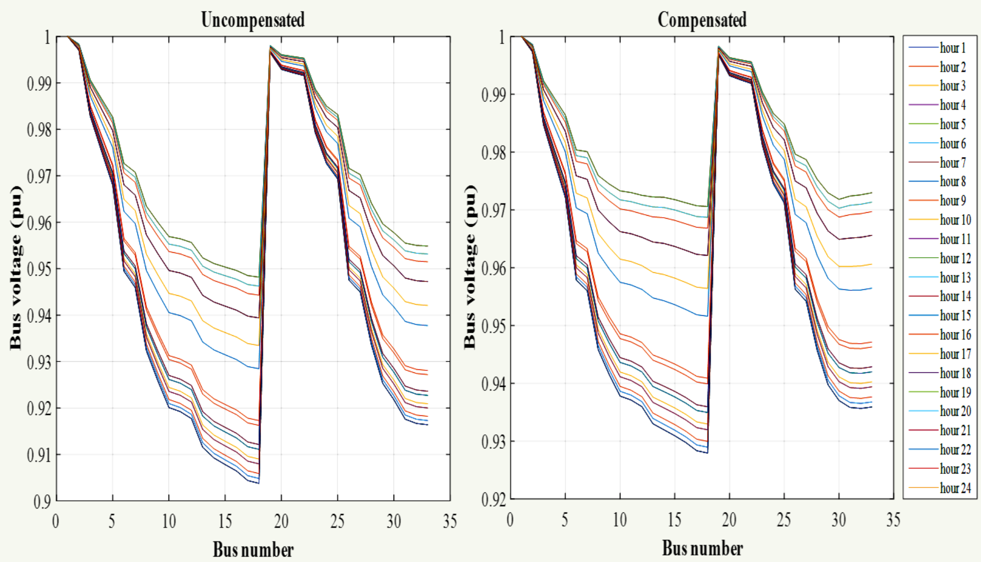


Fig 4.3. Hourly bus voltages of uncompensated and compensated 33-node system.

In comparison to the uncompensated system, the study demonstrates a significant improvement in the voltage profiles at each hour for the compensated system due to the strategic placement of capacitors at the chosen buses. This enhancement highlights the efficacy of strategically positioning capacitors to stabilize voltage levels across the network when subjected to different load circumstances.

For a comprehensive analysis of the outcomes derived from various optimization strategies, refer to Table 4.1. This table presents the ideal positions and dimensions of the shunt capacitors as determined by each approach.

Table 4.1. Optimal locations and sizes for 33-node: comparative study

Comparison Criteria	**Base case**	**Techniques**					
		AVOA		**GTO**		**EO**	
		Bus	***Size***	***Bus***	***Size***	***Bus***	***Size***
Optimal location and size (KVAR) of capacitors	_	13 14 15 18 31 32 33	150 100 50 100 150 150 150	13 14 16 18 31 32 33	150 100 100 50 150 150 150	13 14 15 18 31 32 33	150 150 50 50 150 150 150
Net injected (KVAR)	_	850		850		850	
Minimum voltage (pu)	0.9037	0.9290		0.9284		0.9279	
Energy loss (KWh)	3567.7170	2626.5164		2626.1586		**2624.7184**	
Energy loss reduction (%)	_	26.3810		26.391		**26.4314**	
Annual cost of energy loss ($/year)	78133.0034	57520.7112		57512.8754		**57481.3348**	
Capacitors cost ($/year)	_	2550		2550		2550	
Total annual cost ($/year)	78133.0034	60070.7112		60062.8754		**60031.3348**	
Net savings ($/year)	_	18062.2922		18070.128		**18101.6686**	
Net savings (%)	_	23.1173		23.1273		**23.1677**	

The results clearly demonstrate that all suggested optimization methods surpass the uncompensated system, attaining greater quality of voltage regulation and overall network performance. Among the implemented algorithms, the EO demonstrated superior performance not only in important comparative criteria like voltage enhancement and loss reduction but also in its ability to converge, as demonstrated by the convergence curve in Figure 4.4. This finding indicates that EO is highly efficacious in rapidly converging to a superior quality solution, thereby establishing it as an auspicious instrument for optimizing capacitor placement in DNs.

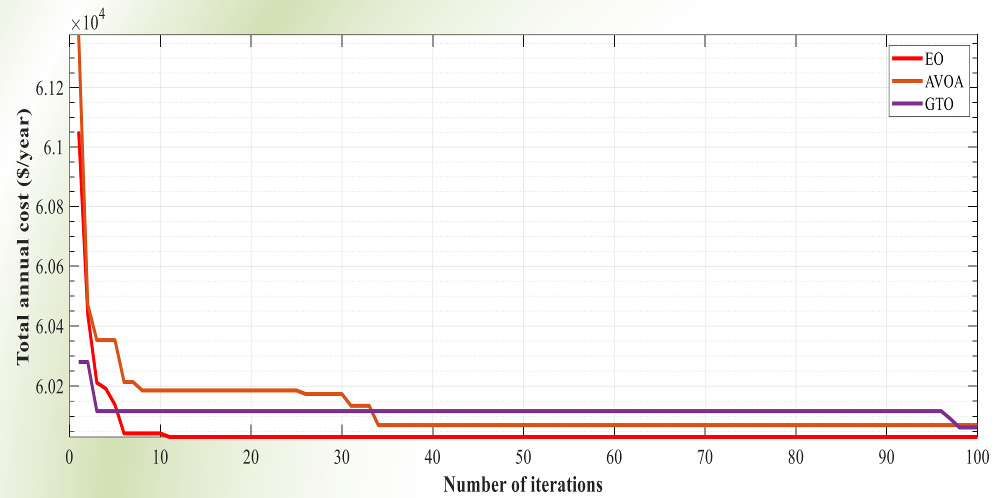


Fig 4.4. Convergence characteristics of the optimization algorithms for IEEE 33-node system.

4.2.2.2 Results for the IEEE 69-node system

The optimization procedure, with a maximum iteration count of T = 200 and a population size of 200, addressed the complexity of the larger test system. This scenario included identifying and selecting 18 voltage-sensitive buses for shunt capacitor installation. The schematic in Figure 4.5 marks these buses in blue. Figure 4.6 illustrates the load fluctuation over a 24-hour period, offering a detailed depiction of the changing demand distributed throughout the network throughout the day. To further clarify the effects of these fluctuations, Figure 4.7 displays the voltage profiles for each hour, using 24 different colors to highlight the variations in voltage levels resulting from hourly load changes.

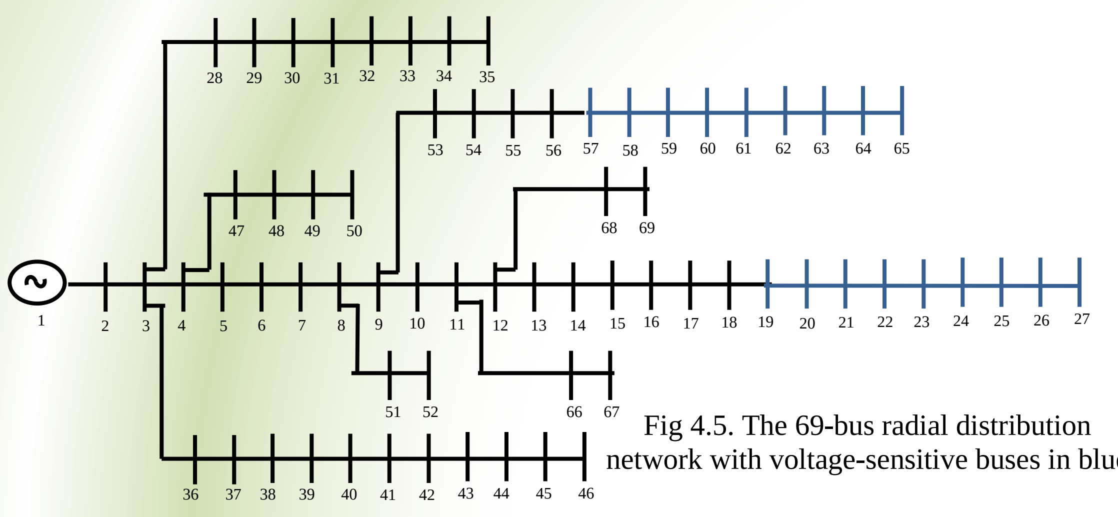


Fig 4.5. The 69-bus radial distribution network with voltage-sensitive buses in blue

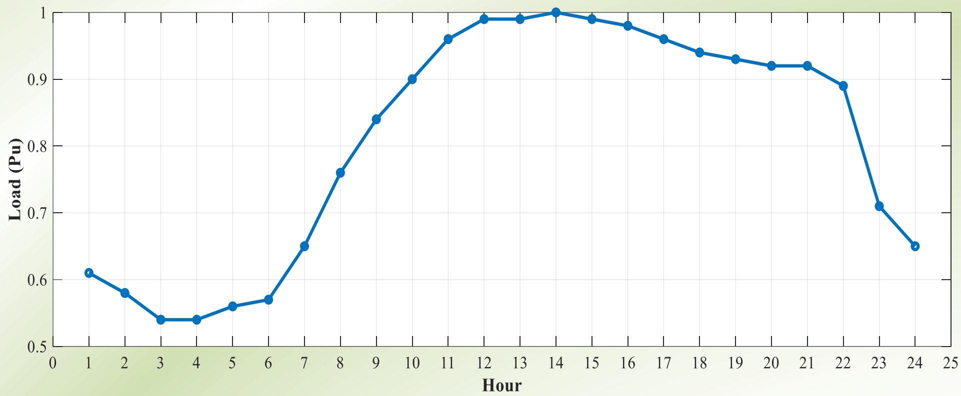


Fig 4.6. Annual daily average load variation for IEEE 69-node system

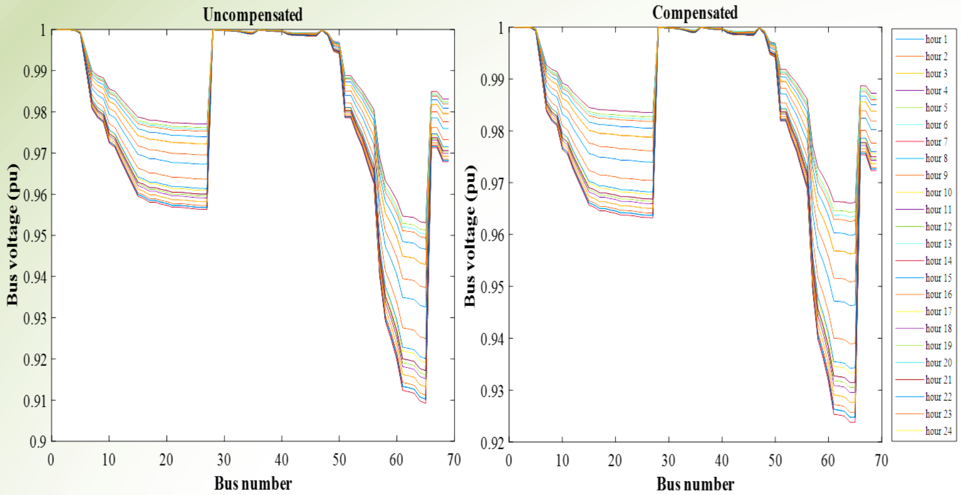


Fig 4.7. Hourly bus voltages of uncompensated and compensated 69-node system.

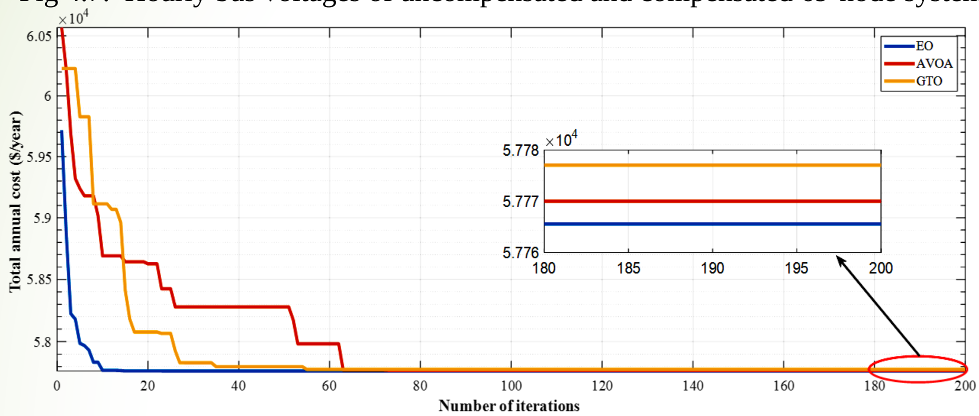


Fig 4.8. Convergence characteristics of the optimization algorithms for 69-bus system.

The analytical findings demonstrate a significant improvement in the voltage profiles throughout each hour for the compensated system, where capacitors are strategically positioned at the best buses that have been determined. The observed improvement is substantial in comparison to the uncompensated system, therefore illustrating the efficacy of appropriate allocation of capacitors in augmenting voltage stability given fluctuating load circumstances.

Table 4.2 provides an extensive analysis of the outcomes derived from each of the suggested optimization methods. This table outlines the optimal positions and dimensions of the shunt capacitor banks as established by each strategy.

Analysis unequivocally demonstrates that all optimization methods provide better results compared to the uncompensated system, resulting in improved voltage regulation and overall system performance. Significantly, the EO stands out as the most efficient among the algorithms that were evaluated, with the highest rates of improvement in voltage and decrease in loss across many comparison criteria. Moreover, the convergence capacity of the EO is emphasized in Figure 4.8, which showcases its remarkable efficiency in quickly achieving an ideal solution. These results highlight the potential of EO as a very effective technique for optimizing the positioning of capacitors in large-scale distribution networks, providing both excellent precision and computational efficiency.

Table 4.2. Optimal sites and sizes of capacitors for 69-node feeder: comparative table

Criteria	**Base case**	**Techniques**					
		AVOA		**GTO**		**EO**	
		Bus	***Size***	***Bus***	***Size***	***Bus***	***Size***
Optimal location and size (KVAR) of capacitors	–	20 21 59 61 62 64 65	100 150 150 150 150 150 150	20 24 26 59 61 62 64 65	150 50 50 150 150 150 150 150	20 21 24 59 61 62 64 65	150 50 50 150 150 150 150 150
Net injected (KVAR)	_	1000		1000		1000	
Minimum voltage (pu)	0.9091	0.9238		0.9238		0.9238	
Energy loss (KWh)	3597.8344	2500.9128		2501.2352		**2500.7103**	
Energy loss reduction (%)	_	30.4883		30.4794		**30.4940**	
Annual cost of energy loss ($/year)	78792.5748	54769.9915		54777.0518		**54765.5574**	
Capacitors cost ($/year)	_	3000		3000		3000	
Total annual cost ($/year)	78792.5748	57769.9915		57777.0518		**57765.5574**	
Net savings ($/year)	_	21022.5833		21015.523		**21027.0174**	
Net savings (%)	_	26.6809		26.6719		**26.6865**	

4.3 Distribution Network Reconfiguration Based on Hourly Load

This experiment tests the EO, AVOA, and GTO algorithms to identify the optimal network reconfiguration that reduces the annual cost of energy losses over a 24-hour period while accounting for hourly load fluctuations. We perform simulations on the 69-node radial distribution test system to determine the strategy that offers the highest level of efficiency and performance [121].

4.3.1 Problem formulation

4.3.1.1 The objective function

The goal is to locate open switches in the DN that provide a radial configuration that reduces annual energy losses cost. Below is the formulation of the objective function:

$$\min(of) = min(C_{Eloss}) \tag{4.8}$$

The annual energy loss cost is determined using the following basic equation:

$$C_{Eloss} = C_{energy} \cdot \left(\sum_{t=1}^{24} \sum_{i=1}^{Nbr} (R_i \cdot Ibr_i^t) \right) \cdot N_{day} \tag{4.9}$$

Where, C_{energy} is the average energy cost (0.06 \$/Kwh), t is the hour in a day, R_i is the resistance of the branch i, Ibr_i^t represents the electric current passing through branch i at a given time $t(h)$, while Nbr denotes the total number of branches and $N_{day} = 365$

The optimization approach yields a network reconfiguration that meets the following constraints:

4.3.1.2 Equality constraints

An essential limitation is represented by the active power balance equation:

$$P_{sub} = \sum_{i=1}^{nbr} P_{loss,i} + \sum_{j=1}^{Nb} P_{load,j} \tag{4.10}$$

Where P_{sub} is real substation power, $P_{load,j}$ is real load demand at bus j, N_b is the number of buses.

4.3.1.3 Inequality constraints

Bus voltage boundaries: The equation below shows the constraints on the magnitudes of voltage at each bus.

$$V_{min} \leq V_i \leq V_{max} \ , i = 1,2, \dots, Nbus \tag{4.11}$$

With, $V_{min} = 0.95\ p.u\ , V_{max} = 1.05\ p.u$

Line current flow limits: It is crucial to consistently maintain all currents flowing through the lines within their prescribed thresholds.

$$I_n \leq I_n^{max} \ , n = 1,2, .. Nbr \tag{4.12}$$

Radiality limitations: When reconfiguring, closing a tie switch (OS) causes one of the previously closed switches to open. This operation maintains the network's radial structure, preventing loops and isolated nodes, and supplies electricity to all linked loads. Radiality testing is achieved thanks to the Depth First Search Tree (DFS) technique [122]. The following equation must be satisfied:

$$\begin{cases} 2 \leq 0S_i \leq Nbr + Nts \ ; i = 1,2, \dots, Nts \\ OS_i \neq OS_j \ ; i, j \,\epsilon \{1,2, \dots, Nts\} \ ; \ i \neq j \end{cases} \tag{4.13}$$

Where, N_{ts} is the number of tie switches.

4.3.2 Tests and results

The simulations were constructed using the MATLAB programming environment to optimize the reconfiguration of the DN. The backward/forward sweep method, a commonly used approach to analyze load flow in a radial DN, was employed to perform the power flow calculations required to assess the effectiveness of the reconfiguration alternatives.

The proposed optimization techniques are evaluated using the 69-node radial distribution system as the benchmark test case. Figure 4.9 illustrates the basic topology of this system. The network comprises 68 closed branches, as well as seven lateral lines and five open switches, allowing adaptability for reconfiguration.

The system functions using power levels of 100 MVA and 12.66 kV, with a maximum active power capacity of 3.8 MW and a maximum reactive power capacity of 2.69 MVAr.

The optimization procedure is carried out with a maximum iteration limit of T = 150, guaranteeing a comprehensive exploration of the solution space

Table 4.3. Optimal network reconfiguration in a 69-node system: A Comparison

Item	Base case	EO	AVOA	GTO
Open switch	69, 70, 71, 72, 73	48, 12, 10, 14, 60	60, 10, 14, 12, 58	9, 12, 14, 58, 60
Daily energy losses	4167.9735	**1331.6203**	1514.8506	1779.2039
Daily energy losses reduction (%)	-	**68.0511**	63.6549	57.3124
$V_{min}\ pu$	0.9090	**0.9905**	0.9904	0.9904
C_{Eloss} ($\$/year$)	91278.6196	**29162.4845**	33175.2281	38964.5654
Net savings ($/year)	-	**62116.1351**	58103.3915	52314.0542
Net savings (%)	-	**68.0511**	63.6549	57.3124

Furthermore, the population size for each method is established at 50, thus striking a balance between the need for effective computing and the necessity for precise solutions. This arrangement enables the algorithms to investigate a broad spectrum of possible network reconfigurations while keeping the computing burden somewhat reasonable.

This network reconfiguration approach incorporates the hourly fluctuation in load demand. Figure 4.11 displays the load characteristics of the test system throughout a 24-hour period. Figure 4.12 displays the convergence curves of the strategies under consideration.

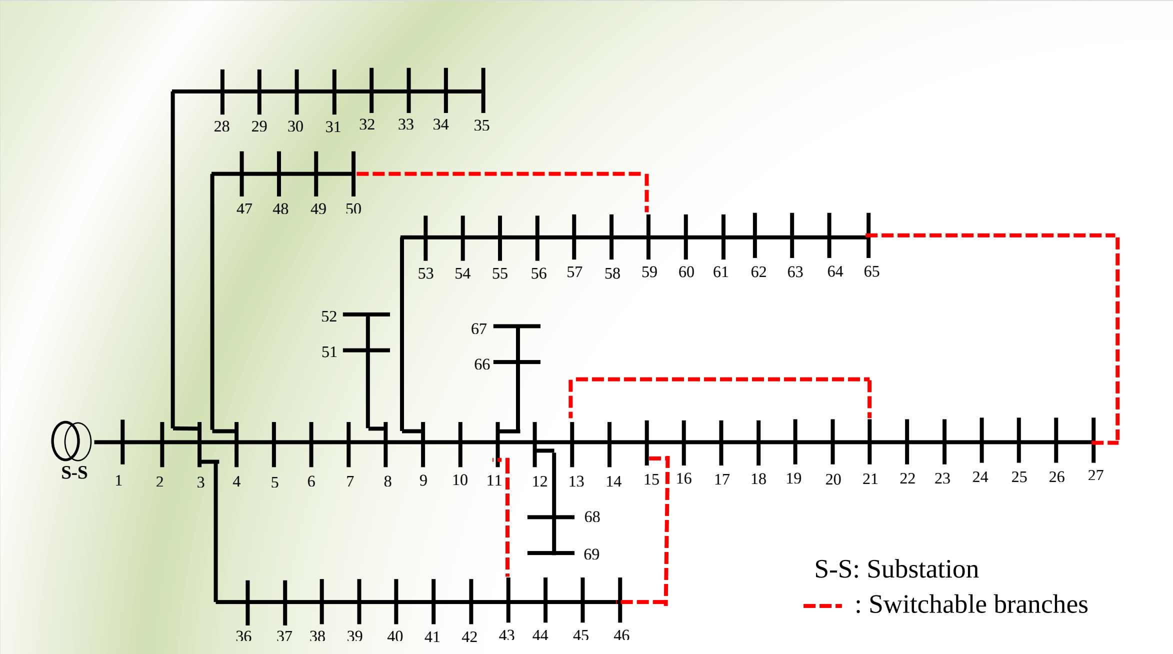


Fig 4.9. The basic configuration of the 69-node system

The EO algorithm's preemptive achievement of the optimum solution over competing algorithms demonstrates its rapid convergence.

