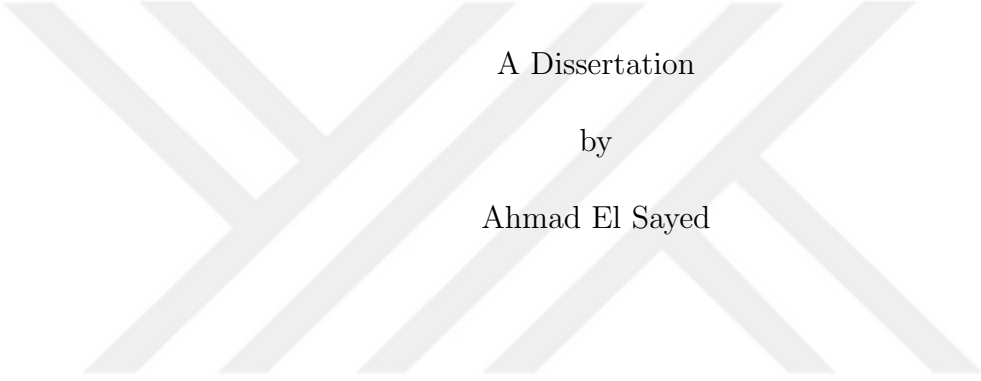


OPTIMAL MULTIPLE DER PLANNING WITH INNOVATIVE ALGORITHMS FOR ENHANCED POWER SYSTEM PERFORMANCE AND COMPUTATIONAL EFFICIENCY



A Dissertation

by

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To those in darkness. May this work bring light and hope

ABSTRACT

Distributed Energy Resources (DERs) are decentralized generation units, including solar PV systems, wind turbines, and energy storage technologies, that are located close to end-users. They play a crucial role in modernizing the energy grid, promoting energy independence, and mitigating the environmental impact of electricity production. This dissertation explores the optimization of DER planning across several key areas. It proposes an integrated framework for capacity planning of grid-connected nanogrids—small solar and energy storage systems that provide kilowatt-level services to individual buildings. The framework employs a techno-enviro-economic assessment to balance cost-effectiveness and sustainability. At the grid scale, widespread random DER deployment can affect grid stability and security, potentially leading to power outages. Finding the optimal capacity and location of DERs in distribution networks with multiple units is challenging and considered an NP-hard optimization problem. This study proposes a method incorporating PSO for hybrid distributed system integration and compares simultaneous and bi-level approaches for determining system size and site selection. A novel method named PS-TVPSO is introduced, addressing traditional PSO limitations by incorporating power grid topology, resistivity, and demand characteristics into the optimization steps to avoid local optima convergence. The effectiveness of these techniques is demonstrated through their application to renewable DERs with storage, significantly improving power system performance and sustainability across several distribution networks. Simulations on IEEE 33-bus and IEEE 69-bus systems, as well as a Norwegian case, validate these findings. The outcomes highlight the significance of the proposed approaches in addressing the complexities of DER planning under realistic scenarios.

ÖZETÇE

Dağıtık Enerji Kaynakları (DER), son kullanıcıların yakınında bulunan, güneş PV sistemleri, rüzgar türbinleri ve enerji depolama teknolojileri dahil olmak üzere merkezi olmayan elektrik üretim birimleridir. Bu kaynaklar, enerji şebekesini modernize etme, enerji bağımsızlığını teşvik etme ve elektrik üretiminin çevresel etkilerini hafifletme konusunda önemli bir rol oynamaktadır. Bu tez, çeşitli kilit alanlarda DER planlamasının optimizasyonunu araştırmaktadır. Şebekeye bağlı nano-şebekelerin kapasite planlaması için entegre bir çerçeve önermektedir. Bu nano-şebekeler bireysel binalara kilowatt seviyesinde hizmetler sağlayan küçük ölçekli güneş ve enerji depolama sistemleridir. Çerçeve, maliyet etkinliği ve sürdürülebilirliği dengelemek için bir teknoloji-çevre-ekonomik değerlendirme metodolojisi kullanmaktadır. Şebekede rastgele DER dağılımı şebeke kararlılığını ve güvenliğini etkileyebilir, potansiyel olarak elektrik kesintilerine yol açabilir. Çok sayıda birime sahip dağıtım şebekelerinde DER'lerin optimal kapasitesini ve yerini bulmak zorlayıcı ve NP-hard bir optimizasyon problemi olarak kabul edilmektedir. Bu çalışma, hibrit dağıtık sistem entegrasyonu için PSO'yu içeren bir yöntem önermekte ve sistem boyutu ile yer seçiminin belirlenmesinde eşzamanlı ve iki seviyeli yaklaşımları karşılaştırmaktadır. Bu çalışmada ayrıca, PS-TVPSO adında yeni bir yöntem tanıtılmakta olup, geleneksel PSO'nun sınırlamalarını aşmak için güç şebekesi topolojisi, dirençlilik ve talep özelliklerini PSO'nun optimizasyon adımlarına dahil etmektedir. Bu tekniklerin etkinliği, depolama ile yenilenebilir DER'lere uygulanarak, çeşitli dağıtım şebekelerinde güç sistemi performansını ve sürdürülebilirliğini önemli ölçüde artırdığı gösterilmektedir. IEEE 33-bus ve IEEE 69-bus sistemleri ile bir Norveç vakası üzerindeki simülasyonlar, bu bulguları doğrulamaktadır. Sonuçlar, önerilen yaklaşımların gerçekçi senaryolar

altında DER planlamasının karmaşıklıklarını ele almada önemini vurgulamaktadır.



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LIST OF ABBREVIATIONS

APSO	Adaptive PSO
BESS	Battery Energy Storage System
CDF	Cumulative Distribution Function
DoD	Depth of Discharge
DER	Distributed Energy Resource
DG	Distributed Generation
EMS	Energy Management System
ESS	Energy Storage System
LP	Linear Programming
MAE	Mean Absolute Error
MILP	Mixed Integer Linear Programming
PSO	Particle Swarm Optimization
PS-TVPSO	Power System Oriented TVPSO
PV	Photovoltaic
RDS	Radial Distribution System
RLE	Relative Error
RMSE	Root Mean Square Error
SSR	Self Sufficiency Ratio
TOU	Time of Use
TVPSO	Time Varying PSO
VDI	Voltage Deviation Index

CHAPTER I

INTRODUCTION

Power systems play a fundamental role in sustaining modern communities, powering a wide range of applications from domestic utilities to industrial processes and transportation. Traditionally, conventional power systems have been the backbone of electricity generation, relying mainly on centralized fossil fuel-based power plants such as coal, natural gas, and nuclear plants. They supply electricity across transmission lines to the distribution network and then to end-users. While these systems have historically met community power needs, they are increasingly confronted with challenges related to sustainability, environmental impact, and resilience. Conventional power systems are typically classified into three main stages: generation, transmission, and distribution, shown in Fig. 1. Transformers are used at various points to maintain voltage levels suitable for each stage. After the distribution stage, the power is delivered to homes, businesses, and industries.

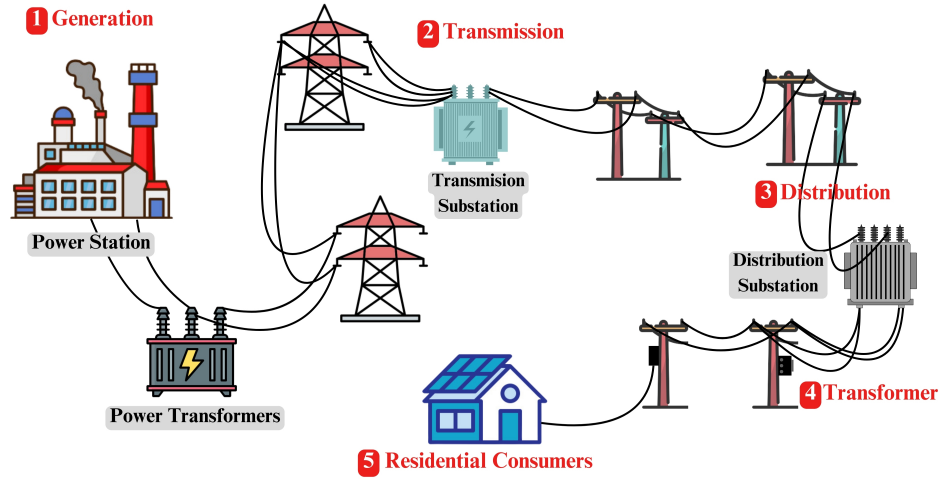


Figure 1: Conventional Power Systems

The three main stages are explained as:

- **Generation:** Electricity is produced at power plants, traditionally fueled by coal, natural gas, oil, and nuclear energy. These power plants convert various types of fuels into electrical power through processes such as combustion and nuclear fission
- **Transmission:** Electricity is transmitted over long distances via high-voltage transmission lines to residential, commercial, and industrial areas. Substations along the network regulate voltage levels using power transformers.
- **Distribution:** Electricity is delivered to end-users through distribution networks, comprising lines, transformers, and substations. Voltage is further reduced before reaching consumers.

In contrast, modern power systems represent a transformation from a conventional structure towards a decentralized and environmentally friendly paradigm, illustrated in Fig. 2.

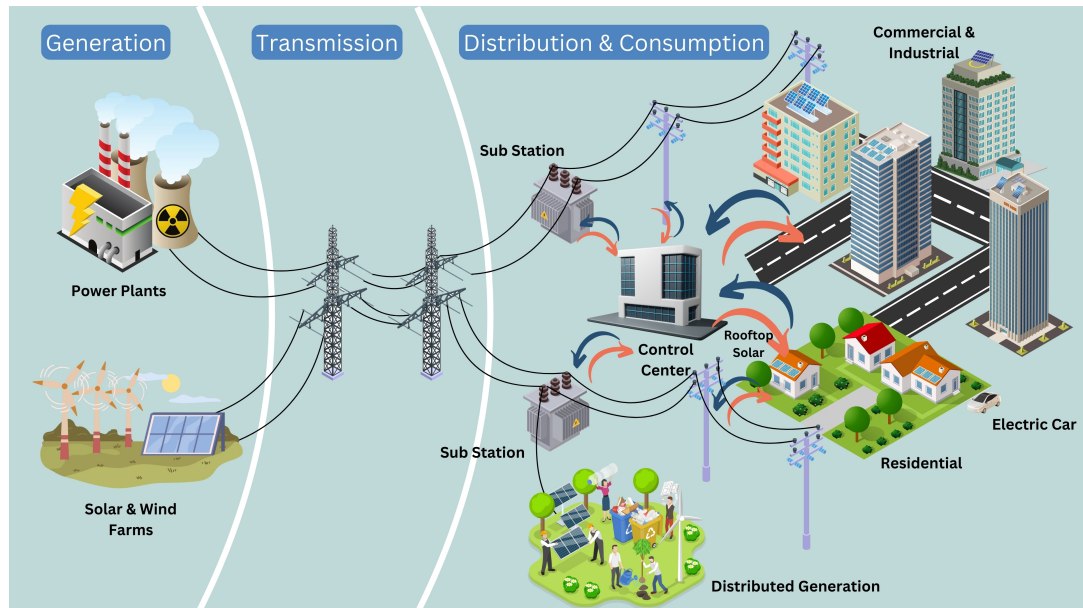


Figure 2: Modern Power Systems

They adopt renewable energy sources (RES) such as solar photovoltaic (PV), wind, and hydroelectric power, along with distributed generation (DG) units such as rooftop solar panels and microturbines. Moreover, they utilize energy storage systems (ESS) such as batteries and pumped hydro storage. Additionally, modern power systems feature smart grid infrastructure for energy management, enabling real-time data analytics and optimal control. This smart infrastructure integrates sensors and communication networks, enhancing grid intelligence and optimal control technologies.

This shift towards modern power systems reflects a strategic response to urgent priorities such as climate change mitigation, energy security, and technological progress. Through the adoption of cleaner energy sources and the utilization of innovative grid management approaches, modern power systems aim to enhance a more sustainable and resilient energy landscape towards meeting the evolving societal demands of the 21st century. The modern electrical power system infrastructure faces numerous challenges, including high power losses and decreased efficiency, and renewable energy variability. Ensuring grid stability, efficiency and reliability necessitates non-traditional approaches to address these issues. One such approach is distributed generation (DG) or distributed energy resources (DER), which involves establishing smaller generators near consumers to offer environmental, economic, and technological benefits, particularly within distribution networks. Utilities can efficiently manage these generators, allowing for rapid adjustments to changes in demand or supply and enhancing the performance of the grid.

1.1 Microgrid and Nanogrid

Integrating DG at consumer locations also introduces microgrids (MGs), marking a new era in power system design. MGs are electrical distribution systems comprising interconnected loads and distributed energy sources, functioning as a single

controllable entity. They can operate in grid-connected or isolated mode, facilitating bi-directional energy exchanges with the utility grid or functioning independently. MGs encompass diverse energy resources, including renewables like solar PV and wind, and other distributed units such as diesel generators and energy storage. The scale of MGs varies, ranging from a campus or village to an island or urban municipality. At the smallest scale of microgrids lies the nanogrid (NG), typically a single building-level system operating either in grid-connected or isolated mode, managing loads below 20 kW. A typical nanogrid architecture is shown in Fig. 3.

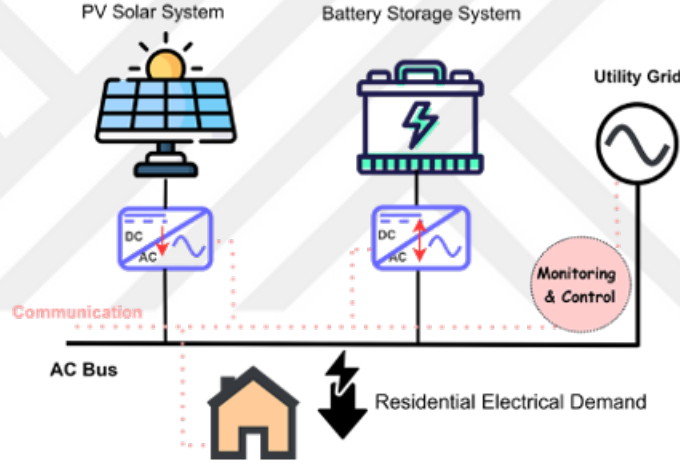


Figure 3: Nanogrid Architecture

NGs utilize clean energy sources like fuel cells, solar panels, and wind turbines, and must have at least one power load and an external connection point. Unlike microgrids, NGs face fewer technical and regulatory challenges, making them widely implemented in homes, rural areas, and small-scale industrial settings.

1.2 DER Integration into Distribution Systems

The integration of DER into radial distribution networks (RDNs) has recently gained attention due to its environmental, economic, and technical benefits. DERs improve

voltage profiles, increase efficiency, and reduce power losses, although their intermittent nature poses challenges in maintaining grid stability. Energy storage technologies have emerged as pivotal components. ESS technologies, such as lithium-ion batteries, pumped hydro storage, and flywheels, play a crucial role in mitigating the intermittency of RES and smoothing out fluctuations in DG output. They provide supplementary power during periods of grid instability or outages, further supporting the grid against disruptions. ESS is capable of storing surplus energy during periods of low demand or high renewable generation and discharging it when needed to balance supply and demand operations. This enhances grid flexibility, facilitates RES integration, and reinforces overall system reliability by avoiding grid instability or outages.

In summary, the transition from conventional to modern power systems signifies a pivotal advancement towards achieving greater sustainability, reliability, and efficiency in distribution systems. The implementation of DER and smart grid technologies underscores a proactive approach to the growing demands and challenges faced by present energy systems. This dissertation aims to address the challenges of optimizing DERs across various scales, from nanogrid to grid-level integration. By proposing novel optimization methods and utilizing time-series data, the study aims to enhance the reliability, efficiency, and sustainability of distribution systems in response to changing energy demands and environmental concerns. Additionally, novel enhancements on metaheuristic algorithms will be proposed to overcome the complexities of DER planning problems. The overarching aim is to foster the development of more dependable, adaptable, and eco-friendly power systems that can effectively address the evolving energy requirements of the 21st century.

1.3 Problem Statement

Traditional DER capacity planning, particularly for nanogrids, often prioritizes peak load requirements, which may lack optimality due to the infrequent nature of peak load occurrences. Conversely, optimizing solely for base load requirements might also be ineffective, compromising reliability and sustainability objectives. On the other hand, DER capacity planning necessitates a multi-perspective analysis where a tradeoff between several requirements, such as reliability, cost-effectiveness, and environmental impact needs to be satisfied. This indicates a critical gap in the current methodologies for DER sizing and operation under realistic conditions.

The optimal integration of large-scale DERs in distribution networks poses a challenging task, particularly in large networks with multiple DERs. Simultaneous sizing and allocation are complex NP-hard problems, requiring innovative strategies to address load and generation variations over time. Enhanced metaheuristic strategies, such as PSO, are backbones in optimizing capacity sizing and allocation by leveraging time-series data such as electricity prices, demand profiles, and solar PV generation profiles. Splitting the tasks into two separate steps—sizing and allocation—and optimizing each individually, is a current discussion in the literature to simplify computations and reduce complexity. This approach requires comprehensive validation and analysis to determine its effects on solution quality and computational efficiency and compare it with centralized methods.

While metaheuristic algorithms for optimizing DER integration offer practical solutions within reasonable timeframes, conventional heuristic optimization methods often overlook key electrical network characteristics due to numerical bias. Therefore, innovative enhancements are needed to improve the PSO search process and prevent premature convergence to local optima. These proposed enhancements should be validated under realistic conditions, including dynamic seasonal demand and generation

scenarios. Furthermore, relying solely on standard test cases and benchmarks is inadequate; these algorithms need to be tested on larger, more complex networks that accurately represent real-world grids to confirm their effectiveness and scalability.

1.4 Dissertation Scope and Structure

This dissertation presents a comprehensive exploration of distributed energy system optimization across several critical areas. Chapter 2 lays the foundation by discussing the fundamentals of DER optimization, including modeling renewable systems, power flow analysis, and optimal power flow concepts. It reviews various optimization methods such as Linear Programming (LP), Mixed-Integer Linear Programming (MILP), and metaheuristic approaches. It also highlights test cases like the IEEE 33-bus, IEEE 69-bus, and Norwegian 124-bus systems commonly used to validate methods and models.

Chapter 3 delves into nanogrid planning and operations, introducing an integrated framework for capacity planning that balances cost-effectiveness and sustainability. This framework employs a techno-enviro-economic assessment approach, evaluating the viability of nanogrid solutions through planner, operator, and evaluator modules. Optimal deployment of DER units within the distribution system is crucial for maintaining grid stability and security. Without proper integration, DERs can adversely affect grid performance and potentially lead to power outages. This challenge is particularly significant in multi-DER integration and larger power networks, where optimal sizing and allocation become increasingly complex. As the problem grows with additional DER units or network expansion, its complexity increases exponentially. Therefore, metaheuristic approaches are preferred for solving DER sizing and siting problems in distribution systems. Given the NP-hard nature of these problems, heuristic algorithms provide practical solutions within reasonable timeframes.

Chapter 4 focuses on optimizing hybrid distributed resources within radial distribution networks. It compares optimization methods and examines centralized versus decentralized approaches. Sensitivity analysis of APSO parameters is conducted to refine optimization algorithms for better efficiency. Metaheuristics especially PSO, often overlooks key electrical network characteristics while optimizing DER planning, due to a numerical bias.

Chapter 5 proposes a novel power system-oriented PSO approach named PS-TVPSO. This approach integrates innovative algorithms designed to enhance the PSO search process and prevent convergence to local optima. These algorithms account for the power grid's topology, resistivity, and demand patterns, guiding the optimization process towards favorable regions for DER deployment.

In Chapter 6, the dissertation applies these new methods to diversified renewable DER with storage, further improving the reliability and sustainability of power systems. This chapter demonstrates the practical application and effectiveness of these advanced optimization techniques in real-world scenarios, paving the way for more integrated and adaptable energy systems. The proposed approaches is validated using IEEE 33-bus, IEEE 69-bus, and Norwegian 124-bus systems.

Finally, Chapter 7 concludes the dissertation, summarizing the key findings and contributions.

CHAPTER II

FUNDAMENTALS OF RESOURCE OPTIMIZATION IN DISTRIBUTION SYSTEMS

This chapter delves into the principles and practical aspects of DER optimization. It provides a comprehensive exploration of the essential elements required for the optimal planning and integration of DER in distribution networks. The discussion begins with the modeling of emerging technologies and examines specific renewable energy systems, including solar photovoltaic and wind energy systems, alongside the crucial role of energy storage systems. Various optimization techniques used in energy systems are illustrated, such as linear programming, mixed integer linear programming, and metaheuristics, with a particular focus on particle swarm optimization (PSO). Furthermore, the chapter covers power flow and optimal power flow analysis, essential for understanding and optimizing the performance of DER within a power grid. Finally, it presents test cases and benchmarks, required to validate and compare optimization methods and models.

2.1 Modeling of Emerging Resources

2.1.1 Solar Photovoltaic Energy System

Solar power systems, derived from the conversion of sun arrays into electricity through PV cells, is a rapidly growing renewable energy source. PV systems capture sunlight and generate direct current (DC) electricity, which can then be converted into alternating current (AC) for use in homes, businesses, and industries. Solar energy is abundant, environmentally friendly, and offers a sustainable solution to meet the world's growing energy demands and environmental concerns. There are numerous

models to calculate the PV output power. A simplified linear model that considers solar radiation and ambient temperature is shown in (1).

$$P_t^{pv} = P_{\text{cap}}^{pv} \cdot \frac{G_t}{1000} [1 + \alpha_t (T_{\text{am}} + [0.0256 \cdot G_t]) - T_{\text{STC}}] \quad (1)$$

Where P_t^{pv} represents the output power of the PV module at time t in kW; P_{cap}^{pv} denotes the rated capacity of the PV module under standard conditions in kWp; G_t stands for solar radiation in W/m²; T_{am} signifies the ambient temperature in °C; α_t indicates the temperature coefficient of the PV module in 1/°C; and T_{STC} represents the cell temperature at standard test conditions in °C.

2.1.2 Wind Energy System

Wind power harnesses the kinetic energy of wind to generate electricity through wind turbines. These turbines consist of blades that capture the wind's energy and convert it into rotational motion, which drives a generator to produce electricity. Wind power is a clean and abundant energy source that has seen significant growth in recent years. A commonly used model to estimate the output power of a wind turbine is the power curve model, which relates the wind speed to the power output of the turbine. The output power calculation of wind turbine is illustrated in (2).

$$P_t^{\text{wind}} = \frac{1}{2} \rho A C_p (V_t)^3 \quad (2)$$

Where P_t^{wind} is the output power of the wind turbine at time t , ρ is the air density in kg/m³, A is the rotor area of the wind turbine in m², and $C_p(V_t)^3$ is the power coefficient of the wind turbine, which is a function of wind speed V_t .

2.1.3 Energy Storage System

Energy storage systems play a crucial role in enhancing the reliability and stability of renewable energy integration. These systems store excess energy generated from RES like solar and wind during periods of high production and release it when demand is high or RES generation is low. Lithium-ion batteries, pumped hydro storage, and other storage technologies enable grid operators to balance supply and demand, smooth out fluctuations in renewable energy output, and provide backup power during grid outages.

When the energy generated by the photovoltaic (PV) system surpasses the demand, the ESS initiates charging. The charging energy of the ESS at time t can be obtained by (3). The ESS discharges according to (4) when the load demand exceeds the generated power.

$$E_t^{\text{ESS}} = E_{(t-\Delta t)}^{\text{ESS}} + \eta_{\text{ch}} P_t^{\text{ch}} \Delta t \quad (3)$$

$$E_t^{\text{ESS}} = E_{(t-\Delta t)}^{\text{ESS}} - \frac{P_t^{\text{dis}} \Delta t}{\eta_{\text{dis}}} \quad (4)$$

Where, E_t^{ESS} , P_t^{ch} , and P_t^{dis} represent ESS energy, charging power, and discharging power respectively; η_{ch} denotes the charging efficiency; and η_{dis} represents the discharging efficiency.

2.2 Optimization in Energy Systems

Optimization techniques play a crucial role in addressing complex problems within energy systems, allowing for the efficient sizing, allocation and operations of resources and the achievement of other various objectives too. This section describes three optimization methods commonly utilized in energy systems problems: Linear Programming, Mixed Integer Linear Programming, and Metaheuristics. Additionally, it discusses the challenges associated with certain power system problems, such as the

non-linearity and non-convexity of Optimal Power Flow (OPF), and introduces Particle Swarm Optimization (PSO) as a metaheuristic approach utilized and developed in this dissertation.

2.2.1 Linear Programming

Linear Programming (LP) is a mathematical optimization technique used to optimize a linear objective function subject to a set of linear equality and inequality constraints.

The general form of an LP problem is as follows:

$$\text{Minimize } c^T x \tag{5}$$

$$\text{Subject to } Ax \leq b \tag{6}$$

$$x \geq 0 \tag{7}$$

Where x is a vector of decision variables; c is the coefficient vector of the objective function to be minimized; A is the coefficient matrix representing the constraints; b is the right-hand side vector of the constraints; and $x \geq 0$ denotes non-negativity constraints on decision variables.

Linear Programming is employed in this dissertation for the capacity planning of grid-connected nanogrids. Specifically, it is used in the Planner module introduced in chapter 3 to determine the optimal sizes of battery energy storage systems (BESS) in kWh and solar PV in kWp, while ensuring cost-effectiveness and system efficiency.

2.2.2 Mixed Integer Linear Programming

Mixed Integer Linear Programming (MILP) extends Linear Programming by allowing decision variables to take integer values in addition to continuous values. MILP problems involve optimizing a linear objective function subject to both linear equality and inequality constraints and integer decision variables on some constraints. MILP

problems are formulated as follows:

$$\text{Minimize } c^T x \tag{8}$$

$$\text{Subject to } Ax \leq b \tag{9}$$

$$Gx \leq h \tag{10}$$

$$Fx = d \tag{11}$$

$$x \in \mathbb{Z}^n \tag{12}$$

Where x is a vector of decision variables, some of which are constrained to be integers, c , A , b , G , h , F , and d are similar to those in LP.