Figure 4.13 shows the voltage profiles for each hour, visually representing fluctuations in network demand using 24 different colors. The hourly intervals of the reconfigured system show a noticeable increase in the voltage profile, indicating a significant deviation from the characteristics specified in the base case.

An increase in V_{min} from 0.9090 per unit (pu) to 0.9905 pu demonstrates the observed improvement. Table 4.3 presents a comprehensive comparison of the various results obtained using the proposed methods for efficient network reconfiguration. The tabulated data clearly demonstrates the superior quality of the results obtained using the specified methods compared to the status pre-reconfiguration. The empirical data clearly show that the EO approach produces the most optimal results.

The EO approach exhibits a higher capacity to control network energy losses, resulting in a substantial decrease from 4167.9735 kWh to 1331.6203 kWh, indicating a remarkable reduction rate of 68%. The efficacy of EO in reducing energy losses within the distribution network is further shown by its superior performance compared to the other optimization approaches assessed in this experiment.

The EO algorithm produces an optimal network reconfiguration that achieves the lowest yearly energy loss costs, reducing them significantly from 91,278.62 $ per year to 29,162.48$ per year.

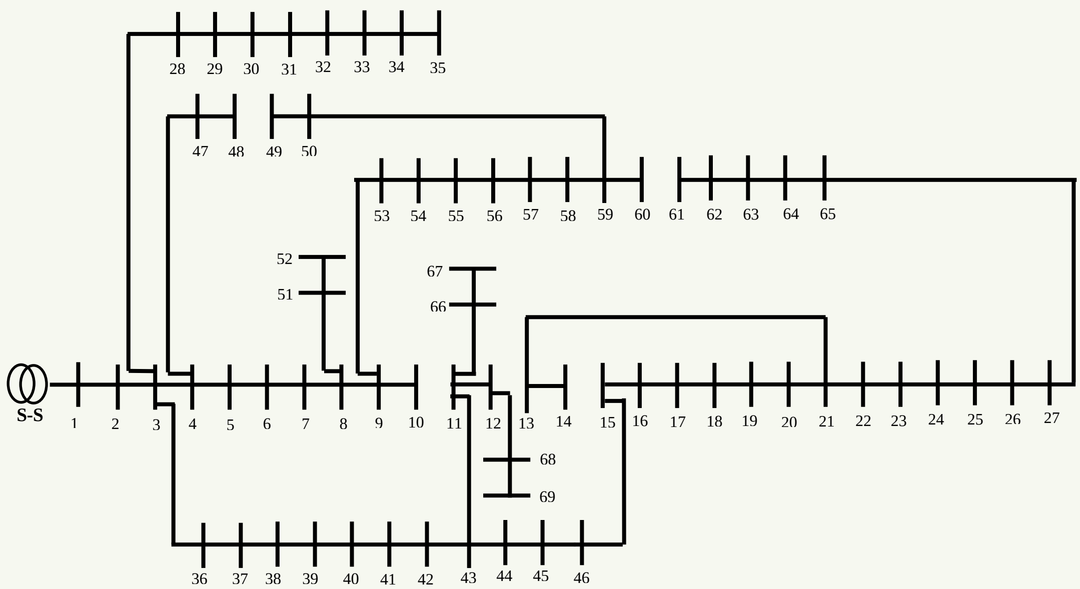


Fig 4.10. Optimal reconfiguration of a 69-node system to minimize annual energy losses cost.

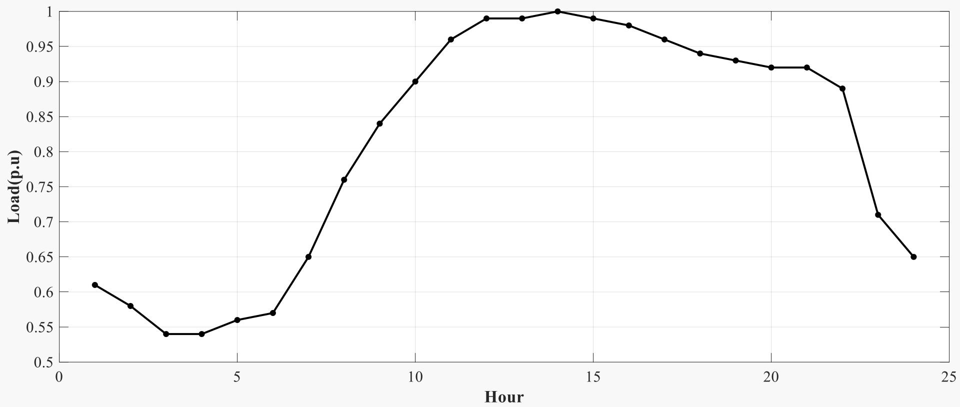


Fig. 4.11. Annual daily average load variation for 69-node system

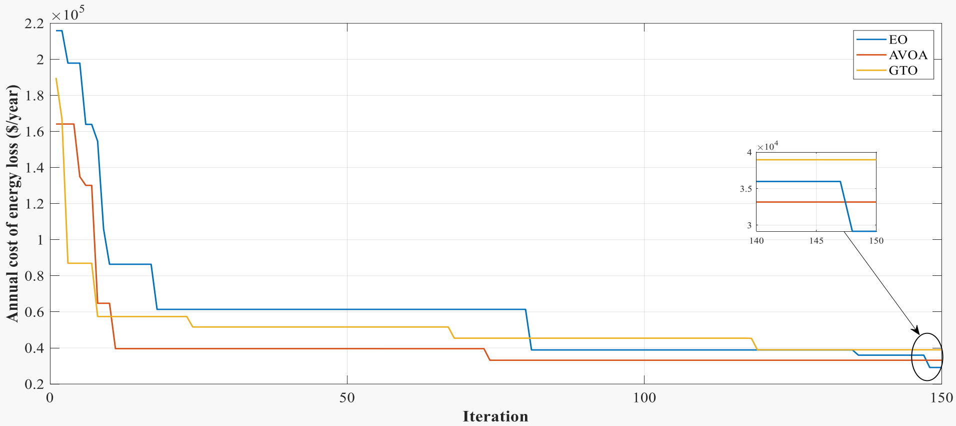


Fig. 4.12. Convergence characteristics of the optimization algorithms

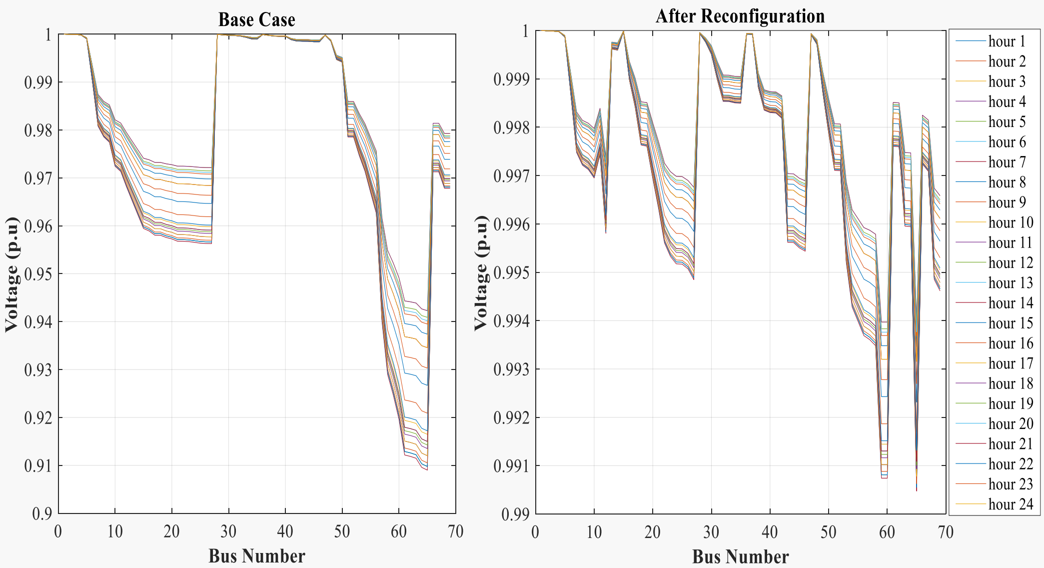


Fig. 4.13. Hourly bus voltages before and after reconfiguration by EO algorithm

The significant decrease in energy loss expenses clearly demonstrates the algorithm's potential to surpass other optimization techniques that were evaluated, establishing it as the most efficient instrument for attaining cost-effective network operation. Furthermore, the EO algorithm achieves the greatest net savings, totaling 62,116.14 $ annually. These figures indicate a net savings rate of 68%, which significantly surpasses the savings attained by other methods. The total results highlight the exceptional performance of the EO approach in providing optimal network reconfiguration options in terms of both energy efficiency and cost-effectiveness, surpassing most competing approaches by a significant margin.

4.4 A Reappraisal

The outcomes derived from these two applications, namely the optimal allocation of capacitor banks and the optimal network reconfiguration, not only demonstrate the smooth implementation of the used optimization methods but also emphasize their capacity to produce high-quality solutions. Indeed, the three algorithms used, EO, AVOA, and GTO, exhibited strong and consistent performance in both cases. Nevertheless, it is clear that the EO algorithm has proven to be the best approach, continuously achieving the most ideal outcomes in comparison to other methods, especially in terms of reducing energy losses and improving cost effectiveness.

The next section of this chapter focusses on the complex problem of simultaneously optimizing network reconfiguration and the allocation of CBs and DG units. In light of the complex and diverse characteristics of this issue, a more advanced methodology is necessary. Thus, we provide an innovative solution approach tailored specially to tackle the complexities of concurrent optimization. In order to achieve this objective, we have chosen the Hybrid Multi-population Algorithm (HMPA), which, by virtue of its intrinsic design features, exceeds the capabilities of the EO algorithm [112]. The selection of HMPA is driven by its hybrid architecture, which integrates the advantages of many populations, thus improving the capacities to explore and exploit spaces. This feature enables the HMPA to efficiently circumvent local optima and attain near-global solutions with enhanced dependability.

The capacity of HMPA to achieve a balance between global search and local refining further supports its selection over EO, making it particularly suitable for simultaneously optimizing network reconfiguration, capacitor allocation, and DG placement. Therefore, with this technique, we want to propose a more complete and efficient solution to the complicated issue of distribution network optimization, beyond the performance constraints of the EO algorithm.

4.5 Concurrent reconfiguration and allocation of capacitor banks and distributed generation

4.5.1 Key stages of the suggested methodology

This part of the experimental protocol presents the hybrid multi-population algorithm (HMPA) as a solution to achieve the dual goals of minimizing the annual substation energy costs (CE_{sub}) and investment costs for devices (CD) while maintaining all operational constraints within acceptable limits. The optimisation procedure focusses on the optimal network reconfiguration while simultaneously allocating CBs and DG (ONRSACD) problem in the radial DN [123]. This approach is tested on the 33-node and 69-node radial distribution networks and accounts for hourly variations in load demand and distributed generation output.

Many variables, such as the time of day, weather conditions, and the nature of users (residential, commercial, or industrial), impact the substantial variations in energy demand that the distribution system encounters throughout the day. The fluctuating demand poses a complicated problem for network operators, who need to meticulously handle network reconfiguration and the positioning of CBs and DG in order to enhance system performance. It is crucial to coordinate and carry out these actions as concurrently as feasible to accommodate the fluctuating energy demands and avoid unnecessary rises in both energy expenses and capital expenditures.

By combining activities of network reconfiguration and optimal placement of CBs and DGs in a unified approach, the proposed methodology offers an effective strategy for improving both the operational efficiency and economic performance of the DN. This simultaneous optimization not only enhances the management of line switches and network states, but also ensures the optimal sizing and placement of devices, leading to more cost-effective and reliable network operation. Figure 4.14 provides a visual depiction of the overall structure of the study, highlighting the key elements of this optimization framework. Because of the inherent cost trade-offs, CE_{sub} and CD are mutually incompatible, implying that achieving of one target automatically prevents the fulfillment of the other. This study is notable for addressing this issue and proposing an approach that promotes an ideal equilibrium between the two.

The aim is to determine the most efficient distribution of resources while maintaining the integrity of both objectives, thereby ensuring that trade-offs are controlled so as to reduce total expenditure. To attain this goal, it is essential to identify the minimum costs (CE_{sub_min} and CD_{min}) that correspond to the lowest total yearly spending (Exp_{tot_min}) in a three-step optimization process:

- Step 1: Minimizing CE_{sub} results in the minimum energy loss cost (CE_{loss_min}), the minimum cost for the energy load (CE_{load_min}), but also the maximum investment cost (CD_{max}). This stage is associated with the implementation of the single objective function 1 (OF_1).
- Step 2: Minimizing CD results in the maximum energy loss cost (CE_{loss_max}) and the maximum of the energy load cost (CE_{load_cost}). This stage pertains to the realization of the single objective function 2 (OF_2).
- Step 3: Optimize the overall cost of yearly expenses related to attaining the multi-objective function 3 (OF_3). The values acquired in the previous phases are used, following a suitable strategy suggested for this purpose, to establish the boundary values of the membership functions. These values serve as inputs to the fuzzy process, enabling the achievement of the highest degree of satisfaction (DS_{max}) in terms of minimizing the total yearly cost.

The study used various optimization techniques, including artificial ecosystem optimization (AEO), Harris Hawks Optimization (HHO), particle swarm optimization (PSO), and moth-flame optimization (MFO), to solve the ONRSACD problem.

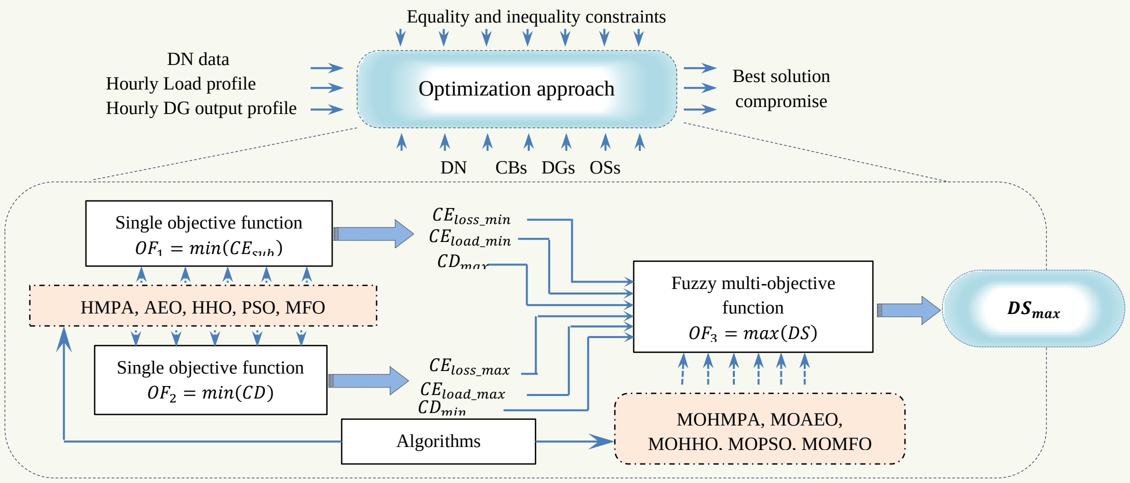


Fig 4.14. Main components of the proposed approach

The algorithms were implemented in single-objective mode and then extended to multi-objective models, i.e. MOHMPA, MOAEO, MOHHO, MOPSO and MOMFO. The single-objective implementations focused on optimizing specific criteria, while the multi-objective implementations aimed to deal with complex trade-offs between conflicting objectives. Comparing the performance of these algorithms in the two contexts enabled a comprehensive evaluation of their effectiveness in solving the ONRSACD problem. The multi-objective implementations were developed within the framework of the fuzzy multi-objective function, which takes into account the inherent trade-offs between energy costs and capital expenditure, resulting in a more balanced and efficient solution.

4.5.2 Optimization problem formulation

The main goal of the network reconfiguration issue, along with the optimal allocation of CBs and DG, is to simultaneously reduce energy prices and investment expenditures. This intricate optimization problem involves many objective functions, each representing different elements of the system's performance, along with an ensemble of necessary equality and inequality constraints. These restrictions ensure that the suggested solutions not only meet the network's technical and operational criteria, but also meet cost considerations. A complex issue of this nature necessitates a refined optimization strategy that carefully balances the often-conflicting goals in order to find a solution that is both economically efficient and technically achievable.

4.5.2.1 Single objective functions

A. Substation energy cost reduction

The first objective function is to minimize the yearly cost of active energy supplied by the substation. It is expressed as follows:

$$OF_1 = min(CE_{sub}) \tag{4.14}$$

Where:

$$CE_{sub} = CE_{loss} + CE_{load} \tag{4.15}$$

- The annual cost of active energy losses

$$CE_{loss} = \frac{1}{Nyr}\left(365K_{Esub} \cdot \sum_{m=1}^{Nyr} PW^m \cdot E_{loss}\right) \tag{4.16}$$

- The annual cost of active energy load demand

$$CE_{load} = \frac{1}{Nyr}\left(365K_{Esub} \cdot \sum_{m=1}^{Nyr} PW^m \cdot E_{load}\right) \tag{4.17}$$

- Daily active energy losses

$$E_{loss} = \sum_{h=1}^{24}\sum_{n=1}^{Nbr} P_{loss}(n)_h \tag{4.18}$$

- Daily reactive energy losses

$$EQ_{loss} = \sum_{h=1}^{24}\sum_{n=1}^{Nbr} Q_{loss}(n)_h \tag{4.19}$$

- Power loss in lines

Figure 4.15 presents a simple radial DN line model.

$$P_{loss}(j,j+1)_h = \left(\frac{P^2(j,j+1)_h + Q^2(j,j+1)_h}{|V_j|_h^2}\right) \cdot R(j,j+1) \tag{4.20}$$

$$Q_{loss}(j,j+1)_h = \left(\frac{P^2(j,j+1)_h + Q^2(j,j+1)_h}{|V_j|_h^2}\right) \cdot X(j,j+1) \tag{4.21}$$

Where

$P_{loss}(j,j+1)_h = P_{loss}(n)_h$, $\qquad Q_{loss}(j,j+1)_h = Q_{loss}(n)_h$

- Daily active energy load demand

$$E_{load} = \sum_{h=1}^{24}\sum_{j=2}^{Nbus} P_{load}(j)_h \tag{4.22}$$

The worth factor [124]. as defined in Equation 4.23, is a crucial tool for cost analysis, combining inflation and interest rates to provide a precise financial picture over time. It helps in assessing

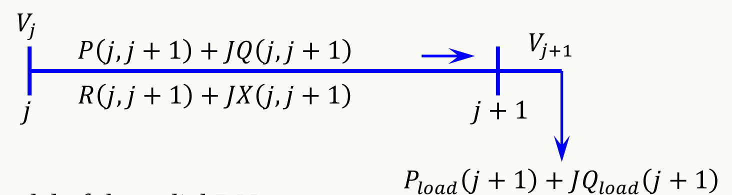


Fig.4.15 Line model of the radial DN

future costs' present value, enabling informed comparisons, and aiding in strategic financial planning by emphasizing the impact of inflation and interest rates on investment choices.

$$PW = \frac{1 + infR}{1 + intR} \tag{4.23}$$

B. Device investment cost minimization

The objective function aims to reduce yearly expenses related to device installation and maintenance, considering both initial costs and long-term operational costs. The function considers factors like device longevity, maintenance frequency, and resource allocation effectiveness. Technical and operational constraints, performance criteria, reliability requirements, and environmental factors also influence the optimization process. The goal is to find a cost-efficient solution that balances initial expenditure with long-term viability, ensuring optimal device performance and minimizing expenses. This objective function is described as follows:

$$OF_2 = min(CD) \tag{4.24}$$

Where:

$$CD = C_{QCB} + C_{DG} + C_{TS} \tag{4.25}$$

- Total CBs investment cost

$$C_{ICB} = C_{QCB} + C_{FCB} \tag{4.26}$$

- Total annual cost of CBs reactive power

$$C_{QCB} = \sum_{i=1}^{Ncb} K_{QCB} \cdot Q_{CBi} \tag{4.27}$$

- Total fixed cost of CBs

$$C_{FCB} = Ncb \cdot K_{FCB} \tag{4.28}$$

- Annual DGs investment cost

$$C_{DG} = A^{UDG} \cdot C_{IDG} + C_{MDG} \tag{4.29}$$

- Total installation cost of DGs

$$C_{IDG} = K_{IDG} \cdot \sum_{i=1}^{Ndg} P_{DGi} \tag{4.30}$$

- Annual operation and maintenance cost of DGs

$$C_{MDG} = \frac{1}{Nyr}\left(365\ K_{EDG} \cdot \sum_{m=1}^{Nyr}\sum_{i=1}^{Ndg}\sum_{h=1}^{24} PW^{m} \cdot P_{DGi,h}\right) \tag{4.31}$$

- Annual TSs investment cost

$$C_{TS} = A^{UTS} \cdot C_{ITS} + A^{URCS} \cdot C_{IRCS} + C_{MTSRCS} \tag{4.32}$$

$$A^{U} = \frac{intR}{1-(1+intR)^{-U}} \quad ; \quad U \in [UDG \quad UTS \quad URCS] \tag{4.33}$$

- Total installation cost of TSs

$$C_{ITS} = \sum_{i=1}^{Nts} L_{TSi} \cdot K_{TS} \tag{4.34}$$

- Total installation cost of remote-controlled switches (RCS)

$$C_{IRCS} = 2 \cdot Nts \cdot K_{RCS} \tag{4.35}$$

- Annual operation and maintenance cost of TSs and RCS

$$C_{MTSRCS} = \sum_{i=1}^{Nts} L_{TSi} \cdot K_{MTS} + 2 \cdot Nts \cdot K_{MRCS} \tag{4.36}$$

The annuity factor A^{U} [125] is a method used to calculate the annual investment cost of devices in electrical distribution networks. It converts a lump-sum investment cost into an equivalent annual expense over the asset's useful life, allowing for a more transparent comparison of investment options. This method also considers interest rates and asset depreciation, ensuring accurate representation of both initial costs and continuous economic consequences throughout the device's operational lifespan.