MILP is commonly used in energy systems for problems involving discrete decision variables, such as unit commitment and battery storage operations. In this research, MILP is employed to calculate the optimal dispatch of BESS while minimizing the total costs, as in Chapter 3 and 6. It is crucial to avoid simultaneous charging and discharging operations, achieved by introducing binary variables into the model.

2.2.3 Metaheuristics

Metaheuristic optimization methods are iterative search algorithms that explore the solution space to find near-optimal solutions for complex optimization problems. These methods are particularly useful for problems with non-linear and non-convex models, where traditional optimization techniques may struggle to find exact solutions. One such metaheuristic method is Particle Swarm Optimization (PSO), which simulates the behavior of a swarm of particles searching for the optimal solution in the solution space.

2.2.3.1 Particle swarm optimization

PSO is inspired by the social behavior of bird flocking, where individuals (particles) in a swarm communicate and cooperate to find the best solution. In PSO, each particle

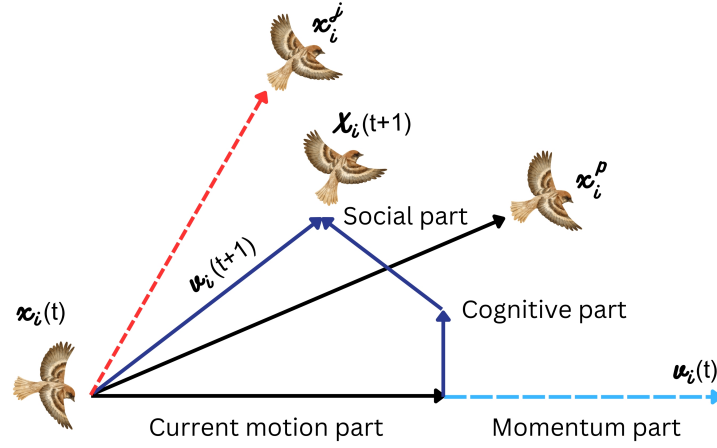


Figure 4: Particle Swarm Optimization

represents a potential solution to the optimization problem and moves through the solution space based on its own experience and the experience of the best-performing particles in the swarm. In the PSO method, the position x_i of each particle represents a potential solution to the problem. Each particle has memory to store its personal best position and the global best position found by the entire swarm. Using this information and its velocity v_i , each particle updates its position $x_i(t+1)$ as illustrated in Fig. 4.

The PSO algorithm represents the population as X , which is generated using a random number generator according to the (13):

$$X = L + \text{rand} \times (U - L) \quad (13)$$

where L and U are the lower and upper bounds of the search domain, respectively.

Each particle x_i in X updates its velocity v_i using (14):

$$v_i(t+1) = w(t)v_i(t) + c_1(t)r_1(x_i^p(t) - x_i(t)) + c_2(t)r_2(x_i^g(t) - x_i(t)) \quad (14)$$

Here, r_1 and r_2 are random numbers, w is the inertia weight that improves convergence speed, c_1 and c_2 are acceleration coefficients, and t represents the current iteration.

The particle's position is updated as (15).

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (15)$$

The next step in the PSO model is to evaluate the quality of each particle by computing the fitness function. The global best solution (x_{gi}) and the best personal position reached by each particle (x_{pi}) are determined. These steps are repeated until the stopping conditions are met, such as reaching a maximum number of iterations or achieving a satisfactory solution quality.

In this dissertation, PSO is utilized extensively. It is applied in the optimization of hybrid distributed resources within radial distribution networks to determine the optimal sizing and siting of DER units in Chapter 4. Furthermore, an enhanced PSO approach, named PS-TVPSO, is introduced in Chapter 5 to address issues of scalability and computational efficiency.

Optimization techniques, including Linear Programming, Mixed Integer Linear Programming, and Metaheuristics such as Particle Swarm Optimization, play a vital role in addressing complex optimization problems in energy systems. These techniques enable the efficient integration of resources, the optimization of system operation, and the achievement of various objectives, contributing to the effective planning, management, and utilization of energy resources.

2.3 Power Flow and Optimal Power Flow Analysis

Power flow analysis constitutes a fundamental tool in the planning and operation of electric power systems, facilitating the determination of steady-state voltages, currents, and power flows across the network. Optimal Power Flow (OPF) represents a sophisticated extension of conventional power flow analysis, maintaining system operation to achieve specific objectives, whether it's minimizing generation costs or power loss, maximizing profit, or mitigating environmental impact.

The power flow equations illustrate the flow of active power (P) and reactive power (Q) within the network, integrating the electrical attributes of lines, generation, and loads.

2.3.1 Active and Reactive Power Balance

Eq. (16) represents the balance of active power (P) at bus i , where PG_i is the active power injected by generators, PL_i is the active power consumed by loads, V_i is the voltage magnitude at bus i , $\sum_{j=1}^N V_j(G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij})$ is the sum of products of voltage magnitudes and conductance/reactance (real and imaginary components) of lines connected to bus i , and N is the total number of buses in the system.

$$PG_i + PL_i = V_i \sum_{j=1}^N V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \quad (16)$$

Eq. (17) represents the balance of reactive power (Q) at bus i , where QG_i is the reactive power injected by generators, QL_i is the reactive power consumed by loads, V_i is the voltage magnitude at bus i , $\sum_{j=1}^N V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij})$ is the sum of products of voltage magnitudes and conductance/reactance (real and imaginary components) of lines connected to bus i , and N is the total number of buses in the

system.

$$QG_i + QL_i = V_i \sum_{j=1}^N V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \quad (17)$$

2.3.2 Active and Reactive Power limits:

Eq. (18) imposes upper and lower limits on the active power output of generators at bus i , where $\overline{PG_i}$ and $\underline{PG_i}$ are the maximum and minimum allowable active power outputs, respectively.

$$\underline{PG_i} \leq PG_i \leq \overline{PG_i} \quad (18)$$

Eq. (19) imposes upper and lower limits on the reactive power output of generators at bus i , where $\overline{QG_i}$ and $\underline{QG_i}$ are the maximum and minimum allowable reactive power outputs, respectively.

$$\underline{QG_i} \leq QG_i \leq \overline{QG_i} \quad (19)$$

2.3.3 Total Power Limits

Eq. (20) imposes a limit on the total apparent power flowing through lines between buses i and j , where $\overline{S_{ij}^2}$ is the maximum allowable total apparent power.

$$(PG_{ij})^2 + (QG_{ij})^2 \leq \overline{S_{ij}^2} \quad (20)$$

2.3.4 Voltage magnitude and angle limits

Eq. (21) imposes upper and lower limits on the voltage magnitude at bus i , where $\overline{V_i}$ and $\underline{V_i}$ are the maximum and minimum allowable voltage magnitudes, respectively.

$$\underline{V_i} \leq V_i \leq \overline{V_i} \quad (21)$$

Eq. (22) imposes upper and lower limits on the voltage phase angle at buses i and j , where $\overline{\theta_{ij}}$ and $\underline{\theta_{ij}}$ are the maximum and minimum allowable voltage phase angle differences, respectively.

$$\underline{\theta_{ij}} \leq \theta_{ij} \leq \overline{\theta_{ij}} \quad (22)$$

2.3.5 Minimizing Active Power Losses

Active power loss quantifies the power dissipation in the system due to resistive losses in lines and other components. The total active power loss P_{loss} in a power system can be calculated as the difference between the total active power generated and the total active power consumed, shown in (23):

$$P_{\text{loss}} = \sum_i PG_i - \sum_i PL_i \quad (23)$$

A main goal in power system optimization is the minimization of active power losses. These losses quantify the dissipation of power within the system due to resistive losses in power lines or branches and associated components.

2.4 Test Cases and Benchmarks

The Institute of Electrical and Electronics Engineers (IEEE) has developed standard test cases for assessing optimization techniques. Among these, the IEEE 33-bus and 69-bus radial distribution systems stand out, shown in Fig. 5 and Fig. 6 respectively. These models represent radial distribution networks, providing standardized scenarios for researchers to apply and evaluate optimization algorithms. The IEEE 33-bus system consists of 33 interconnected buses and 32 branches, forming a radial distribution network. It is characterized by its simplicity yet realistic representation of a distribution network. The system includes various load demands and has a total real power demand of 3.715 MW and reactive power demand of 2.3 MVar. It provides

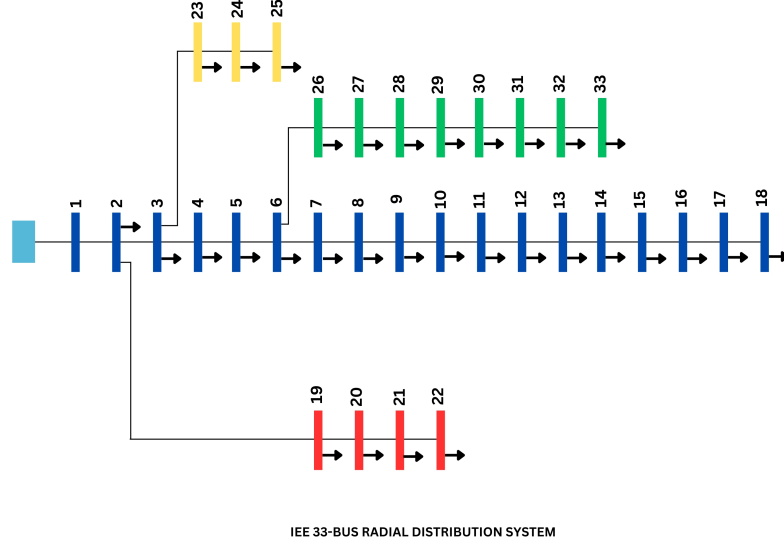
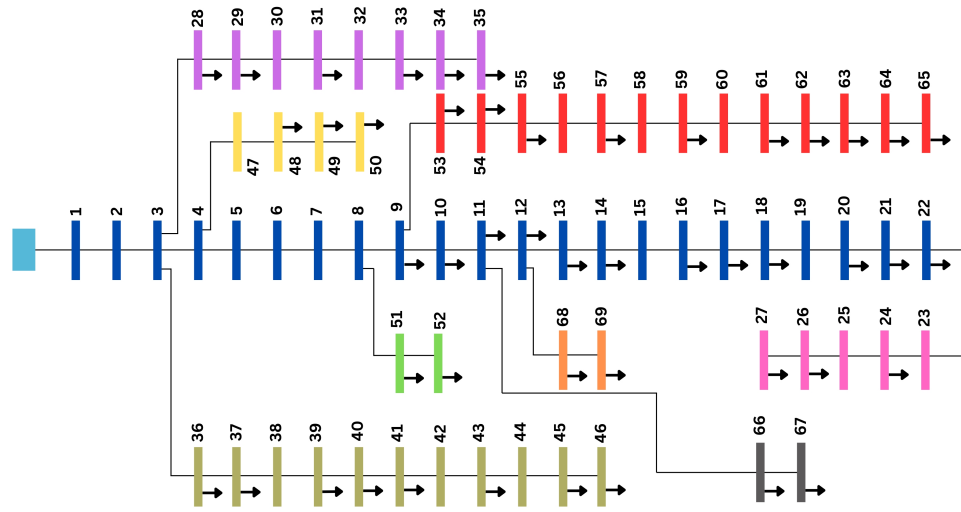


Figure 5: IEEE33 Test Case

a straightforward framework for testing optimization algorithms aimed at improving voltage profiles, reducing power losses, and enhancing overall system reliability. The network includes several candidate buses for the placement of DER units and energy storage systems, making it an ideal test case for DER allocation studies.

The IEEE 69-bus system extends the complexity of the IEEE 33-bus system with additional buses and loads. It comprises 69 buses and 68 branches, with a total real power demand of 3.802 MW and reactive power demand of 2.694 MVar. This system is a more representative of real-world distribution networks with increased complexity and operational challenges. The increased number of buses and branches offers a more challenging environment for optimization, particularly in terms of voltage regulation, loss minimization, and DER placement.

In addition to the IEEE test cases, the Norwegian 124-bus system is utilized to ensure the applicability of the proposed methods to real-world scenarios. This system is a detailed representation of an actual distribution network in Norway, consisting of 124 buses and 123 branches. It includes a diverse load profiles and operational constraints.



IEEE 69-BUS RADIAL DISTRIBUTION SYSTEM

Figure 6: IEEE69 Test Case

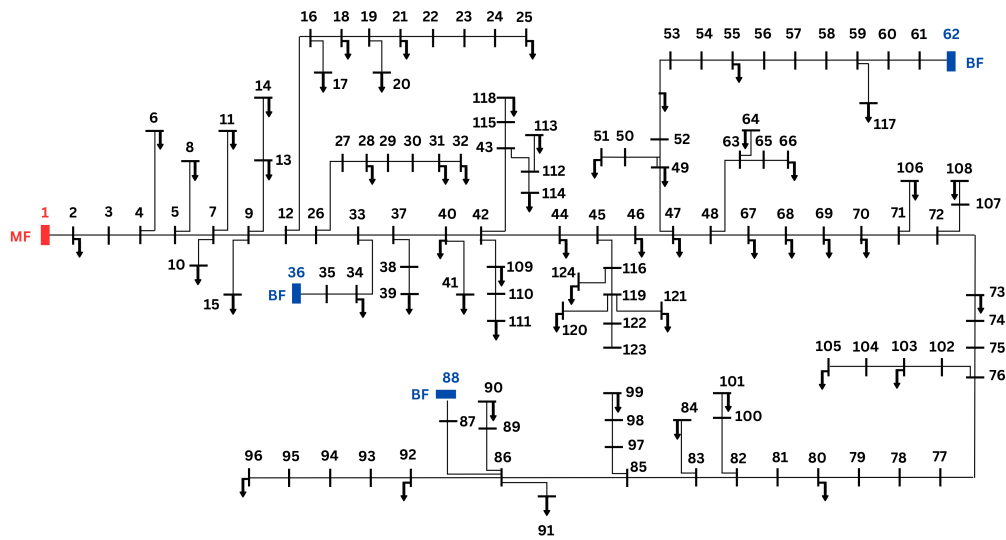


Figure 7: Norwegian Medium Voltage Network

Using these test cases, this dissertation implements various case studies addressing multiple DER planning problems. The IEEE 33-bus and 69-bus systems are primarily used to evaluate the optimization techniques in distribution network planning and operation. These systems help in understanding the performance of the proposed algorithms in standard scenarios, allowing for comparisons with existing methods. The Norwegian 124-bus system complements this by providing insights into the methods' effectiveness in real-world applications, ensuring that the solutions developed are both theoretically and practically viable.

CHAPTER III

A NOVEL STRATEGY FOR OPTIMAL NANOGRID PLANNING AND OPERATIONS

This chapter presents an integrated framework designed for capacity planning of grid-connected nanogrid, a small solar and energy storage system that can provide kilowatt-level services to individual buildings. This framework comprehensively evaluates nanogrid cost-effectiveness, sustainability, and reliability, employing a multifaceted techno-enviro-economic assessment approach. Traditional nanogrid capacity planning often prioritizes peak load requirements, which may lack optimality owing to occasional peak load occurrences. Conversely, optimizing solely for base load requirements might also fall short of effectiveness, compromising reliability and sustainability objectives. The proposed framework employs a three-step, integrated process for nanogrid (NG) capacity planning. Firstly, the Planner module identifies optimal asset sizing considering a two-day look-ahead logic. Then, the Operator module serves as a digital twin for the system, conducting hourly calculations over a short-term horizon. Lastly, the Evaluator module evaluates technical, environmental, and economic metrics for each solution, assessing the effectiveness of asset-sizing decisions.

3.1 Introduction

The aging electrical power system infrastructure suffers from several challenges, leading to high power losses and eventually decreasing efficiency [1]. The cost of rebuilding infrastructure is so high that non-traditional approaches to address the challenges are needed [2]. Therefore, distributed generation (DG) emerges as a promising concept. DG involves setting up smaller generators near consumers, offering benefits for the

environment, economy, and technology, especially within distribution networks [3]. Furthermore, utilities can control these generators for better operational reliability [4]. This control enables quick adaptations to fluctuations in demand or supply, strengthening the grid’s dependability. Incorporating DG into consumer premises signifies the emergence of a novel power system paradigm known as a microgrid (MG). According to the International Council on Large Electric Systems (CIGRE) [5], the microgrid is an electrical distribution system with interconnected loads and distributed energy sources, such as DG, that function as a single controllable entity. It can operate in grid-connected or isolated mode [6]. In the grid-connected mode, bi-directional energy exchanges between the microgrid and the utility become feasible, allowing the microgrid’s power output to deviate from local demand requirements. Conversely, during islanded operation, wherein the microgrid operates independently from the utility grid, local power generation and Battery Energy Storage Systems (BESS) must sufficiently meet the demand, given the unavailability of the utility grid [7]. Microgrids encompass diverse hybrid energy resources, particularly renewables like solar PV and wind, and distributed generation, such as diesel generators and energy storage [8]. The scale of assets within a microgrid fluctuates according to the specific application, encompassing settings ranging from a campus or village to the expansive dimensions of an island or urban municipality [9] [10]. However, the smallest microgrid, NG, is a single building at the kW level and can operate either in grid-connected or isolated mode by following the local energy demand and generation availability [11]. NGs, commonly situated in residential dwellings, rural locales, or small-scale industrial settings, manage loads below 20 kW. They primarily leverage clean energy sources, including fuel cells, solar arrays, and wind turbines [12] [13]. As per the Lawrence Berkeley National Laboratory, an NG must include at least one load or sink of power—which could be energy storage—and at least one external connection point [14]. An NG, in comparison to a microgrid, encounters fewer technical and

regulatory obstacles, contributing to their substantial deployment [15]. To enhance the sustainability of energy generation and to provide flexibility for the next generation of power system infrastructure, renewable energy resources [16] [17] and energy storage [18] are considered the assets in an NG. Renewable energy sources enhance sustainability; however, due to their intermittency and variability, they pose reliability challenges, and thus, a trade-off between sustainability and reliability should be navigated.

3.2 *Related Work*

The optimization of asset sizing for a reliable and sustainable NG assumes paramount importance in achieving optimal self-sufficiency, offering grid relief, and ensuring cost-effectiveness. Consequently, potential challenges arising from integrating renewables can be mitigated [19] [20]. In the design procedure of a PV-based microgrid or an NG, the optimal sizing of their components ensures the optimal utilization of the available solar energy and associated storage devices [21]. Optimal BESS sizing improves reliability and resilience [22]. An optimal hybrid sizing can be considered in profitability analysis for off-grid microgrids, such as in the mining industry [23]. Several papers have studied the microgrid and NG from technical and operational [24] [25], environmental [26] [27], and economic [28] [29] perspectives. The authors in [30] presented a convex optimization-based ESS scheduling algorithm that minimizes the monthly bills. In addition, a new concept of a supply charge is introduced to encourage consumers to store the surplus solar energy that can potentially cause reverse power flow in the grid. Notably, authors in [31] introduced a design for hybrid NG for a camp located in Saudi Arabia's Western region. The method considers two conflicting objectives in the optimization problem: the loss of power supply probability and energy cost. Using four variants of Particle Swarm Optimization (PSO), four algorithms are combined for various NG elements, achieving a solution that balances

cost-effectiveness and reliability. A techno-economic approach is proposed by the authors [32] to optimize NG size in tropical regions of the Amazon. The method considers multiple renewables to achieve lower levelized energy costs, net present costs, and low per capita energy consumption. The authors [23] modeled off-grid NG sizing by Mixed Integer Linear Programming (MILP) and solved it using robust optimization. The optimization model minimizes investment costs of solar PV and battery systems in the NG. The reliability is ensured by energy storage from periods of high PV output and utilizing it in periods of power shortage.

3.3 Contribution

Traditional nanogrid capacity planning often prioritizes peak load requirements, which may lack optimality owing to occasional peak load occurrences. Conversely, optimizing solely for base load requirements might also fall short of effectiveness, compromising reliability and sustainability objectives. The proposed framework employs a three-step, integrated process for nanogrid (NG) capacity planning. This research fills a critical gap in NG sizing and operation under realistic conditions by proposing a comprehensive framework that optimizes capacity planning. The strategy’s lookahead logic, combined with the multilevel optimization approach, allows for advanced planning and dispatch up to 2 days in advance, resulting in cost savings, increased self-sufficiency, and more efficient use of renewable energy resources.

3.4 Methodology

The proposed methodology for capacity planning of NGs comprises a three-step framework acting as a multi-level program. These three modules are the Planner, Operator, and Evaluator. The three steps form a comprehensive decision support framework, ensuring a balanced consideration of technical, environmental, and financial metrics.

- **Planner:** This module calculates the daily optimal capacities of the BESS (kWh)

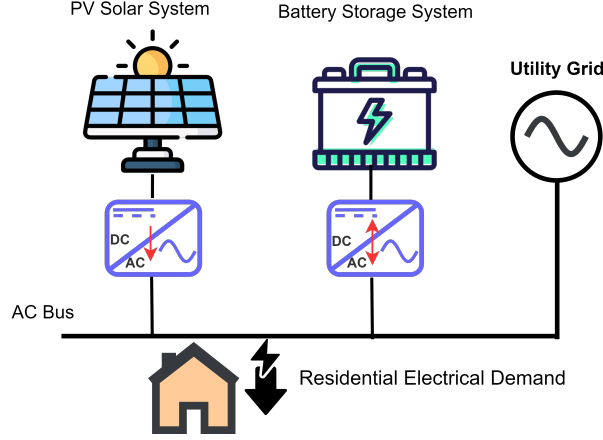


Figure 8: Proposed Nanogrid Architecture

and PV (kW) system, considering a 2-day look-ahead. After running this for a year, we get 365 daily optimal capacity solutions.

- **Operator:** This module takes each of the 365 daily optimal capacity solutions from the Planner module, assumes it as the fixed capacity for the entire year, and calculates the optimal dispatch of BESS and PV based on the annual data.
- **Evaluator:** This module evaluates each of the 365 solutions from the Operator module based on 15 different metrics, which cover technical, environmental, and financial factors. It does not necessarily provide a single best solution but presents the results for each metric for every solution. The customer can then select the solution that best meets their specific requirements.

The proposed methodology presents a systematic and adaptable framework for NG capacity planning. While it might not guarantee a single optimal solution, it offers a robust and practical approach tailored to the complexities of several real-world scenarios. This methodology will undergo testing using an AC NG architecture, as depicted in Fig. 8, similar to the AC NG architecture introduced by [33].

As shown in Fig. 9, the methodology starts with importing input data and assumptions. Input data include energy prices, demand, solar PV generation profile,

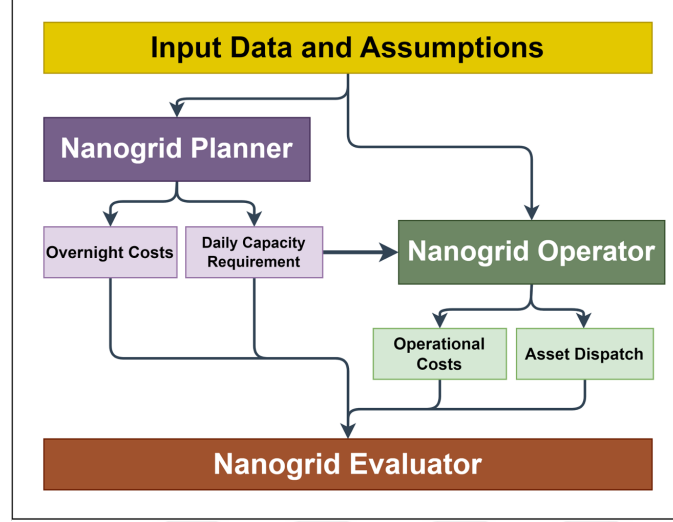


Figure 9: Nanogrid Capacity Sizing Strategy

BESS and solar PV asset parameters. The Planner is a linear programming problem that finds the optimal sizes of BESS in kWh and solar PV in KWp. Later, the Operator is a mixed-integer programming problem that finds the hourly optimal dispatch of the assets. In the last phase, the Evaluator uses the outputs of previous modules and calculates several technical, economic, and financial metrics. The resultant metrics are a decision support mechanism for the desirable NG capacity.

3.4.1 Planner Module

The Planner module operates as the first stage of the proposed decision support framework. The Planner module aims to calculate the daily optimal capacities of the BESS (kWh) and PV (kW) system for each day of the year. To maintain the simplicity and clarity of the module, the time value of money and costs related to managing and sustaining the investment over the project's lifetime have not been considered. The planning modules typically minimize the cost of purchasing (fixed cost) and operating (variable cost) the assets while still meeting the supply and demand balance. To do this, an LP problem is developed to determine the optimal size of the PV panels and BESS for a given load profile and set of constraints. Capacity optimization problems

inspire the proposed model, but it contains differences. One of the differences is the optimization window of the problem. Generally, capacity optimization problems consider an hourly demand profile for a year to find the optimal sizes; however, the Planner module searches for the optimal size of assets for each day in a year while considering the look-ahead logic. Look-ahead logic is a strategy that allows the model to consider not only the conditions of the current day but also anticipate the general trends for the next two days. This is done by considering 72 hours of data for each iteration: 24 hours for the current day and 48 hours for the next two days. This means that when determining the optimal capacities for the current day, the model already knows the conditions expected for the next two days, as shown in Fig 10.