The annuity factor also aids in evaluating the financial feasibility of investments in different economic situations, such as fluctuations in interest rates or inflation. This approach allows for a more strategic assessment of capital expenditures in electrical distribution networks, considering both current and future currency depreciation.

The annuity factor enhances financial planning by providing a reliable foundation for evaluating investment alternatives, ensuring the selection of the most economically efficient and financially viable options for long-term infrastructure development.

4.5.2.2 Fuzzy multi-objective function

The aim is to determine the optimal compromise between the aforementioned competing expenses. This is described in the following:

$$\min MOF = [CE_{loss}, CE_{load}, CD] \tag{4.37}$$

Equation 4.37 describes an integrated multi-objective optimization technique that addresses three crucial objectives in the global objective function. The fuzzy multi-objective optimization problem requires the definition of a membership function (μ) [126] for each objective function, which specifies the maximum and minimum values of the function. The objective is to maximize the degree of satisfaction (DS) in order to determine the most favorable trade-off solution. In this particular context, it is of utmost importance to meticulously ascertain and modify the range in which the membership functions operate, as this directly impacts the potential values of the objective functions. Adjustments of this nature are critical for achieving equilibrium between exploration and exploitation in the solution space, fostering variety in the obtained solutions and enabling significant compromises between conflicting goals.

To fully utilize the exploratory and exploitative capabilities of each optimization algorithm, this research does not establish predefined upper and lower limits for membership functions. Alternatively, the optimization algorithms dynamically establish these limits, following the approach illustrated in Figure 4.16. This approach exploits the inherent tensions among the various goals and aims to find a middle ground between reducing investment expenses and optimizing operating effectiveness. For example, decreasing capital expenditures generally improves efficiency, but this enhancement has the drawback of increased energy expenditure at substations due to higher energy loss costs. On the other hand, prioritizing the reduction of substation energy requirements can result in increased equipment investment.

The proposed method dynamically balances these competing objectives, ensuring that the optimization process takes into account both short-term and long-term cost implications while balancing capital investment and operational efficiency trade-offs.

When implementing the objective function OF_1, each algorithm generates the most efficient network configuration and also estimates the optimal allocation of DGs and CBs.

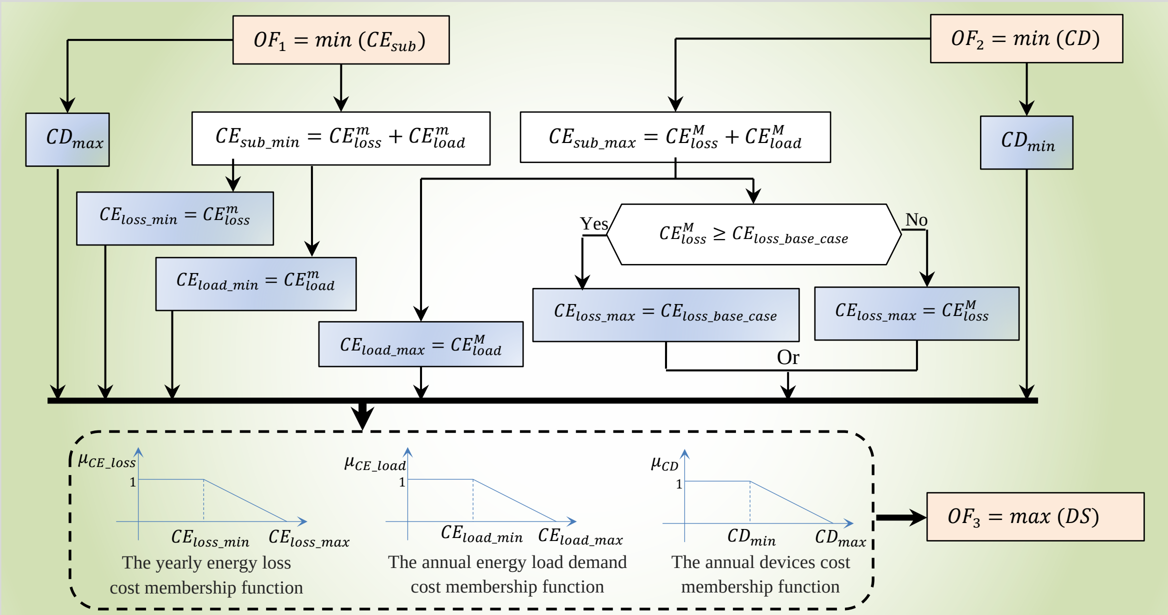


Fig.4.16 The strategy of setting maximum and minimum limits for fuzzy membership functions

An optimal solution to the ONRSACD problem is obtained by minimizing the cost of the energy supplied by the substation, symbolized as CE_{sub} while simultaneously increasing the investment cost for the required equipment, denoted as CD. Following optimization, the resultant value of CD is assigned to CD_{max}, reflecting the highest equipment investment required in this specific setup.

According to Eq. (4.15), the substation's total energy cost is divided into two primary components: energy loss cost CE_{loss} and the load demand cost CE_{load}. In order to assign the outcomes to their respective minimum values i.e., CE_{loss_min} and CE_{load_min} , the algorithm endeavors to minimize these components individually as part of the optimization process. Under the current network configuration and allocation of DGs and CBs, these minimum values represent the lowest achievable costs for energy losses and load demand.

The algorithm's approach, as depicted in Figure 4.16, guarantees that the energy supplied by the substation is optimized for cost efficiency by minimizing the losses incurred and the cost associated with meeting the network's load demand, despite the increase in investment costs. The trade-offs inherent in the optimization process are underscored by the meticulous balance between managing increased equipment investment and minimizing operational energy costs. This reflects the overarching objective of achieving an economically efficient solution for network reconfiguration.

Furthermore, the algorithm generates a solution to the ONRSACD problem that decreases the equipment investment cost (CD) when addressing the objective function OF_2. However, this often results in an increase in the substation's energy cost (CE_{sub}), potentially surpassing its value in the base case scenario. The primary cause of the increase in CE_{sub} is the energy loss cost (CE_{loss}), as the load demand cost (CE_{load}) cannot surpass the base case's measured cost. Operational limits typically fix or restrict load demand costs, while changes in the network configuration are more susceptible to energy losses.

Given that the maximum possible value of CE_{sub_max} is the sum of two components CE_{loss}^{M} and CE_{load}^{M} the algorithm assigns the value of CE_{load}^{M} to CE_{load_max} . For the energy loss component, the algorithm compares CE_{loss}^{M} with the cost of the base case energy losses. If CE_{loss}^{M} exceeds the base case energy loss cost, the algorithm retains the base case value as CE_{loss_max} ensuring that the maximum possible energy loss cost does not exceed the predefined threshold set by the base case scenario.

As a result, attaining objective function OF_1 enables the derivation of CD_{max}, CE_{loss_min} and CE_{load_min}. Conversely, realizing objective function OF_2 facilitates the deduction of CD_{min}, CE_{loss_max} and CE_{load_max} values.

These contrasting outcomes underscore the inherent tradeoffs between managing energy supply costs and minimizing equipment investment. Often, optimizing one objective leads to an increase in the other. This dual-objective framework guarantees that the algorithm maintains or minimizes operational energy costs across the network while simultaneously reducing capital expenditures.

The fuzzy multi-objective optimization is then formulated as follow.

$$OF_3 = \max(DS) \tag{4.38}$$

Where:

$$DS = \min\left(\mu_{CE_{loss}}, \mu_{CE_{load}}, \mu_{CD}\right) \tag{4.39}$$

The membership functions exhibiting fuzziness adhere to the scheme depicted in Figure 4.16 and follow the subsequent formulation:

$$\mu_{CE_{loss}} = \begin{cases} 1\ ; & CE_{loss} \leq CE_{loss\_min} \\ \dfrac{CE_{loss\_max} - CE_{loss}}{CE_{loss\_max} - CE_{loss\_min}}; & CE_{loss\_min} < CE_{loss} < CE_{loss\_max} \\ 0\ ; & CE_{loss} \geq CE_{loss\_max} \end{cases} \tag{4.40}$$

$$\mu_{CE_{load}} = \begin{cases} 1\ ; & CE_{load} \leq CE_{load\_min} \\ \dfrac{CE_{load\_max} - CE_{load}}{CE_{load\_max} - CE_{load\_min}}; & CE_{load\_min} < CE_{load} < CE_{load\_max} \\ 0\ ; & CE_{load} \geq CE_{load\_max} \end{cases} \tag{4.41}$$

$$\mu_{CD} = \begin{cases} 1\ ; & CD \leq CD_{min} \\ \dfrac{CD_{max} - CD}{CD_{max} - CD_{min}}; & CD_{min} < CD < CD_{max} \\ 0\ ; & CD \geq CD_{max} \end{cases} \tag{4.42}$$

In this way, each algorithm endeavors to attain the highest level of satisfaction within the predetermined parameters of its membership function. The total annual expenditure cost is then used to compare the results of the various methods, as outlined in Eq. 4.43. Consequently, the evaluation of the various methods is completed. This comparison allows for a comprehensive assessment of each algorithm's cost efficiency, ensuring the selection of the solution that best balances the competing objectives.

$$Exp_{tot} = CE_{sub} + CD \tag{4.43}$$

4.5.2.3 Constraints

Each of the objective functions reported above is bound by constraints specified in equations (4.44) - (4.55). These constraints must be consistently met throughout the day, taking into consideration fluctuating hourly load and distributed generation (DG) output.

A. Equality constraints

The equations for power balance arise from the classic concept of energy conservation. These considerations apply to the whole system, including both active and reactive power components. The equations establish that the aggregate power input into the system, encompassing contributions from both DGs and CBs, is equivalent to the aggregate power consumption, including power losses. Expressed in the following manner:

$$P_{sub} + \sum_{i=1}^{Ndg} P_{DGi} = \sum_{j=1}^{Nbus} P_{load}(j) + \sum_{n=1}^{Nbr} P_{loss}(n) \tag{4.44}$$

$$Q_{sub} + \sum_{i=1}^{Ncb} C_{CBi} = \sum_{b=j}^{Nbus} Q_{load}(j) + \sum_{n=1}^{Nbr} Q_{loss}(n) \tag{4.45}$$

B. Inequality constraints:

- **Voltage limits**

The following formula determines the limitations on the magnitudes of voltage on all buses.

$$V_{min} \leq V_j \leq V_{max} \quad ; \quad j = 1,2, \dots, N_{bus} \tag{4.46}$$

With, $V_{min} = 0.95\ pu, \quad V_{max} = 1.05\ pu$

- **Line current flow limitations**

It is necessary to consistently maintain all currents transmitted in the lines within their allowed limits.

$$I_n \leq I_n^{max} \quad ; \quad n = 1,2, \dots, Nbr \tag{4.47}$$

- **CBs sizing and location constraints**

The reactive power and location of CBs must be generated in respect of the constraints below:

$$Q_{CB\_min} \leq Q_{CBi} \leq Q_{CB\_max} \ ; \quad i = 1,2, \dots, Ncb \tag{4.48}$$

With, $Q_{CB\_min} = 0, \quad Q_{CB\_max} = 1000\ kvar$

$$Q_{CBi} = S \cdot Q_0 \tag{4.49}$$

$$\sum_{i=1}^{Ncb} Q_{CBi} \leq MAQ \tag{4.50}$$

$$2 \leq LOC_{CBi} \leq Nbus \ , \qquad i = 1,2, \dots, Ncb \tag{4.51}$$

With, $LOC_{CBi} \neq LOC_{CBj}\ ; \quad i,j \in \{1,2, \dots, Ncb\}; \quad i \neq j$

- **DGs constraints**

This study examines photovoltaic (PV) distributed generations (DGs) that inject active power into the electrical distribution network. These DGs share technical characteristics like power capacity, efficiency, and operational behavior. To ensure optimal integration, constraints such as network stability, voltage limits, line capacity, and power flow restrictions must be considered. The location and size of DGs must be strategically chosen to avoid overloading the network and minimize energy losses. Accurate forecasting of DG output and system reliability must also be considered, considering variations in solar irradiance, seasonal fluctuations, and weather conditions. The active power and location of DGs must be provided according to the following constraints:

$$P_{DGmin} \leq P_{DGi} \leq P_{DGmax} \ ; \quad i = 1,2,\dots,Ndg \tag{4.52}$$

With, $P_{DGmin} = 100\ kw$, $P_{DGmax} = 1000\ kw$

$$\sum_{i=1}^{Ndg} P_{DGi} = PR \cdot MAP \ ; \quad 0.1 \leq PR \leq 0.6 \tag{4.53}$$

$$2 \leq LOC_{DGi} \leq Nbus \ ; \qquad i = 1,2,\dots,Ndg \tag{4.54}$$

With, $LOC_{DGi} \neq LOC_{DGj}$; $\quad i,j \in \{1,2,\dots,Ndg\}$; $\quad i \neq j$

- **Switch opening and radiality constraints**

The reconfiguration process involves adjusting tie switches (TSs) and open switches (OSs) while adhering to radiality check constraints. This ensures the network remains free of loops, simplifying power flow analysis and fault isolation. The Depth-First Search (DFS) algorithm manages this process by systematically traversing the network, identifying potential cycles, and ensuring power is supplied without violating the radial structure. Maintaining a radial configuration is crucial for protection coordination, fault detection, and service restoration. The reconfiguration process, guided by the DFS algorithm, optimizes power flows, reduces energy losses, improves voltage profiles, and balances load across the network. These adjustments enhance the efficiency and reliability of the electrical distribution system while ensuring operational constraints, such as thermal limits and voltage stability, are not compromised. Strategic reconfiguration of TSs and OSs can improve the integration of distributed generation, optimize the network's response to load and generation fluctuations, and achieve cost savings through more efficient energy distribution. The overall process is governed by the following formulas.

$$2 \leq OSi \leq Nbr + Nts \quad ; \quad i = 1,2,\dots,Nts \tag{4.55}$$

With, $OSi \neq OSj$; $\quad i,j \in \{1,2,\dots,Nts\}$; $\quad i \neq j$

With, number of loops = 0 and number of isolated nodes = 0

4.5.2.4 HMPA implementation for solving the ONRSACD problem

The Hybrid Multi-Population Algorithm (HMPA) is implemented to tackle the ONRSACD problem, with the primary goal of achieving a balance between minimizing energy costs and reducing equipment investment expenditures. The HMPA is particularly well-suited for this complex, multi-objective optimization problem due to its ability to handle conflicting objectives, explore diverse solutions across multiple populations, and effectively combine exploration and exploitation strategies.

The implementation of HMPA begins by generating several initial populations, each representing a potential configuration of the distribution network, including the placement of DGs and CBs. Each population focuses on optimizing key elements of the problem, such as network reconfiguration, DG placement, or CB allocation, allowing for parallel exploration of the solution space while maintaining diversity among potential solutions. Throughout the optimization process, HMPA leverages cross-population interactions to exchange information and enhance the overall search process. This hybridization approach allows the algorithm to escape local optima, ensuring that it effectively navigates the highly non-linear and multi-modal nature of the ONRSACD problem. Additionally, adaptive mechanisms within HMPA adjust key parameters dynamically, such as crossover and mutation rates, to maintain a balance between intensifying the search around promising solutions and exploring new regions of the solution space.

The implementation also includes a radiality check for each network configuration to ensure that the radial structure of the distribution network is preserved. This is achieved through the DFS algorithm, which verifies that no closed loops are formed, maintaining the simplicity and reliability of the radial topology. Furthermore, the algorithm evaluates each candidate solution based on the overall annual expenditure cost, including energy losses, substation energy costs, and investment costs for equipment. The HMPA assigns different objective functions to the populations to address these conflicting objectives, ensuring a comprehensive exploration of the trade-offs between energy and investment costs.

The HMPA's dynamic balance of exploration and exploitation, combined with its multi-population structure, makes it a robust tool for solving the ONRSACD problem. The result is an optimal or near-optimal configuration of the distribution network, with strategic placement of DGs and CBs that maximizes techno-economic benefits while adhering to operational constraints.

The pseudo-code of the HMPA for ONRSACD problem

Input: Read the system data.
Output: Optimal parameters of OS, CB and DG.
Initialization:
% Assign the parameters of the HMPA
$Npop$: Number of populations
Max_it: Maximum number of iterations
% Problem initializing

1. Define the objective function $f(\vec{X})$; $f(\vec{X}) \in \{OF_1, OF_2, OF_3\}$; $\vec{X} = [x_1, \dots, x_D]$
2. Set the lower bound $(\overrightarrow{Lb})$ and upper bound $\overrightarrow{Ub}$ vectors of control variables.
3. A population of $Npop$ individuals is represented by a matrix:

$$X^{It} = \left[\vec{X}_1^{It}, \vec{X}_2^{It}, \dots, \vec{X}_{Npop}^{It}\right]^T = \begin{bmatrix} x_{1,1}^{It} & x_{1,2}^{It} & \cdots & x_{1,D}^{It} \\ x_{2,1}^{It} & x_{2,2}^{It} & \cdots & x_{2,D}^{It} \\ \vdots & \vdots & \ddots & \vdots \\ x_{Npop,1}^{It} & x_{Npop,2}^{It} & \cdots & x_{Npop,D}^{It} \end{bmatrix} \quad (4.56)$$

Each $\vec{X}_i (i = 1, \dots, Npop)$ represents a solution vector of the ONRSACD problem variables and is expressed as follows:

$$\begin{cases} \vec{X}_i = \begin{bmatrix} OS_1, \dots, OS_{Nts}, LOC_{DG,1}, \dots, LOC_{DG,Ndg}, P_{DG,1}, \dots, P_{DG,Ndg}, \\ LOC_{CB,1}, \dots, LOC_{CB,Ncb}, Q_{CB,1}, \dots, Q_{CB,Ncb}, PR \end{bmatrix}; \\ i = 1, \dots, Npop \end{cases} \quad (4.57)$$

In the HMPA each individual of the population is randomly initialized using the $unifrmd$ function:

$$\vec{X}_i = unifrmd(Lb, Ub); i = 1, \dots, Npop \quad (4.58)$$

4. Check for limits and constraints violation and repairing
5. For each solution vector run power flow computation and compute the objective function value
6. Divide the population into three sub-populations as explained in section 3.9.3.1
7. Find the local best of each sub-population and set the current iteration $It = 1$

% Main loop:

8. $While\ (It < Max\_It)\ do$

% For sub_pop1

9. Update $\vec{X}_i$ in sub_pop1 using the $unifrmd$ function as follows:
   $\vec{X}_i = unifrmd(Lb, Ub); i = 1, \dots, length(sub\_pop1)$
10. Check for limits constraints violation and repairing
11. For each solution vector run power flow computation and compute the objective function value

39. Check for limits and constraints violation and repairing
40. For each solution vector run power flow computation and compute the objective function value.

% For sub_pop3

41. $For\ i = 1: length(sub\_pop3)$
42. $If\ rand < 0.5$
43. Update $\vec{X}_i$ in sub_pop3 by AEO
44. $Else$
45. Update $\vec{X}_i$ in sub_pop3 by HHO
46. $End\ if$
47. Check for limits and constraints violation and repairing.
48. For each solution vector run power flow computation and compute the objective function value.
49. Apply the greedy selection
50. $If\ rand < 0.5$

12. Apply the greedy selection
13. Generate quazi-opposite position of $\vec{X}_i$ in sub_pop1
14. Check for limits and constraints violation and repairing
15. For each solution vector run power flow computation and compute the objective function value.
16. Apply the greedy selection
17. Find the local best in sub_pop1
18. Run CLS on the local best of sub_pop1
19. Check for limits and constraints violation and repairing
20. For each solution vector run power flow computation and compute the objective function value

% For sub_pop2

21. $For\ i = 1: length(sub\_pop2)$
22. $If\ rand < 0.5$
23. Update $\vec{X}_i$ in $sub_pop2$by AEO
24. $Else$
25. Update $\vec{X}_i$ in sub_pop2 by HHO
26. $End\ if$
27. Apply the greedy selection
28. $If\ rand < 0.5$
29. Update $\vec{X}_i$ in sub_pop2 by LF method
30. $Else$
31. Update $\vec{X}_i$ in sub_pop2 by LS method
32. $End\ if$
33. Check for limits and constraints violation and repairing
34. For each solution vector run power flow computation and compute the objective function value.
35. Apply the greedy selection
36. $End\ for$
37. Find the local best in sub_pop2
38. Run CLS on the local best of sub_pop2

51. Update $\vec{X}_i$ in sub_pop3 by LF method
52. $Else$
53. Update $\vec{X}_i$ in sub_pop3 by LS method
54. $End\ if$
55. Check for limits and constraints violation and repairing.
56. For each solution vector run power flow computation and compute the objective function value
57. Apply the greedy selection
58. $End\ for$
59. Find the local best in sub_pop3
60. Run CLS on the local best of sub_pop3
61. $if\ mod(It, H) == 0$
62. % For sub_pop1
63. Find the local best in sub_pop1
64. $if\ rand < 0.5$
65. Transfer the local best of sub_pop1 to sub_pop2
66. $Else$
67. Transfer the local best of sub_pop2 to sub_pop3
68. $End\ if$
69. % For sub_pop2
70. $If\ lenght(sub\_pop2) > MNM$ % $lenght(sub\_pop2) = NM$
71. Transfer solution in sub_pop2 with $counter\ > Thr$ to sub_pop1
72. $End\ if$
73. $If\ lenght(sub\_pop3) > MNM$ % $lenght(sub\_pop3) = NM$
74. Transfer solution in sub_pop3 with $counter\ > Thr$ to sub_pop1
75. $End\ if$
76. Find the global best solution of the three sub-populations
77. $It = It + 1$
78. $End\ while$
79. Return the global best solution.