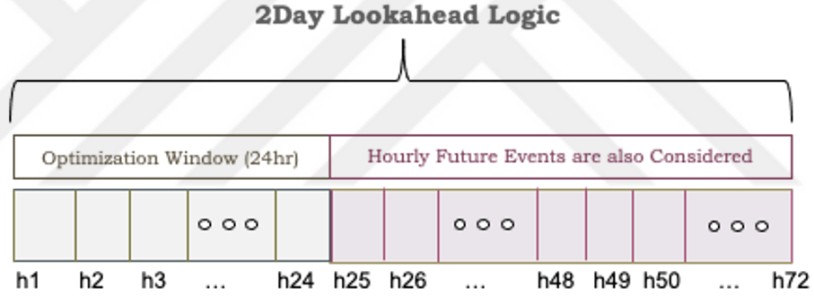


Figure 10: 2-Day Lookahead Logic Concept

This will enable the BESS to be optimized to handle future events. The second difference is in how the overnight cost of assets is considered in the Planner module. Generally, the annuity of investment is used in capacity optimization models in the literature; however, due to the daily basis approach adopted in this study, the overnight cost of assets is assumed to be in per diem for a given expected lifetime of the asset. The Planner module is developed in the standard form of linear programming (LP). Once the optimal capacities for the current day are determined, the model rolls forward to the next day, bringing in new data for the look-ahead period and repeating the optimization process. This sequence is carried out for an entire year, resulting in a set of 365 daily optimal capacity solutions, as shown in Fig. 11,

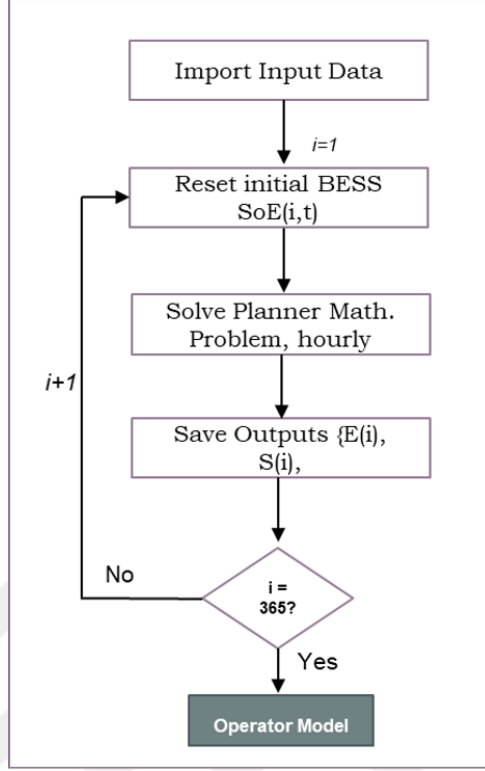


Figure 11: Flow Chart of the Planner Module

which illustrates the flowchart of the Planner.

The LP program minimizes the per diem total cost, comprised of BESS overnight cost, PV overnight cost, and import cost (generally the cost of energy received from the grid) as in (24). In addition, a set of constraints must be satisfied on an hourly interval. Constraint (25) initializes the state of energy (SoE) in BESS as a β percent of its entire energy capacity. Constraint (26) maintains the supply-demand balance on an hourly basis throughout the optimization horizon (24 hours plus look-ahead). Solar production, battery discharge, and imported power from the grid on the left-hand side of the equation should be balanced with the sum of the demand and the BESS charging energy. The SoE is defined in Constraint (27) as a difference equation by accumulating the energy charged at time t on top of the SoE at time $t-1$ and subtracting discharge energy at time t . Constraint (28) is a box constraint to limit the SoE so that it does not exceed the total BESS energy capacity. Constraints (29)

and (30) limit the BESS charging power so that it does not exceed the available empty energy capacity in BESS and the maximum charging capacity assumed by the user. Similarly, the BESS discharge capability is limited in Constraints (31) and (32) to not exceed the available energy already accumulated in BESS and to respect the maximum discharging capacity assumed by the user. Finally, Constraint (33) ensures that the hourly import energy from the grid does not exceed the grid import capability assumed by the user (generally the contract capacity).

$$\min ((E \cdot \text{OC}^E) \cdot \alpha^E) + ((S \cdot \text{OC}^S) \cdot \alpha^S) + \sum_t \rho_t \cdot g_t \cdot \Delta t \quad (24)$$

$$e_t = \beta \cdot E, \quad t = 1 \quad (25)$$

$$s_t + d_t + g_t = l_t + c_t, \quad \forall t \in \{1, \dots, T\} \quad (26)$$

$$e_t = e_{t-1} + \mu_c \cdot c_t \cdot \Delta t - \frac{d_t}{\mu_d} \cdot \Delta t, \quad \forall t \in \{2, \dots, T\} \quad (27)$$

$$0 \leq e_t \leq E, \quad \forall t \in \{1, \dots, T\} \quad (28)$$

$$0 \leq c_t \leq E - e_{t-1}, \quad \forall t \in \{2, \dots, T\} \quad (29)$$

$$0 \leq c_t \leq \gamma \cdot E, \quad \forall t \in \{1, \dots, T\} \quad (30)$$

$$0 \leq d_t \leq e_{t-1}, \quad \forall t \in \{2, \dots, T\} \quad (31)$$

$$0 \leq d_t \leq \gamma \cdot E, \quad \forall t \in \{1, \dots, T\} \quad (32)$$

$$0 \leq g_t \leq G, \quad \forall t \in \{1, \dots, T\} \quad (33)$$

3.4.2 Operator Module

In the second step, the Operator module takes each of the 365 daily optimal capacity solutions provided by the Planner module and treats them as fixed capacities for the entire year. Using the annual data, the Operator module calculates the optimal dispatch of BESS and PV for each solution while minimizing the total energy

cost purchased from the grid. The problem is formulated as a mixed-integer linear programming (MILP) problem, solved hourly over a 72-hour planning horizon (24 hours as an optimization window with a 2-day look-ahead logic). The inputs to the Operator module are the capacity solutions for the BESS (kWh) and PV (kWp), as shown in Fig. 12, and the load profile for the NG.

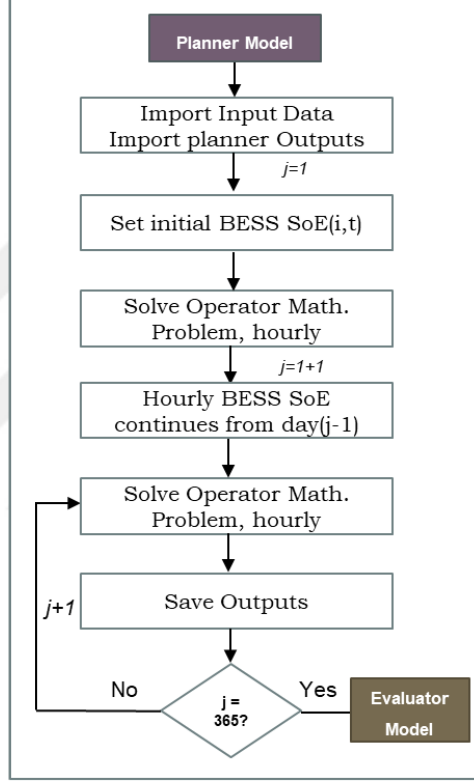


Figure 12: The Operator Process Flow Chart

The model considers factors such as the energy storage system’s efficiency, the energy cost from the grid, and limits on the charging and discharging rates of the battery. The state of energy (SoE) maintains its continuity from day to day throughout the horizon, in which the initial hour dispatch of each day depends on the previous day’s last hour SoE. The algorithm runs for 365 different capacity cases and provides hourly dispatch results for annual operations. The Operator module minimizes the import cost while respecting a set of constraints. The objective function is the minimization of the energy cost from the grid as given in (34). Constraints (25-29), (31),

and (33), as discussed in the Planner module above, are included. Additionally, Constraints (36) and (37) are included to limit the charging and discharging capabilities and to prevent simultaneous charging/discharging occurrences.

$$\text{Minimize } \sum_t \rho_t \cdot g_t \quad (34)$$

$$\text{subject to } (25 - 29), (31), (33) \quad (35)$$

$$0 \leq c_t \leq \gamma \cdot E \cdot u_t, \quad \forall t \quad (36)$$

$$0 \leq d_t \leq \gamma \cdot E \cdot (1 - u_t), \quad \forall t \quad (37)$$

3.4.3 Evaluator Module

Technical, economic, and financial evaluations are also crucial for an informed decision leading to a plausible capacity-sizing solution. The Evaluator calculates a series of metrics, inspired by [34] and [35] to evaluate the performance of each solution. The flowchart of the Evaluator is presented in Fig. 13.

The definition, unit, and mathematical formula of these metrics are elaborated in Table 1. The NG Evaluation process explained in the flowchart leads to the optimal NG capacity planning and operation solutions, provides a multi-perspective analysis of any NG capacity solution, and decides on the optimal size that fulfills the reliability, cost-effectiveness, renewable integration, self-sustainability, and many other requirements. Each metric can be given a certain weight to identify its importance from the user's perspective, and the performance comparison between the solutions can be conducted accordingly. Metrics used in the NG Evaluator are of different weights and can be adjusted by the user to prioritize specific metrics and ignore others if needed.

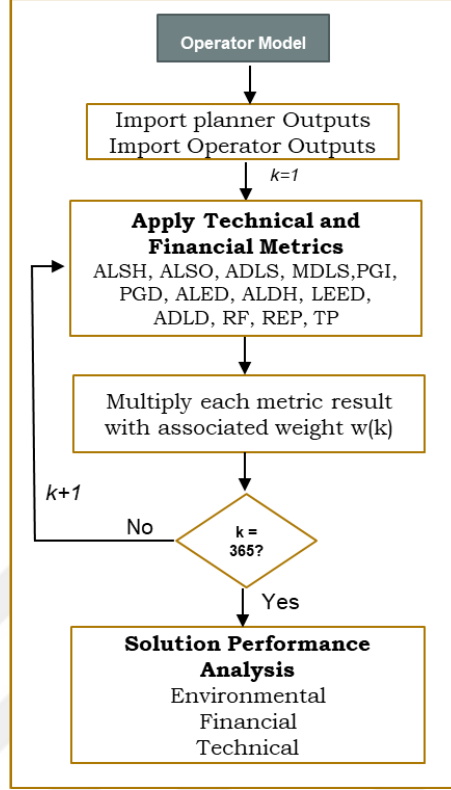


Figure 13: The Evaluator Process Flow Chart

3.5 Case Study

The proposed modules were simulated in MATLAB using YALMIP [36] and CPLEX. Hourly data on demand, solar profile, and time of use electricity prices were extracted from [37], [38], and [39] respectively and shown in Fig. 14. TOU rates change within a day, but they repeat their pattern daily. The demand profile in kW shows higher amplitudes in summer than in winter months. The solar profile is the hourly solar generation in kWh.

Additionally, the technical and financial parameters for the case studies are listed in Table 2. Regarding the BESS duration, it is chosen to be four hours means that the BESS power capability in kW represents quarter of the BESS energy capacity in kWh.

In Operator implementation, the Initial SoE on the first day is chosen to be 60

Table 1: Description of Evaluator Metrics

Index	Name	Unit	Category	Description
ALSH	Annual Local-Sufficiency Hours	hour	Technical	$\sum_{t=1}^T LSH_t$
ALSO	Annual Local-Sufficiency Occurrences	Occurrence	Technical	$\sum_{t=1}^T LSO_t$
ADLS	Average Duration of Local Sufficiency	hour	Technical	$\frac{\sum_{so} DLS_{so}}{ALSO}$
MDLS	Maximum Duration of Local Sufficiency	hour	Technical	$\max(DLS_o)$
PGI	Percentage of Grid Independence	p.u	Technical	$\frac{ALSH}{T}$
PGD	Percentage of Grid Dependency	p.u	Technical	$1 - PGI$
ALED	Annual Local Energy Deficiency	kWh/yr	Technical	$\sum_{t=1}^T (D_t - G_t)$
ALDH	Annual Local-Deficiency Hours	hour	Technical	$\sum_{t=1}^T LDH_t$
LEED	Local Expected Energy Deficiency	kWh	Technical	$\frac{ALED}{ALDH}$
ADLD	Average Duration of Local Deficiency	hour	Technical	$\frac{\sum_{do} DLD_{do}}{ALDO}$
RF	Renewable Fraction	p.u	Environmental	$\frac{\sum_{t=1}^T (A_t - C_t) \times 100}{\sum_{t=1}^T D_t}$
REP	Renewable Energy Penetration	p.u	Environmental	$\frac{\max(A_t - C_t) \times 100}{\max(D_t)}$
REC	Renewable Energy Curtailment	kWh	Environmental	$\sum_{t=1}^T (A_t - U_t)$
TOS	Total Operational Savings	\$	Economic	$\sum_{t=1}^T (G_t - I_t) \times a_t$
TC	Total Cost	\$	Economic	$OC^e + OC^s + IC$

percent of the BESS capacity at the beginning of operations. The SoE at the end of each day of operation is used as the initial SoE of the next day to achieve a continuous BESS operation throughout the year.



Figure 14: Hourly demand and solar generation profiles

Table 2: Definition of Parameters

Definition	Symbol	Value	Unit
Solar PV Overnight Cost	OC^S	550	\$/kW
Solar PV Lifetime	LT^S	25	Years
PV Per Diem factor	α^S	$1/(LT^S \times 365)$	p.u
BESS Overnight Cost	OC^e	450	\$/kWh
BESS Lifetime	LT^e	15	Years
BESS Duration	BSDU	4	Hours
Charging/discharging maximum ratio	γ	$1/BSDU$	p.u (Ratio Of E)
BESS Per Diem factor	α^e	$1/(LT^e \times 365)$	p.u
Maximum power drawn from the grid (kW)	G	10	kW

3.6 Simulation Results and Discussion

3.6.1 Planner Simulations

The Planner module runs for 365 days on an hourly basis for the given inputs with an optimization window of 24 hours and a look-ahead logic of 2 days. In every figure

below, the x-axis denotes the identification number of a given day, beginning with 1, symbolizing January 1st, and culminating at 365, representing December 31st. Fig. 15 illustrates the fluctuating trends of optimal BESS and PV sizes over a year, revealing distinct seasonal patterns.

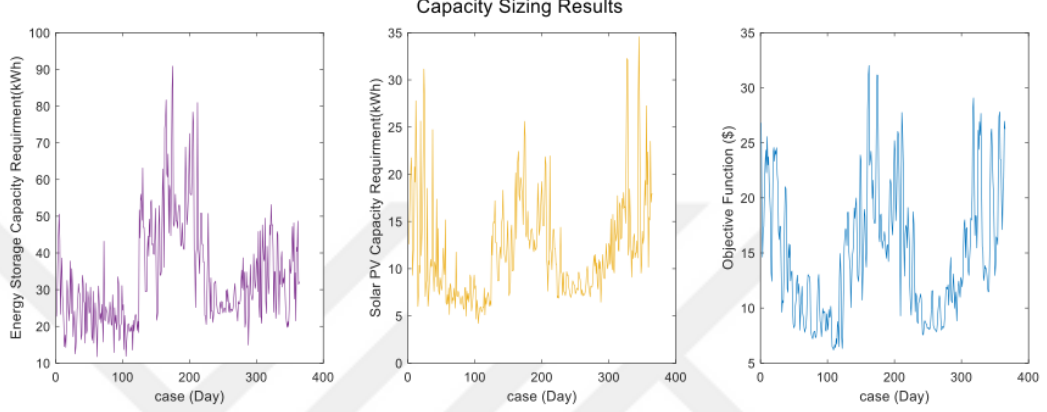


Figure 15: The 365 NG Capacity Sizing Solutions

The optimal BESS size escalates during summer months due to higher solar generation levels that permit the BESS to charge more energy and be ready for dispatch during high-price periods. Similarly, the requirements for PV size also surge in the summer due to high energy demand. Additionally, there are notable spikes in the winter months of December and January. They are strategic provisions to ensure adequate PV capacity during periods of reduced solar availability. The reasoning would be to maximize solar energy utilization and minimize reliance on grid imports even during less sunny winter days. The objective cost, on the other hand, largely shadows the trends of BESS and PV sizing. During winter days, despite the BESS size not being as high as on summer days, the objective function still shows an increase due to more significant imports from the grid where solar PV generation is not sufficiently available. A mixed illustration is given in Fig. 16 to explain the changes in BESS and solar PV capacities throughout the year.

The BESS energy capacity and solar PV capacity are shown using purple and yellow circles, respectively. The size of each circle directly corresponds to the capacity

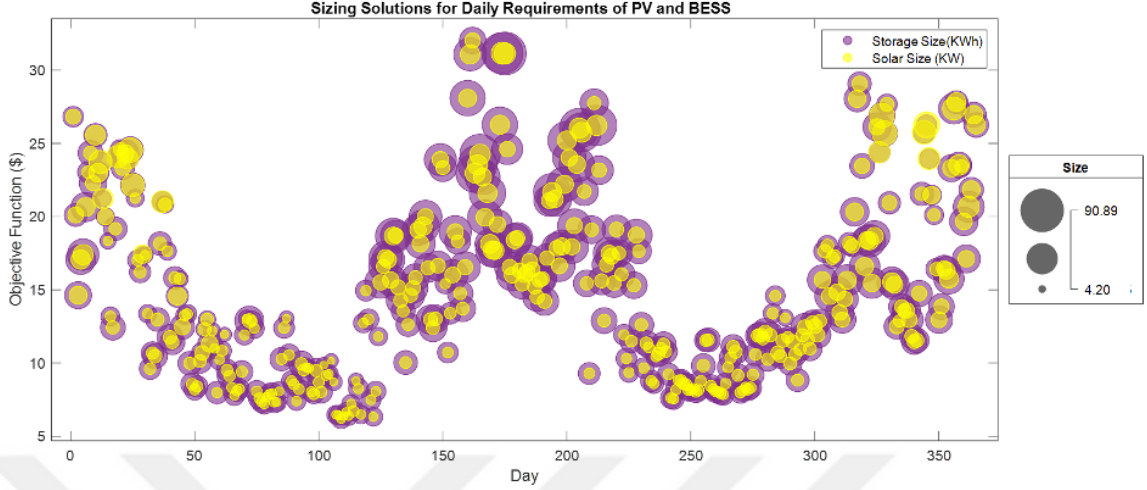


Figure 16: PV and BESS Size Comparison Based on Objective Solution

of the respective energy source: a larger circle indicates a higher capacity. The planner module has provided insights into the day-to-day optimal capacities of the BESS and solar PV, considering the changing demand and solar availability throughout the year. However, the optimal capacities suggested for summer days might be less effective during winter and vice versa. The Operator module will serve a critical role in this regard. It evaluates the impact of operating the system under a "fixed" capacity, as determined by the Planner module for each day over the entire year. Essentially, it answers the question: "What if we had this fixed capacity of BESS in kWh and solar PV in kWp for an entire year?". Therefore, combining the Planner and Operator modules will provide a more comprehensive decision-making tool that bridges the gap between daily optimal solutions and their long-term implications.

3.6.2 Operator Simulations

The Operator module is simulated where the Initial SoE on the first day is chosen to be 60 percent of the BESS capacity at the beginning of operations. The SoE at the end of each day of operation is used as the initial SoE of the next day to achieve a continuous BESS operation throughout the year. The algorithm runs for 365 different capacity cases released by the Planner and provides hourly dispatch results for annual

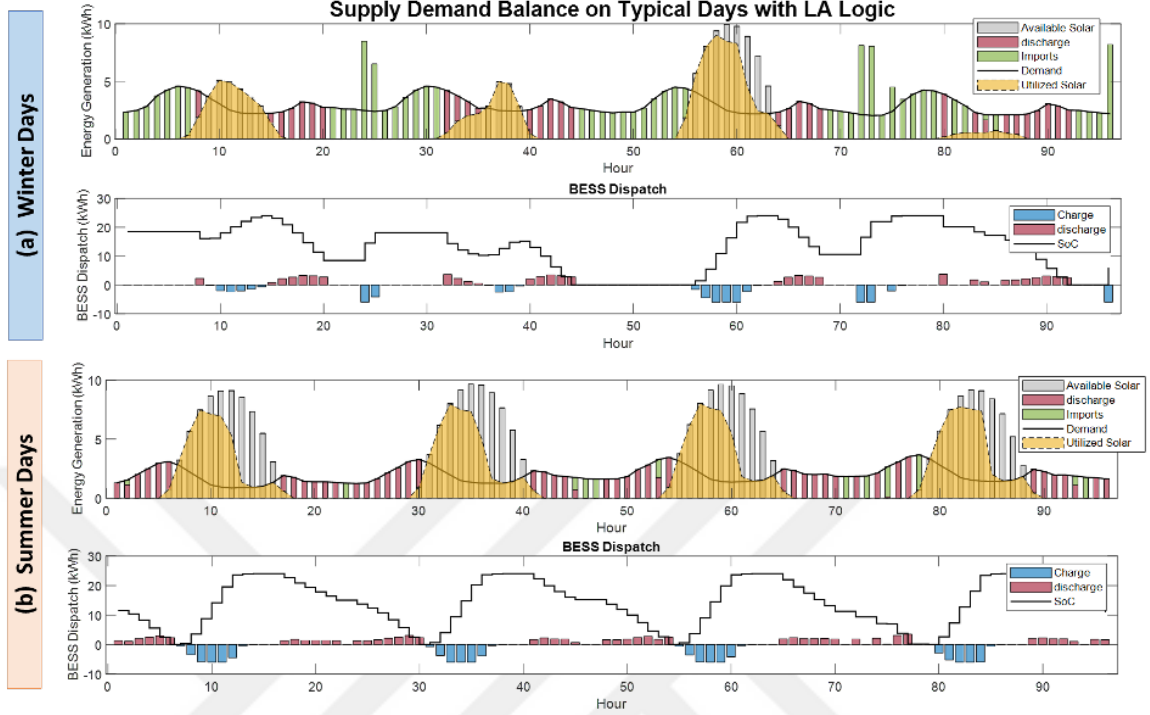


Figure 17: Winter and Summer NG operational dispatch for four consecutive days operations. One capacity case, comprising a PV size of 12 kW and a BESS size of 24 kWh, was chosen to present operational results. The asset dispatch decisions for four consecutive days are illustrated in Fig. 17 (a) and (b) for winter and summer, respectively.

Throughout the year, the primary objective of the NG is to achieve local energy self-sufficiency. This is managed by harnessing solar power whenever it is plentiful or utilizing energy stored in the BESS when solar production is insufficient to meet the demand. Excess solar energy is stored in the BESS during high solar production and low demand. This stored energy is dispatched during high demand and low solar production periods, effectively shifting renewable energy usage to align better with demand patterns. However, once the BESS reaches its maximum state of charge (SoC) at 100 percent, additional solar production is inevitably curtailed, highlighting the trade-off between storage capacity and renewable energy utilization. During periods of high demand where solar production and stored energy in the BESS are inadequate,

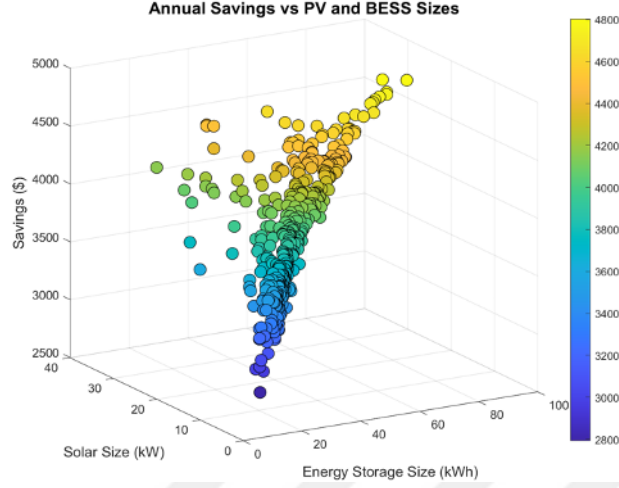


Figure 18: Cost savings versus solar size vs BESS size

the NG turns to grid imports to meet its energy requirements. Fig. 18 illustrates the operation cost savings by the 365 sizing solutions received from the Planner. The cost savings differ between the annual utility bill with and without the NG. As a result, the higher the BESS and PV capacity, the higher the cost savings. From the annual cost savings perspective, the highest cost savings of approximately \$4,801 are achieved with the capacity solutions of approximately 26 kWp of PV and approximately 85 kWh of BESS.

Executing the Operator module enabled a comprehensive understanding of how each 365 daily solution would perform over the entire year. However, with such a multitude of potential optimal solutions, determining the final system configuration necessitates an informed decision-making criterion. The transition from the Operator module to the Evaluator module addresses this need. The Evaluator module significantly refines decision-making, offering a multi-dimensional analysis of each potential solution. Instead of favoring any metric, it provides a diverse set of metrics to evaluate the performance of each solution from different perspectives.

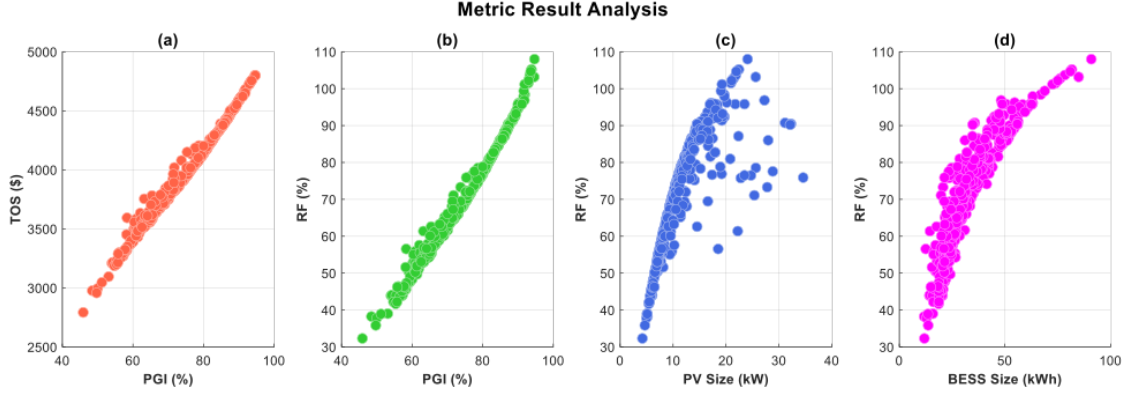


Figure 19: Correlations between Local Sufficiency Metrics

3.6.3 Evaluator Simulations

After the Planner and the Operator modules, the results of the Evaluator module are presented in this section. To put a perspective on two opposite sides of metrics, one for sufficiency-related metrics and one for deficiency-related metrics are examined. Fig. 19 reports the correlations between the proposed sufficiency metrics (TOS, RF, PGI) for different cases.