4.5.3. Simulation results and discussions

The suggested methodology is evaluated using IEEE 33-bus and IEEE 69-bus balanced radial DNs. The fundamental architecture and parameters of these networks are shown in Figures 20, 24, and Table 4.4, respectively. All algorithms are executed using the MATLAB program. Calculation of power flow is accomplished using the backward/forward sweep method.

Table 4.4. Test systems parameters

Parameters		**33-bus system**					**69-bus system**				
EP_{loss} (KWh/24h)		3663.178					3941.021				
EQ_{loss} (KWh/24h)		2480.2467					1790.2355				
V_{min} (24h)		0.9045					0.9091				
V_{max} (24h)		1					1				
OS		33,34,35,36,37					69, 70, 71, 72, 73				
TS Length (Km)	Branch	33	34	35	36	37	69	70	71	72	73
	length	4	8	10	6	5	5	8	7	8	8
Annual expenditures ($/year)		1180267.8255					1213261.6093				
Location of different customers											
Residential		1 to 7, 12 to 18, 28 to 32					1 to 15, 19,23,25 to 29, 49,50,53 to57, 60 to 63, 51, 52,36 to 41,45,46				
Industrial		19 to 22					68, 69, 33 to 55, 66,67				
Commercial		10, 11, 24, 26					22, 24, 30 to 32, 42				
Educational institution		8, 25, 27					16, 17, 18, 58, 59, 43				
Sanatorium		9, 23, 33					20, 21, 47, 48				

Table 4.5. Algorithms parameters

Algorithm	**Parameter**	**Value**
HMPA	THr	100
	H	5
	MNM	10
	k	10
	$CP1$ and $CP2$	0.5
	ρ, δ and L	$rand$
AEO	r_1, r_2 and r	$rand$
	h	$2 \times rand - 1$
HHO	r_1, r_2, r_3, r_4, and q	$rand$
	E_0	$(-1,1)$
	J	$2 \times (1 - rand)$
MFO	Spiral constant	1
	Converge constant	-1 to -2
	Number of flames	$N - l \times \frac{N-1}{T}$
PSO	W_{max}	0.9
	W_{min}	0.2
	C_1 and C_2	2
	v_{max}	$v_{max} = (Ub - Lb) \times 0.2$
	v_{min}	$v_{min} = -V_{max}$

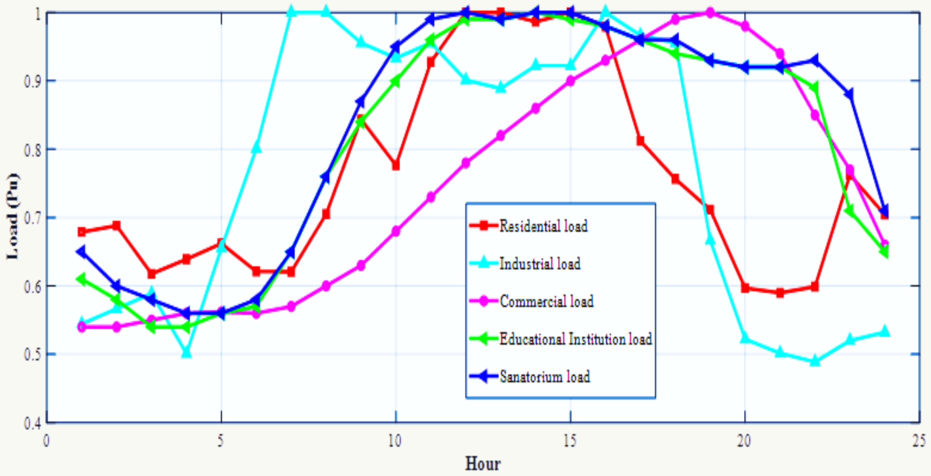


Fig.4.17. The hourly variations of different categories of loads.

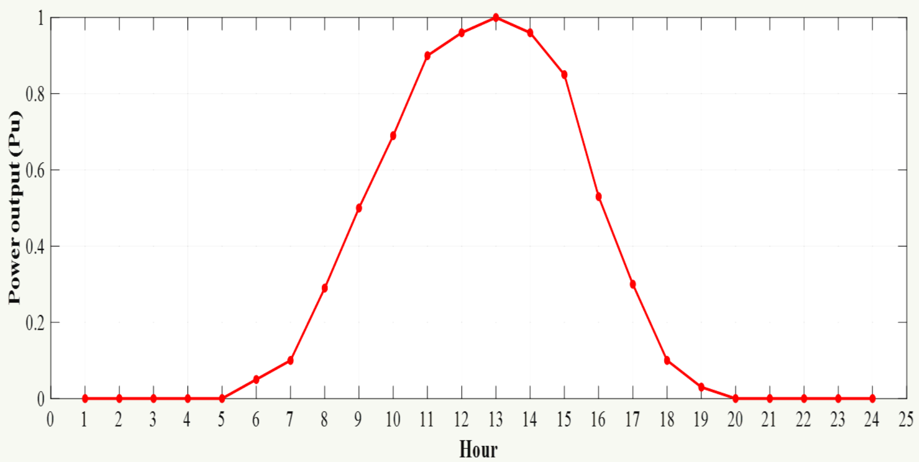


Fig.4.18. The hourly variations of DG output.

Figure 4.17 illustrates the use of many hourly profiles in this research to enhance realism and account for hourly load fluctuations. These profiles include five different load ranges: residential, commercial, industrial, educational institution, and health sector-related. The proposed approach additionally considers the hourly fluctuations in DG outputs, as seen in Figure 4.18. Table 4.5 presents the parameter values corresponding to each method in their respective settings. These settings are the default parameters recommended by the authors in the original research. Drawing from reference [110], the present work has established a predetermined threshold of 1000 for the maximum number of iterations (Max_It) and 50 for the population ($Npop$).

4.5.3.1. The 33-bus network

The single-line diagram of this test system is shown in Fig.4.23. It includes 32 normally closed branches, three laterals, and five normally OSs with $MAP = 3.7MW$ and $MAQ = 2.3MVAr$ at the base values 100 MVA and 12.66 KV.

A. Objective function 1

Table 4.6. illustrates the ONRSACD problem's outcomes for the 33-bus test system, with an emphasis on CE_{sub} reduction. The HMPA algorithm effectively reduces CE_{sub} from 1180267.82 \$/year in the base case to 876276.0539 \$/year after optimization. In addition, the algorithm accomplishes a minimum E_{sub} of 53814.1334 kWh over a 24-hour period, as well as a minimum CE_{loss} of 19129.77 \$/year and a minimum E_{loss} of 1174.80 kWh over 24 hours. As compared to the results achieved by AEO, HHO, MFO, and PSO, these optimized values are lower, proving that the HMPA algorithm performs better in this case.

Additionally, the HMPA algorithm generates the maximum annual equipment investment cost CD of 584310.92\$/year. The algorithm has made a strategic investment decision, justifying an increase in capital expenditure through a substantial reduction in the operational energy cost CE_{sub}. The algorithm achieves overall cost effectiveness by balancing this trade-off.

Figure 4.19. displays the convergence curves for all the optimization techniques examined. It is evident that the HMPA algorithm exhibits a faster convergence rate compared to the other approaches, therefore emphasizing its effectiveness in achieving an optimum solution.

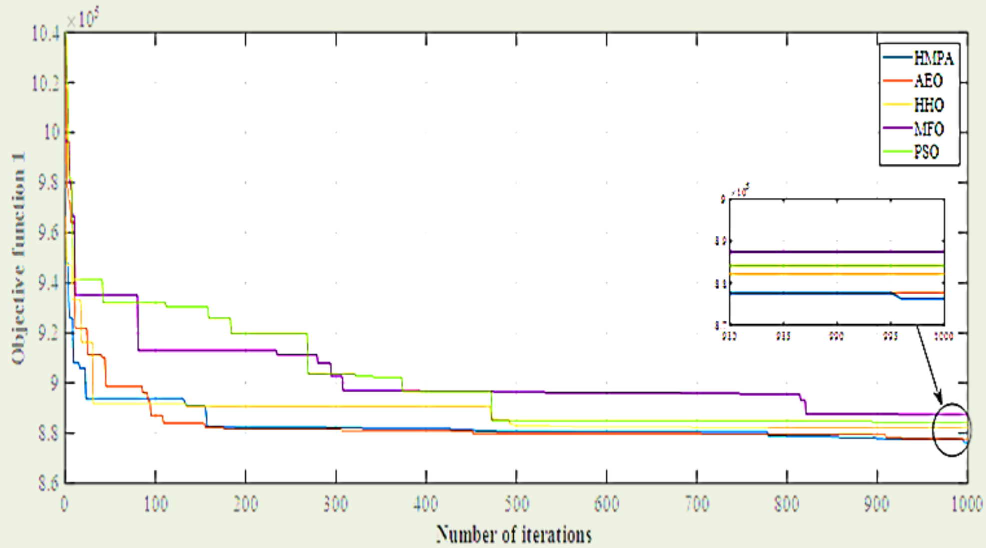


Fig.4.19. Convergence curves for OF_1_33_bus DN

Table 4.6. Optimization outcomes for OF_1_33-bus DN

	OS	LOC_{DG}	DG Size (KW)	LOC_{CB}	CB Size (KVAR)	E_{loss} (KWh)	EQ_{loss} (KVARh)	PR	E_{sub} (KWh/24h)	E_{load} (KWh/24h)	CD ($/year)	CE_{sub} ($/year)	CE_{load} ($/year)	CE_{loss} ($/year)
Base case	33													
	34													
	35					3663.178	2480.2467		72482.9692	68819.7912		1180267.82	1120618.9014	59648.9241
	36													
	37													
HMPA	8	5	573.8255	14	50									
	13	10	285.7581	15	300									
	28	13	214.1905	30	800	**1174.8032**	903.8917	**0.59992**	**53814.1334**	52639.3302	**584310.9207**	**876276.0539**	857146.2856	**19129.7682**
	32	31	705.4216	22	200									
	7	3	449.5179											
AEO	32	16	151.8069	6	250									
	7	9	316.4295											
	28	32	577.5352	30	450	1253.0252	912.1887	0.59969	53898.7207	52645.6954	514385.0117	877653.4202	857249.9332	20403.487
	10	23	575.1418	31	450									
	34	12	606.9235	22	200									
HHO	11	18	398.7243	11	300									
	7	29	652.0512	24	200									
	34	31	419.2135	27	250	1540.5755	1093.1602	0.59994	54179.455	52638.8795	460968.6093	882224.7253	857138.9472	25085.7781
	28	33	610.5358	13	250									
	36	8	148.251	25	400									
MFO	28	15	482.1752	9	200									
	33	19	219.6897	13	50									
	36	23	345.5892	25	250	1829.2652	1338.9798	0.59881	54498.6457	52669.3805	492888.3947	887422.2283	857635.6061	29786.6222
	14	26	623.4503	31	400									
	8	8	553.6701	18	450									
PSO	6	7	667.3822	3	200									
	28	15	264.1126	28	300									
	8	19	397.0561	21	150	1630.32	1695.7176	0.59894	54296.108	52665.7879	583859.3616	884124.2291	857577.1062	26547.1229
	12	25	441.4293	30	450									
	30	23	455.0892	16	300									

Furthermore, although the HMPA, AEO, and HHO approaches all yield positive results in terms of decreasing substation energy costs CE_{sub} and its related components (i.e. E_{loss}, CE_{loss}, and E_{sub}) in comparison to the base case scenario, the main objective of the HMPA algorithm is to minimize CD. Thus, although the CE_{sub} and its associated elements have been enhanced, the decrease in CE_{sub} is not completely optimal, as it reflects the compromise between limiting capital expenditures and lowering operating expenses.

Figure 4.20 displays the convergence curves for all optimization techniques. The HMPA method distinguishes itself by demonstrating a notably accelerated convergence compared to the other algorithms, characterized by a smooth and stable curve that ensures steady advancement towards the best solution. These results illustrate the effectiveness of the HMPA approach in rapidly identifying a cost-efficient solution, therefore establishing it as a pragmatic option for real-time optimization challenges.

Figures 4.22 and 4.23 depict the voltage profile and network topology, respectively, of the optimum solution obtained using the HMPA technique. Despite the focus on decreasing CD, the network structure emphasizes the redesigned topology that reduces losses and boosts operating efficiency, while the voltage profile displays a better and more stable distribution of voltage levels throughout the network.

B. Objective function 2

Table 4.7 includes the results of the ONRSACD optimization problem, which was designed to reduce the equipment investment cost CD of the 33-node test system. The HMPA method yields an optimal solution with a minimum CD value of 584,310.92 $/year, significantly lower than the results from other algorithms including AEO, HHO, MFO, and PSO. HMPA is a highly effective approach for addressing this specific objective due to its superior performance in attaining the lowest investment cost among these methods.

Furthermore, although the HMPA, AEO, and HHO approaches all yield positive results in terms of decreasing substation energy costs CE_{sub} and its related components (i.e. E_{loss}, CE_{loss}, and E_{sub}) in comparison to the base case scenario, the main objective of the HMPA algorithm is to minimize CD. Thus, although the CE_{sub} and its associated elements have been enhanced, the

decrease in CE_{sub} is not completely optimal, as it reflects the compromise between limiting capital expenditures and lowering operating expenses.

Figure 4.20 displays the convergence curves for all optimization techniques. The HMPA method distinguishes itself by demonstrating a notably accelerated convergence compared to the other algorithms, characterized by a smooth and stable curve that ensures steady advancement towards the best solution. These results illustrate the effectiveness of the HMPA approach in rapidly identifying a cost-efficient solution, therefore establishing it as a pragmatic option for real-time optimization challenges.

Figures 4.22 and 4.23 depict the voltage profile and network topology, respectively, of the optimum solution obtained using the HMPA technique. Despite the focus on decreasing CD, the network structure emphasizes the redesigned topology that reduces losses and boosts operating efficiency, while the voltage profile displays a better and more stable distribution of voltage levels throughout the network.

Finally, Table 4.10 presents a thorough commercial evaluation of the costs associated with the device used in the execution of the HMPA algorithm. This study provides meaningful insights into the financial viability of the optimized network topology, demonstrating the equilibrium between initial investment expenses and long-term operating cost reductions. The findings highlight the practical use of the HMPA approach, not only in reducing CD, but also in guaranteeing a financially feasible solution that is in line with the distribution network's techno-economic objectives.

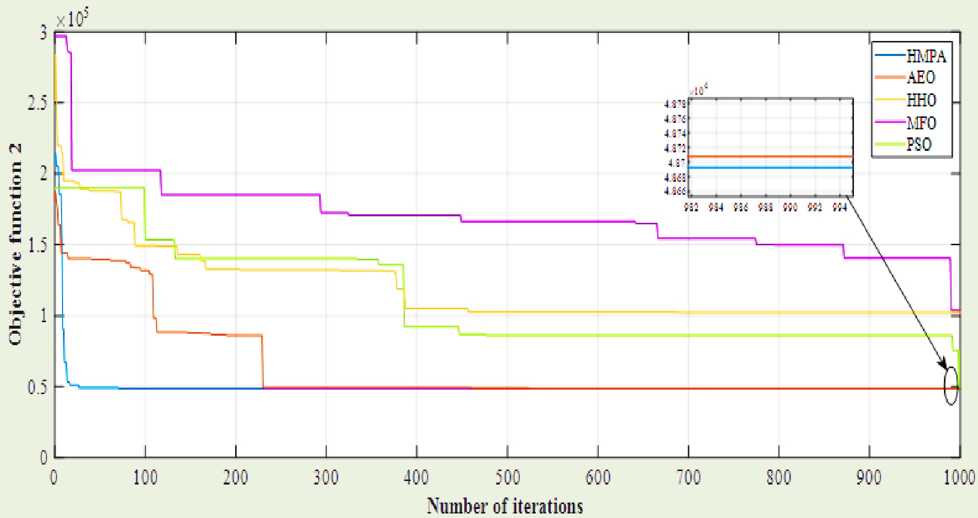


Fig.4.20. Convergence curves for OF_2_33-node DN

Table 4.7. Optimization outcomes for OF_2_33-node

	OS	LOC_{DG}	DG Size (KW)	LOC_{CB}	CB Size (KVAR)	E_{loss} (KWh)	EQ_{loss} (KVARh)	PR	E_{sub} (KWh/24h)	E_{load} (KWh/24h)	CD ($/year)	CE_{sub} ($/year)	CE_{load} ($/year)	CE_{loss} ($/year)
Base case	33													
	34													
	35					3663.178	2480.2467		72482.9692	68819.7912		1180267.8255	1120618.9014	59648.9241
	36													
	37													
HMPA	33	9	92.5536	11	50									
	34	20	39.4605	17	50									
	35	26	72.3369	22	50	2714.2079	1779.4547	0.1	71533.999	66647.1613	**48693.0373**	1129437.6232	1085241.1412	44196.4819
	36	30	114.7061											
	37	18	52.5399	5	50									
AEO	34	8	72.7394	33	100									
	35	12	83.499											
	36	19	56.5625	9	50	2560.1527	1686.6469	0.1	71379.9439	66122.6047	48707.0511	1118387.5277	1076699.5853	41687.9424
	37	27	84.813	30	50									
	33	20	73.8994	28	50									
HHO	14	13	93.3195	32	50									
	34	17	70.4633	15	50									
	35	25	63.5345	21	50	11845.9269	10544.6942	0.1001	80665.7181	66581.3551	102291.4345	1277061.3376	1084169.5929	192891.7446
	37	30	87.7943	29	50									
	33	4	56.7475											
MFO	36	3	53.4820	16	50									
	34	9	143.2355	9	50									
	3	15	57.2880	10	50	7180.729	5402.8063	0.11961	73814.3453	66633.6162	103698.0064	1201947.1305	1085020.5815	116926.5489
	35	29	101.1066	21	50									
	33	11	89.2493	23	100									
PSO	33	4	74.5054	11	50									
	34	17	76.9928	13	50									
	35	18	80.5198	21	50	2637.2575	1726.2303	0.10201	68705.6568	66068.3992	49683.4056	1118760.4076	1075816.9379	42943.4697
	36	28	51.942	31	50									
	37	2	95.0197	10	50									

C. Objective function 3

In accordance with the approach outlined in Section 4.5.2.2, Table 4.8 displays the boundary values of the membership functions for each algorithm. The boundary values play a critical role in determining the bounds within which the membership functions work, therefore impacting the compromises between competing goals throughout the optimization procedure. Table 4.9 provides a summary of the outcomes of the fuzzy multi-objective ONRSACD optimization problem on the 33-bus test system. In order to achieve an ideal trade-off between CE_{loss}, CE_{load}, and CD, the optimization procedure seeks to reduce three conflicting cost components. As described in Equation (4.43), the compromise solution is determined by the minimal value of the total yearly spending Exp_{tot}.

Table 4.8. Membership functions limits for OF_3_33-node

Objective function	Limits	HMPA	AEO	HHO	MFO	PSO
OF_1	CE_{sub_min}	876276.0539	877653.4202	882224.7253	887422.2283	884124.2291
	CE_{load_min}	8574146.2856	857246.9332	857138.9472	857635.6061	857577.1062
	CE_{loss_min}	19129.7682	20403.487	25085.7781	29786.6222	26547.1229
	CD_{max}	584310.9207	514385.0117	460968.6093	492888.3947	583859.3616
OF_2	CD_{min}	48693.0373	48707.0511	102291.4345	103698.0064	49683.4056
	CE_{sub_max}	1129437.6232	118387.5277	1277061.3376	1201947.1305	1118760.4076
	CE_{load_max}	1085241.1412	1076699.5853	1084169.5929	1085020.5815	1075816.9379
	CE_{loss_max}	44196.4819	41687.9424	59648.9241	59648.9241	42943.4697

The MOHMPA (Multi-Objective Hybrid Multi-Population Algorithm) technique attains the minimum expense Exp_{tot} value of 1319627.56 $/year. The acquired outcome is notably inferior to those achieved by the other algorithms, namely MOAEO, MOHHO, MOMFO, and MOPSO. The MOHMPA approach clearly demonstrates better performance by not only reducing the overall spending but also more precisely balancing the trade-offs between the opposing goals, leading to reduced additional costs compared to the other techniques.

Figure 4.21 depicts the convergence curves for all the applied techniques. The MOHMPA approach exhibits accelerated convergence, efficiently achieving an optimum solution ahead of the other algorithms.

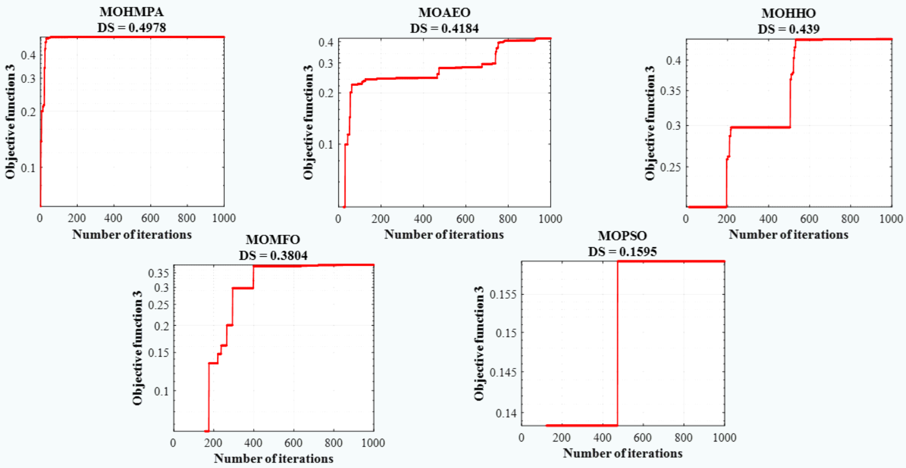


Fig.4.21. Convergence curves for OF_3_33-node DN

A smooth and steady curve distinguishes the convergence of the approach, indicating its effective navigation of the solution space and avoidance of oscillations or premature convergence. The voltage profile and network architecture of the optimal solution determined using the MOHMPA approach are shown in Figures 4.22 and 4.23, respectively.