For example, Fig. 19 (a) shows that as the NG supplies more demand from the local generation (while PGI is increasing), the import from the grid decreases; therefore, the TOS increases. A similar correlation is observed between the PGI and RF in Fig. 19 (b). A hundred percent of PGI means no import from the grid to NG; hence, renewable generation has only satisfied the annual demand, leading to 100 percent RF. Finally, Fig. 19 (c) and (d) show the NG sizes versus the RF; as the PV and BESS sizes increase, the RF increases exponentially. However, in some cases, especially in Fig. 19 (c), some outliers that do not follow the general relationship are observed. For example, four cases have a PV size greater than 30 kW, and three have a corresponding RF value of 90 percent. However, the fourth case gives relatively less RF (only 75 percent) even though it is associated with the largest PV size. This outlier can be justified by the size of the BESS of this particular case since it is 40 percent less than that in the other 3 cases.

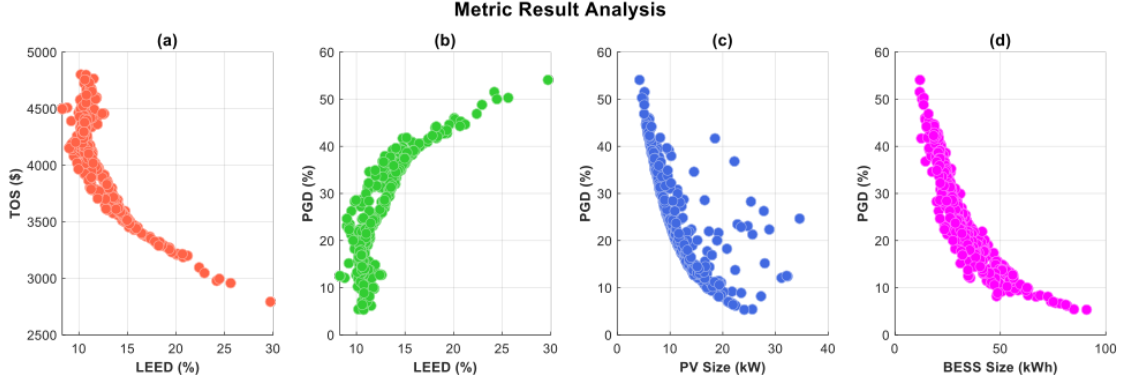


Figure 20: Correlations between Local Deficiency Metrics

On the other hand, the correlations between deficiency metrics (LEED, PGD) are depicted in Fig. 20. The inverse proportionality between LEED and TOS is observed in Fig. 20 (a).

It is also interesting to notice that even a minor LEED increase significantly reduces TOS. Fig. 20 (b) states that as the average hourly expected energy deficiency increases (related to the NG size), the NG becomes more dependent on the grid to cover the load, increasing PGD exponentially. In contrast to sufficiency metrics, the PGD decreases exponentially concerning the increase in PV and BESS sizes, as shown in Fig. 20 (c) and (d). Additionally, it is observed that the change in RF and PGD is more sensitive to the change in PV size than the change in BESS size. The consumers can determine the size of PV and BESS that meets their comfort by weighing each metric concerning its importance.

• Technical Assessment

In assessing 365 distinct sizing solutions based on the technical metrics proposed within this study, the primary objective was to evaluate each solution's capability to operate independently from the main power grid. One sizing solution was recorded as the best representation of local sufficiency, featuring a photovoltaic (PV) size of 24 kW and a BESS capacity of 91 kWh. This solution recorded a total annual cost of \$3,570. Notably, the critical technical metrics associated with this solution are

presented in Table 3. The analysis reveals a total annual local sufficiency duration of 8,293 hours and occurred 130 times throughout the year. This means that the probability of local sufficiency is up to 95 percent. Moreover, the average duration of local sufficiency was 64 hours, with an exceptional maximum duration of 2,918 hours. In contexts such as rural areas, where continuous electricity supply may not be guaranteed, there is a need to rely on local resources to mitigate the impacts of blackouts. This solution is the most viable option for ensuring reliability in such circumstances.

Table 3: Main Technical Metric Values

Metric	Value	PV Size(kW)	BESS Size(kWh)	Total Cost(\$)
ALSH	8,293 (hours)	24	91	3,570
ALSO	130 (Occurrences)			
ADLS	64 (hours)			
MDLS	2,918 (hours)			
PGI	95 (Percentage)			

- **Environmental Assessment**

Considering environmental metrics and interests, the two relevant metrics are renewable fraction and renewable energy penetration, as shown in Table 4. In the context of the optimized sizing solution with the most favorable environmental metrics, the PV size is 26 kW, the BESS size is 85 kWh, and the total cost is \$3,430. This sizing solution achieves an RF of 94 percent, indicating a high proportion of renewable energy sources utilized, while the REP is 224 percent. These metrics underscore the environmental sustainability of the proposed solution, enhancing renewable energy adoption.

- **Economic Assessment**

Table 4: Main Environmental Metric Values

Metric	Value	PV Size (kW)	BESS Size (kWh)	Total Cost (\$)
RF	94 (%)	26	85	3,430
REP	224 (%)			

When assessing the economic aspects, the primary metrics used are the total cost and Total Operating Savings shown in Table 5. Among the presented sizing solutions, one stands out economically, featuring a Total Cost of \$2,085, with a PV size of 12 kW and a BESS size of 24 kWh. This solution demonstrates a lower total cost compared to others. Conversely, while the solution with a PV size of 26 kW and a BESS size of 85 kWh has a higher Total Cost of \$3,430, it yields substantial Total Operating Savings of \$4,801. It indicates minimal energy purchasing was achieved, with a prevalence of renewable resources known for cost-effectiveness. These economic metrics offer valuable insights into the cost-effectiveness of each solution, assisting stakeholders in the NG planning process.

Table 5: Main Economic Metric Values

Metric	Value	PV Size (kW)	BESS Size (kWh)	Total Cost (\$)
TC	2,085 (\$)	12	24	2,085
TOS	4,801 (\$)	26	85	3,430

3.7 Conclusion

This chapter has proposed a comprehensive, three-step framework acting as a multi-level program for optimizing capacity planning of grid-connected NG. The framework incorporates a lookahead logic-based approach with a short optimization window, enabling effective utilization of renewable energy resources and achieving local energy self-sufficiency. The Planner module calculates the optimal sizes of the BESS in kWh and PV system in kWp, with higher values observed during summer due to increased

demand and solar potential. On the other hand, the Operator module imports each of the 365 daily optimal capacity solutions from the Planner module, assumes it as the fixed capacity for the entire year, and calculates the optimal dispatch of BESS and PV for each capacity solution. One of the key benefits of the proposed strategy is the ability to shift renewable energy from high solar-low demand periods to low solar-high demand periods, resulting in a more efficient use of energy resources. By storing excess PV energy in the BESS, the system can avoid importing energy from the grid during high-price periods, leading to significant cost savings. The Evaluator module considers various metrics related to reliability, environmental impact, and the microgrid's or NG's financial viability. These metrics include Annual Local-Sufficiency, Renewable Fraction, Total Profit, and others. This multi-perspective evaluation ensures that the sizing solutions provided by the strategy can be reliably adopted, taking into account various essential aspects. Furthermore, the proposed framework is scalable and can be applied to larger microgrid capacities beyond the kW range. It can be extended to analyze microgrids with capacities reaching several MWs or even more, making it a valuable tool for decision-makers and planners in the energy sector. This research fills a critical gap in NG sizing and operation under realistic conditions by proposing a comprehensive framework that optimizes capacity planning. The strategy's lookahead logic, combined with the multilevel optimization approach, allows for advanced planning and dispatch up to 2 days in advance, resulting in cost savings, increased self-sufficiency, and more efficient use of renewable energy resources. The wide range of evaluation criteria ensures that the strategy's sizing solutions are reliable and can be applied in real-world scenarios. Ultimately, the proposed strategy has the potential to contribute to the global transition towards 100 percent renewable targets, decentralized energy networks, and enhanced reliability in the electricity sector. As a future work, incorporating the physical network into NG assessment offers a more comprehensive analysis, enabling insights on optimal

NG placement. The implications of NG placement, such as network losses, voltage regulation, and interaction with the central grid, were not within the scope of the current research. However, they hold significant promise for future investigations.



CHAPTER IV

HYBRID DER SIZING AND ALLOCATION IN DISTRIBUTION SYSTEMS USING ADAPTIVE PSO: A COMPARATIVE STUDY

This chapter compares two methods for optimizing the integration of Hybrid Distributed Resources (HDRs) into radial distribution networks (RDNs). HDR in this chapter refers to a renewable resource such as PV solar and an energy storage system, acting as a hybrid energy system. Both methods utilize adaptive Particle Swarm Optimization (APSO) for optimization purposes. The first method adopts a centralized approach, simultaneously determining system size and site selection. In contrast, the second method, a decentralized approach, employs a bi-level framework. Initially, the system capacity is determined based on total demand and generation balance, followed by an allocation step to optimally allocate the sized system. Allocation considers minimizing losses, maintaining voltage profiles, and other power flow constraints. Sensitivity analysis is conducted on the APSO parameters to examine their impact on the optimization process. The comparative analysis aims to identify which methodology performs better in terms of convergence speed, solution quality, computational efficiency, and grid performance enhancement. Results reveal that while the centralized approach converges faster, the bi-level framework exhibits a higher likelihood of achieving the globally optimal solution. This study underscores the significance of optimization methodologies in navigating the complexities of hybrid energy system planning, providing insights for cost-effective and efficient distribution network planning while enhancing grid efficiency and stability.

4.1 *Introduction*

The conventional power generation methods coupled with the ever-increasing demand for electricity and economic concerns have encouraged the power industry to transit toward more reliable, cost-effective and environmentally friendly power generation solutions [40]. One of the prominent solutions to overcome the drawbacks of conventional power generation methods is the integration of distributed energy resources (DER) especially renewable energy sources such as PV arrays, wind turbines, and battery energy storage systems (BESS) into the grid distribution network. Distributed Energy Resources (DER) refer to a diverse array of small-scale, decentralized energy generation and storage technologies that are typically located near the end-users. These resources are capable of generating electricity, heat, or cooling and are often integrated into local energy systems to enhance reliability, reduce transmission losses, and promote sustainability. DER contrasts with traditional, centralized power generation units, which rely on large power plants located far from consumers [41],[42]. Radial distribution networks (RDNs) are the most traditional structure of distribution networks. Feeders in a radial network are the main distribution lines that extend from the distribution substations to deliver electrical power to residential, commercial, and industrial premises. They have a single point of supply, originating from the substation, and branch out to secondary feeders that further distribute power to end-users [43]. However, some of the transferred power is converted to heat due to the electric resistance in the distribution lines [44]. Recently, the deployment of DER in the RDNs has increased rapidly thanks to its environmental, economic, and technical benefits. DER improves voltage profile, increases efficiency, and reduces power losses [45]. While the supply of renewable energy is inexhaustible, its intermittent nature causes fluctuations in power generation. Furthermore, in the episodes of high-energy harnesses, the generation might exceed the demand resulting in reverse power flow, overvoltage issues, grid instability, increased power losses, and energy curtailment.

This scenario is more likely to occur in distribution networks with high renewable energy penetration ratios [46]. Therefore, battery energy systems (BESS) are widely utilized to decrease the renewable energy curtailment and supply the load during the lack of energy supply [47]. Historically, BESS technologies were costly and less deployed despite their advantages. However, with the advancement in BESS technologies, its cost has declined and its integration with renewable energy systems has become prevalent [48]. To profit from DER and BESS it is crucial to size and place them optimally, since it is not economical to build them at every bus, especially in large networks [49]. Nevertheless, the determination of the optimal size and location of DER in a distribution network is a challenging task. The simultaneous sizing and allocation is a complex non-deterministic-polynomial time (NP-hard) problem and it is more likely to find suboptimal solutions [47], [19].

4.2 Related Works

Numerous studies in the literature investigated the optimal sizing and allocation problem from various aspects such as improving the reliability [43], [50, 51, 52], reduce power losses and improve voltage profile [53, 54, 55, 56]. The researchers have developed several methodologies to optimally plan, size and allocate DER considering them as a dispatchable units [57] such as mixed integer programming [58, 59], analytical approaches [46], [60, 61, 62], and heuristic methods [63, 64, 65]. The authors in [66] applied coefficient PSO approach to reduce the total energy loss by optimally sizing and positioning renewable energy generation coupled with gravity storage system. Authors in [67] proposes loss voltage sensitivity index based approach that combines voltage sensitivity index (VSI) and loss sensitivity index (LSI) to find the best location for DG. Ref [40] proposes the same approach in [67] and compares the results with the conventional GA. Ref [68] implements simulated annealing (SA) for optimal selection, operation and allocation of DER and BESS in medium voltage distribution

networks considering four scenarios. Authors in [69] proposes two-stage optimization approach to optimize the size and location of BESS in smart grids considering time-varying grid tariffs and demand response programs. Table 6 Illustrates the related works in the literature about the problem.

4.3 Contribution

This chapter contributes to optimizing the integration of hybrid distributed resources into radial distribution networks by introducing and comparing two different methods for determining the size and allocation of HDR. The first method, known as the centralized approach, involves making decisions about HDR size and placement from a single control point. In contrast, the decentralized approach employs a bilevel process, where HDR size is determined first based on overall demand and generation, followed by allocation decisions. The evaluation encompasses convergence speed, solution quality, computational efficiency, and grid performance enhancement, providing valuable insights into the trade-offs inherent in each methodology. Additionally, the study acknowledges the importance of considering system dynamics, such as hourly generation, electricity prices, and demand profiles.

4.4 Methodology

4.4.1 Hybrid Distributed Resource (HDR)

HDRs in this context refer to a combination of renewable energy sources, such as solar photovoltaic (PV) arrays and BESS, integrated into the distribution system.

4.4.1.1 Modeling of PV module

There are numerous models in the literature to calculate the PV output power. This study uses a simplified model that considers solar radiation and ambient temperature

Table 6: Related Work of DER Planning Problem

Ref	DER tech	Distribution network	Power flow method/tool	Methods	Objective function		Time-varying	Time-varying	Highlight
					Multi	Single			
[4]	BESS	IEEE 30	forward backward	PSO	✓	-	load	generation	Proposes approach to locate and size BESS to maximize the reliability.
[32]	BESS	IEEE 14	DCOPF	SeDuMi	✓	-	-	✓	Determines the location concerning power exchange, then set the optimal size
[27]	PV, WT, GT	IEEE 33	-	Firefly algorithm	✓	-	-	-	Implements MOFA algorithm considering six objective functions
[17]	PV	IEEE 33, IEEE 69	MATLAB	analytical	-	✓	-	-	Proposes analytical approach to size and locate multiple PVs
[33]	BESS	Unbalanced RDN	DigSILENT	GALP	✓	-	✓	✓	Optimizes capacity, location, and daily charge and discharge profile of the BESS
[20]	-	IEEE 16, IEEE 69, IEEE 83	KNITRO, CPLEX	CPLEX	-	✓	-	-	Develops MILP for simultaneous network reconfiguration and optimal DG placement
[16]	PV	IEEE 33	-	BAT algorithm	-	✓	-	-	Allocates PV in the DNs optimally, and compares the method with GA, and PSO
[34]	BESS	IEEE 24	MATPOWER-DCOPF	GA	-	✓	✓	✓	Proposes two-stage framework concerning connectivity constraints to optimize BESS deployment in RDNs
[35]	PV, WT	IEEE 33, IEEE 92	-	AHA	✓	-	✓	✓	Proposes AHA to replace and size DG units in two RDNs, and compares the results with other algorithms
[36]	-	IEEE 33, IEEE 69	Newton Raphson	ABC	✓	-	-	-	Implements ABC algorithm on different benchmarks and compares the results with GA
[11]	-	IEEE 33	Pandapower	PSO	-	✓	-	-	Compares five variants of PSO in solving the allocation and sizing problem
[21]	PV	RDN in Alaska	PYPOWER	MILP, PSO	-	✓	-	-	Solves microgrid planning problem concerning both MILP and PSO, then compares the results
This work	PV, BESS	IEEE 33	MATPOWER	APSO	✓	✓	✓	✓	Optimally sizes and allocates PV, and BESS in two stages considering economic, environmental and technical objectives.

as shown in (38) .

$$P_t^{pv} = P_{cap}^{pv} \cdot \frac{G_t}{1000} [1 + \alpha_t (T_{am} + [0.0256 \cdot G_t]) - T_{STC}] \quad (38)$$

Where P_t^{pv} is the output power of the PV module at time t in kW, P_{cap}^{pv} is the rated capacity of the PV module under standard conditions in kWp, G_t is the solar radiation in W/m², T_{am} is the ambient temperature in °C, α_t is the temperature coefficient of the PV module in 1/°C, and T_{STC} is the cell temperature at standard test conditions in °C.

4.4.1.2 Modeling of Energy Storage System

The energy storage system (ESS) ensures sustainable power supply during periods of insufficient solar radiation. When the energy generated by the photovoltaic (PV) system surpasses the demand, the ESS initiates charging. The charging energy of the ESS at time t can be obtained by (39). The ESS discharges according to (40)) when the load demand exceeds the generated power.

$$E_t^{ESS} = E_{t-1}^{ESS} + \eta_{ch}[E_t^{pv} - E_t^{Load}] \quad (39)$$

$$E_t^{ESS} = E_{t-1}^{ESS} - \frac{E_t^{Load} - E_t^{pv}}{\eta_{dis}} \quad (40)$$

Where E_t^{ESS} , E_t^{pv} , and E_t^{Load} represent the ESS energy, PV generation, and load demand in kWh, respectively. η_{ch} is the charging efficiency and η_{dis} is the discharging efficiency.

4.4.2 Adaptive Particle Swarm optimization

The APSO algorithm starts with the initialization step, a population of potential solutions, referred to as particles, is randomly generated. Diversity within the particles across the solution space is also carefully considered through a diversity metric.

These particles represent the distributed resources (DR) such as solar PV and BESS sizing and allocation within the distribution network shown in (41).

$$x_p = [\text{DR}_{j,p}^{\text{size}}, \text{DR}_{j,p}^{\text{location}}] \quad (41)$$

Each particle's fitness or objective function value is evaluated, indicating its overall quality with respect to the optimization goals. In this specific case, the objective involves minimizing capital (CAPEX) and operational (OPEX) costs, as well as addressing constraints related to power flow, network, and other considerations. The particles then undergo iterative updates. Each particle adjusts its position within the solution space based on its own previous best position and the best position found by any particle in the population. This cooperative behavior of particles is analogous to a swarm of birds searching for the best path as explained in chapter 2. The particle with the best fitness value is deemed the global best, representing the overall optimal solution. The APSO algorithm's flowchart is illustrated in Fig. 21.

The APSO algorithm proceeds through multiple iterations, seeking to converge toward a solution that balances the trade-offs between costs, constraints, and the allocation of PV and BESS components across the network. Convergence behavior is shaped by an adaptive inertia weight, which determines the trade-off between exploration and exploitation, and the diversity among the solutions. The adaptive inertia weight is considered exponential and calculated by (42).

$$w_{\text{it}} = \max \left(w_{\text{fin}}, w_{\text{ini}} \exp \left(-k \frac{\text{it}}{\text{IT}} \right) \right) \quad (42)$$

In this way, the APSO algorithms aim to discover a cost-effective and operationally efficient combination of PV and BESS sizing and allocation for a distribution network with a temporal perspective, accounting for variations in load, solar generation, and

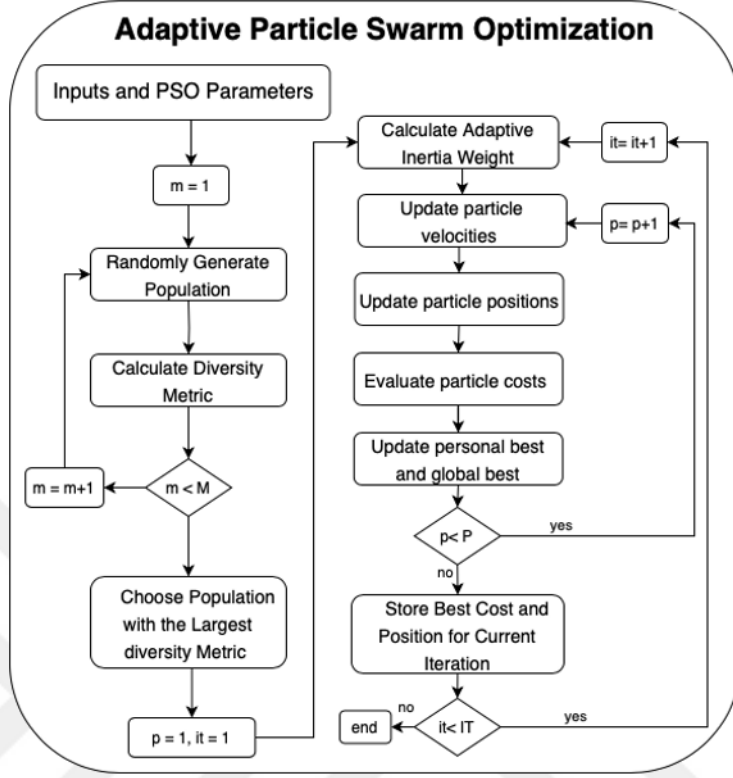


Figure 21: Flowchart of APSO

energy prices over time.

4.4.3 Centralized Method

The Centralized Method is employed to simultaneously optimize the capacity sizes and allocation of HDR, comprising solar PV (MWp) and BESS (MWh). As depicted in the pseudo code in Algorithm 1, the method begins by defining a control variable that includes both a continuous part and an integer part, corresponding to sizes and allocations, respectively. This control variable represents the solution and is iteratively updated based on the method's criteria. Following this, the population is initialized, comprising a group of particles. The optimal dispatch is determined by the energy management system (EMS), described in section 4.4.5, to ensure supply-demand balance. Energy import from the grid supplements solar intermittency and meets demand when the battery capacity is insufficient, aiming to minimize energy

costs accumulated in the cost function, named fitness. The compliance of energy operations with physical network constraints, including voltage magnitude and angle limits, as well as active and reactive power limits, is verified by the Violation Checker, described in section 4.4.6. Optimizing PV and BESS allocation involves strategically placing units at specific nodes in the distribution system to minimize total line losses, with line losses factored into the fitness function. The method operates over 12 representative days throughout the year, with hourly time steps and a predefined termination criteria.

Algorithm 1 Centralized Method using APSO

```

1: Import Data: Time Series data, Network Data, APSO parameters.
2: Start APSO and Define Solution = [ $S\_size, E\_size, S\_loc, E\_loc$ ]
3: Initialization based on (Fig. 21)
4: for  $i$  in Max Iterations  $IT$  do
5:   for  $p$  in Population  $P$  do
6:     Call EMS&FinancialFitnessCalculator( $S\_size, E\_size$ )
7:     Call Violation Checker&TechFitnessCalculator( $S\_size, E\_size, S\_loc, E\_loc$ )
8:     Calculate  $Cost(p) = FinancialFitness + TechnicalFitness$ 
9:     if  $Cost(p) < PersonalBest(i)$  then
10:       $PersonalBest(i) = Solution(p)$ 
11:     end if
12:     Calculate  $w\_adaptive$ 
13:     Update  $Vel_p$  and  $Pos_p$ 
14:   end for
15:   Update  $PersonalBest(i)$ 
16:   Update  $GlobalBestSol$ 
17: end for
18: Return  $GlobalBestSol[S\_size * E\_size, S\_loc * E\_loc]$ 

```

4.4.4 Decentralized Method

This method introduces a bi-level optimization framework for addressing the sizing and allocation of PV (MWp) and BESS (MWh) systems in two successive steps. As illustrated in Algorithm 2, there are two control variables defined as Solution1 and Solution2, and related to sizing and allocation steps respectively.

At first, sizing and operational optimization occur, utilizing APSO to determine the optimal capacities of the HDR units along with their energy dispatch. This level

Algorithm 2 Decentralized Method using APSO

```
1: Import Data: Time Series data, Network Data, APSO parameters.
2: Start APSO and Define Solution1 = [ $S\_size$ ,  $E\_size$ ]
3: Initialization based on (Fig. 21)
4: for  $i$  in Max Iterations  $IT$  do
5:   for  $p$  in Population  $P$  do
6:     Call EMS&FinancialFitnessCalculator( $S\_size$ ,  $E\_size$ )
7:     Calculate  $Cost1(p) = FinancialFitness$ 
8:     if  $Cost1(p) < PersonalBest1(i)$  then
9:        $PersonalBest1(i) = Solution1(p)$ 
10:    end if
11:    Calculate  $w\_adaptive$ 
12:    Update  $Vel_p$  and  $Pos_p$ 
13:  end for
14:  Update  $PersonalBest1(i)$ 
15:  Update  $GlobalBestSol1$ 
16: end for
17: Return  $GlobalBestSol1[S\_size * E\_size^*]$ 
18: Start APSO2 and Define Solution2 = [ $S\_loc$ ,  $E\_loc$ ]
19: Initialization based on (Fig. 21)
20: for  $i$  in Max Iterations  $IT$  do
21:   for  $p$  in Population  $P$  do
22:     Call Violation Checker&TechFitnessCalculator( $S\_size^*$ ,  $E\_size^*$ ,  $S\_loc$ ,  $E\_loc$ )
23:     Calculate  $Cost2(p) = TechnicalFitness$ 
24:     if  $Cost2(p) < PersonalBest2(i)$  then
25:        $PersonalBest2(i) = Solution2(p)$ 
26:    end if
27:    Calculate  $w\_adaptive$ 
28:    Update  $Vel_p$  and  $Pos_p$ 
29:  end for
30:  Update  $PersonalBest2(i)$ 
31:  Update  $GlobalBestSol2$ 
32: end for
33: Return  $GlobalBestSol2[S\_loc * E\_loc^*]$ 
```

focuses on achieving a cost-effective EMS solution that maximizes local sufficiency, increases the renewable energy utilization, and minimizes grid energy import costs while respecting to operational constraints. At second, the optimal decisions from the first level are fed into a network checker to optimize component allocation, aiming to minimize distribution line losses. This level evaluates network constraints and strategically places PV and BESS units within the distribution system. Together, these levels create a comprehensive bi-level optimization method, executed over 12

representative days with hourly time steps and a predefined termination criteria, ensuring balanced optimization for both sizing and allocation.

4.4.5 EMS and Financial Fitness Calculator

The energy management system (EMS) module starts with importing time series input data such as demand and solar profiles (p.u) in addition to technical and financial assumptions associated with solar PV and battery systems. Then, it inputs the PV (MWp) and BESS (MWh) sizes that are generated by the APSO and start the time interval loop. By the PV and BESS sizes, the EMS decides on solar utilization, battery dispatch, grid imports on hourly basis throughout the horizon according to the flow chart in Fig (22), explained in the following conditions:

- If solar generation P_t^{pv} exceeds demand P_t^d , satisfy the load needed from solar $P_t^{(pv-d)}$ and enable battery charging P_t^{chr} only if battery state of energy SoE_t is not full. Once the battery is full, curtail the excess generation P_t^{ex} .
- If solar generation P_t^{pv} is less than demand P_t^d , check the battery's state of energy SoE_t , and allow discharging P_t^{dis} until satisfying the demand P_t^d .
- If solar P_t^{pv} and battery discharge P_t^{dis} cannot satisfy the required demand P_t^d , allow importing from the grid P_t^{imp} until the demand is fulfilled.
- Calculate the PV capex, BESS capex, and total grid import costs and add them to the fitness function to be sent back to the APSO for optimization purposes.

4.4.6 Violation Checker and Technical Fitness Calculator

The intermittent nature of solar PV generation and the varying charging and discharging patterns of batteries can introduce fluctuations and imbalance in the system. Network Validation module is necessary when sizing and allocating battery and solar PV systems in hybrid systems to ensure operational safety, optimize hybrid system

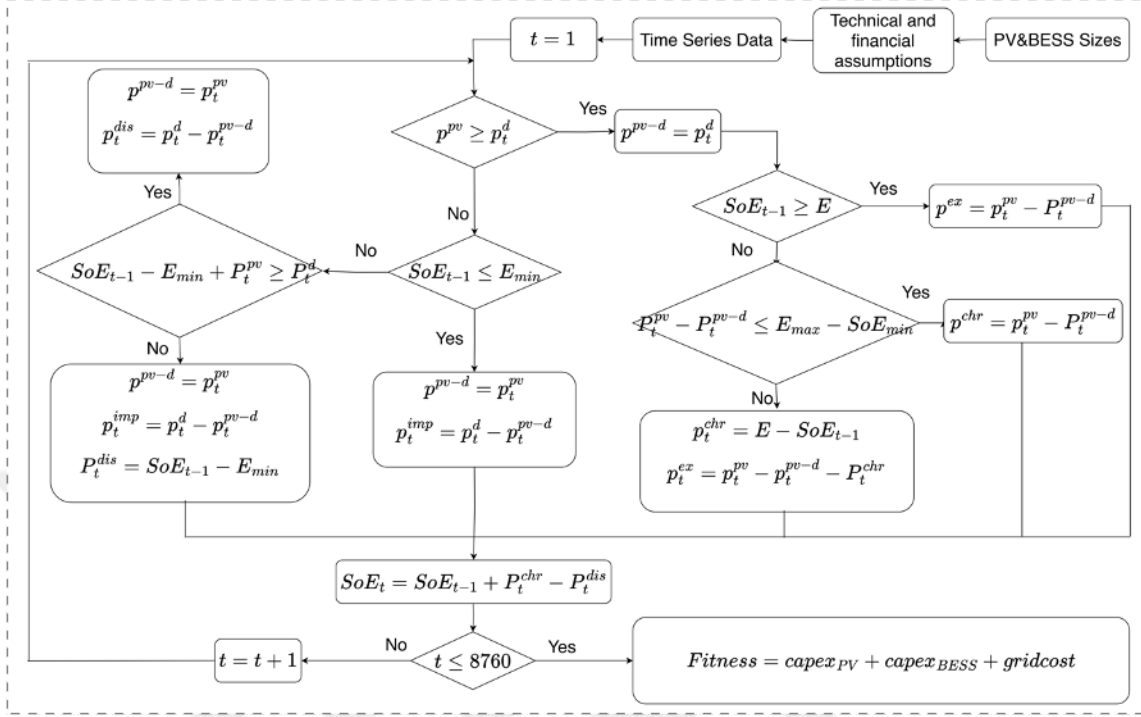


Figure 22: Flowchart of EMS and Financial Fitness Calculator

placement, maintain grid stability, and comply with regulatory standards. It enables the effective integration of hybrid system technologies while preserving the reliability and performance of the distribution grid. Distribution systems have physical and operational limitations that must be considered to ensure safe and reliable operation. These constraints include voltage limits, thermal limits of power lines and transformers, and power flow balance requirements. The detailed process of this module is shown in Fig. (23). Given the control variables, which encompass the sizing and allocation decisions, as well as load data and results from the Energy Management System (EMS), the function dynamically configures the network parameters for each time step. It updates the generator allocation for solar and storage and performs power flow simulations to assess the network's behavior. Notably, it also calculates penalty factors for violations such as slack bus power, bus voltage, reactive power generation, and line capacity. These penalties are used to evaluate the quality of the allocation and sizing solutions. Finally, Network Validation accumulates penalties

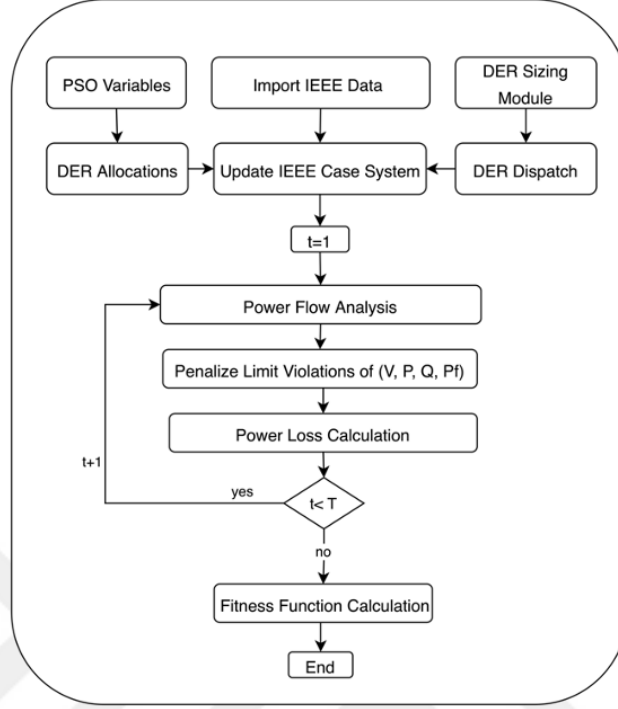


Figure 23: Flowchart of Network Validation and Allocator

across all time steps, providing a comprehensive measure of the network's performance. The resulting network cost and other vital information are then used to guide the optimization process, ensuring that the proposed strategy leads to efficient and reliable hybrid system planning and allocation.

4.4.6.1 PF and OPF Analysis

Power flow analysis is a vital component of this distribution-level hybrid system planning. It's integral to the 'Violation Checker and Technical Fitness Calculator', optimizing PV and BESS unit allocation. Throughout the evaluation, power flow ensures technical reliability, economic viability, and network constraint compliance. Violations trigger penalties to quantify their impact. Optimal power flow minimizes the total power loss over time, represented by the sum of power losses at each time step, while maintaining the system efficiency and physical constraints within the limits.

The power loss at each time step $P_{\text{loss},t}$ is calculated by (53) as the difference between the total power injected into the system by the utility and hybrid distributed resources (HDRs) and the total power consumed by loads. The power balance equations showed in (45) and (46) ensure that the active and reactive power injected by the utility, HDRs, and consumed by loads at each node satisfy Kirchhoff's voltage law. It is crucial to mention here that $P_{i,t}^{\text{HDR}}$ represents the sum of power generated by hybrid distributed resource such as solar, $P_t^{\text{pv-d}}$ and battery discharge P_t^{dis} . Their optimal values have been calculated previously by the EMS model. Constraints (47) and (48) are imposed to limit the voltage magnitude at each node, and the voltage phase angle difference between connected nodes within predefined bounds. These constraints ensure that the system operates within specified limits, optimizing power flow while maintaining stability.

$$\text{Min} \sum_t P_{\text{loss},t} \quad (43)$$

Subject to

$$P_{\text{loss},t} = \sum_i P_{i,t}^{\text{utility}} + \sum_i P_{i,t}^{\text{HDR}} - \sum_i \text{PL}_{i,t} \quad (44)$$

$$P_{i,t}^{\text{utility}} + P_{i,t}^{\text{HDR}} + \text{PL}_{i,t} = V_{i,t} \sum_{j=1}^N V_j (G_{ij} \cos \theta_{ij,t} + B_{ij} \sin \theta_{ij,t}) \quad (45)$$

$$Q_{i,t}^{\text{utility}} + \text{QL}_{i,t} = V_{i,t} \sum_{j=1}^N V_j (G_{ij} \sin \theta_{ij,t} - B_{ij} \cos \theta_{ij,t}) \quad (46)$$

$$\underline{V}_i \leq V_{i,t} \leq \overline{V}_i \quad (47)$$

$$\underline{\theta}_i \leq \theta_{i,t} \leq \overline{\theta}_i \quad (48)$$

4.4.7 Method Performance Assessment

4.4.7.1 Statistical Analysis

Statistical analysis, including metrics like mean absolute error (MAE), relative error (RLE), and root mean square error (RMSE), is crucial in assessing the performance of the proposed optimization methods due to their variability and stochastic nature. These metrics will provide insights on the accuracy of the results across multiple runs. To perform this analysis, each algorithm runs for 20 time. Performance metrics: RLE, RMSE, and MAE are calculated as shown in (49), (50), (51), respectively [70, 71].

$$RLE = \frac{\sum_{i=1}^M (x_i - x_{\min})}{x_{\min}} \quad (49)$$

$$RMSE = \sqrt{\frac{1}{M} \sum_{i=1}^M (x_i - x_{\min})^2} \quad (50)$$

$$MAE = \frac{\sum_{i=1}^M (x_i - x_{\min})}{M} \quad (51)$$

Where M is the total number of observations (runs), x_i is the current convergence and $x_{\min}$ is the minimum convergence value.

4.4.7.2 Voltage Deviation Index (VDI)

VDI indicates how each bus voltage fluctuates from the nominal voltage. This metric assesses the voltage quality before and after integrating HDR to the network. Moreover, it compares the voltage improvement achieved by the two proposed methods and provides another key technical index to evaluate their optimization performance. VDI is calculated by averaging the absolute deviation of nodal voltages from the nominal voltage over all buses and time steps, as given in (52), [72, 73].

$$VDI_t = \frac{1}{N} \sum_{i=1}^N |(V_0 - V_{i,t})| \quad (52)$$

where V_0 is the nominal voltage magnitude, equal to 1 pu, T represents the number of hours, N is the number of buses, and $V_{i,t}$ denotes the voltage magnitude of bus i at time t .

4.5 Case Study

In the simulations, a comprehensive dataset was utilized to validate and compare the methods proposed in previous sections. The input data includes time series electricity prices, specifically Time of Use (TOU) prices, which are crucial for capturing dynamic price variations throughout the day. Additionally, an hourly demand profile per unit was considered, allowing the identification of actual demand when scaled to match the peak demand, typically provided by IEEE test cases. The hourly solar PV profile for the specific site across 12 representative days under consideration is integrated into the simulations, enabling the consideration for the variability nature of solar power generation. Solar PV generation was determined by multiplying the per unit profile with the optimized PV capacity size in MWp. Fig. 24 illustrates the time series data that have been used in the case study.

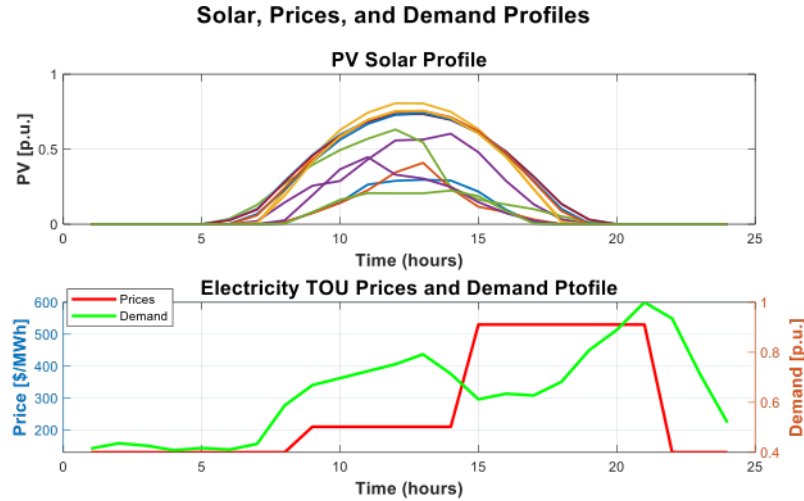


Figure 24: Time Series Input Data

To ensure the feasibility and applicability of the methods in real-world scenarios,

financial and technical assumptions were incorporated shown in Table 7. These assumptions include overnight capital costs of Photovoltaic (PV) systems and Battery Energy Storage Systems (BESS), as well as the respective lifetimes of PV panels and BESS units. Furthermore, system efficiencies, which play a pivotal role in determining actual energy utilization during energy conversion and storage processes, were considered. The BESS energy capacity is assessed in MWh but its power capability is in MW. A BESS duration of 1 hour means that the power capability is identical to its maximum capacity.

Table 7: Technical and Financial Assumptions

Definition	Value	Unit
Solar PV Overnight Cost	1.291 million	\$/MW
Solar PV Lifetime	25	Years
BESS Overnight Cost	500 thousand	\$/MWh
BESS Lifetime	15	Years
BESS Charging Efficiency	0.9	p.u
BESS Discharging Efficiency	0.9	p.u
BESS Depth of Discharge (DoD)	20	Percent
Maximum power drawn from the grid	10	MW

The simulations use the IEEE 33-bus case study for evaluating the practicality and effectiveness of the hybrid system planning and allocation strategies proposed in previous sections. This radial distribution network features a mix of buses, peak loads, lines and is widely used in literature to analyze different power and energy system aspects.

Different case studies have been simulated to compare the effectiveness of two methods, the centralized and the decentralized, using APSO configurations. A structured approach has been employed and summarized in Table 8. It includes Base Case, representing the default parameters and four other sensitivity cases. Sensitivity cases introduce changes to key APSO parameters in order to examine strategies' performance and parameter sensitivity under various conditions. The changes are mainly

the population swarm number and parameter k in the adaptive weight equation. The APSO terminates its execution when there is no solution improvements for 15 consecutive iterations or reached the maximum iteration limit. To mitigate premature convergence, a minimum iteration threshold of 20 iterations is set before termination.

Table 8: Simulated Case Study Parameters

Case Study	Swarm Size	c1	c2	Win	Wfin	k	Termination Conditions
Base Case (Pop25, k2)	25	2	2	1	0.4	2	1. 20 Minimum Iterations 2. If no Solution Improvement for 15 iterations
Pop15 Case	15	2	2	1	0.4	2	
Pop35 Case	35	2	2	1	0.4	2	
K1 Case	25	2	2	1	0.4	1	
K3 Case	25	2	2	1	0.4	3	

4.6 Simulation Results and Discussion

In this section, centralized and decentralized methods are evaluated through simulations through the APSO setup. A comparison will take place across the different case studies to discuss the effectiveness and identify potential trade-offs.

4.6.1 Convergence Analysis

In Fig. 25, a comprehensive comparison of the performance of centralized and decentralized methods in optimizing the total fitness function value in an APSO framework. Each subplot represents one of the 20 independent APSO runs, with the x-axis denoting the iterations and the y-axis representing the objective function value (total fitness cost). As illustrated in centralized subplot, the algorithm converges to an average total cost of \$115,555. The maximum iteration value within the 20 runs is 75. On the other hand, decentralized method, depicted in Subplot 2 and 3, takes longer total iterations to converge to its optimal solution. this is due to the presence of two separated algorithms running successively. The average fitness reached to \$114,657

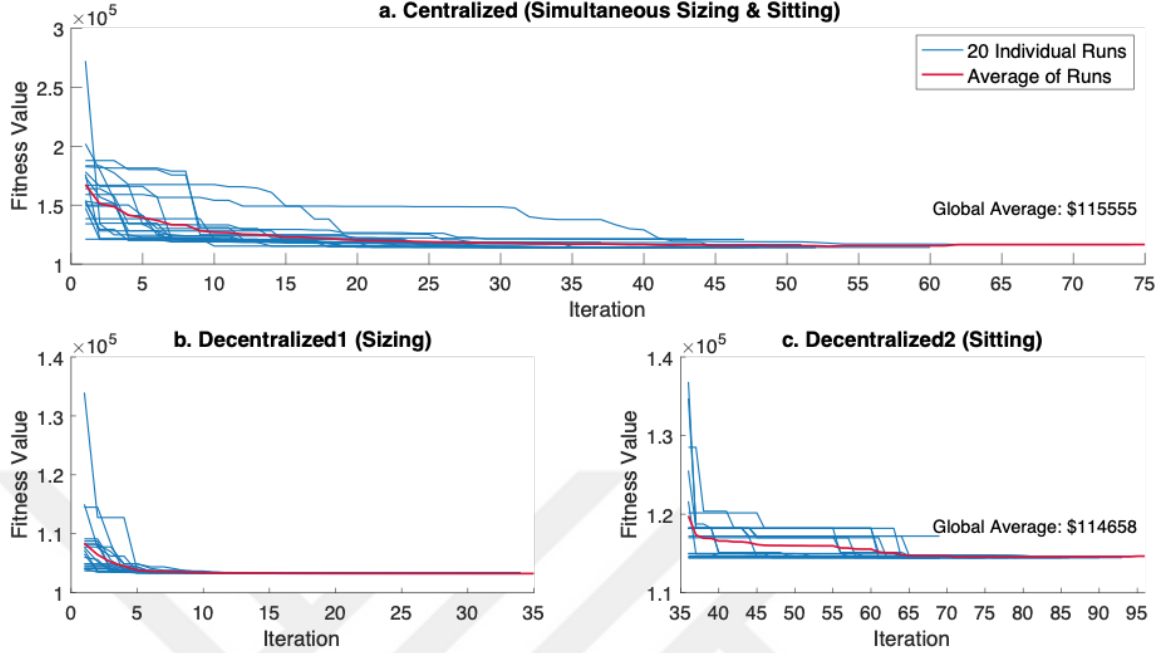


Figure 25: Fitness Function and Convergence Comparison

which is less than the centralized method solution.

To conduct a statistical analysis for the proposed optimization methods, focusing on the HDR sizing and allocation as the optimization problem, centralized and decentralized methods 20 runs were performed. All outcomes from each run were collected and then comparatively analyzed using statistical metrics such as Mean, Standard Deviation (SD), Relative Error (RLE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), as described in Section (4.3.8). RLE serves as a measure of accuracy to assess the precision of the data generated by each optimization method concerning its best value (minimum fitness). Specifically, RLE quantifies the accuracy of data produced by algorithms by considering its minimum value as a reference. MAE measures the average magnitude of the difference between the results produced by each algorithm and its best value achieved thus far. A higher MAE value indicates greater dispersion in the data. In RMSE, the difference between the two values is squared before averaging, giving relatively more weight to the error. The statistical details of the APSO performance results are presented in Table 9. In comparing the

centralized and decentralized methods, error metrics indicate better performance for the decentralized method across both fitness value and computational time. Specifically, the decentralized method demonstrates results of 0.06, 441, and 1,016 for RLE, MAE, and RMSE respectively, while the centralized method shows 0.25, 1,399, and 2,716 for the same metrics. Additionally, regarding computational time, the decentralized method exhibits greater efficiency over the centralized method.

Table 9: Algorithm Performance Statistics

Feature	Case	Min	Max	Mean	Median	SD	RLE	MAE	RMSE
Time	Centralized	548	1,349	799	768	190	9.19	252	312
	Decentralized	552	1,037	736	676	159	6.65	184	240
Fitness	Centralized	114,156	121,507	115,555	114,191	2,389	0.25	1,399	2,716
	Decentralized	114,462	117,205	114,658	114,464	799	0.06	324	844

4.6.2 Technical Analysis

The technical result comparison of both methods is illustrated in Table 10. In No Hybrid System case, the total operational cost is \$243,229, representing the cost of power generation. It is noted that the system has experienced relatively high-power losses of 35.21 MWh.

After applying the centralized method, PV and BESS capacity sizes have recorded 21.24 MW and 34.57 MWh respectively. This case has shown a significant power losses reduction to 11.64 MWh, representing a 66.94 percent reduction compared to the No Hybrid System case. In terms of cost effectiveness, the total cost has recorded

Table 10: Technical Result Comparison

Case	PV Size (MW)	BESS Size (MWh)	Power Loss (MWh)	Loss Reduction (%)	Total Cost (\$)	Cost Reduction (%)
No Hybrid System	-	-	35.21	-	\$243,229	-
Base Centralized	21.24	34.57	11.64	66.94	\$115,555	52.49
Base Decentralized	21.72	34.93	11.39	67.65	\$114,658	52.86

\$115,555 with a cost reduction of 52.49 percent compared to No Hybrid System case. Planning for HDR using the Decentralized method show that PV size is slightly larger at 21.72 MW, and the BESS capacity size is 34.93 MWh. This configuration further reduces power losses to 11.50 MWh, achieving a remarkable 67.65 percent reduction compared to the No Hybrid System. The total cost is \$114,658, resulting in a cost reduction of 52.86 percent.

Fig. 26 illustrates the voltage profiles across the 33 buses in a network under different scenarios: without HDR, with HDR planned by the Centralized method, and with HDR planned by the Decentralized method. In the visualization, warmer colors represent higher voltages closer to the nominal value of 1 per unit, while cooler colors indicate lower voltages, which are less desirable. Across all three cases, voltages fluctuate over time and demonstrate spatial variations throughout the network. A notable observation is the significant improvement in voltage profile when HDR is integrated.

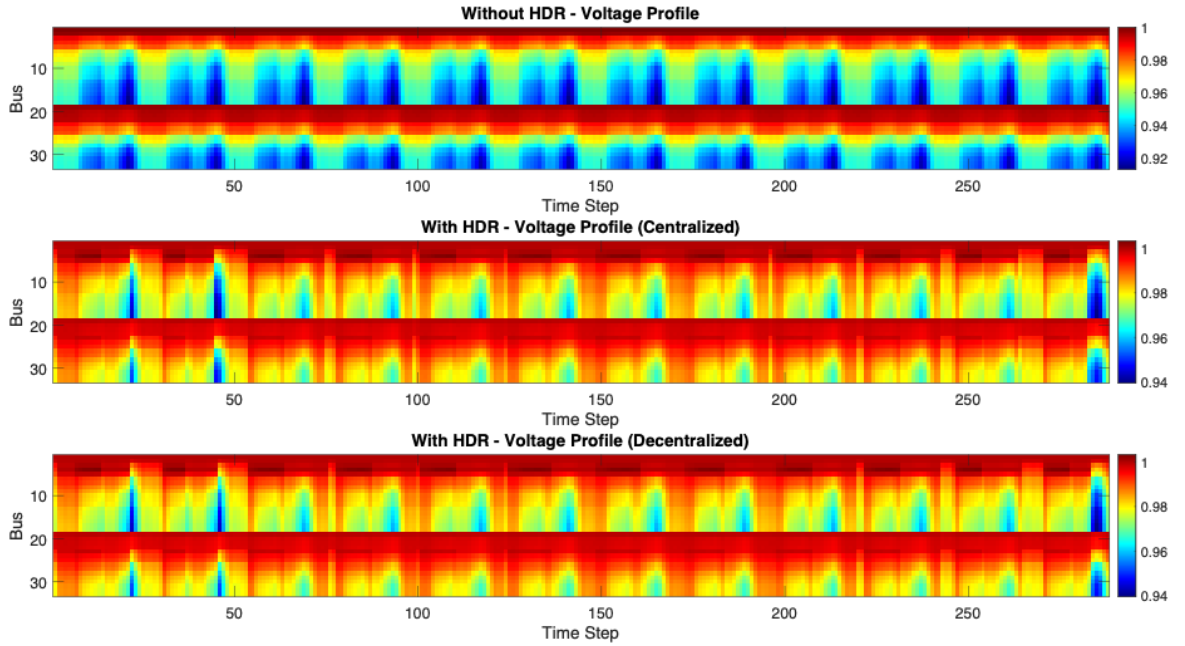


Figure 26: Voltage Stability Improvement across Cases

Fig. 27 illustrates the distribution of VDI values across three cases: without HDR, with HDR planned by the Centralized method, and with HDR planned by the Decentralized method. Variations in central tendency and spread are observed among the methods, with mean VDI values of approximately 0.038, 0.0132, and 0.0130, respectively. These values indicate that both HDR integration methods significantly reduce voltage deviations compared to the case without HDR. Furthermore, the mean VDI suggests that the Decentralized method performs slightly better than the Centralized one in terms of voltage stability, as it achieves a marginally lower mean VDI value.