The voltage profile across the network exhibits enhanced voltage stability, with minimal deviations from nominal values, ensuring the redesigned network operates within acceptable voltage thresholds. The analysis of the network topology reveals an optimal arrangement that maximizes energy efficiency and improves power dispersion, resulting in a further reduction in operating expenses.

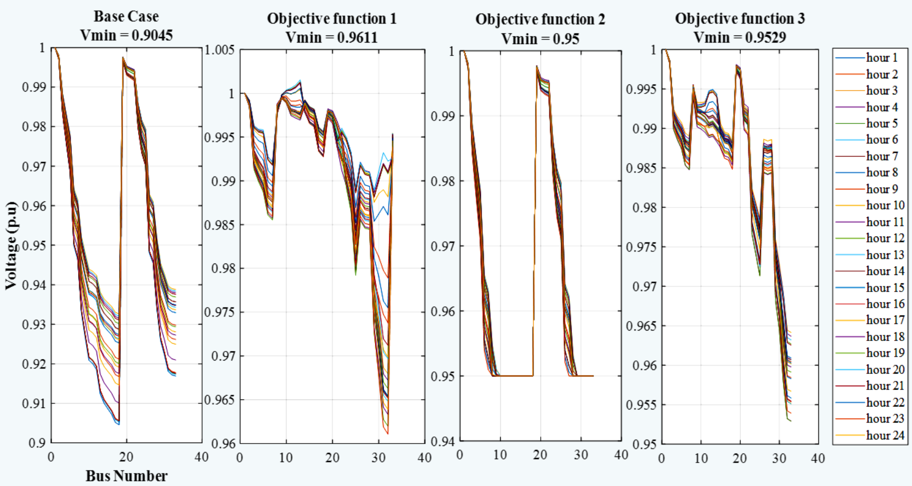


Fig.4.22. Voltage profile for the 33-node before and after ONRSACD via the HMPA

Table 4.9. Fuzzy multi-objective optimization results for OF_3_33-node

	OS	LOC_{DG}	DG Size (KW)	LOC_{CB}	CB Size (KAVAR)	E_{loss} (KWh)	EQ_{loss} (KVARh)	PR	E_{sub} (KWh/24h)	E_{load} (KWh/24h)	CD ($/year)	CE_{sub} ($/year)	CE_{load} ($/year)	CE_{loss} ($/year)
Base case	33													
	34													
	35					3663.178	2480.2467		72482.9692	68819.7912		1180267.8255	1120618.9014	59648.9241
	36													
	37													
MOHMPA	7	14	53.1741	23	200									
	28	25	293.2804	13	250									
	35	31	393.1728	2	50	1857.9718	1346.553	0.3391	61532.0161	59674.0442	**317678.2789**	1001949.2798	**971695.2165**	**30254.0633**
	36	12	289.704	21	150									
	14	7	230.4134	28	100									
MOAEO	7	10	214.3326	17	100									
	36	14	258.9413	18	100									
	11	23	225.052	8	100	1775.2361	1263.484	0.30913	62257.3945	60482.1584	319344.5141	1013760.8938	984854.0478	28906.8459
	28	33	261.9412	15	150									
	34	29	188.1671	32	250									
MOHHO	7	3	194.3982	7	300									
	11	2	259.5294	12	50									
	28	23	174.9691	30	100	2280.6713	1721.2869	0.30995	62740.9544	60460.2830	303491.4492	1021634.8837	984497.8432	37137.0405
	36	25	231.86	28	100									
	35	15	290.6908	22	150									
MOMFO	14	10	147.8886	16	100									
	29	14	305.3902	6	150									
	7	17	221.7556	22	100	2753.0238	2989.5618	0.27805	64073.6884	61320.6646	344833.9532	1043336.3003	998507.7645	44828.5358
	33	25	76.6929	26	150									
	37	29	281.2101	9	150									
MOPSO	7	3	225.0345	10	150									
	28	4	200.9303	30	550									
	13	6	887.6029	22	100	2350.3506	2404.9605	0.42407	61820.6599	59470.3093	498679.7492	1006649.3782	968377.7232	38271.655
	21	13	522.9601	18	150									
	31	11	338.8826											

Exp_{tot} ($/year)					
Base case	MOHMPA	MOAEO	MOHHO	MOMFO	MOPSO
1180267.8255	**1319627.559**	1333105.408	1325126.333	1388170.2536	1505329.127

Additional expenditures exceeding the base case Exp_{tot} ($/year)				
MOHMPA	MOAEO	MOHHO	MOMFO	MOPSO
139359.7335	152837.5825	144858.5075	207902.4281	325061.3015

Table 4.10 displays a comprehensive commercial cost analysis of the devices used in the MOHMPA algorithm's final solution. The present study emphasizes the financial viability of the optimized network by demonstrating that the algorithm not only reduces Exp_{tot} but also guarantees that the capital expenditure needed for network reconfiguration and device placement is economically efficient. The findings emphasize the MOHMPA approach's capacity to provide a strong and economically feasible solution, effectively managing both technical efficiency and financial factors.

Table 4.10. The device commercial cost analysis for the HMPA final solution (33-node)

	Device cost	OF_1	OF_2	OF_3
CBs cost	C_{ICB} ($)	4675	4100	5375
	C_{QCB} ($/year)	675	100	375
	C_{FBC} ($)	4000	4000	5000
DGs cost	C_{DG} ($)	291444.4349	48593.0373	164734.3082
	$A^{UDG} \cdot C_{IDG}$ ($/year)	97872.7177	16318.4883	55320.9892
	C_{MDG} ($/year)	193571.7172	32274.5489	109413.319
TSs cost	C_{TS} ($/year)	292191.4857	0	152568.9707
	$A^{UTS} \cdot C_{ITS}$ ($/year)	251576.923	0	129600.2330
	$A^{URCS} \cdot C_{IRCS}$ ($/year)	22614.5626	0	13568.7376
	C_{MTSRCS} ($/year)	18000	0	9400

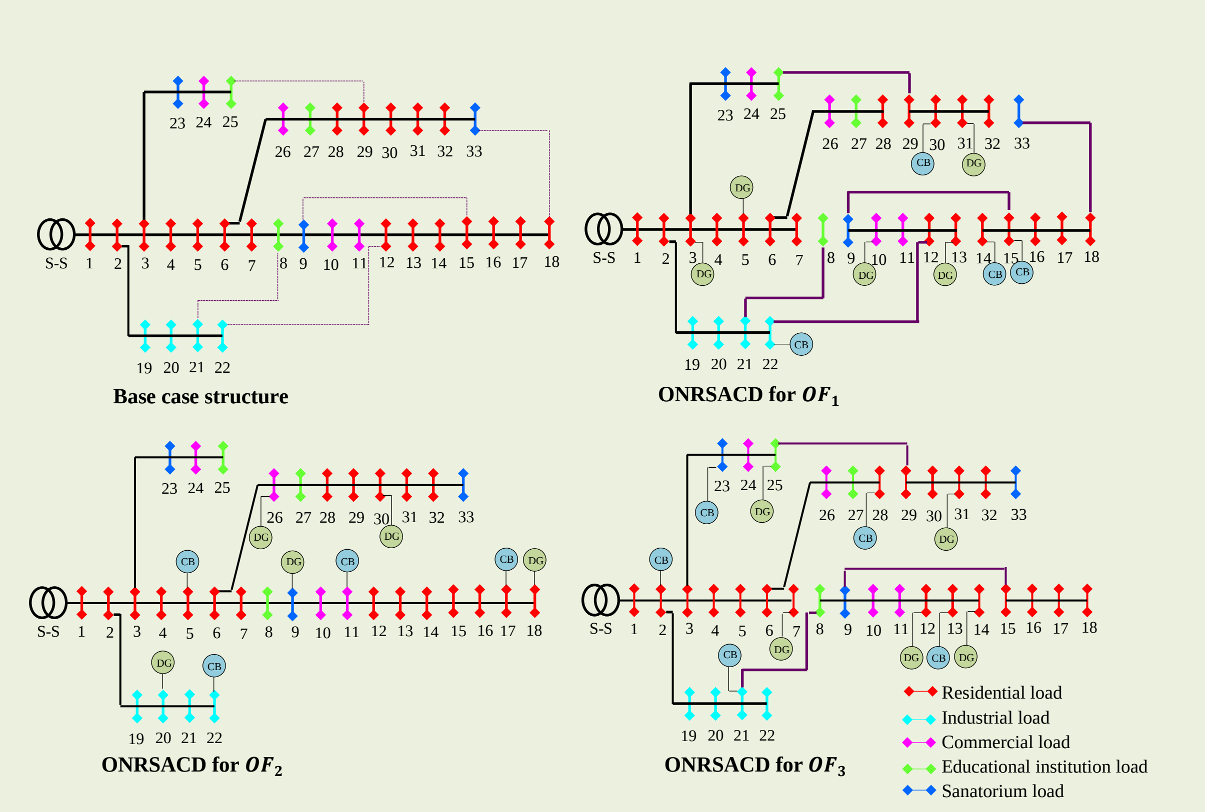


Fig.4.23. The 33-bus DN configuration before and after the ONRSACD via the HMPA

4.5.3.2. The 69-bus network

Figure 4.28 displays the single-line diagram of the test system. The system consists of 68 usually closed branches, seven lateral branches, and five OSs. The system's fundamental values are 100 MVA and 12.66 KV, with a MAP of 3.8 MW and a MAQ of 2.69 MVAr. The load and line data of the test network are provided in reference [120].

A. Objective function 1

Table 4.11 presents the results of implementing the ONRSACD optimization problem on the 69-bus test system. The goal was to reduce CE_{sub}. The HMPA optimization methods successfully reduced the CE_{sub} from 1213261.61 $/year in the base case to 900212.25 $/year. The HMPA has achieved a minimum E_{sub} of 55284.11 kWh over a 24-hour period, a minimum CE_{loss} of 20275.36 $/year, and a minimum E_{loss} of 1,245.16 kWh/24h, in addition to this substantial cost reduction. These optimized values outperform those obtained using the AEO, HHO, MFO, and PSO methods.

HMPA adopts a balanced approach, in contrast to other methods that prioritize minimizing CD (equipment investment cost) but produce suboptimal results with respect to CE_{sub} and its related components (i.e. E_{loss}, CE_{loss}, and E_{sub}). It ensures that the investment in devices does not result in disproportionate expenditure by prioritizing the minimization of the primary objective function CE_{sub} while maintaining a relatively modest CD.

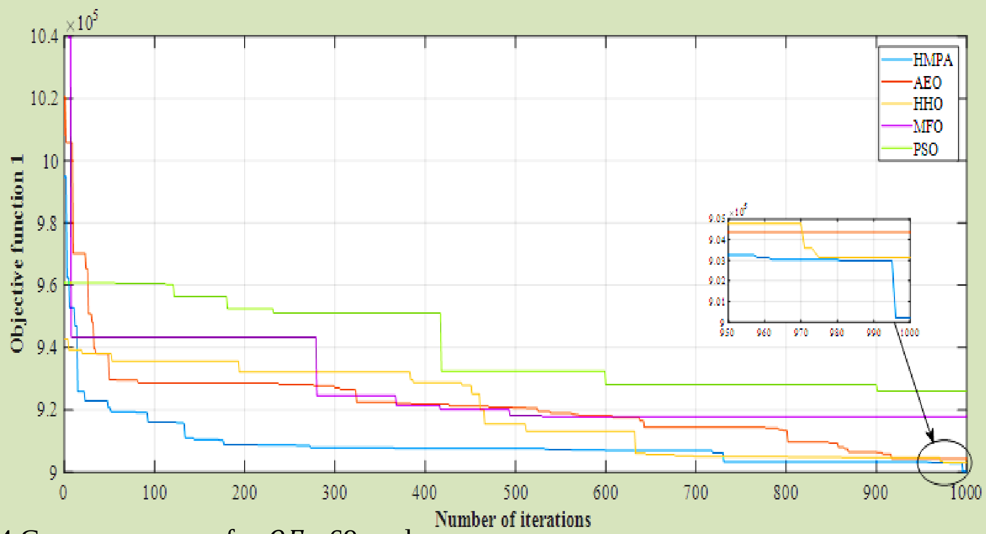


Fig.4.24 Converge curves for OF_1_69-node

Table 4.11. Optimization results for OF_1_69-bus

	OS	LOC_{DG}	DG Size (KW)	LOC_{CB}	CB Size (KVAR)	E_{loss} (KWh)	EQ_{loss} (KVARh)	PR	E_{sub} (KWh/24h)	E_{load} (KWh/24h)	CD ($/year)	CE_{sub} ($/year)	CE_{load} ($/year)	CE_{loss} ($/year)
	69													
	70													
Base case	71					3941.021	1790.2355		74509.1936	70568.1725		1213261.6093	1149088.4620	64173.1473
	72													
	73													
	14	17	661.4727	4	100									
	54	57	788.5808	9	500									
HMPA	60	47	181.2781	27	150	1245.1565	1013.6986	0.59891	55284.1105	54038.954	615088.4149	**900212.2511**	879936.8934	20275.3576
	12	43	302.8224	59	300									
	10	48	342.5979	56	550									
	45	64	621.4114	42	100									
	4	14	758.9384	47	350									
AEO	20	9	310.7519	15	450	1520.6375	1129.8184	0.59966	55538.9384	54018.3008	615460.4215	904361.7108	879600.5908	24761.1199
	10	48	387.6257	65	150									
	60	28	200.8691	7	550									
	14	8	217.3014	4	600									
	60	20	201.8393	6	50									
HHO	12	40	1035.1218	27	50	1417.5933	1016.514	0.59864	55463.9676	54046.3743	614979.7593	903140.9333	880057.7213	23083.212
	10	25	175.6173	62	100									
	48	5	645.8498	10	850									
	9	18	726.8669	12	350									
	60	59	213.4039	51	500									
MFO	45	36	902.3793	53	250	2352.66	1947.2008	0.59984	56366.1239	54013.4639	615547.5456	917831.0878	879521.8285	38309.2593
	18	32	229.4594	55	100									
	58	29	208.1534	16	400									
	15	15	282.2496	24	300									
	8	32	565.0055	3	350									
PSO	45	45	479.0225	53	200	2771.8959	1947.0828	0.5966	56874.8244	54102.9285	613936.0981	926114.4523	880978.6149	45135.8374
	42	40	464.0322	50	300									
	60	19	477.6302	29	450									

HMPA achieves an optimal balance between costs and network performance through an efficient trade-off between capital investment and operational savings, outperforming other methods.

Figure 4.24 depicts the convergence curves of all the optimization techniques employed. The exceptional convergence velocity of the HMPA algorithm allows it to achieve the optimal solution much faster than alternative approaches.

The HMPA convergence curve is characterized by a uniform and steady progress toward the optimal solution, devoid of unpredictable variations or premature convergence. This underscores HMPA's capacity to efficiently and comprehensively explore the solution space.

Figures 4.27 and 4.28 illustrate the voltage profile and network structure, respectively, that correspond to the optimal solution achieved by the HMPA approach. The voltage profile exhibits enhanced voltage stability throughout the network, with fewer deviations from the nominal values, ensuring that the system functions within acceptable voltage thresholds. The network structure analysis reveals an optimal topology that minimizes inefficiencies and maximizes power flow distribution, resulting in a reduction in operational expenses.

Table 4.15 presents a comprehensive commercial cost analysis of the devices used in HMPA's final solution. This analysis emphasizes the financial viability of the optimized configuration, illustrating that the algorithm effectively reduces CE_{sub}without necessitating extravagant capital expenditure, rendering the solution economically and technically optimal. The findings underscore the efficacy of HMPA in providing an economically viable solution for the 69-bus test system.

B. Objective function 2

Table 4.12 shows the results of the ONRSACD optimization problem for the 69-node test system, with the explicit objective of lowering the equipment investment cost CD. The HMPA algorithm generates an optimal solution by limiting the CD value to a minimum of 49883.37 $/year. This outcome much surpasses the results achieved with the other algorithms, such as AEO, HHO, MFO, and PSO, highlighting the superior effectiveness of HMPA in reducing capital costs

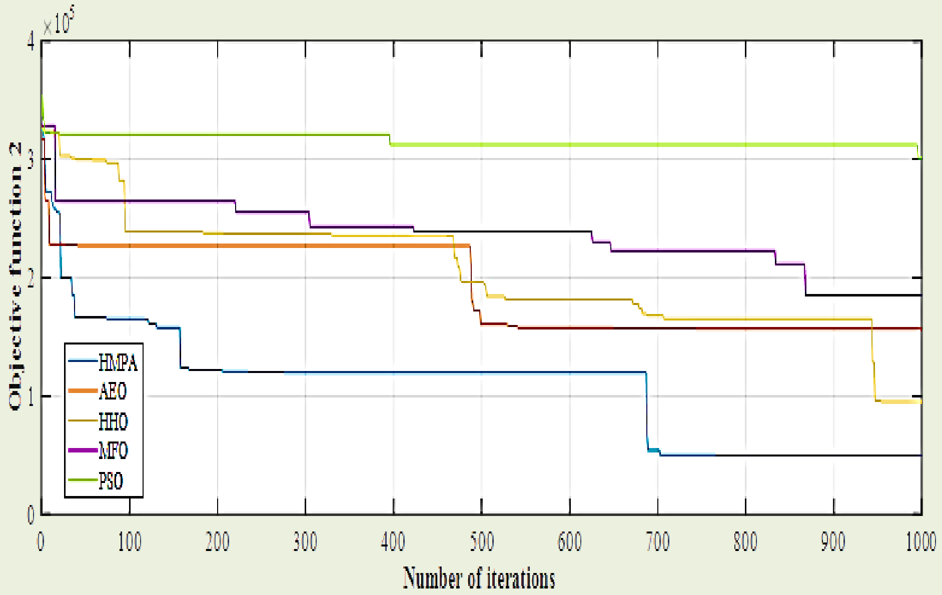


Fig.4.25. Convergence curves for OF_2_69-bus DN

Aside from minimizing CD, HMPA also achieves the highest overall solution quality when assessed across several key performance indicators. It not only reduces the substation energy cost CE_{sub} but also minimizes E_{sub}, CE_{loss}, and E_{loss}. These enhancements in operational efficiency demonstrate HMPA's ability to balance the trade-offs between capital investment and network performance optimization. The algorithm's ability to produce lower costs and higher performance across various metrics makes it the most effective solution to the ONRSACD problem.

Figure 4.25 shows the comparative benefit of the HMPA approach in terms of convergence speed compared to other optimization strategies. The HMPA algorithm consistently achieves convergence to the best solution at a faster rate compared to other methods. It exhibits a smooth and steady development without premature convergence or excessive oscillations. The accelerated convergence of HMPA enables the identification of solutions of superior quality within a shorter time domain, thus establishing its practicality and reliability as a tool for addressing real-time or large-scale optimization problems.

Figures 4.27 and 4.28, which illustrate the voltage profile and network configuration of the optimal solution, offer further insights into the performance of HMPA. The voltage profile shown in Figure 4.27 represents an enhanced and consistent voltage distribution across the network. This ensures that the system functions within acceptable voltage thresholds, therefore improving the overall reliability and safety of the network.

Table 4.12. Optimization results for OF_2_69-bus DN

	OS	LOC_{DG}	DG Size (KW)	LOC_{CB}	CB Size (KVAR)	E_{loss} (KWh)	EQ_{loss} (KVARh)	PR	E_{sub} (KWh/24h)	E_{load} (KVARh/24h)	CD ($/year)	CE_{sub} ($/year)	CE_{load} ($/year)	CE_{loss} ($/year)
Base case	69													
	70													
	71					3941.021	1790.2355		74509.1936	70568.1725		1213261.6093	1149088.4620	64173.1473
	72													
	73													
HMPA	71	26	75.0303	30	50									
	72	53	32.9858											
	70	63	28.4846	44	100	2788.498	1338.8333	0.10004	70595.5652	67807.0671	**49883.3680**	1149534.5057	1104128.3291	45406.1766
	69	59	104.2759	37	50									
	73	32	139.5409	20	100									
AEO	73	23	119.844	49	50									
	70	47	103.8877	25	50									
	37	51	28.8207	33	50	61382.0336	42927.5125	0.10006	129188.6287	67806.5951	156995.2116	2103627.7020	1104120.6439	999507.0581
	72	66	52.6411	48	50									
	12	26	75.1889	19	50									
HHO	70	26	118.4371	4	50									
	9	45	33.0301	8	50									
	72	47	98.8032	54	50	7819.8225	5457.6551	0.10009	75625.6204	67805.7979	95321.8575	1231440.8127	1104107.6619	127333.1508
	71	56	53.9295	68	100									
	73	30	76.2923											
MFO	11	61	69.97633	40	50									
	69	25	107.0593	32	50									
	70	8	120.6514	27	50	94544.1914	42936.0066	0.10789	162134.8308	67590.6393	185280.6627	3420791.1012	1100604.1536	2320186.9475
	54	59	54.32351	44	50									
	73	5	58.11795	33	100									
PSO	7	19	81.2405	18	100									
	18	36	77.0535											
	39	42	90.8089	26	100	94557.8957	42940.7395	0.10854	162789.7876	68231.8918	300857.1309	16054757.0211	1111045.9126	14943711.1084
	43	49	66.4451	41	50									
	70	62	97.0627	42	50									

The improved network topology shown in Figure 4.28 demonstrates an efficient layout that reduces energy losses while preserving the radial structure required for both successful power distribution and fault isolation.