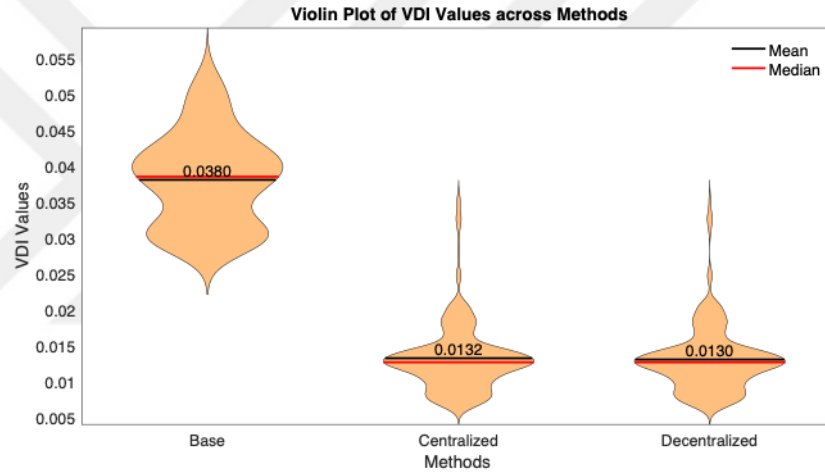


Figure 27: VDI across different cases

4.6.3 Sensitivity Analysis

Sensitivity analyses were conducted on the parameter k in the adaptive weight equation of the APSO algorithm. This parameter plays a crucial role in determining the rate of weight reduction during optimization. A higher k value promotes exploration, whereas a lower k value emphasizes exploitation. In the base case, k was set to 2, and sensitivities were applied with $k=1$ and $k=3$. A comparison of different performance metrics, especially error-based metrics such as RLE, RMSE, and MAE was conducted between the Centralized and Decentralized methods. Twenty simulation runs were conducted per method, and error calculations were applied to the converged fitness

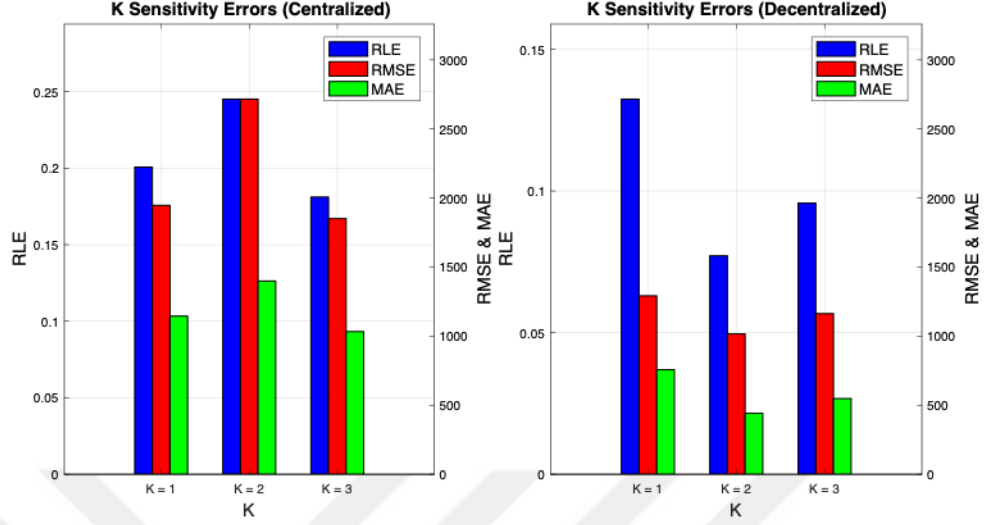


Figure 28: Computational Performance Under Parameter 'k' Sensitivities

values associated with each run. Fig. 28 illustrates the results of these sensitivity analyses and compares them with the base case. In the Centralized method, $k=2$ resulted in the largest error, while in the Decentralized method, the situation was reversed. Additionally, the Decentralized method exhibited notably lower values of RLE, RMSE, and MAE compared to the Centralized method.

Table 11 shows the average total costs as fitness values in addition to simulation time for both centralized and decentralized methods.

For centralized method, the average converged costs are \$115,301, \$115,555, and \$115,188 for $k=1, 2$, and 3 respectively. Also, the time spent was recorded 777 seconds, 799 seconds, and 512 seconds. For decentralized method, the average converged costs are, \$115,219, \$114,657, and \$115,010 for $k=1, 2$, and 3 respectively. Also, the time

Table 11: Numerical Results of Parameter 'k' Sensitivity Cases

Case	Centralized		Decentralized	
	Fitness Value	Computation Time(s)	Fitness Value	Computation Time(s)
$k = 1$	115,301	777	115,219	503
$k = 2$	115,555	799	114,658	736
$k = 3$	115,188	512	115,010	681

spent was recorded 503 seconds, 736 seconds, and 681 seconds.

In the sensitivity analysis of population number nPop for both Centralized and Decentralized methods, varying the population size from 15 to 25 particles (base case) and then to 35 particles reveals a significant impact on the optimization process. It is known that increasing the number of particles within the APSO population leads to more efficient solutions but also increases computational cost. 20 runs per method were conducted to assess the impact and compare it between Centralized and Decentralized methods. Fig. 29 illustrates the error results of these sensitivity analyses and compares them with the base case.

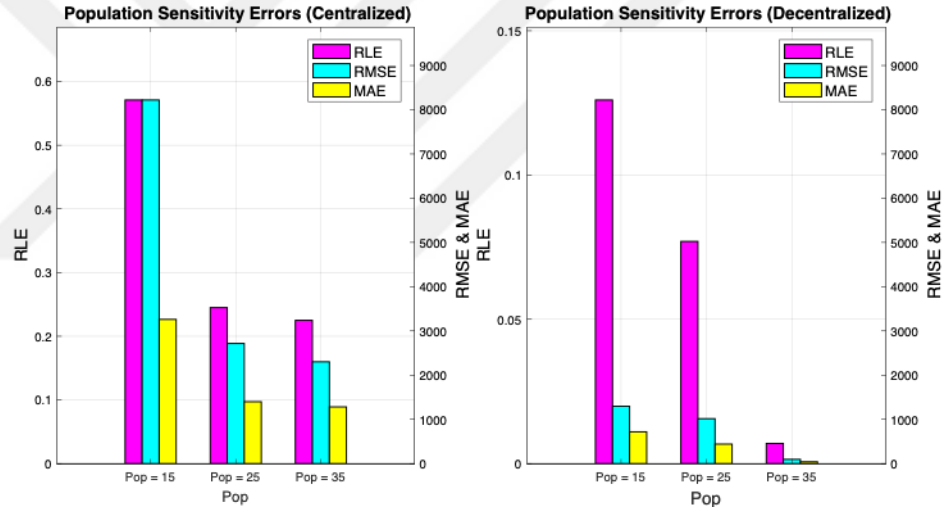


Figure 29: Computational Performance Under Population Sensitivities

In the Centralized method, increasing the population size from 15 to 25 particles results in a major decrease in all errors. However, further increasing the population size from 25 to 35 doesn't show major differences in error reduction. Conversely, in the Decentralized method, there is a notable decrease in all error values every time the population size increases from 15 to 25 and then to 35 particles. This suggests that the Decentralized method naturally benefits from increasing the population size, showing consistent improvements with each increment. Furthermore, the Decentralized method consistently yields lower error values compared to the Centralized method,

indicating its reliability in achieving higher-quality results.

Table 12 shows the total costs as the converged fitness values in addition to simulation time for both centralized and decentralized methods. For centralized method, the converged fitness values are \$117,415, \$115,555, and \$115,436 for population sizes 15, 25, and 35 respectively. Also, the time spent was recorded 717 seconds, 799 seconds, and 937 seconds respectively. For decentralized method, the converged fitness values are, \$115,181, \$114,586, and \$114,503 for population sizes 15, 25, and 35 respectively. Also, the time spent was recorded 425 seconds, 736 seconds, and 795 seconds respectively.

Table 12: Numerical Results of Population Sensitivity Cases

Case	Centralized		Decentralized	
	Fitness Value	Computation Time(s)	Fitness Value	Computation Time(s)
Pop15	117,415	717	115,181	425
Pop25	115,555	799	114,586	736
Pop35	115,436	937	114,503	795

The CDF plots presented for both Centralized and Decentralized methods offer a comprehensive understanding of the overall performance across the various conducted cases. Each subplot in Fig. 30 illustrates the distribution of objective values, providing valuable insights into the system's behavior under different scenarios. Notably, the plots show distinct performance characteristics among different cases, including the 'Base' case and sensitivities such as 'pop15,' 'pop35,' 'k1,' and 'k3'. One observation is shown in the Decentralized method's analysis, where the 'pop35' configuration stands out for its exceptional performance, exhibiting minimal objective values and clustering closely to the y-axis. This suggests that a larger population size of 35 particles leads to superior optimization outcomes in the Decentralized approach. Conversely, the Centralized method reveals its limitations, notably with the 'pop15' configuration displaying the worst performance, marked by higher objective values

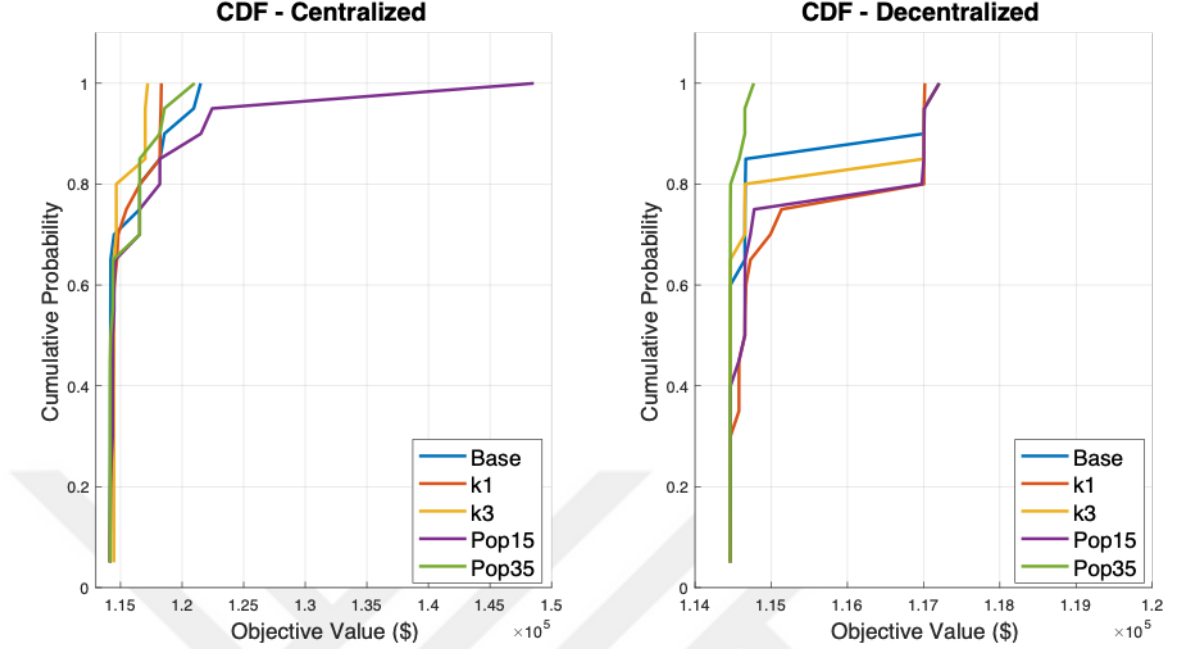


Figure 30: Cumulative Distribution Function Comparisons

distributed further along the x-axis. This underscores the significance of parameter selection and configuration optimization in enhancing the efficiency and effectiveness of optimization algorithms.

4.7 Conclusion

The pursuit of optimizing hybrid energy systems for distribution networks has witnessed significant developments, particularly in balancing efficiency, cost-effectiveness, and reliability. The integration of distributed renewables, especially hybrid systems into radial distribution networks has emerged as a necessary solution to address issues associated with conventional power generation methods. However, challenges persist in sizing and allocating these resources optimally within the network, especially in the face of dynamic variations in demand, renewable energy generation, and prices.

This study contributes a comprehensive comparison between two methods for optimal planning of HDRs. Both methods utilize APSO for optimization purposes. The first method adopts a centralized approach, simultaneously determining system size

and site selection. In contrast, the second method, a decentralized approach, employs a bi-level framework. This analysis reveals differences in their performance characteristics. The decentralized approach demonstrates a higher likelihood of attaining the global optimal solution. This aligns with the objective of balancing speed and accuracy in hybrid system planning.

Without a hybrid system, the total operational cost is \$243,229, with high power losses of 35.21 MW. The centralized method reduces power losses to 13.32 MWh, a 66.94 percent reduction, and cuts costs to \$115,555, a 52.49 percent decrease. The decentralized method further reduces power losses to 11.50 MWh, a 67.65 percent reduction, with a total cost of \$114,658, representing a 52.86 percent cost reduction. Voltage stability is significantly improved with the integration of HDR. Both methods effectively reduce voltage deviations compared to the scenario without HDR, with the decentralized method showing a slight edge in voltage stability, as indicated by a marginally lower mean Voltage Deviation Index (VDI).

Sensitivity analysis reveals the importance of parameter selection and configuration optimization, to achieve the trade-offs between computational efficiency and solution quality. In the decentralized method, the 'pop35' configuration, with a population size of 35 particles, demonstrates superior optimization outcomes, underscoring the significance of parameter selection in enhancing the efficiency and effectiveness of optimization algorithms.

CHAPTER V

OPTIMIZING MULTIPLE DER INTEGRATION USING POWER SYSTEM ORIENTED TVPSO

Distributed energy resources (DERs) have become essential for enhancing the reliability, efficiency, and resilience of distribution systems. Optimal deployment of DER units within distribution systems is crucial, relying heavily on the proper sizing and siting of these units. Without appropriate integration, DERs can negatively impact grid stability and security. While metaheuristic approaches are widely preferred in the literature for solving DER sizing and siting problems, they often overlook key electrical network characteristics due to their numerical bias. This chapter introduces a novel power system-oriented Particle Swarm Optimization (PSO) approach, named PS-TVPSO, designed to minimize real power loss in distribution networks. The proposed approach optimizes a mixed continuous and integer control variable simultaneously, where the continuous part is for the sizing of DER and the integer part is for the allocation.

5.1 *Introduction*

In recent years, distributed energy resources (DERs) have become vital for enhancing the reliability, efficiency, and resilience of distribution systems. DERs offer essential services such as load balancing during peak demand, maintain voltage levels, integrating renewable energy sources, and providing ancillary services like frequency regulation and black start capabilities. This shift towards DERs marks a significant advancement in electricity generation and distribution, benefiting both utility

providers and end-users. However, optimally deploying DER units within the distribution system relies on optimal sizing and siting of these units. Without proper integration, DERs can negatively impact grid stability and security and potentially may lead to power outages. This challenge is occurring specifically in multi-DER configurations and larger power networks, where identifying the optimal size and allocation becomes increasingly complex. As the size of the problem grows with additional DER units or network expansion, the complexity increases exponentially [74]. Therefore, a metaheuristic approach is preferable for solving DER sizing and siting problems in distribution systems. The optimal DER deployment problem falls into the category of NP-hard problems, making it impossible to solve optimally in polynomial time [74]. Heuristic algorithms offer practical solutions within reasonable timeframes.

5.2 *Related Work*

Various heuristic and metaheuristic algorithms have been proposed and tested in the literature to find optimal solutions for DER sizing and allocation on predefined networks, aiming to minimize total costs [75], reduce power loss [76], improve voltage profiles [65], and enhance power factor correction [77]. Some papers have applied a single objective function [78], while others have utilized multi-objective functions [79]. A comprehensive review conducted by [80] focused on optimal Distributed Generation Allocation (ODGA) methods and their impact on power quality and system reliability. Among the metaheuristic methods, Particle Swarm Optimization (PSO) is considered a prominent choice in many investigations for its fast convergence and promising solution quality [76], [79], [77], [81]. A comparison of PSO variants for optimizing DG integration in power networks was performed in [82], showing that TVPSO achieved the highest loss reduction, thus enhancing system efficiency through multiple DG integrations. In the context of DG planning, most researchers have optimized

DG allocation by examining the installation of different generators with predefined sizes before optimizing the size of DGs for identified optimal locations, which reduces problem complexity and susceptibility to local optima [81]. Conversely, Pareto-based multi-objective Particle Swarm Optimization (MOPSO) was introduced in [75] to emphasize the simultaneous determination of the optimal size and location of DGs. Moreover, the adoption of PSO in multi-objective frameworks, such as those emphasizing simultaneous optimization of cost, loss, and voltage quality, underscores its flexibility and effectiveness [83], [84], [85]. Optimization methods have been tested on well-known IEEE test network benchmarks such as IEEE33, IEEE69, and IEEE85, as well as on real case scenarios such as the Norwegian case [78], Chittagong, Bangladesh [86], and a medium-voltage (MV) European network [87]. Integrating multiple DG units may cause scalability challenges in PSO frameworks [42]. The recent advancements have led to the development of PSO variants [88], [89], [90] showcasing improved convergence time and solution quality. To enhance the efficiency of optimizers, many researchers have proposed hybridization of multiple metaheuristics, such as hybrid analytical-PSO [80], TS-PSO, ACO-ABCO, PSO-ABCO, and GA-JFPSO (Jumping Frogs PSO) [91]. Alongside PSO, various heuristic and metaheuristic algorithms have been examined in the context of DG planning problems in distribution systems to enhance system performance. These include the Jaya Algorithm, Genetic Algorithm (GA) [92], Firefly Algorithm [93], Improved Harmony Search Algorithm (IHSA) [94], HSA [95], Hummingbird Algorithm [96], improved analytical (IA) method [97], Artificial Bee Colony (ABC) Algorithm [98], a hybrid of ant colony optimization and artificial bee colony algorithm [99], and Harris Hawks Optimization (HHO) [100]. Finally, the exploration of physics-based metaheuristic techniques showcases promising results. For instance, Black Hole Optimization (BHO) and the Lightning Search Algorithm (LSA) have shown potential performance in optimizing microgrid (MG) operations [101]. Each of these methods offers different strengths in optimizing voltage

profiles and minimizing power losses while integrating DGs.

5.3 Contribution

Heuristic algorithms offer practical solutions within reasonable timeframes. Despite their effectiveness, existing literature on DER sizing and allocation using heuristic optimization methods often overlooks key electrical network characteristics due to their numerical bias. For instance, nodes that are numerically close in the system's representation might not be directly connected in the actual topology. For example, bus 13 in IEEE33 network doesn't have to be electrically connected to bus 14 however it is numerically the closest to bus 13. Therefore, numerical approach in PSO will assume there is a highly likelihood to find a better solution at bus 14 but based on electrical network they are not even closed to each other. Consequently, the searching process may be trapped for a long time in a local optimum when conducted without considering the network's actual connectivity. Moreover, as the line resistance is proportional to active power loss, it is important to consider line flow while searching for the optimal DER allocation that minimizes the total power loss. When a DER is placed near the network terminals, it generates power that is consumed locally or by nearby loads. This reduces the current that must flow from the feeder through the entire resistive structure of the network to the end buses leading to a less total power losses. However, when a DER is placed near the feeder, the generated power reduces the load seen by the feeder but doesn't significantly reduce the current in the downstream segments of the network. This chapter proposes a novel power system oriented PSO approach named PS-TVPSO to minimize real power loss in distribution networks. The proposed approach optimizes a mixed continuous and integer control variable simultaneously, where the continuous part is for the sizing of DER and the integer part is for the allocation. The proposed approach integrates innovative algorithms designed to enhance the PSO search process and prevent it from

falling into local optima. These algorithms include the Connectivity-Driven Intensification Algorithm, Resistivity-Driven Intensification Algorithm, and Demand-Driven Candidate Generator. The Connectivity-Driven Intensification Algorithm analyzes electrical connectivity among nodes, generating solution candidates aligned with the grid's physical topology. This ensures that the PSO explores spaces aligned with the electrical structure, prioritizing actual physical neighbors over numerical ones during the search. This approach thus avoid getting stuck at local optima, especially in later iterations where the step size is smaller. Moreover, the Resistivity-Driven Intensification Algorithm targets terminal regions relative to the feeder, addressing resource allocation challenges and guiding the PSO toward regions where energy flow is more efficient with DER, minimizing losses and voltage drops. Additionally, Demand-Driven Candidate Generator prioritizes resource allocation in the areas with high energy demands. Large power flowing for long distances to satisfy the large demand areas is costly in terms of active power losses within the lines. Thus, directing the DER allocation towards the high-demanding areas leads to local energy sufficiency. While the proposed algorithms contribute to intensification by focusing on potential candidates, their distinct approaches ensure a balanced search process by enhancing local searches and exploring underutilized areas, respectively. The proposed approach has been tested on IEEE 33, IEEE 69 systems, and the Norwegian 124 bus system. A comprehensive comparison of the proposed approach with several variants of the PSO and other heuristic algorithms, from the literature, has been conducted. The results showed that the proposed approach outperformed the other algorithms in terms of solution quality and variability. This highlights the robustness and effectiveness of the proposed approach in solving optimal DG planning problems.

5.4 Problem Definition

5.4.1 Power Network Connectivity

Common metaheuristic optimization methods, notably PSO, have limitations in addressing crucial electrical network characteristics due to their numerical bias. Fig. 31 illustrates a radial distribution network with nodes that exhibit disparities between numerical and physical connections. Certain nodes are physically connected despite lacking direct numerical connections (e.g., 3 and 23), while others are numerically but not physically connected (e.g., 18 and 19).

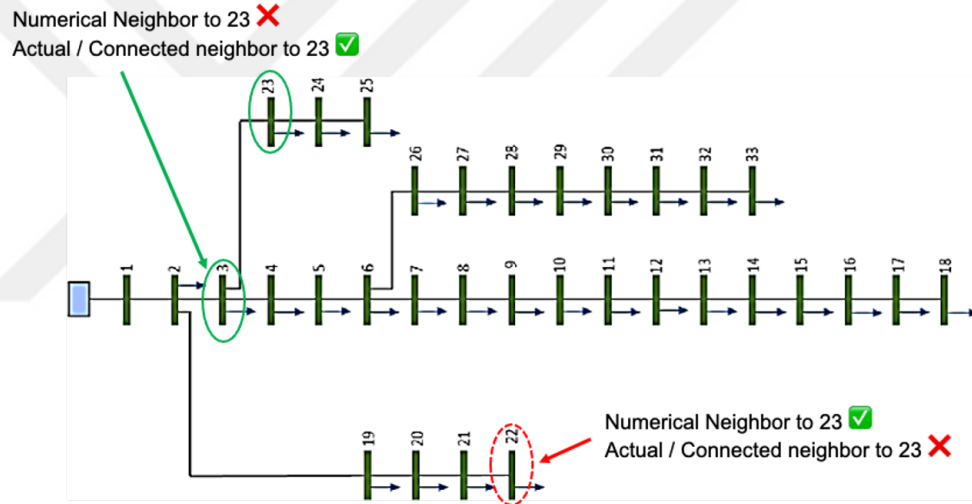


Figure 31: Electrical network connectivity observations—IEEE33

This presents challenges for metaheuristic algorithms such as PSO when searching for optimal solutions. As the algorithm progresses towards convergence, the difficulty arises of navigating from numerically connected nodes to physically connected ones due to limitations in step size. For instance, transitioning from node 3 to a physically close optimal node like 23 with a small step size may lead to local optima traps. Therefore, instead of strict numerical connections, node connections can cause the classical PSO search step to overlook actual node neighbors and shift towards more numerical-based neighbors during the solution search.

5.4.2 Power Losses Analysis

The resistivity of near and far ends of a radial network and their effects on the system's total power losses will be investigated in this section. Due to the resistivity concept, the impact of the demand at the far end is higher in terms of losses than the demand at a bus closer to the transformer. Consider an indicative radial network with a single feeder line with N buses numbered from 1 (near the feeder) to N (far end of the feeder) as shown in Fig. 32. Let P_i be the active power demand at bus i . The resistance and reactance of the line segment between bus i and $i + 1$ are R_i and X_i , respectively. The current flowing in the segment between bus i and $i + 1$ can be represented as I_i .

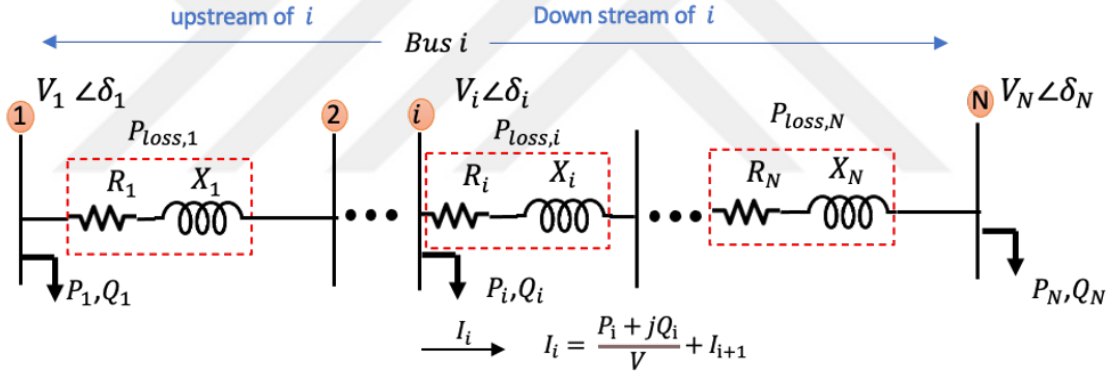


Figure 32: Simple Radial Network Features

5.4.2.1 Power Loss Calculations

The power loss $P_{\text{loss},i}$ in the line segment between bus i and $i + 1$ is calculated by:

$$P_{\text{loss},i} = R_i I_i^2 \quad (53)$$

where I_i is the current flowing through the branch between bus i and $i + 1$.

To find I_i , the currents from all downstream loads are summed up. The current I_i is calculated as:

$$I_i = \frac{P_i + jQ_i}{V_i} + I_{i+1} \quad (54)$$

where P_i is the active power demand at bus i , jQ_i is the reactive power demand at bus i , V_i is the voltage at bus i , and I_{i+1} is the current in the downstream line segment. For simplicity, V_i is approximately constant and equal to V (voltage at the feeder bus).

$$I_i \approx \frac{P_i + jQ_i}{V} + I_{i+1} \quad (55)$$

Starting from the farthest bus N , the current flowing through each branch can be recursively expressed by:

$$I_N = \frac{P_N + jQ_N}{V} \quad (56)$$

$$I_{N-1} = \frac{P_{N-1} + jQ_{N-1}}{V} + I_N \quad (57)$$

$$I_{N-2} = \frac{P_{N-2} + jQ_{N-2}}{V} + I_{N-1} \quad (58)$$

$$\vdots \quad (59)$$

$$I_1 = \frac{P_1 + jQ_1}{V} + I_2 \quad (60)$$

The total power loss in the network is the sum of the power losses in all branches:

$$P_{\text{loss,total}} = \sum_{i=1}^{N-1} P_{\text{loss},i} \quad (61)$$

$$P_{\text{loss,total}} = \sum_{i=1}^{N-1} R_i \left(\frac{P_i + jQ_i}{V} + I_{i+1} \right)^2 \quad (62)$$

5.4.2.2 Impact of Demand on Losses at Far End vs Near the Feeder

To compare the impact of demand at the far end versus near the feeder on power losses, it is crucial to analyze their relative contribution to flowing current and, as a result, to total power losses. Consider two separate cases where active demand (reactive component is neglected) is considered at bus 1 (near the feeder) first, then bus N (the terminal bus). The demand is assumed to be constant and other buses' demands are zero.

For demand at bus 1 (near the feeder):

$$I_1 = \frac{P_1}{V} \quad (63)$$

$$P_{\text{loss,total},1} = P_{\text{loss},1} = R_1 \left(\frac{P_1}{V} \right)^2 \quad (64)$$

For demand at bus N (terminal bus):

$$I_N = \frac{P_N}{V} \quad (65)$$

$$I_{N-1} = I_N = \frac{P_N}{V} \quad (66)$$

$$I_{N-2} = I_{N-1} = I_N = \frac{P_N}{V} [8pt] \quad (67)$$

$$I_1 = I_2 = \dots = I_N = \frac{P_N}{V} [8pt] \quad (68)$$

Therefore, the total losses contributed by P_N :

$$P_{\text{loss,total},N} = \sum_{i=1}^{N-1} R_i \left(\frac{P_N}{V} \right)^2 \quad (69)$$

$$P_{\text{loss,total},N} = \left(\frac{P_N}{V} \right)^2 \sum_{i=1}^{N-1} R_i \quad (70)$$

Clearly, $P_{\text{loss,total},N}$ includes contributions from all line resistances R_i from bus 1 to bus $N - 1$, while $P_{\text{loss},1}$ includes only R_1 as line resistance.

$$R_1 \ll \sum_{i=1}^{N-1} R_i \quad (71)$$

Thus,

$$P_{\text{loss,total},1} \ll P_{\text{loss,total},N} \quad (72)$$

The demand at the far end of the network (bus N) contributes to losses in every branch along the path back to the feeder, leading to a higher cumulative loss. In contrast, the demand near the feeder (bus 1) only affects the immediate branch, resulting in lower overall losses. Therefore, the impact on losses of demand at the far end of a radial network is higher than the impact of demand at a bus near the feeder.

When a DER is placed near the network terminals, it generates power that is consumed locally or by nearby loads. This reduces the current that must flow from the feeder through the entire length of the network to the end buses. However, when

a DER is placed near the feeder, the generated power reduces the load seen by the feeder but doesn't significantly reduce the current in the downstream segments of the network. As a result, the reduction in losses is less compared to placing the DER at the end of the network.

5.5 Methodology

5.5.1 Time Varying PSO

The PSO algorithm starts with the initialization step, where a population of potential solutions, referred to as particles, is randomly generated. Equation (73) defines the position x_p of each particle p in the PSO algorithm's search space. Each particle p is a vector containing the size and location of DER. Each particle's fitness or objective function value is evaluated, indicating its overall quality with respect to the optimization goals. The particles then undergo iterative updates. The particles adjust their positions within the solution space based on their own previous best position and the best position found by any particle in the population. This cooperative behaviour of particles is analogous to a swarm of birds searching for the best path. The particle with the best fitness value is deemed the global best, representing the overall optimal solution. The PSO algorithm proceeds through multiple iterations, seeking to converge toward a solution that balances the trade-offs between costs, constraints, and the allocation of DER and components across the network. Convergence behaviour is shaped by parameters like inertia weight w_{it} , cognitive acceleration coefficient $c_{1,it}$, and the social acceleration coefficient $c_{2,it}$. Equation (74) calculates the inertia weight w_{it} at iteration it in the PSO algorithm. It exponentially adjusts the inertia weight over iterations based on the initial inertia weight w_{ini} , the final inertia weight w_{fin} , a decay rate k , and the current iteration it out of a total number of iterations IT . This TVPSO adjusts the inertia weight exponentially during the optimization process to promote exploration in the early stages (high inertia) and exploitation in the later

stages (low inertia). Acceleration coefficients $c_{1,it}$ and $c_{2,it}$ are linearly computed by minimum and maximum cognitive coefficients in addition to iteration number based on (75) and (76) respectively. Updating the particle velocities $v_{p,it}$ of particles p at iteration it with the new calculated w_{it} , $c_{1,it}$, and $c_{2,it}$ takes place as in (77). It also considers stochasticity by introducing rand , a random value between 0 and 1 while computing $v_{p,it}$. Then, the position $x_{p,it}$ of particle p at iteration it updates based on the current position and the new computed velocity $v_{p,it}$ as shown in (78). It represents the movement of the particle in the search space. The PSO keeps iterating and choosing the best global solution.

$$x_p = [\text{DG}_{j,p}^{\text{size}}, \text{DG}_{j,p}^{\text{location}}] \quad (73)$$

$$w_{it} = \max \left(w_{\text{fin}}, w_{\text{ini}} \exp \left(-k \frac{\text{it}}{\text{IT}} \right) \right) \quad (74)$$

$$c_{1,it} = c_{\text{max}} - \frac{(c_{\text{max}} - c_{\text{min}})}{\text{IT}} \cdot \text{it} \quad (75)$$

$$c_{2,it} = c_{\text{min}} + \frac{(c_{\text{max}} - c_{\text{min}})}{\text{IT}} \cdot \text{it} \quad (76)$$

$$v_{p,it} = w_{it}v_{p,it} + c_{1,it} \cdot \text{rand} \cdot (x_{p,\text{best}} - x_{p,it}) + c_{2,it} \cdot \text{rand} \cdot (x_{G,\text{best}} - x_{p,it}) \quad (77)$$

$$x_{p,it} = x_{p,it-1} + v_{p,it} \quad (78)$$

5.5.2 Power System Oriented TVPSO (PS-TVPSO)

The proposed Power System oriented TVPSO is a novel approach to address the complex challenges within DER planning optimization. The conventional PSO faces challenges in terms of local optima traps and lack of consideration for network characteristics. In response to these limitations, the proposed approach integrates network - related algorithms, including the Connectivity - Driven Intensification Algorithm, Resistivity - Driven Intensification Algorithm, and Demand - Driven Candidate Generator to strategically enhance PSO search towards the global optimal solution. These

algorithms understand the power grid’s topology, resistivity and demand patterns to guide the optimization process towards favourable regions including potential candidates to deploy the DER units. Before the end of each iteration, where the PSO reveals a current population and current best solution, the algorithms generate solution candidates and an evaluation takes place against the current best solution. If a better solution is found, the current best solution will be replaced with the new one generated by these algorithms. Moreover, the generated candidates integrate the current population so that they play both intensification and diversification roles to strategically guide the future PSO search towards favourable regions in the search space. To avoid radical population alterations, control mechanisms regulate the number of candidates imported and the replacement of existing particles, ensuring a balanced exploration-exploitation trade-off. This comprehensive approach illustrated in Fig. 33 combines advanced optimization methods with domain-specific knowledge, aiming to transform the DER integration optimization. It promises to provide efficient, robust, and domain relevant solutions that revolutionize the current metaheuristic optimization applications.

5.5.3 Connectivity-Driven Intensification Algorithm

The Connectivity-Driven Intensification Algorithm, a core algorithm in the proposed framework, operates by examining the electrical connectivity among nodes in the power grid. By analyzing the network topology, it generates solution candidates that align with the physical nodal connections within the grid. This ensures that the PSO algorithm explores solution spaces that are aligned with the grid’s electrical structure, addressing a critical limitation of conventional PSO.

The provided Algorithm 3 demonstrates the implementation of the Connectivity-Driven Intensification Algorithm. It begins by importing the necessary inputs, including branch data B , solution vector S of length L , and candidate length K . A

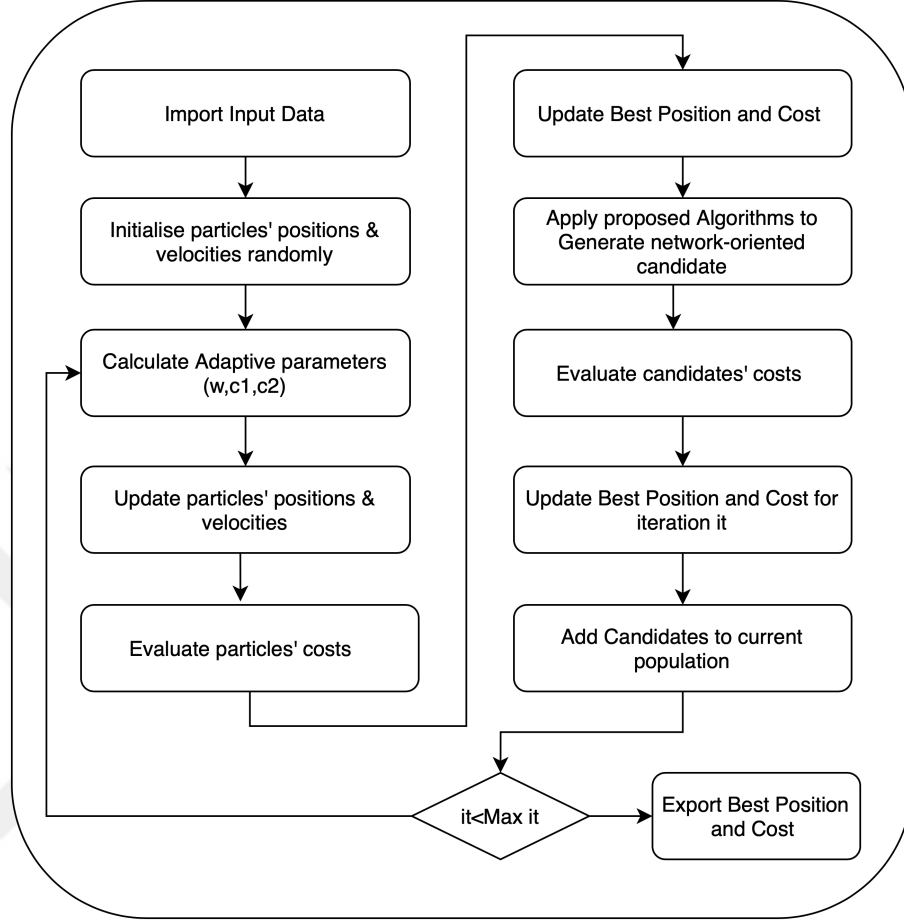


Figure 33: Proposed Network Oriented TVPSO Flowchart

connectivity matrix C is initialized with all elements set to zero. The matrix is populated such that for each i connected to j , the entries C_{ij} are set to 1, reflecting the network's connections. To generate neighbor candidates, a candidate matrix N is initialized. For each candidate k , an empty array c_k is initialized. For each item s_i inside S , the set of connected nodes $C(s_i)$ is identified. A random node m is selected from $C(s_i)$ and assigned to c_k . The updated candidate c_k is then stored in the k -th row of N .

5.5.4 Resistivity-Driven Intensification Algorithm

The Resistivity-Driven Intensification Algorithm addresses resource allocation challenges within the power grid by targeting areas at the terminal ends and adjacent

Algorithm 3 Connectivity-Driven Intensification Algorithm

- 1: **Import inputs:** B , S of length L , and K
- 2: **Initialize Connectivity Matrix:**

$$C \in \mathbb{R}^{N \times N}, \quad C_{ij} \leftarrow 0 \quad \forall i, j \in N$$

- 3: **Populate Connectivity Matrix:**
- 4: **for** each branch $b(i, j) \in B$ **do**
- 5: $C_{ij} \leftarrow 1, \quad C_{ji} \leftarrow 1$
- 6: **end for**
- 7: **Generate Neighbour Candidates:**

$$N \in \mathbb{R}^{K \times L}, \quad N[k, :] \leftarrow c_k \quad \forall k \in \{1, \dots, K\}$$

- 8: **for** each node $s_i \in S$ **do**
 - 9: $C(s_i) = \{m \mid C(n_i, m) = 1\}$
 - 10: $c_k \leftarrow m$ (random node $m \in C(s_i)$)
 - 11: **end for**
-

edges of the network, where energy flow is more efficient with DER, minimizing losses and voltage drops. In networks lacking DER, transmitting energy from the feeder to these terminal areas leads to significant losses due to the necessity of energy traversing long distances with high accumulated resistance, resulting in high loss and voltage drops. By prioritizing these areas, the algorithm optimizes resource allocation, facilitating the placement of DERs to efficiently supply energy to nearby nodes while minimizing losses.

The Resistivity-Driven Intensification Algorithm begins by importing branch data B , resistance R , solution vector S of length L , and candidate length K . The connectivity matrix C is imported from Algorithm 1. The sum of each row in the connectivity matrix is calculated to identify the terminal nodes T . For each terminal node t in T , adjacent nodes A_t are identified. Candidate solutions are generated by initializing a candidate matrix N first. For each candidate k , a new solution S^* is initialized from S and updated with chosen nodes from the subsets of terminal and adjacent nodes.

Algorithm 4 Resistivity-Driven Intensification Algorithm

- 1: **Import inputs:** B, R, S, K
- 2: **Import Connectivity Matrix from Algorithm 1:** C
- 3: **Calculate the sum of each row in C :**

$$s = \sum_{j=1}^N C_{ij} \quad \forall i = 1, 2, \dots, N$$

- 4: **Identify Terminal nodes and Adjacent nodes:**

$$T \leftarrow \{i \mid s_i = 1\}, \quad A_t \leftarrow \{j \mid C_{tj} = 1\} \quad \forall t \in T$$

- 5: **Generate Candidate Solutions:**

$$N \in \mathbb{R}^{K \times L}, \quad N[k, :] \leftarrow S^* \quad \forall k \in \{1, \dots, K\}$$

- 6: $S^* \leftarrow S$
 - 7: $S^*[\text{change}] \leftarrow$ Chosen nodes from subset of $[T; A]$
-

5.5.5 Demand-Driven Candidate Generator

The Demand-Driven Candidate Generator plays a crucial role in the proposed approach by prioritizing resource allocation in the areas with high energy demands. By strategically allocating DERs to these regions, it reduces power flow within branches and minimizes losses. Large power flowing for long distances to satisfy the large demand areas is costly in terms of active power losses within the lines. Directing the DER allocation towards the high-demanding areas leads to local energy sufficiency, where the DERs flow energy to higher demand nodes and their surroundings. The extra energy will be flowing towards other regions. The complete pseudocode is shown in (Algorithm 5).

The Demand-Driven Intensification Algorithm starts by importing bus data B_{bus} , demand D , and branch data B_{branch} . It initializes a Total Demand array T with the dimension of the number of nodes and calculates the total connecting demands for each node. The demands are then sorted in descending order, and the nodes with the highest values are selected as the subset S_{sel} . Candidate solutions are generated

Algorithm 5 High Demand-Driven Intensification Algorithm

- 1: **Import inputs:** $B_{\text{bus}}, B_{\text{branch}}, D$
- 2: **Calculate Total Connected Demand:** $T \in \mathbb{R}^N$
- 3: **Calculate the sum of each row in C :**

$$T_i = \sum_{j=1}^M D_{ij} \quad \forall i = 1, 2, \dots, N, \quad m : \text{connected demands}$$

- 4: **Select high demanding areas:**

$$S_{\text{sel}} \leftarrow \text{indices of highest values of } T$$

- 5: **Generate Candidate Solutions:**

$$N \in \mathbb{R}^{K \times L}, \quad N[k, :] \leftarrow S^* \quad \forall k \in \{1, \dots, K\}$$

- 6: $S^* \leftarrow S$
 - 7: $S^*[\text{change}] \leftarrow \text{Chosen nodes from subset of } S_{\text{sel}}$
-

by first initializing a candidate matrix N . For each candidate, a new solution S^* is initialized and updated with nodes from the S_{sel} subset. The updated solution is stored in N , and the unique candidate solutions are returned.

5.5.6 Optimal Power Flow and Fitness Evaluation

Power flow analysis is a vital component of this distribution-level hybrid system planning. Throughout the evaluation, power flow analysis shown in Fig. 34 ensures technical reliability, economic viability, and network constraint compliance. Violations trigger penalties to quantify their impact. Optimal power flow minimizes the total active power loss, while maintaining the system efficiency and physical constraints within the limits.

$$\text{Min } P_{\text{loss}} \tag{79}$$

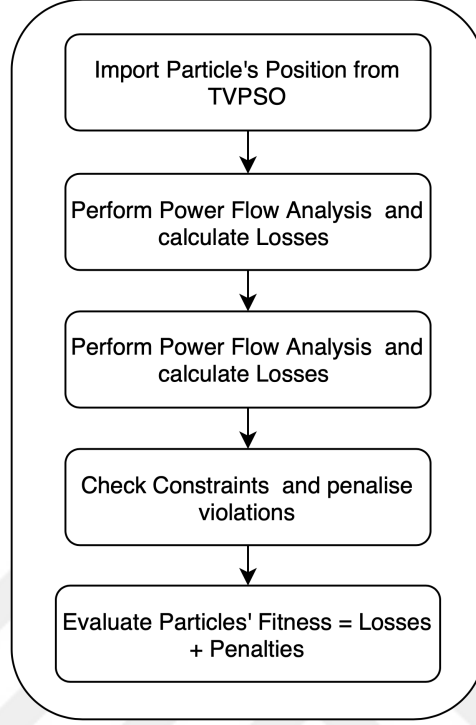


Figure 34: TVPSO Fitness Evaluation Flowchart

Subject to:

$$P_{\text{loss}} = \sum_i P_i^{\text{utility}} + \sum_i P_i^{\text{DER}} - \sum_i \text{PL}_i \quad (80)$$

$$P_i^{\text{utility}} + P_i^{\text{DER}} + \text{PL}_i = V_i \sum_{j=1}^N V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \quad (81)$$

$$Q_i^{\text{utility}} + \text{QL}_i = V_i \sum_{j=1}^N V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \quad (82)$$

$$V_i^{\min} \leq |V_i| \leq V_i^{\max} \quad (83)$$

$$\theta_{ij}^{\min} \leq \theta_{ij} \leq \theta_{ij}^{\max} \quad (84)$$

The power loss P_{loss} is calculated by (80) as the difference between the total power injected into the system by the utility and DERs and the total power consumed by loads. The power balance equations showed in (81) and (82) ensure that the active

and reactive power injected by the utility, DERs, and consumed by loads at each node satisfy Kirchhoff's voltage law. It is crucial to mention here that the sum of P_i^{DER} represents the sum of power generated by multiple distributed resources. Constraints (83) and (84) are imposed to limit the voltage magnitude at each node, and the voltage phase angle difference between connected nodes within predefined bounds. These constraints ensure that the system operates within specified limits, optimizing power flow while maintaining stability.

5.6 Case Study

The case studies conducted in this study aim to assess the proposed approach, for multiple DER planning and allocation, in terms of solution quality, system performance, and computational efficiency. MATLAB simulations were employed to assess the performance of the strategy, utilizing PS-TVPSO configurations. Two benchmark power networks, namely the IEEE 33-bus and IEEE 69-bus systems [24], were selected to validate these investigations. Additionally, the Norwegian 124-bus system [102] was utilized to ensure the methods are applicable to real-world scenarios.

Table 13: Simulated case study parameters.

Case	Population Size	Max Iteration	$c_{\min}$	$c_{\max}$	w_{ini}	w_{fin}
IEEE 33 - 2DER	20	100	1.5	2.5	1	0.4
IEEE 33 - 3DER	20	100	1.5	2.5	1	0.4
IEEE 33 - 4DER	50	100	1.5	2.5	1	0.4
IEEE 69 - 2DER	35	100	1.5	2.5	1	0.4
IEEE 69 - 3DER	50	100	1.5	2.5	1	0.4
IEEE 69 - 4DER	75	150	1.5	2.5	1	0.4
Norwegian - 2DER	50	150	1.5	2.5	1	0.4
Norwegian - 3DER	100	150	1.5	2.5	1	0.4
Norwegian - 4DER	150	200	1.5	2.5	1	0.4

Utilizing data from these networks, different case studies were implemented on multiple DG planning problems. The detailed parameters of the designed cases are

summarized in Table 13. Additionally, the results will be compared with those from the existing literature, where various heuristic methods were used, to examine performance and solution quality. Moreover, an analysis will be conducted to assess how well overall power grid performance is improved by the proposed approach.

5.7 Simulation Results and Discussion

To confirm the validation of the proposed approach, the study is tested on IEEE33-bus, IEEE69-bus and the Norwegian124-bus systems for several case studies. (1) Systems are simulated without any DER integration. (2) Systems are simulated while 2 DER systems are implemented. (3) Systems are simulated while 3 DER systems are integrated. (4) Finally, Systems are simulated considering 4 DER units are implemented. All the cases are implemented in MATLAB 2024 to optimize DER integration, total minimize power losses, and maintain the grid stability and security. The PC used is 2,3 GHz Quad-Core Intel Core i7 @ 32 GB 3733 MHz RAM.

5.7.1 IEEE33 Simulations

The results of the proposed methods and ones of relevant methods in literature are listed in Table 14. The comparison takes place in terms of DER allocation, DER sizes, active power loss and percentage of loss reduction. In case 2 DER integration, the resultant sites and sizes have shown differences between the proposed methods and the ones in the literature. The best sites and sizes resulted in this case are 13, 30 and 844kW, 1159kW respectively. Moreover, it is proved that the proposed methods have performed the best in terms of active power loss and loss reduction percentage recording, 85.91 kW and 57.52 percent respectively. Moving to 3 DER integration, the power loss has shown 71.4kW with a loss reduction of 64.70 percent with respect to the case with no DER.

Compared with other methods mentioned in the literature, the proposed methods have performed well showing the same power loss reduction as the best results

Table 14: Performance comparison of different DER allocation methods for IEEE 33-bus system

Case	IEEE33	DER Allocation	DER Size (kW)	Active Power Loss(kW)	Loss Reduction (%)
2 DER - IEEE33	No DER	-	-	202.26	-
	VCPSO [103]	13	867	88.2	56.39
		30	1323		
	[104]	6	3133	105.7	47.74
		16	365		
	LSF [97]	18	720	100.69	50.22
		33	900		
	IA [97]	6	1800	91.63	54.70
		14	720		
	ELF [97]	12	1020	87.63	56.67
		30	1020		
	PSO [92]	6	1899	91.2	54.91
		14	650		
3 DER - IEEE33	TVPSO [82]	13	844	85.91	57.52
		30	1159		
	TVPSO [82]	23	1100	71.4	64.70
		29	1072		
		13	754		
	BPSO [82]	6	1452	84.5	58.22
		32	596		
		15	464		
	APSO [82]	32	639	78.3	61.29
		13	585		
		6	1224		
	e1PSO [82]	13	754	71.4	64.70
		29	1072		
		23	1100		
	e2PSO [82]	12	835	85.4	57.78
		6	50		
		29	1142		
	HSA [95]	30	1119	72.8	64.01
		25	842		
		13	780		
	IA [97]	6	900	81.06	59.92
		12	900		
		31	720		
	ELF [97]	13	900	74.27	63.28
		30	900		
		24	900		
	Proposed – PS-TVPSO	14	753	71.4	64.70
		24	1098		
		30	10734		

achieved.

Fig. 35 illustrates the results of 30 runs performed for each case, reflecting the convergence behavior over iterations. Additionally, the average among the 30 runs per iteration is mentioned, providing insights into the overall trend of convergence.