Moreover, Table 4.15 offers a comprehensive analysis of the commercial costs associated with the devices utilized in HMPA's final solution. The commercial study demonstrates the solution's financial feasibility, showing that HMPA not only reduces operating expenses and capital expenditures but also ensures the long-term sustainability and cost-efficiency of the network's infrastructure investment. HMPA demonstrates its suitability as the most resilient and economically viable approach for addressing the ONRSACD problem in the 69-node test system by achieving optimum outcomes in terms of both performance and cost.

C. Objective function 3

The strategy defined in Section 4.5.2.2 yielded the boundary values of the membership functions for each optimization method, as shown in Table 4.13. These membership functions are essential in the fuzzy multi-objective optimization process since they establish the range in which each objective function performs. This technique guarantees that the optimization process well manages the competing goals, directing the algorithms to discover compromise solutions.

Table 4.14 shows the results of the fuzzy multi-objective ONRSACD optimization problem that was run on the 69-bus DN test system.

Table 4.13. Membership functions limits for OF_3_69-bus DN

Objective function	Limits	HMPA	AEO	HHO	MFO	PSO
OF_1	CE_{sub_min}	900212.2511	904361.7108	903140.9333	917831.0878	926114.4523
	CE_{load_min}	879936.8934	879600.5908	880057.7213	879521.8285	880978.6149
	CE_{loss_min}	20275.3576	24761.1199	23083.212	38309.2593	45135.8374
	CD_{max}	615088.4149	615460.4215	614979.7593	615547.5456	613936.0981
OF_2	CD_{min}	49883.3680	156995.2116	95321.8575	185280.6627	300857.1309
	CE_{sub_max}	1149534.5057	2103627.7020	1213440.8127	3420791.1012	16054757.0211
	CE_{load_max}	1104128.3291	1104120.6439	1104107.6619	1100604.1536	1111045.9126
	CE_{loss_max}	45406.1766	64173.1473	64173.1473	64173.1473	64173.1473

This optimization aims to minimize three competing costs: CE_{loss}, CE_{load}, and CD. The goal is to find a compromise solution that yields the minimum total annual expenditure, Exp_{tot}, as defined in Equation 4.43

We examined all the algorithms, and MOHMPA produced the lowest Exp_{tot} of 1440069.41$/year. This outcome surpasses the performance of competing multi-objective algorithms such as MOAEO, MOHHO, MOMFO, and MOPSO by a considerable margin. The results indicate that MOHMPA is superior to the other optimization techniques because it achieves a reduced overall expenditure while minimizing new financial burdens.

Furthermore, MOHMPA's higher convergence rate emphasizes its superior performance. Figure 4.26 displays the convergence graphs for all algorithms, indicating that MOHMPA attains the optimal solution more quickly than the other methods. The method exhibits smooth and persistent convergence, indicating its effective exploration of the solution space, unencumbered by local optima. The aforementioned attributes render MOHMPA very efficient in addressing complex multi-objective situations, as it adeptly manages many competing goals while prioritizing the reduction of total costs.

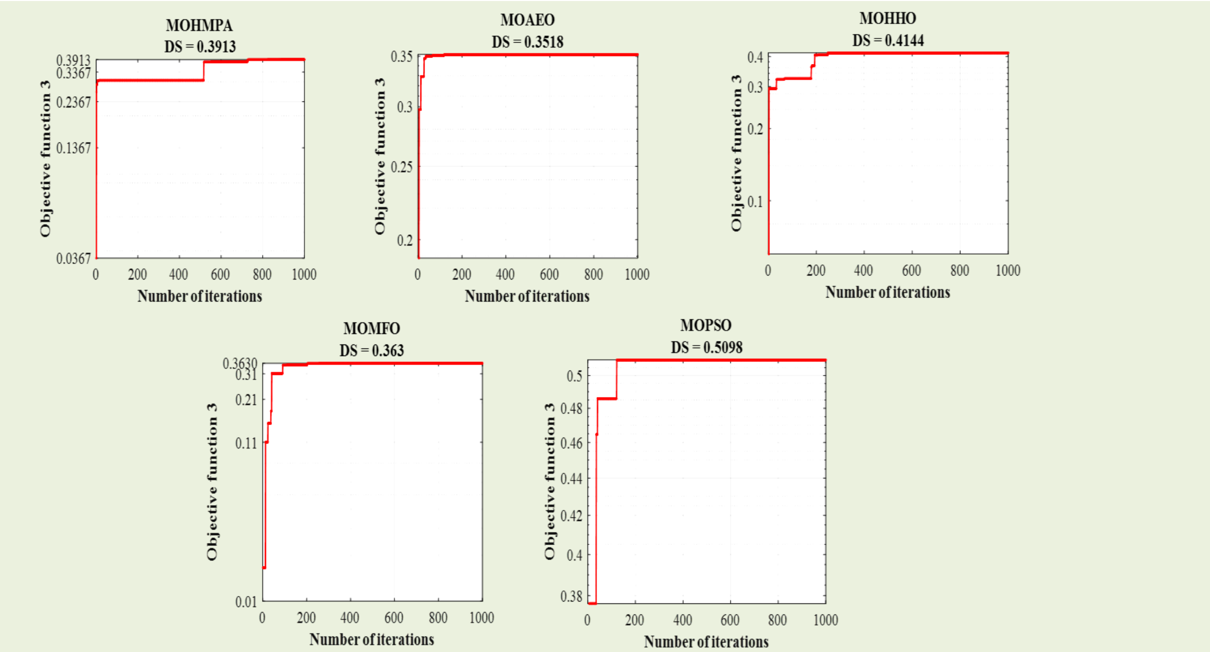


Fig.4.26 Convergence curves for OF_3_69-node

Table 4.14. Fuzzy multi-objective optimization results for OF_3_69-bus DN

	OS	LOC_{DG}	DG Size (KW)	LOC_{CB}	CB Size (KVAR)	E_{loss} (KWh)	EQ_{loss} (KVARh)	PR	E_{sub} (KWh/24h)	E_{load} (KWh/24h)	CD ($/year)	CE_{sub} ($/year)	CE_{load} ($/year)	CE_{loss} ($/year)
Base case	69													
	70													
	71					3941.021	1790.2355		74509.1936	70568.1725		1213261.6093	1149088.4620	64173.1473
	72													
	73													
MOHMPA	14	15	337.2227	12	200									
	60	35	72.6435	13	200									
	12	42	233.3802	20	150	1826.6237	1499.9072	0.29525	64246.3916	62419.7678	393920.9165	1046148.4918	1016404.8811	29743.6106
	9	55	355.1297	66	200									
	72	54	123.9937	47	50									
MOAEO	14	58	368.166	62	250									
	60	50	263.1628	16	100									
	57	20	87.10927	59	250	2593.3969	1879.8811	0.27583	65548.9193	62955.5223	454057.0983	1067358.0472	1025128.7763	42229.2709
	45	69	211.1232	2	50									
	9	7	119.0131	65	100									
MOHHO	72	19	312.166	15	150									
	10	37	143.5017	23	250									
	14	64	320.9339	31	50	2769.1439	2272.0234	0.3067	64872.778	62103.634	399640.1565	1056348.1798	1011257.1544	45091.0254
	60	9	222.1546	48	300									
	18	58	167.1582	68	100									
MOMFO	59	9	227.7144	59	100									
	4	30	289.9358	35	150									
	10	34	146.6031	42	200	2831.9392	2155.5024	0.28651	65492.9095	62660.9702	459362.6076	1066446.0178	1020332.4712	46113.5466
	20	47	210.288	14	150									
	14	37	214.4642	18	150									
MOPSO	69	21	351.6332	10	100									
	20	35	205.3619	29	150									
	49	23	144.0624	63	200	2588.986	3194.7435	0.30417	64762.5119	62173.5258	422751.8864	1054552.6759	1012395.2291	42157.4468
	45	2	275.2403	16	350									
	60	24	179.9897	18	50									

Exp_{tot} ($/year)

Base case	MOHMPA	MOAEO	MOHHO	MOMFO	MOPSO
1213261.6093	**1440069.408**	1521415.1455	1455988.336	1525808.6255	1477304.5624

Additional expenditures exceeding the base case Exp_{tot} ($/year)

MOHMPA	MOAEO	MOHHO	MOMFO	MOPSO
226807.7987	308153.5362	242726.7267	312547.0162	264042.9531

Figures 4.27 and 4.28 depict the voltage profile and network architecture of the optimum solution generated by MOHMPA, respectively. The voltage profile demonstrates improved voltage stability across the network, with few deviations from the expected values, ensuring safe and effective power distribution. The optimized network configuration enhances performance via reduced energy losses and streamlined power flows, therefore facilitating the overarching objective of decreasing Exp_{tot}.

Table 4.15. Device commercial cost analysis for the HMPA final solution (69-node DN)

Device cost		OF_1	OF_2	OF_3
CBs cost	C_{ICB} ($)	5800	4150	5400
	C_{QCB} ($/year)	800	150	400
	C_{FBC} ($)	5000	4000	5000
DGs cost	C_{DG} ($)	297726.2998	49733.3680	16770.0589
	$A^{UDG} \cdot C_{IDG}$ ($/year)	99982.2903	16701.4336	49288.2444
	C_{MDG} ($/year)	197744.0095	33031.9343	97481.8144
TSs cost	C_{TS} ($/year)	316562.1151	0	246750.8576
	$A^{UTS} \cdot C_{ITS}$ ($/year)	274447.5524	0	213459.2074
	$A^{URCS} \cdot C_{IRCS}$ ($/year)	22614.5626	0	18091.6501
	C_{MTSRCS} ($/year)	19500	0	15200

Lastly, Table 4.15 offers a thorough commercial cost analysis of the devices employed in the final MOHMPA solution.

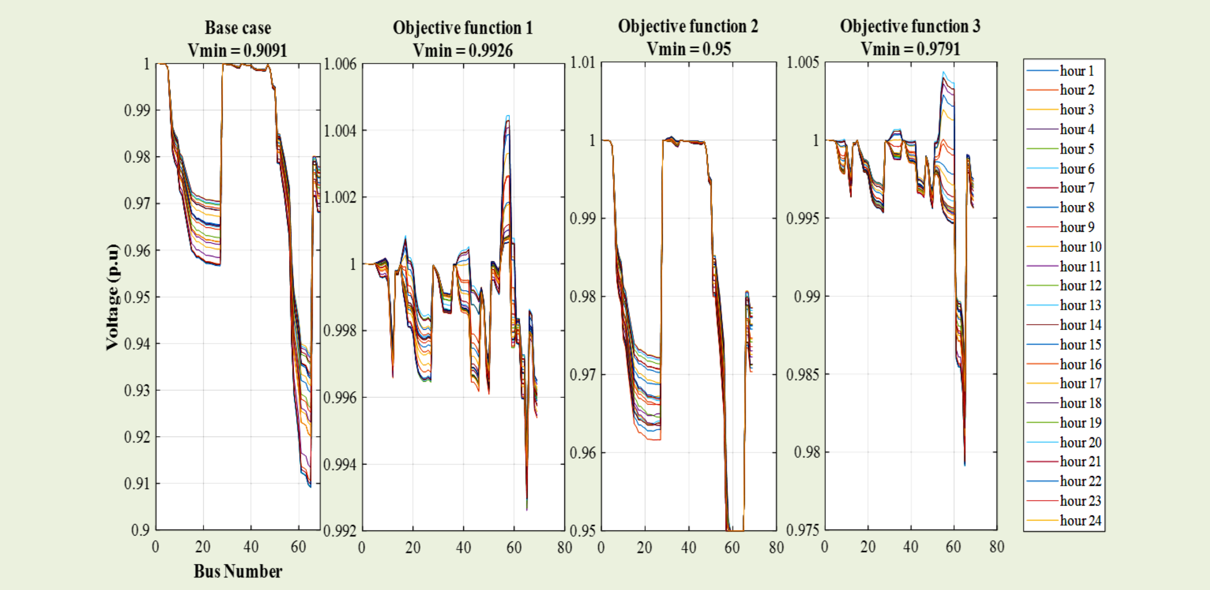


Fig.427. Voltage profile for the 69-node DN before and after ONRSACD via HMPA

This analysis emphasizes the financial viability of the optimized configuration, demonstrating that the MOHMPA method not only reduces operational and investment costs, but also guarantees that capital expenditures on network devices are within economically viable limits. The results confirm that MOHMPA provides a cost-effective and balanced solution, obtaining superior performance in both technical and economic metrics.

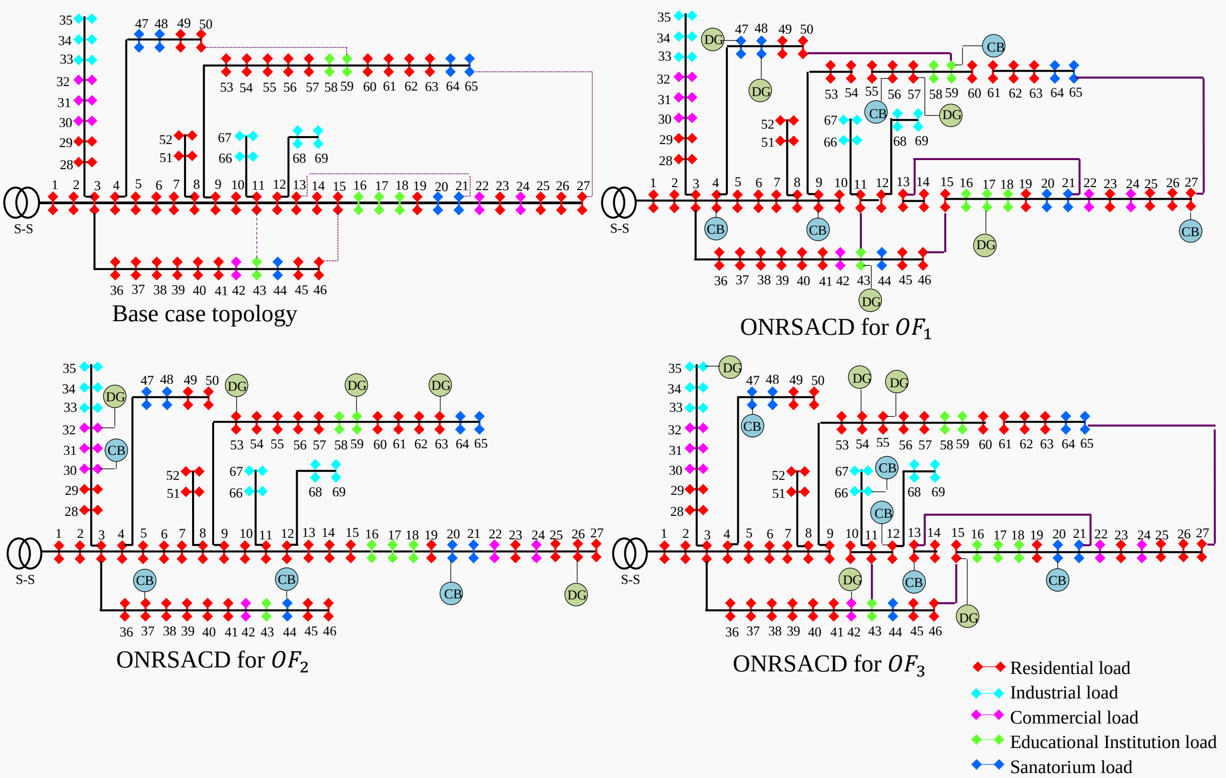


Fig.4.28 The 69-node configuration before and after ONRSACD via the HMPA algorithm

4.6 Conclusion

This chapter focuses on the experimental component of our thesis and provides a full description of the empirical procedure. The methodology includes two fundamental experiments. In the first experiment, we apply three modern optimization techniques, namely Equilibrium Optimizer (EO), African Vultures Optimization Algorithm (AVOA), and Gorilla Troops Optimization (GTO), to solve the optimal capacitor banks allocation and optimal DN reconfiguration problems. The results show that all three approaches are effective and fairly simple to implement. Nevertheless, the EO approach slightly outperforms the other two in terms of solution quality. This is the first time these techniques have been used in this particular field, introducing a new methodology to the domain.

The second experiment employs the HMPA approach to solve the ONRSACD problem, marking the first instance of its use in this particular setting. The decision to use HMPA over EO was based on a thorough literature review, which included comparison studies conducted by HMPA and EO developers. These studies demonstrated that HMPA yielded better outcomes. HMPA's demonstrated capacity to effectively address larger and more intricate optimization problems justifies its selection as the prime choice for the ONRSACD issue, making it especially suitable for the goals of this work.

This chapter describes a new multi-objective optimization approach to solve the ONRSACD problem. The objective is to optimize the techno-economic advantages while ensuring compliance with operational limitations. The suggested methodology utilizes the HMPA method to establish an optimal balance between opposing costs, including substation energy cost (CE_{sub}) and device investment cost (CD). The single-objective HMPA method first optimized the reduction of CE_{sub}, then proceeded to minimize CD. The optimization process follows an original, adapted strategy to ensure that maximizing one target would not impede the achievement of the other. This step permits the establishment of upper and lower limits for the membership functions linked to each objective function.

The second step integrated a fuzzy-based approach with the multi-objective MOHMPA method to identify an optimal compromise solution. To adapt to load variations, the proposed approach considered different hourly load profiles for various consumer groups, including residential, commercial, industrial, educational institutions, and healthcare facilities. In addition, it incorporated the hourly profile of distributed generation power outputs to enhance reliability and precision and conducted a comprehensive series of tests on both the 33-bus and 69-bus distribution test systems.

Advanced metaheuristic algorithms, such as ecosystem-based optimization (AEO), Harris-Hawkins optimization (HHO), particle swarm optimization (PSO), and moth-flame optimization (MFO), were used to explore the optimization problem in depth. We implemented these algorithms in both single-objective and multi-objective frameworks. We conducted a thorough performance evaluation to compare these approaches with the HMPA algorithm. The findings highlighted that HMPA exhibited superior efficiency and convergence speed compared to the other algorithms. Furthermore, its performance showed improvement as the complexity of the system rose. Furthermore, the MOHMPA algorithm demonstrated its superiority and efficacy by providing an optimal compromise option that reduced the overall yearly cost while incurring minimal additional costs.

CONCLUSIONS AND OUTLOOK

The present thesis has thoroughly examined the optimization problem that is inherent in contemporary electrical distribution networks, with a specific emphasis on improving operational efficiency and economic feasibility. Categorized into four chapters, the work gradually cultivated a profound comprehension of the theoretical underpinnings and sophisticated optimization methods necessary for resolving intricate issues in distribution systems.

The first chapter encompassed a comprehensive examination of electrical distribution networks, with a specific emphasis on their key role in providing stable and reliable electricity to consumers. In particular, it scrutinized how distribution systems have evolved with the integration of distributed generation, renewable energy sources, and the increasing complexity resulting from smart grid technology. This chapter established a theoretical basis for comprehending the operational and optimization difficulties encountered by modern networks, namely the need to achieve a satisfactory balance between efficiency, cost, and reliability.

The second chapter examined fundamental methods for improving network performance, emphasizing network reconfiguration, optimal capacitor banks, and distributed generation allocation. The analytical evaluation of these techniques focused on their growing capacity to enhance voltage profiles, minimize energy losses, and optimize the overall functioning of the network when implemented simultaneously. The chapter highlighted the need to incorporate optimization approaches to address the increasing intricacy of contemporary distribution networks, where operational limitations and economic demands require more advanced solutions.

Metaheuristic optimization approaches, which have become prevalent in solving complex optimization problems, are the focus of the third chapter. We studied them carefully to determine their effectiveness in tackling the complex, multi-objective challenges of power distribution grids. This chapter demonstrates that by tailoring these algorithms to the specific needs of distribution networks, we can enhance their effectiveness. This chapter has laid the foundations for the development of a more sophisticated hybrid multi-objective optimization technique.

In the fourth chapter, we introduce the hybrid multi-population algorithm (HMPA), a new multi-objective optimization method that optimizes network rearrangement and capacitor bank and generator distribution (ONRSACD). This approach aimed to maximize techno-economic benefits while respecting operational limits, successfully reconciling competing objectives such as substation energy cost and device capital cost. We first used the single-objective HMPA approach to reduce these costs in accordance with an adaptive approach that manages the conflict between the objectives and ensures that optimizing one objective does not compromise the other. The algorithm can therefore define its own lower and upper limits for the membership functions linked to each objective function.

We included a fuzzy-based model in the multi-objective HMPA method (MOHMPA) in order to improve the optimization process and better manage trade-offs between competing objectives. We evaluated the effectiveness of this multi-objective method on test distribution systems with 33 and 69 nodes. The results show that MOHMPA outperforms other methods, namely MOAEO, MOHHO, MOPSO, and MOFMO when it comes to the quality of the solutions and the speed of convergence. Extensive testing, including varying load profiles between different groups of consumers and dynamic generation from dispersed generation units, verified the proposed methodology. In the end, the MOHMPA offered an optimal compromise solution, making it possible to obtain the lowest overall annual cost with little additional expenditure.

To sum up, this thesis improves the optimization of electrical distribution networks by combining techniques like network reconfiguration, capacitor bank positioning, and distributed generation with cutting-edge metaheuristic optimization algorithms. This study presents a new multi-objective method that is a strong way to solve optimization problems in distribution networks while keeping a balance between cost-effectiveness and operational efficiency.

Prospects for the Future

Building on the findings of this study, we have identified several potential avenues for future research:

1. Expansion into larger and more intricate systems:

The present thesis primarily examined 33-bus and 69-bus test systems. However, future research should explore the potential application of the suggested optimization approach to larger and more intricate distribution networks. Real-world networks are greatly more complex, encompassing larger quantities of buses, feeders, and dispersed energy resources. Empirical evaluation of the proposed multi-objective HMPA on larger networks would yield significant insights into its scalability, performance, and possible constraints in managing heightened complexity.

2. Dynamic Reconfiguration and Real-Time Optimization

An area of potential development in this study is the adaptation of the proposed HMPA method for real-time optimization and dynamic network reconfiguration. Given the considerable variability of renewable energy sources such as solar and wind, the ability to undertake real-time reconfiguration according to the current grid conditions would improve the network's resilience and efficiency. Implementing a real-time, adaptive optimization framework that utilizes Hybrid Multi-Population Algorithm (HMPA) could allow operators to promptly and effectively react to fluctuations in demand, generation, and fault conditions, guaranteeing consistent and optimal performance.

3. Energy Storage Systems (ESS) Integration:

Further investigation has the potential to improve the existing model by integrating Energy Storage Systems (ESS) into the optimization framework. Advanced Energy Storage Systems (ESS) can significantly contribute to grid operations stabilization by storing surplus energy during periods of low demand and releasing it when required. Future research could improve the integration of intermittent renewable energy by finding the best ways to use distributed generators (DGs), capacitor banks, and energy storage systems (ESS). This would make the network more stable and cost-effective as a whole.

4. Integration of FACTS systems

The integration of Flexible AC Transmission Systems (FACTS) with network reconfiguration and distributed generation (DG) is a highly valuable and promising area of study. The FACTS devices, including Static VAR Compensators (SVCs) and Static Synchronous Compensators (STATCOMs), provide sophisticated control features that can improve voltage stability, power flow management, and the overall flexibility of telecom networks. Future research can investigate the synergistic effects of integrating FACTS with reconfiguration and DG placement to optimize network performance, namely in terms of delivering higher power quality, minimizing losses, and increasing system reliability.

Incorporating FACTS into the optimization framework may afford enhanced precision in regulating network parameters, so facilitating improved management of reactive power and voltage levels throughout the network. Implementing this integrated strategy would enhance the robustness and effectiveness of distribution systems, especially as networks integrate greater proportions of renewable energy sources. Adopting such a viewpoint would improve the study's progress by effectively addressing the technical and economic obstacles encountered in contemporary power systems.

5. HMPA-Machine-Learning Hybridization:

The integration of machine learning (ML) models with metaheuristic optimization algorithms presents a promising avenue for research. For instance, by analyzing past data, we can train machine learning models to forecast the most efficient setups. This prediction can then guide the optimization process and accelerate convergence. By integrating predictive analytics into the optimization framework, this hybrid approach has the potential to provide faster and more precise solutions. This would reduce computational time and improve the algorithm's adaptability to changing network conditions.

6. Integration of Environmental and Social Goals

Although the main emphasis of this thesis was on techno-economic optimization, future research could broaden the scope to encompass environmental and social goals. Potential additions to the multi-objective framework include reducing carbon emissions, maximizing renewable energy integration, and optimizing network configurations to minimize social disruptions such as power outages. Implementing such improvements would synchronize the optimization process with sustainability objectives, offering a more comprehensive approach to network management.

7. Practical Application and Real Case Studies

Future research should prioritize applying the optimization approach to real-world distribution networks in order to verify the practical usefulness of the proposed HMPA method. Engaging in partnerships with utility companies to apply the suggested algorithm to real distribution systems would offer valuable experiential knowledge regarding possible obstacles and improvements. By applying real-world case studies, we can identify operational limitations that simulation settings may not fully account for, thereby ensuring the approach's resilience in real-life scenarios.

8. Demand response program integration

The integration of demand response (DR) programs into the optimization framework is a promising subject for further investigation. Demand response (DR) programs provide consumers with incentives to modify their energy usage in accordance with grid conditions, enhancing the stability of the network. The integration of Demand Response (DR) with HMPA would provide a more flexible method for load management, enhancing the efficiency of both the supply-side (generation and storage) and the demand-side of the distribution network.

9. Deregulation integration

The deregulation of the electrical distribution sector is a crucial subject for further study, particularly when integrated with network reconfiguration, distributed generation, and FACTS systems. Deregulation brings about market-oriented competition in the energy industry, enabling greater flexibility in energy pricing, the establishment of independent power producers, and the decentralization of decision-making activities. This transition has the potential to generate both advantageous prospects and challenges for distribution network administration and enhancement.

In deregulated environments, research may focus on the impact of market-driven factors on the positioning and functioning of distributed generators (DGs), strategies for reconfiguring networks, and the use of Flexible Alternating Current Transmission System (FACTS) devices. In a deregulated market, the optimization of these components must take into account not just technical limitations but also economic aspects, including volatile energy prices, contractual arrangements, and regulatory adherence. By integrating these technologies in a deregulated environment, we can achieve novel approaches to optimize efficiency and reduce operational expenses, thereby fostering the development of more sustainable and competitive energy distribution models.

The adoption of this research approach would yield significant insights into the dynamic power distribution landscape and the emerging optimization issues in deregulated markets.

10. Automated communication and information systems integration for preparing distribution networks for smart grid operations.

The integration of intelligent communication and information systems is a critical research area, particularly in the context of preparing distribution networks for smart grid deployment. Intelligent power grids depend significantly on sophisticated communication technologies, including Internet of Things (IoT) devices, real-time data analysis, and machine-to-machine communication, to facilitate dynamic and immediate regulation of the power system. Future studies can concentrate on improving the responsiveness, flexibility, and efficiency of distribution networks by integrating these intelligent systems with network reconfiguration, placing distributed generations, and FACTS devices.

Real-time monitoring, predictive analytics, and automated decision-making enabled by these intelligent systems can significantly enhance the performance of optimization algorithms. The incorporation of communication technologies would facilitate more precise regulation of power distribution, energy storage systems, and load management activities. Furthermore, intelligent systems can enhance overall system reliability and resilience by facilitating better coordination between distributed energy resources and the main grid.

Adopting this viewpoint would greatly enhance the progress of smart grids, as the combination of optimization methods and intelligent systems can lead to more flexible, robust, and environmentally friendly energy networks. Furthermore, it corresponds with the worldwide progression towards digitizing the power industry, establishing it as a progressive and influential field of study.

Appendix

Table.4.16. The hourly load and DG output variations data.

Hour	DG output (pu)	Load type				
		Residential (pu)	Industrial (pu)	Commercial (pu)	Educational institution (pu)	Sanatorium (pu)
1	0	0.67885	0.54444	0.54	0.61	0.65
2	0	0.68816	0.56666	0.54	0.58	0.6
3	0	0.61767	0.58888	0.55	0.54	0.58
4	0	0.63912	0.50111	0.56	0.54	0.56
5	0	0.66202	0.65555	0.562	0.56	0.56
6	0.05	0.62115	0.80111	0.56	0.57	0.58
7	0.1	0.62089	0.99999	0.57	0.65	0.65
8	0.29	0.70498	1	0.6	0.76	0.76
9	0.5	0.84366	0.95555	0.63	0.84	0.87
10	0.69	0.77659	0.93333	0.68	0.9	0.95
11	0.9	0.92763	0.95555	0.73	0.96	0.99
12	0.96	1	0.90111	0.78	0.99	1
13	1	1	0.88888	0.82	0.99	0.99
14	0.96	0.98635	0.92222	0.86	1	1
15	0.85	1	0.92222	0.90	0.99	1
16	0.53	0.97917	0.99999	0.93	0.98	0.98
17	0.3	0.81203	0.96666	0.96	0.96	0.96
18	0.1	0.75653	0.95555	0.99	0.94	0.96
19	0.03	0.71154	0.66666	1	0.93	0.93
20	0	0.59684	0.52222	0.98	0.92	0.92
21	0	0.58988	0.50155	0.94	0.92	0.92
22	0	0.59879	0.48888	0.85	0.89	0.93
23	0	0.7623	0.52011	0.77	0.71	0.88
24	0	0.70429	0.53222	0.66	0.65	0.71

Bibliography

[1] H. M. Ryan, Ed., *High Voltage Engineering Testing*. Institution of Engineering and Technology, 2013. doi: 10.1049/PBPO066E.

[2] I. Diahovchenko and L. Petrichenko, “Assessment of energy losses in power distribution systems with individual prosumers and energy communities,” *J. Eng.*, vol. 2023, no. 3, Mar. 2023, doi: 10.1049/tje2.12243.

[3] V. C. Gungor *et al.*, “A Survey on Smart Grid Potential Applications and Communication Requirements,” *IEEE Trans. Ind. Informatics*, vol. 9, no. 1, pp. 28–42, Feb. 2013, doi: 10.1109/TII.2012.2218253.

[4] I. Alotaibi, M. A. Abido, M. Khalid, and A. V. Savkin, “A comprehensive review of recent advances in smart grids: A sustainable future with renewable energy resources,” *Energies*, vol. 13, no. 23, 2020, doi: 10.3390/en13236269.

[5] J. et al. European Commission, Joint Research Centre, Roca Reina, J., Volt, J., Carlsson, “Clean Energy Technology Observatory, Novel thermal energy storage in the European Union – Status report on technology development, trends, value chains and markets,” 2023. doi: https://data.europa.eu/doi/10.2760/394103.

[6] H. Farhangi, “The path of the smart grid,” *IEEE Power Energy Mag.*, vol. 8, no. 1, pp. 18–28, Jan. 2010, doi: 10.1109/MPE.2009.934876.

[7] A. K. Erenoğlu, O. Erdinç, and A. Taşcıkaraoğlu, “History of Electricity,” in *Pathways to a Smarter Power System*, Elsevier, 2019, pp. 1–27. doi: 10.1016/B978-0-08-102592-5.00001-6.

[8] M. E. El-Hawary, *Introduction to Electrical Power Systems*. Wiley, 2008. doi: 10.1002/9780470411377.

[9] A. I. Aya Al Shaltounia, “Smart Load Flow Analysis using Conventional method and modern method,” *IJADT*, vol. VOL 2, no. 1, pp. 43–66, 2023.

[10] J. Song, M. Cheah-Mane, E. Prieto-Araujo, and O. Gomis-Bellmunt, “Short-circuit analysis of grid-connected PV power plants considering inverter limits,” *Int. J. Electr. Power Energy Syst.*, vol. 149, p. 109045, Jul. 2023, doi: 10.1016/j.ijepes.2023.109045.

[11] J.D. Glover, M.S. Sarma ,T.J. Overby, *Power System Analysis & Design*, CENGAGE Le. 2017.

[12] B. Stott and O. Alsac, “Fast Decoupled Load Flow,” *IEEE Trans. Power Appar. Syst.*, vol. PAS-93, no. 3, pp. 859–869, May 1974, doi: 10.1109/TPAS.1974.293985.

[13] P. Chen, Z. Chen, and B. Bak-Jensen, “Probabilistic load flow: A review,” in *2008 Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, IEEE, Apr. 2008, pp. 1586–1591. doi: 10.1109/DRPT.2008.4523658.

[14] S. Duman, S. Rivera, J. Li, and L. Wu, “Optimal power flow of power systems with controllable wind-photovoltaic energy systems via differential evolutionary particle swarm optimization,” *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 4, Apr. 2020, doi: 10.1002/2050-7038.12270.

[15] S. V. Satyanarayana and P. Madhavi, “Machine Learning for Load Forecasting in Power Systems,” *E3S Web Conf.*, vol. 453, p. 01008, Nov. 2023, doi: 10.1051/e3sconf/202345301008.

[16] T. A. Short, *Electric Power Distribution Handbook*. CRC Press, 2018. doi:

10.1201/b16747.

[17] W. H. Kersting, *Distribution System Modeling and Analysis*, CRC Press. 2018.

[18] K. Maresch, G. Marchesan, G. Cardoso, and A. Borges, “An underfrequency load shedding scheme for high dependability and security tolerant to induction motors dynamics☆,” *Electr. Power Syst. Res.*, vol. 196, p. 107217, Jul. 2021, doi: 10.1016/j.epsr.2021.107217.

[19] M. Bollen and F. Hassan, *Integration of Distributed Generation in the Power System*. Wiley, 2011. doi: 10.1002/9781118029039.

[20] F. Ullah *et al.*, “A comprehensive review of wind power integration and energy storage technologies for modern grid frequency regulation,” *Heliyon*, vol. 10, no. 9, p. e30466, May 2024, doi: 10.1016/j.heliyon.2024.e30466.

[21] F. R. Islam, K. Prakash, K. A. Mamun, A. Lallu, and H. R. Pota, “Aromatic Network: A Novel Structure for Power Distribution System,” *IEEE Access*, vol. 5, pp. 25236–25257, 2017, doi: 10.1109/ACCESS.2017.2767037.

[22] R. E. Brown, *Electric Power Distribution Reliability*. CRC Press, 2017. doi: 10.1201/9780849375682.

[23] W. Ma *et al.*, “Voltage regulation methods for active distribution networks considering the reactive power optimization of substations,” *Appl. Energy*, vol. 284, p. 116347, Feb. 2021, doi: 10.1016/j.apenergy.2020.116347.

[24] J. Xuan, J. Zheng, P. Shi, J. Chen, M. Lin, and Z. Hu, “Reliability Evaluation of Distribution System Considering Distributed Generation Correlation,” *J. Phys. Conf. Ser.*, vol. 1585, no. 1, p. 012029, Jul. 2020, doi: 10.1088/1742-6596/1585/1/012029.

[25] M. McPherson and B. Stoll, “Demand response for variable renewable energy integration: A proposed approach and its impacts,” *Energy*, vol. 197, p. 117205, Apr. 2020, doi: 10.1016/j.energy.2020.117205.

[26] K. H. Mohd Azmi, N. A. Mohamed Radzi, N. A. Azhar, F. S. Samidi, I. Thaqifah Zulkifli, and A. M. Zainal, “Active Electric Distribution Network: Applications, Challenges, and Opportunities,” *IEEE Access*, vol. 10, pp. 134655–134689, 2022, doi: 10.1109/ACCESS.2022.3229328.

[27] Z. Yu, H. Gao, X. Cong, N. Wu, and H. H. Song, “A Survey on Cyber–Physical Systems Security,” *IEEE Internet Things J.*, vol. 10, no. 24, pp. 21670–21686, Dec. 2023, doi: 10.1109/JIOT.2023.3289625.

[28] G. Nourbakhsh, G. Eden, D. McVeigh, and A. Ghosh, “Chronological Categorization and Decomposition of Customer Loads,” *IEEE Trans. Power Deliv.*, vol. 27, no. 4, pp. 2270–2277, Oct. 2012, doi: 10.1109/TPWRD.2012.2204072.

[29] M. Mohammed, A. Abdulkarim, A. S. Abubakar, A. B. Kunya, and Y. Jibril, “Load modeling techniques in distribution networks: a review,” *J. Appl. Mater. Technol.*, vol. 1, no. 2, pp. 63–70, Mar. 2020, doi: 10.31258/Jamt.1.2.63-70.

[30] L. Zhang *et al.*, “A review of machine learning in building load prediction,” *Appl. Energy*, vol. 285, p. 116452, Mar. 2021, doi: 10.1016/j.apenergy.2021.116452.

[31] A. K. Zarabie, S. Lashkarbolooki, S. Das, K. Jhala, and A. Pahwa, “Load Profile Based Electricity Consumer Clustering Using Affinity Propagation,” in *2019 IEEE International Conference on Electro Information Technology (EIT)*, IEEE, May 2019, pp. 474–478. doi: 10.1109/EIT.2019.8833693.

[32] H. C. Jeong, M. Jang, T. Kim, and S.-K. Joo, “Clustering of Load Profiles of Residential Customers Using Extreme Points and Demographic Characteristics,” *Electronics*, vol. 10, no. 3, p. 290, Jan. 2021, doi: 10.3390/electronics10030290.

[33] H. Wu, J. Wang, Y. Ren, R. Bi, M. Sun, and W. Wei, “Response reliability and risk analysis of users under time-of-use price,” *IET Gener. Transm. Distrib.*, vol. 16, no. 5, pp. 839–850, Mar. 2022, doi: 10.1049/gtd2.12331.

[34] P. D. Necoechea-Porras, A. López, and J. C. Salazar-Elena, “Deregulation in the Energy Sector and Its Economic Effects on the Power Sector: A Literature Review,” *Sustainability*, vol. 13, no. 6, p. 3429, Mar. 2021, doi: 10.3390/su13063429.

[35] M. G. Pollitt, N.-H. M. von der Fehr, B. Willems, C. Banet, C. Le Coq, and C. K. Chyong, “Recommendations for a future-proof electricity market design in Europe in light of the 2021-23 energy crisis,” *Energy Policy*, vol. 188, p. 114051, May 2024, doi: 10.1016/j.enpol.2024.114051.

[36] M. Khalid, “Smart grids and renewable energy systems: Perspectives and grid integration challenges,” *Energy Strateg. Rev.*, vol. 51, p. 101299, Jan. 2024, doi: 10.1016/j.esr.2024.101299.

[37] M. Stecca, L. Ramirez Elizondo, T. Batista Soeiro, P. Bauer, and P. Palensky, “A Comprehensive Review of the Integration of Battery Energy Storage Systems into Distribution Networks,” *IEEE Open J. Ind. Electron. Soc.*, pp. 1–1, 2020, doi: 10.1109/OJIES.2020.2981832.

[38] Y. Li, B. Feng, B. Wang, and S. Sun, “Joint planning of distributed generations and energy storage in active distribution networks: A Bi-Level programming approach,” *Energy*, vol. 245, p. 123226, Apr. 2022, doi: 10.1016/j.energy.2022.123226.

[39] N. Hadjsaïd and J. Sabonnadi`re, Eds., *Electrical Distribution Networks*. Wiley, 2013. doi: 10.1002/9781118601280.

[40] A. Shafieezadeh, U. P. Onyewuchi, M. M. Begovic, and R. DesRoches, “Age-Dependent Fragility Models of Utility Wood Poles in Power Distribution Networks Against Extreme Wind Hazards,” *IEEE Trans. Power Deliv.*, vol. 29, no. 1, pp. 131–139, Feb. 2014, doi: 10.1109/TPWRD.2013.2281265.

[41] N. L. Dehghani, Y. Mohammadi Darestani, and A. Shafieezadeh, “Optimal Life-Cycle Resilience Enhancement of Aging Power Distribution Systems: A MINLP-Based Preventive Maintenance Planning,” *IEEE Access*, vol. 8, pp. 22324–22334, 2020, doi: 10.1109/ACCESS.2020.2969997.

[42] D. Razmi, T. Lu, B. Papari, E. Akbari, G. Fathi, and M. Ghadamyari, “An Overview on Power Quality Issues and Control Strategies for Distribution Networks With the Presence of Distributed Generation Resources,” *IEEE Access*, vol. 11, pp. 10308–10325, 2023, doi: 10.1109/ACCESS.2023.3238685.

[43] A. G. Ismail, M. A. El-Dabah, and I. A. Nassar, “Enhancement of Electrical Distribution Networks Performance Using the Load Management Methodology,” *Energy Reports*, vol. 6, pp. 2066–2074, Nov. 2020, doi: 10.1016/j.egyr.2020.07.018.

[44] T. Jamasb and C. Marantes, “Electricity distribution networks: investment and regulation, and uncertain demand,” in *The Future of Electricity Demand*, Cambridge University Press, 2011, pp. 379–400. doi: 10.1017/CBO9780511996191.022.

[45] A. Muratov, Z. Saparniyazova, I. I. Bakhadirov, and A. Bijanov, “Analysis of electricity loss calculation methods in distribution networks,” *E3S Web Conf.*, vol. 289, p. 07017, Jul. 2021, doi: 10.1051/e3sconf/202128907017.

[46] J. Tuunanen, S. Honkapuro, and J. Partanen, “Power-based distribution tariff structure: DSO’s perspective,” in *2016 13th International Conference on the European Energy Market (EEM)*, IEEE, Jun. 2016, pp. 1–5. doi: 10.1109/EEM.2016.7521249.

[47] K. Bell and S. Gill, “Delivering a highly distributed electricity system: Technical, regulatory and policy challenges,” *Energy Policy*, vol. 113, pp. 765–777, Feb. 2018, doi: 10.1016/j.enpol.2017.11.039.

[48] J. Romero Aguero and A. Khodaei, “Grid Modernization, DER Integration & Utility Business Models - Trends & Challenges,” *IEEE Power Energy Mag.*, vol. 16, no. 2, pp. 112–121, Mar. 2018, doi: 10.1109/MPE.2018.2811817.

[49] Y.-C. Tsao, T. Dedimas Beyene, V.-V. Thanh, and S. G. Gebeyehu, “Power distribution network design considering dynamic and differential pricing, buy-back, and carbon trading,” *Comput. Ind. Eng.*, vol. 172, p. 108567, Oct. 2022, doi: 10.1016/j.cie.2022.108567.

[50] O. Ivanov, B.-C. Neagu, G. Grigoras, and M. Gavrilas, “Optimal Capacitor Bank Allocation in Electricity Distribution Networks Using Metaheuristic Algorithms,” *Energies*, vol. 12, no. 22, p. 4239, Nov. 2019, doi: 10.3390/en12224239.

[51] A. Rezaee Jordehi, “Allocation of distributed generation units in electric power systems: A review,” *Renew. Sustain. Energy Rev.*, vol. 56, pp. 893–905, Apr. 2016, doi: 10.1016/j.rser.2015.11.086.

[52] M. R. Behbahani, A. Jalilian, A. Bahmanyar, and D. Ernst, “Comprehensive Review on Static and Dynamic Distribution Network Reconfiguration Methodologies,” *IEEE Access*, vol. 12, pp. 9510–9525, 2024, doi: 10.1109/ACCESS.2024.3350207.

[53] B. H. Alajrash, M. Salem, M. Swadi, T. Senjyu, M. Kamarol, and S. Motahhir, “A comprehensive review of FACTS devices in modern power systems: Addressing power quality, optimal placement, and stability with renewable energy penetration,” *Energy Reports*, vol. 11, pp. 5350–5371, Jun. 2024, doi: 10.1016/j.egyr.2024.05.011.

[54] A.MERLIN and H.BACK, “Search for a minimal-loss operating spanning tree configuration in an urban power distribution system.,” *Power Syst Comput Conf (Proceedings. Power Syst. Comput. Conf. 5th 750901 Vol.1-2*, vol. 5th, no. 1, 1975.

[55] S. Civanlar, J. J. Grainger, H. Yin, and S. S. H. Lee, “Distribution feeder reconfiguration for loss reduction,” *IEEE Trans. Power Deliv.*, vol. 3, no. 3, pp. 1217–1223, Jul. 1988, doi: 10.1109/61.193906.

[56] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” *IEEE Trans. Power Deliv.*, vol. 4, no. 2, pp. 1401–1407, Apr. 1989, doi: 10.1109/61.25627.

[57] K. Nara, A. Shiose, M. Kitagawa, and T. Ishihara, “Implementation of genetic algorithm for distribution systems loss minimum re-configuration,” *IEEE Trans. Power Syst.*, vol. 7, no. 3, pp. 1044–1051, 1992, doi: 10.1109/59.207317.

[58] H. H. Alhelou, E. Heydarian-Forushani, and P. Siano, *Flexibility in Electric Power Distribution Networks*. Boca Raton: CRC Press, 2021. doi: 10.1201/9781003122326.

[59] M. Mahdavi, H. H. Alhelou, A. Bagheri, S. Z. Djokic, and R. A. V. Ramos, “A Comprehensive Review of Metaheuristic Methods for the Reconfiguration of Electric Power Distribution Systems and Comparison With a Novel Approach Based on Efficient Genetic Algorithm,” *IEEE Access*, vol. 9, pp. 122872–122906, 2021, doi: 10.1109/ACCESS.2021.3109247.

[60] H. Souifi, O. Kahouli, and H. Hadj Abdallah, “Multi-objective distribution network reconfiguration optimization problem,” *Electr. Eng.*, vol. 101, no. 1, pp. 45–55, Apr. 2019, doi: 10.1007/s00202-019-00755-3.

[61] A. Tanjung, “Reconfiguration of Power Supply System Distribution 20 Kv: PT. PLN (Persero) Dumai Area Case,” *IOP Conf. Ser. Earth Environ. Sci.*, vol. 175, p. 012101, Jul. 2018, doi: 10.1088/1755-1315/175/1/012101.

[62] N. Tung Linh, “A Novel Combination of Genetic Algorithm, Particle Swarm Optimization, and Teaching-Learning-Based Optimization for Distribution Network Reconfiguration in Case of Faults,” *Eng. Technol. Appl. Sci. Res.*, vol. 14, no. 1, pp. 12959–12965, Feb. 2024, doi: 10.48084/etasr.6718.

[63] N. Xia *et al.*, “Fuzzy Logic Based Network Reconfiguration Strategy During Power System Restoration,” *IEEE Syst. J.*, vol. 16, no. 3, pp. 4735–4743, Sep. 2022, doi: 10.1109/JSYST.2021.3123325.

[64] R. Wu and S. Liu, “Multi-Objective Optimization for Distribution Network Reconfiguration With Reactive Power Optimization of New Energy and EVs,” *IEEE Access*, vol. 11, pp. 10664–10674, 2023, doi: 10.1109/ACCESS.2023.3241228.

[65] X. Ji, Z. Yin, Y. Zhang, B. Xu, and Q. Liu, “Real-time autonomous dynamic reconfiguration based on deep learning algorithm for distribution network,” *Electr. Power Syst. Res.*, vol. 195, p. 107132, Jun. 2021, doi: 10.1016/j.epsr.2021.107132.

[66] N. Gholizadeh and P. Musilek, “Explainable reinforcement learning for distribution network reconfiguration,” *Energy Reports*, vol. 11, pp. 5703–5715, Jun. 2024, doi: 10.1016/j.egyr.2024.05.031.

[67] D. R. S. N.M. Neagle, “Loss reduction from capacitors installed on primary feeders,” *AIEE Trans.*, vol. 75, no. III, pp. 950–959, 1956.

[68] J. V. Schmill, “Optimum Size and Location of Shunt Capacitors on Distribution Feeders,” *IEEE Trans. Power Appar. Syst.*, vol. 84, no. 9, pp. 825–832, Sep. 1965, doi: 10.1109/TPAS.1965.4766262.

[69] H. Dura, “Optimum Number, Location, and Size of Shunt Capacitors in Radial Distribution Feeders A Dynamic Programming Approach,” *IEEE Trans. Power Appar. Syst.*, vol. PAS-87, no. 9, pp. 1769–1774, Sep. 1968, doi: 10.1109/TPAS.1968.291982.

[70] Y. G. Bae, “Analytical Method of Capacitor Allocation on Distribution Primary Feeders,” *IEEE Trans. Power Appar. Syst.*, vol. PAS-97, no. 4, pp. 1232–1238, Jul. 1978, doi: 10.1109/TPAS.1978.354605.

[71] J. Grainger and S. Lee, “Optimum Size and Location of Shunt Capacitors for Reduction of Losses on Distribution Feeders,” *IEEE Trans. Power Appar. Syst.*, vol. PAS-100, no. 3, pp. 1105–1118, Mar. 1981, doi: 10.1109/TPAS.1981.316577.

[72] J. E. W. J.B. Bunch, R.D. Miller, “Distribution system integrated voltage and reactive power control,” *IEEE Trans. Power Appar. Syst.*, no. 284–289, 1982.

[73] S. H. L. J.J. Grainger, S. Civanlar, “Optimal design and control scheme for continuous capacitive compensation of distribution feeders,” *IEEE Trans. Power Appar. Syst.*, vol. 10, pp. 3271–3278, 1983.

[74] T. Basso, “IEEE 1547 and 2030 standards for distributed energy resources interconnection and interoperability with the electricity grid,” 2014.

[75] A. K. Singh and S. K. Parida, “A review on distributed generation allocation and planning in deregulated electricity market,” *Renew. Sustain. Energy Rev.*, vol. 82, pp.

4132–4141, Feb. 2018, doi: 10.1016/j.rser.2017.10.060.

[76] M. Pesaran H.A, P. D. Huy, and V. K. Ramachandaramurthy, “A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms,” *Renew. Sustain. Energy Rev.*, vol. 75, pp. 293–312, Aug. 2017, doi: 10.1016/j.rser.2016.10.071.

[77] S. Mishra, D. Das, and S. Paul, “A comprehensive review on power distribution network reconfiguration,” *Energy Syst.*, vol. 8, no. 2, pp. 227–284, May 2017, doi: 10.1007/s12667-016-0195-7.

[78] M. Alanazi, A. Alanazi, A. Almadhor, and Z. A. Memon, “Multiobjective reconfiguration of unbalanced distribution networks using improved transient search optimization algorithm considering power quality and reliability metrics,” *Sci. Rep.*, vol. 12, no. 1, p. 13686, Aug. 2022, doi: 10.1038/s41598-022-17881-x.

[79] K. Mahmoud and M. Lehtonen, “Direct approach for optimal allocation of multiple capacitors in distribution systems using novel analytical closed-form expressions,” *Electr. Eng.*, vol. 103, no. 1, pp. 245–256, Feb. 2021, doi: 10.1007/s00202-020-01073-9.

[80] U. Raut and S. Mishra, “A new Pareto multi-objective sine cosine algorithm for performance enhancement of radial distribution network by optimal allocation of distributed generators,” *Evol. Intell.*, vol. 14, no. 4, pp. 1635–1656, Dec. 2021, doi: 10.1007/s12065-020-00428-2.

[81] T. P. Nguyen, T. A. Nguyen, T. V.-H. Phan, and D. N. Vo, “A comprehensive analysis for multi-objective distributed generations and capacitor banks placement in radial distribution networks using hybrid neural network algorithm,” *Knowledge-Based Syst.*, vol. 231, p. 107387, Nov. 2021, doi: 10.1016/j.knosys.2021.107387.

[82] H. Lotfi, R. Ghazi, and M. bagher Naghibi-Sistani, “Multi-objective dynamic distribution feeder reconfiguration along with capacitor allocation using a new hybrid evolutionary algorithm,” *Energy Syst.*, vol. 11, no. 3, pp. 779–809, Aug. 2020, doi: 10.1007/s12667-019-00333-3.

[83] O. Badran, S. Mekhilef, H. Mokhlis, and W. Dahalan, “Optimal reconfiguration of distribution system connected with distributed generations: A review of different methodologies,” *Renew. Sustain. Energy Rev.*, vol. 73, pp. 854–867, Jun. 2017, doi: 10.1016/j.rser.2017.02.010.

[84] K. S. Sambaiah and T. Jayabarathi, “Loss minimization techniques for optimal operation and planning of distribution systems: A review of different methodologies,” *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 2, Feb. 2020, doi: 10.1002/2050-7038.12230.

[85] M. K. and J. S., “Integrated approach of network reconfiguration with distributed generation and shunt capacitors placement for power loss minimization in radial distribution networks,” *Appl. Soft Comput.*, vol. 52, pp. 1262–1284, Mar. 2017, doi: 10.1016/j.asoc.2016.07.031.

[86] J. Salehi, M. R. Jannati Oskuee, and A. Amini, “Stochastics multi-objective modelling of simultaneous reconfiguration of power distribution network and allocation of DGs and capacitors,” *Int. J. Ambient Energy*, vol. 39, no. 2, pp. 176–187, Feb. 2018, doi: 10.1080/01430750.2017.1280084.

[87] M. Mohammadi, A. M. Rozbahani, and S. Bahmanyar, “Power loss reduction of distribution systems using BFO based optimal reconfiguration along with DG and

shunt capacitor placement simultaneously in fuzzy framework," *J. Cent. South Univ.*, vol. 24, no. 1, pp. 90–103, Jan. 2017, doi: 10.1007/s11771-017-3412-1.

[88] P. P. Biswas, P. N. Suganthan, and G. A. J. Amaratunga, "Distribution Network Reconfiguration Together with Distributed Generator and Shunt Capacitor Allocation for Loss Minimization," in *2018 IEEE Congress on Evolutionary Computation (CEC)*, IEEE, Jul. 2018, pp. 1–7. doi: 10.1109/CEC.2018.8477894.

[89] P. Gangwar, S. N. Singh, and S. Chakrabarti, "Multi-objective planning model for multi-phase distribution system under uncertainty considering reconfiguration," *IET Renew. Power Gener.*, vol. 13, no. 12, pp. 2070–2083, Sep. 2019, doi: 10.1049/iet-rpg.2019.0135.

[90] V. B. Pamshetti, S. Singh, and S. P. Singh, "Combined Impact of Network Reconfiguration and Volt-VAR Control Devices on Energy Savings in the Presence of Distributed Generation," *IEEE Syst. J.*, vol. 14, no. 1, pp. 995–1006, Mar. 2020, doi: 10.1109/JSYST.2019.2928139.

[91] H. B. Tolabi, A. L. Ara, and R. Hosseini, "A new thief and police algorithm and its application in simultaneous reconfiguration with optimal allocation of capacitor and distributed generation units," *Energy*, vol. 203, p. 117911, Jul. 2020, doi: 10.1016/j.energy.2020.117911.

[92] S. R. Biswal, G. Shankar, R. M. Elavarasan, and L. Mihet-Popa, "Optimal Allocation/Sizing of DGs/Capacitors in Reconfigured Radial Distribution System Using Quasi-Reflected Slime Mould Algorithm," *IEEE Access*, vol. 9, pp. 125658–125677, 2021, doi: 10.1109/ACCESS.2021.3111027.

[93] M. M. Sayed, M. Y. Mahdy, S. H. E. Abdel Aleem, H. K. M. Youssef, and T. A. Boghdady, "Simultaneous Distribution Network Reconfiguration and Optimal Allocation of Renewable-Based Distributed Generators and Shunt Capacitors under Uncertain Conditions," *Energies*, vol. 15, no. 6, p. 2299, Mar. 2022, doi: 10.3390/en15062299.

[94] M. Kandasamy, R. Thangavel, T. Arumugam, J. Jayaram, W.-W. Kim, and Z. W. Geem, "Performance Enhancement of Radial Power Distribution Networks Using Network Reconfiguration and Optimal Planning of Solar Photovoltaic-Based Distributed Generation and Shunt Capacitors," *Sustainability*, vol. 14, no. 18, p. 11480, Sep. 2022, doi: 10.3390/su141811480.

[95] S. E. De León-Aldaco, H. Calleja, and J. Aguayo Alquicira, "Metaheuristic Optimization Methods Applied to Power Converters: A Review," *IEEE Trans. Power Electron.*, vol. 30, no. 12, pp. 6791–6803, Dec. 2015, doi: 10.1109/TPEL.2015.2397311.

[96] R. B. E.H. Abdelkhalk, *Optimizations and Programming: Linear, Nonlinear, Dynamic, Stochastic, and Applications with matlab*. ISTE Ltd and John Wiley & Sons, Inc., 2021.

[97] S. M. Almufti, A. Ahmad Shaban, Z. Arif Ali, R. Ismael Ali, and J. A. Dela Fuente, "Overview of Metaheuristic Algorithms," *Polaris Glob. J. Sch. Res. Trends*, vol. 2, no. 2, pp. 10–32, Apr. 2023, doi: 10.58429/pgjsrt.v2n2a144.

[98] V. Ganesan *et al.*, "Quantum inspired meta-heuristic approach for optimization of genetic algorithm," *Comput. Electr. Eng.*, vol. 94, p. 107356, Sep. 2021, doi: 10.1016/j.compeleceng.2021.107356.

[99] X. S. Yang, *Nature-Inspired Metaheuristic Algorithms*. Luniver Press, 2010.

[100] H. M. Abdullah, S. Park, K. Seong, and S. Lee, "Hybrid Renewable Energy System Design: A Machine Learning Approach for Optimal Sizing with Net-Metering Costs," *Sustainability*, vol. 15, no. 11, p. 8538, May 2023, doi: 10.3390/su15118538.

[101] I. Boussaïd, J. Lepagnot, and P. Siarry, "A survey on optimization metaheuristics," *Inf. Sci. (Ny).*, vol. 237, pp. 82–117, Jul. 2013, doi: 10.1016/j.ins.2013.02.041.

[102] S. Dey, S. De, and S. Bhattacharyya, "Introduction to Hybrid Metaheuristics," 2018, pp. 1–38. doi: 10.1142/9789813270237_0001.

[103] C. Blum and G. R. Raidl, *Hybrid Metaheuristics*. in Artificial Intelligence: Foundations, Theory, and Algorithms. Cham: Springer International Publishing, 2016. doi: 10.1007/978-3-319-30883-8.

[104] N. Gunantara, "A review of multi-objective optimization: Methods and its applications," *Cogent Eng.*, vol. 5, no. 1, p. 1502242, Jan. 2018, doi: 10.1080/23311916.2018.1502242.

[105] S. Verma, M. Pant, and V. Snasel, "A Comprehensive Review on NSGA-II for Multi-Objective Combinatorial Optimization Problems," *IEEE Access*, vol. 9, pp. 57757–57791, 2021, doi: 10.1109/ACCESS.2021.3070634.

[106] N. G. S. LALWANI, S. SINGHAL, R. KUMAR, "A Comprehensive survey: Applications of multi-objevtive particle swarm optimization (MOPSO) algorithm," *Trans actions Comb.*, vol. 2 (1), pp. 39–101, 2013, doi: 10.22108/toc.2013.2834.

[107] X. Li, X. Li, K. Wang, and S. Yang, "A strength pareto evolutionary algorithm based on adaptive reference points for solving irregular fronts," *Inf. Sci. (Ny).*, vol. 626, pp. 658–693, May 2023, doi: 10.1016/j.ins.2023.01.073.

[108] Y. Zhu, Y. Qin, D. Yang, H. Xu, and H. Zhou, "An enhanced decomposition-based multi-objective evolutionary algorithm with a self-organizing collaborative scheme," *Expert Syst. Appl.*, vol. 213, p. 118915, Mar. 2023, doi: 10.1016/j.eswa.2022.118915.

[109] X. Yuan *et al.*, "Multi-objective optimal power flow based on improved strength Pareto evolutionary algorithm," *Energy*, vol. 122, pp. 70–82, Mar. 2017, doi: 10.1016/j.energy.2017.01.071.

[110] L. Hu, Y. Yang, Z. Tang, Y. He, and X. Luo, "FCAN-MOPSO: An Improved Fuzzy-Based Graph Clustering Algorithm for Complex Networks With Multiobjective Particle Swarm Optimization," *IEEE Trans. Fuzzy Syst.*, vol. 31, no. 10, pp. 3470–3484, Oct. 2023, doi: 10.1109/TFUZZ.2023.3259726.

[111] N. Ghorbani, A. Kasaeian, A. Toopshekan, L. Bahrami, and A. Maghami, "Optimizing a hybrid wind-PV-battery system using GA-PSO and MOPSO for reducing cost and increasing reliability," *Energy*, vol. 154, pp. 581–591, Jul. 2018, doi: 10.1016/j.energy.2017.12.057.

[112] S. Barshandeh, F. Piri, and S. R. Sangani, "HMPA: an innovative hybrid multi-population algorithm based on artificial ecosystem-based and Harris Hawks optimization algorithms for engineering problems," *Eng. Comput.*, vol. 38, no. 2, pp. 1581–1625, Apr. 2022, doi: 10.1007/s00366-020-01120-w.

[113] W. Zhao, L. Wang, and Z. Zhang, "Artificial ecosystem-based optimization: a novel nature-inspired meta-heuristic algorithm," *Neural Comput. Appl.*, vol. 32, no. 13, pp. 9383–9425, Jul. 2020, doi: 10.1007/s00521-019-04452-x.

[114] H. C. [24] A.A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, "Harris hawks optimization: algorithm and application," *Futur. Gener Comput Syst*, vol. 97, pp. 849–

872, 2019.

[115] A. Faramarzi, M. Heidarinejad, B. Stephens, and S. Mirjalili, “Equilibrium optimizer: A novel optimization algorithm,” *Knowledge-Based Syst.*, vol. 191, p. 105190, Mar. 2020, doi: 10.1016/j.knosys.2019.105190.

[116] B. Abdollahzadeh, F. Soleimanian Gharehchopogh, and S. Mirjalili, “Artificial gorilla troops optimizer: A new nature-inspired metaheuristic algorithm for global optimization problems,” *Int. J. Intell. Syst.*, vol. 36, no. 10, pp. 5887–5958, Oct. 2021, doi: 10.1002/int.22535.

[117] B. Abdollahzadeh, F. S. Gharehchopogh, and S. Mirjalili, “African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems,” *Comput. Ind. Eng.*, vol. 158, p. 107408, Aug. 2021, doi: 10.1016/j.cie.2021.107408.

[118] A. Bouhanik, A. Salhi, and D. Naimi, “Optimal Capacitor Allocation Based On Hourly Load Variation Via New Optimization Algorithms,” in *2022 19th International Multi-Conference on Systems, Signals & Devices (SSD)*, IEEE, May 2022, pp. 2035–2040. doi: 10.1109/SSD54932.2022.9955910.

[119] G. W. Chang, S. Y. Chu, and H. L. Wang, “An Improved Backward/Forward Sweep Load Flow Algorithm for Radial Distribution Systems,” *IEEE Trans. Power Syst.*, vol. 22, no. 2, pp. 882–884, May 2007, doi: 10.1109/TPWRS.2007.894848.

[120] O. D. Montoya, W. Gil-González, and A. Garcés, “On the Conic Convex Approximation to Locate and Size Fixed-Step Capacitor Banks in Distribution Networks,” *Computation*, vol. 10, no. 2, p. 32, Feb. 2022, doi: 10.3390/computation10020032.

[121] A. Bouhanik, A. Salhi, D. Naimi, Y. Zahraoui, and S. Mekhilef, “Distribution Network Reconfiguration Based on Hourly Load Variation Via New Optimization Algorithms,” in *2023 International Conference on Electrical Engineering and Advanced Technology (ICEEAT)*, IEEE, Nov. 2023, pp. 1–5. doi: 10.1109/ICEEAT60471.2023.10426483.

[122] S. Eng, O. Penangsang, R. S. Wibowo, I. Suryawati, and C. Chhlonh, “Distribution System Restoration Using Spanning Tree Based on Depth First Search Visual in GUI,” in *2019 5th International Conference on Science and Technology (ICST)*, IEEE, Jul. 2019, pp. 1–6. doi: 10.1109/ICST47872.2019.9166413.

[123] A. Bouhanik, A. Salhi, D. Imene, and D. Naimi, “An efficient hybrid multi-population algorithm (HMPA) for enhancing techno-economic benefits,” *Soft Comput.*, Jul. 2024, doi: 10.1007/s00500-024-09807-8.

[124] L. B. A. Tarquin, *Engineering Economy*, Seventh. New York: McGraw-Hill Companies, 2012.

[125] C. Gu, X. Yan, Z. Yan, and F. Li, “Dynamic pricing for responsive demand to increase distribution network efficiency,” *Appl. Energy*, vol. 205, pp. 236–243, Nov. 2017, doi: 10.1016/j.apenergy.2017.07.102.

[126] E. Ehsani, N. Kazemi, E. U. Olugu, E. H. Grosse, and K. Schwindl, “Applying fuzzy multi-objective linear programming to a project management decision with nonlinear fuzzy membership functions,” *Neural Comput. Appl.*, vol. 28, no. 8, pp. 2193–2206, Aug. 2017, doi: 10.1007/s00521-015-2160-0.