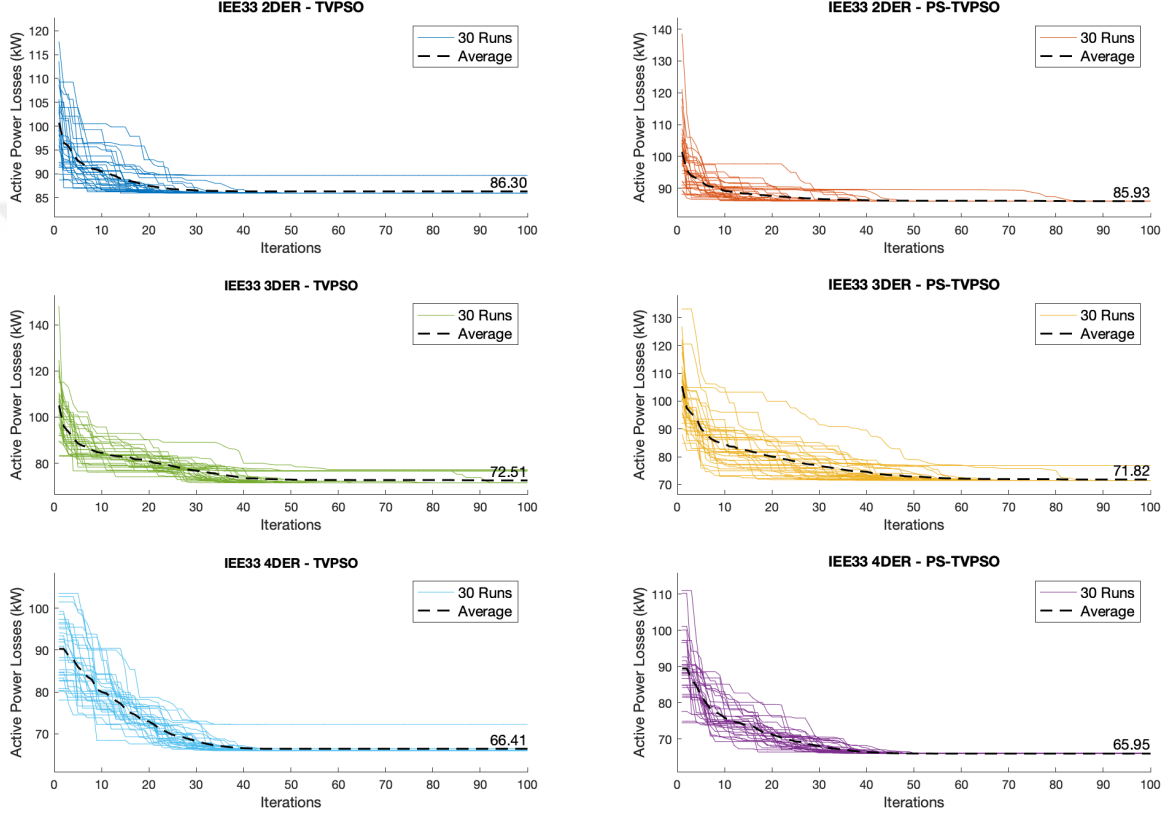


Figure 35: Proposed Method's Computational Performance - IEEE33

Observing the results, the percentage of deviation from the average is lower in the proposed approach, PS-TVSP0, compared to the base cases, TVSP0. Specifically, for the IEEE33 scenario with 2DER, the average converged value recorded 86.30 kW for the TVSP0 case, while with PS-TVSP0, it was slightly lower at 85.93 kW. Similarly, for the IEEE33 scenario with 3DER, the average converged value was 72.51 kW for the TVSP0 case, and with PS-TVSP0, it reduced to 71.82 kW. For the IEEE33 scenario with 4 DER, the average converged value was 66.41 kW for the base case, and with PS-TVSP0, it reduced to 65.95 kW. This implies that as the number of DER

increases, computational complexity rises, requiring enhanced methods for improved performance.

Table 15 outlines the computational performance statistics for the IEEE 33-bus system with 2, 3, and 4 DERs using both the base TVPSO and the PS-TVSP0.

Table 15: Computational Performance Statistics – IEE33

IEEE33	Metric	2 DER	3 DER	4 DER
Base - TVPSO	Mean	86.30	72.51	66.41
	Median	85.91	71.46	65.93
	Standard Deviation	1.14	2.13	1.59
	Minimum	85.91	71.46	65.93
	Maximum	89.66	77.28	72.22
	Computational Time	101	105	112
PS - TVPSO	Mean	85.93	71.82	65.95
	Median	85.91	71.46	65.93
	Standard Deviation	0.03	1.36	0.04
	Minimum	85.91	71.46	65.93
	Maximum	85.96	76.81	66.11
	Computational Time	103	106	113

The data reveals a trend of decreasing mean and median values as the number of DERs increases, indicating improved optimization outcomes with additional DERs. For the base TVPSO, the mean values decline from 86.30 for 2 DERs to 66.41 for 4 DERs, with corresponding median values showing a similar trend. However, the base TVPSO displays considerable variability, with standard deviations of 1.14, 2.13, and 1.59 for 2, 3, and 4 DERs respectively. Conversely, the PS-TVSP0 shows significantly reduced variability, with standard deviations of 0.03, 1.36, and 0.04, highlighting its stability and consistent performance. The PS-TVSP0 also achieves lower mean and median values across all DER scenarios, suggesting better optimization quality compared to the base TVPSO. For example, with 4 DERs, the mean value for PS-TVSP0 is 65.95 versus 66.41 for the base TVPSO. These findings underscore the superiority of PS-TVSP0 in delivering efficient optimization results for DER allocation in IEEE33

network.

5.7.2 IEEE69 Simulations

Table 16 compares the results of various methods in optimizing DER allocation and size within IEEE 69 cases, particularly comparing configurations with 2DER, 3DER and 4DER integration. The PS-TVPSO shows competitive outcomes compared to other methods referenced in the literature. It exhibits a relatively improved loss reduction percentage, 69.14 percent.

The simulations conducted for 2DER, 3DER, and 4DER scenarios within IEEE69 took place for 30 runs, shown in Fig. 36. In the 2DER scenarios, none of the runs deviated from the optimal solution, indicating robust convergence and a high degree of consistency. Coming to the 3DER scenario, the runs have converged to close values. This convergence trend proves the effectiveness of the optimization algorithms in navigating the complexity introduced by the additional DER components. Moreover, in the 2DER scenario within IEEE69, the average converged value showed a reduction from 72.05 in base case to 71.67 in with PS-TVPSO case, while in the 3DER setting, it decreased from 69.79 to 69.47. For the IEEE69 scenario with 4 DER, the average converged value was 68.41 kW for the base case, and with PS-TVPSO, it reduced to 68.17 kW. These improvements show the effectiveness of the proposed optimization method in enhancing network performance and minimizing active power loss. Furthermore, the analysis revealed that, as the number of DER components increased, the loss reduction within the network also intensified. This highlights the potential benefits of scaling up DER deployment, suggesting a positive correlation between DER integration and network performance enhancement.

Table 17 presents the computational performance statistics for the IEEE 69-bus system with 2, 3, and 4 DERs using both the base TVPSO algorithm and PS-TVPSO.

Table 16: Simulation Result Comparison – IEEE69

Case	IEEE69 - 2DERs	DER Allocation	DER Size (kW)	Active Power Loss(kW)	Loss Reduction (%)
2 DER - IEEE69	No DER	-	-	224.95	-
	ACO-ABC [99]	18	530.9	71.66	68.14
		61	1781.8		
	AF [93]	16	526.3	71.78	68.09
		60	1759.7		
	EA-OPF [94]	17	531	71.68	68.14
		61	1781		
	PSO [92]	18	477.4	71.96	68.01
		61	1866.1		
	Heuristic [96]	17	520	71.8	68.08
		61	1733		
	APSO [105]	17	531.17	71.66	68.14
		61	1781.46		
	MGSA [105]	17	573.24	71.73	68.11
		61	1786.9		
	Proposed – PS-TVPSO	17	531.47	71.67	68.14
		61	1781.45		
3 DER - IEEE69	QOTLBO [106]	15	591.9	72.41	67.81
		61	818.8		
		63	900.3		
	AF [93]	10	514.3	69.44	69.13
		17	381.7		
		60	1693.6		
	EA-OPF [93]	11	527	69.43	69.14
		18	380		
		61	1719		
	PSO [92]	11	501.2	69.89	68.93
		18	482.2		
		61	1770.4		
	Heuristic [96]	12	471	69.7	69.02
		21	312		
		61	1689		
	Analytical-PSO [107]	11	510	69.6	69.06
		17	380		
		61	1670		
	APSO [81]	17	536.27	71.71	68.12
		61	1173.75		
		64	522.81		
	MGSA [81]	15	562.65	71.9	68.04
		61	1190.11		
		63	523.31		
	Proposed – PS-TVPSO	18	380.35	69.42	69.14
		61	1718.96		
		11	526.81		

The results show that both mean and median values decrease as the number of DERs increases, indicating better optimization outcomes with more DERs. The base TVPSO exhibits significant variability, with standard deviations of 0.99, 0.84, and 0.60 for 2, 3, and 4 DERs respectively, while PS-TVSPSO demonstrates much lower standard deviations, notably zero for 2 DERs. The PS-TVSPSO also consistently achieves lower mean and median values compared to the base TVPSO, indicating superior optimization quality. For instance, with 4 DERs, the mean value for PS-TVSPSO is 68.17 versus 68.41 for the base TVPSO. Additionally, the maximum values for PS-TVSPSO are consistently lower.

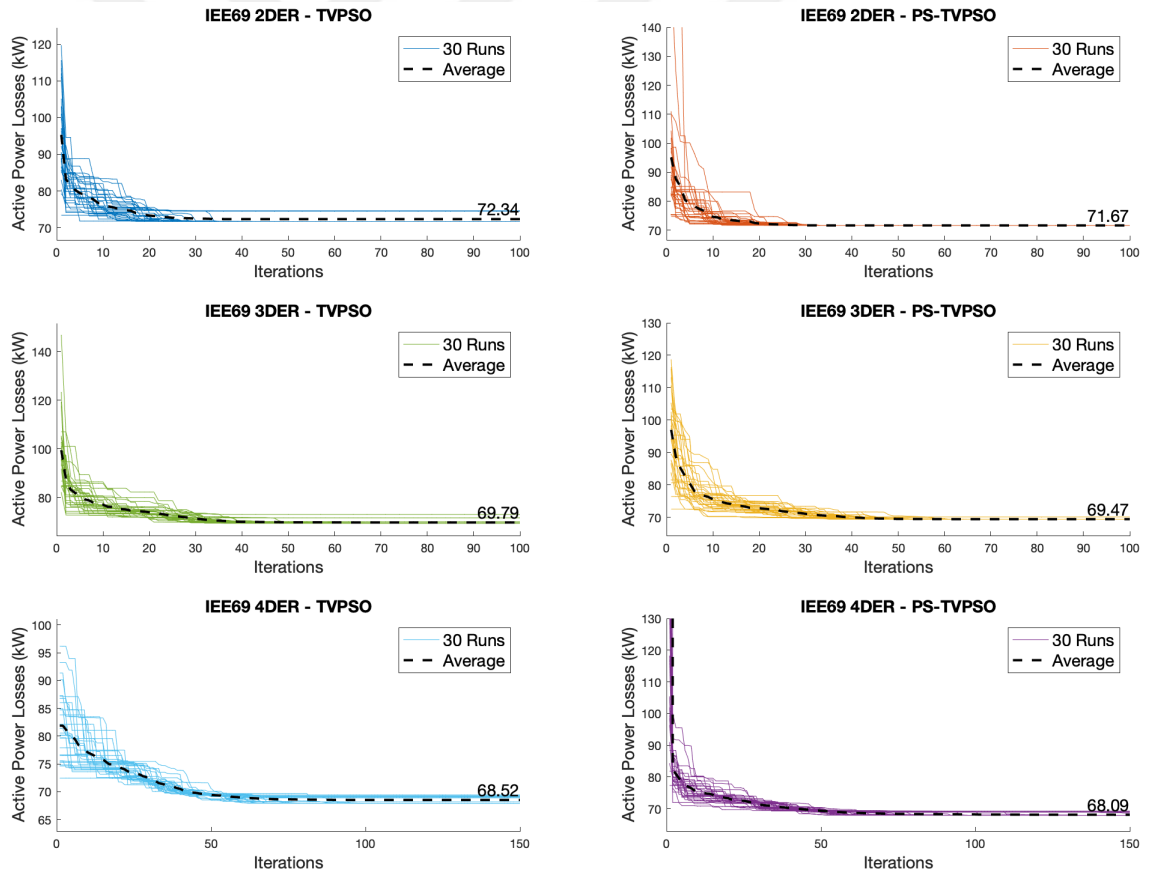


Figure 36: Proposed Method's Computational Performance - IEEE69

Table 17: Computational Performance Statistics – IEEE69

IEEE69	Metric	2 DER	3 DER	4 DER
Base - TVPSO	Mean	72.05	69.79	68.41
	Median	71.67	69.43	68.13
	Standard Deviation	0.99	0.84	0.60
	Minimum	71.67	69.43	67.92
	Maximum	74.60	73.09	69.51
	Computational Time (s)	110	114	180
PS - TVPSO	Mean	71.67	69.47	68.17
	Median	71.67	69.43	67.92
	Standard Deviation	0	0.19	0.47
	Minimum	71.67	69.43	67.92
	Maximum	71.67	70.16	69.25
	Computational Time (s)	111	116	182

5.7.3 Norwegian Case Simulations

The simulations for the Norwegian system were conducted for 30 runs in scenarios with 2, 3, and 4 DERs for base TVPSO and PS-TVPSO applications, shown in Fig. 37. In the 2DER scenario, the average value decreased from 18.39 to 18.19, with almost all runs achieving the optimal solution, indicating PS-TVPSO's robust convergence and high consistency. In the 3DER scenario, the average value decreased from 15.95 to 15.84, with all 30 runs converging to values close to the optimal solution, demonstrating the effectiveness of the PS-TVPSO in handling increased complexity.

For the 4DER scenario, the average value decreased from 14.68 to 14.59, despite the higher complexity introduced by the additional DERs. The proposed method led to a closer convergence of all runs, showing its capability in navigating complex problems in real case scenarios.

Table 18 presents the computational performance statistics for the Norwegian system with 2, 3, and 4 DERs using both the base TVPSO algorithm and the proposed PS-TVPSO. The results show a consistent decrease in mean and median values as

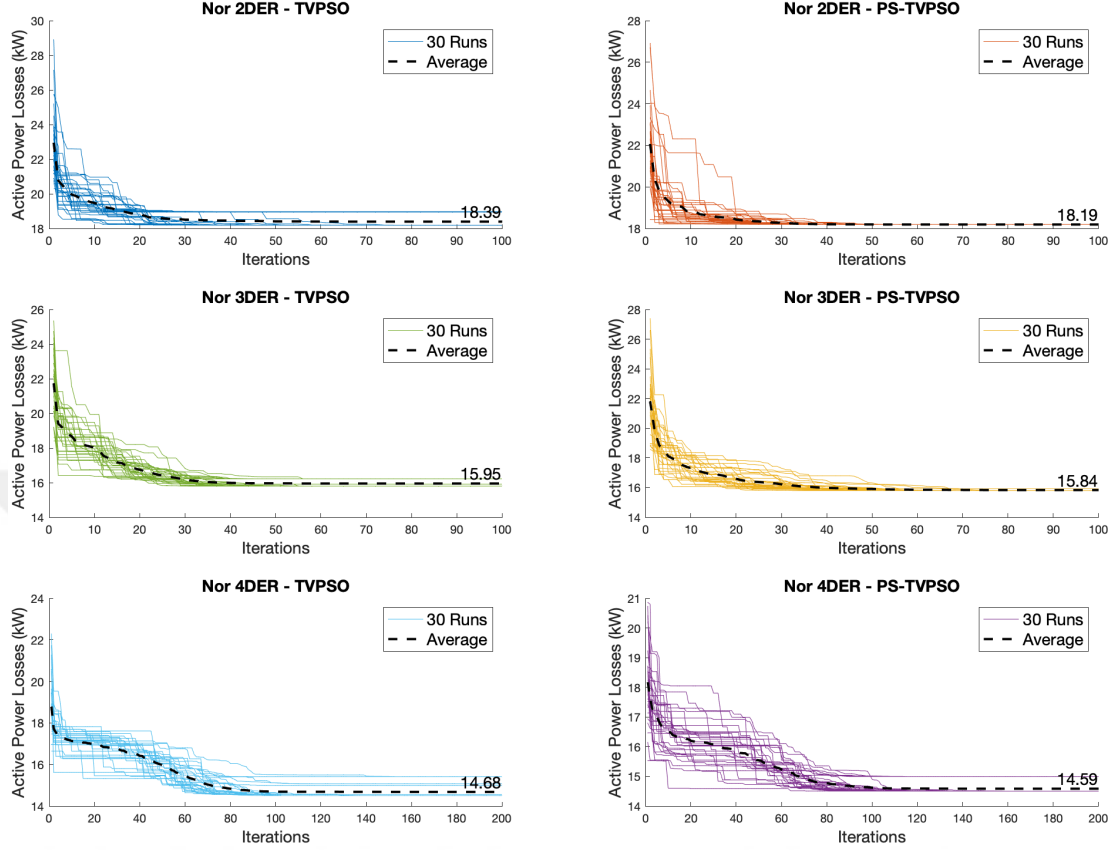


Figure 37: Proposed Method's Computational Performance - Norwegian

the number of DERs increases, indicating improved optimization results with the addition of more DERs. For the base TVPSO, the mean values drop from 18.39 with 2 DERs to 14.68 with 4 DERs, and the median values follow a similar downward trend. However, the base TVPSO exhibits notable variability, with standard deviations of 0.34, 0.18, and 0.29 for 2, 3, and 4 DERs respectively. In contrast, the PS-TVPSO demonstrates significantly reduced variability, with standard deviations of 0, 0.06, and 0.18, reflecting its enhanced stability and consistent performance. The PS-TVPSO consistently achieves lower mean and median values compared to the base TVPSO, suggesting superior optimization quality. For example, with 4 DERs, the mean value for PS-TVPSO is 14.59 versus 14.68 for the base TVPSO. Additionally, the maximum values for PS-TVPSO are consistently lower than those for the base TVPSO, indicating fewer occurrences of suboptimal solutions. Overall, the proposed

Table 18: Computational Performance Statistics – Norwegian

Norwegian	Metric	2 DER	3 DER	4 DER
Base - TVPSO	Mean	18.39	15.95	14.68
	Median	18.19	15.92	14.55
	Standard Deviation	0.34	0.18	0.29
	Minimum	18.19	15.79	14.50
	Maximum	18.97	16.22	15.42
	Computational Time (s)	174	194	288
PS - TVPSO	Mean	18.19	15.84	14.59
	Median	18.19	15.79	14.50
	Standard Deviation	0	0.06	0.18
	Minimum	18.19	15.79	14.50
	Maximum	18.19	15.92	14.99
	Computational Time (s)	176	202	292

PS-TVSP0 variant not only improves optimization quality but also ensures more consistent performance, making it a preferable choice for minimizing active power losses in real distribution networks.

5.7.4 Algorithm Performance Comparison

The Cumulative Distribution Function (CDF) plots shown in Fig. 38 provide important insights into the convergence behavior across different scenarios. The scenarios include, IEEE33 2DER, IEEE33 3DER, IEEE33 4DER, IEEE 69 2DER, IEEE 69 3DER, IEEE 69 4DER, Norwegian 2DER, Norwegian 3DER, and Norwegian 4DER with and without the proposed network-oriented algorithms of PS-TVPSO.

Notably, the CDF curves exhibit a steep incline in scenarios utilizing the proposed algorithms, indicating a rapid convergence toward optimal or near-optimal solutions.

Moreover, the close alignment or convergence of CDF curves reflects the consistency in convergence across iterations in scenarios employing the algorithms. These findings underscore the effectiveness of the proposed algorithms in enhancing convergence speed and achieving high-quality solutions when compared to the base case.

The impact of integrating multiple DER units within the IEEE33 and IEEE69

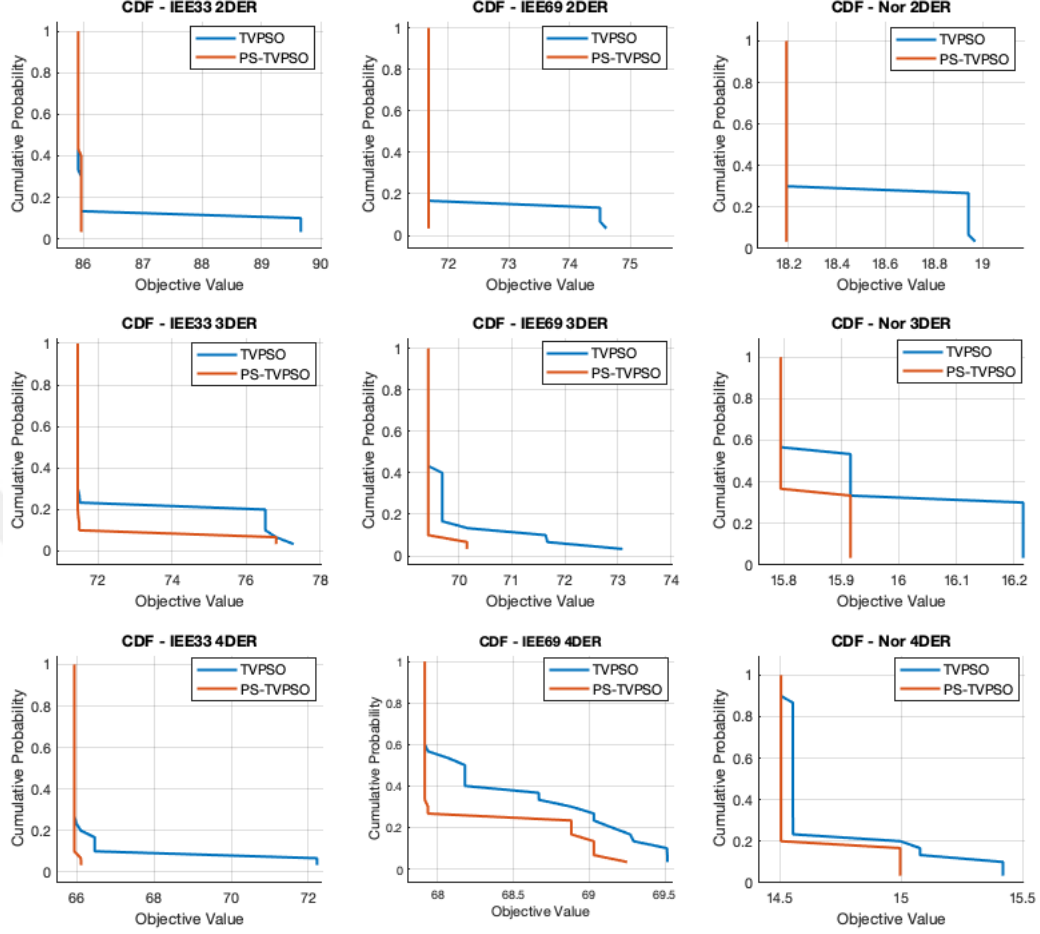


Figure 38: Proposed Method's CDF Comparison

networks is shown in Fig. 39. Integrating 2DER units have reflects a significant improvement in voltage levels across all networks. However, as additional DER units is also considered, the results didn't show high voltage improvement compared to 2 DER case.

As shown in Fig. 40 Voltage Deviation Index (VDI) decreased from 0.052, 0.027, and 0.032 to 0.02, 0.007, and 0.006, respectively, demonstrating enhanced voltage stability. Adding more DER units resulted in a slight further decrease in VDI. The substantial reduction in VDI underscores the effectiveness of DER integration in improving voltage stability within power networks.

For power loss reduction, shown in Fig. 41, the integration of DER units also shows significant benefits. Adding 2 DER units achieved reductions of 58%, 68%,

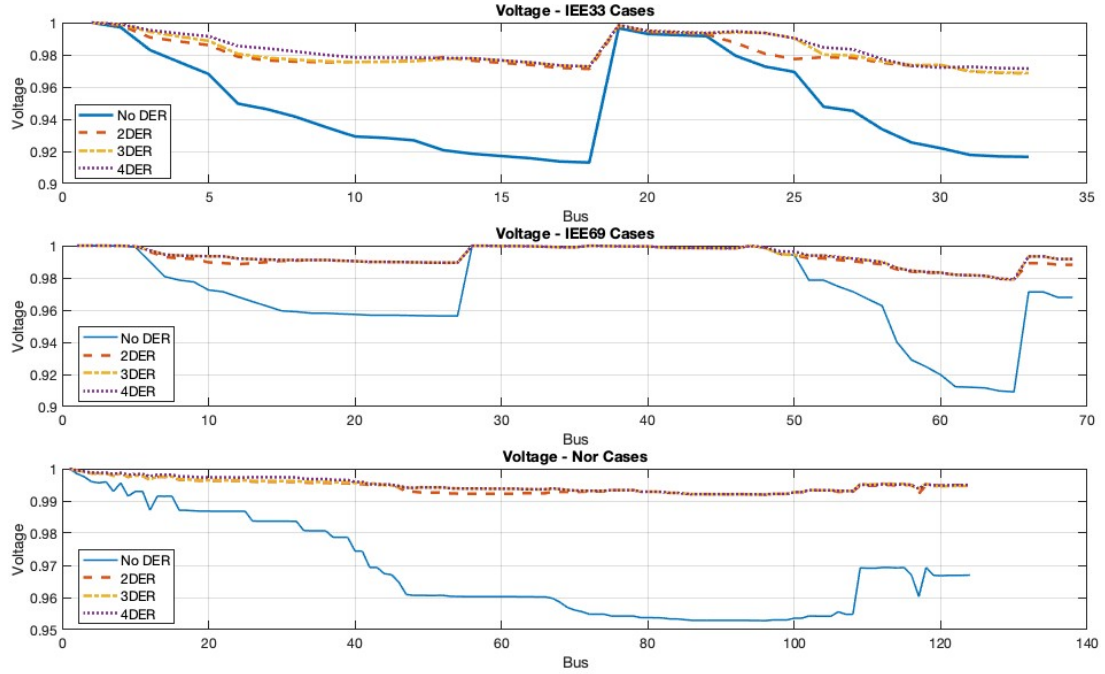


Figure 39: Nodal voltage Results

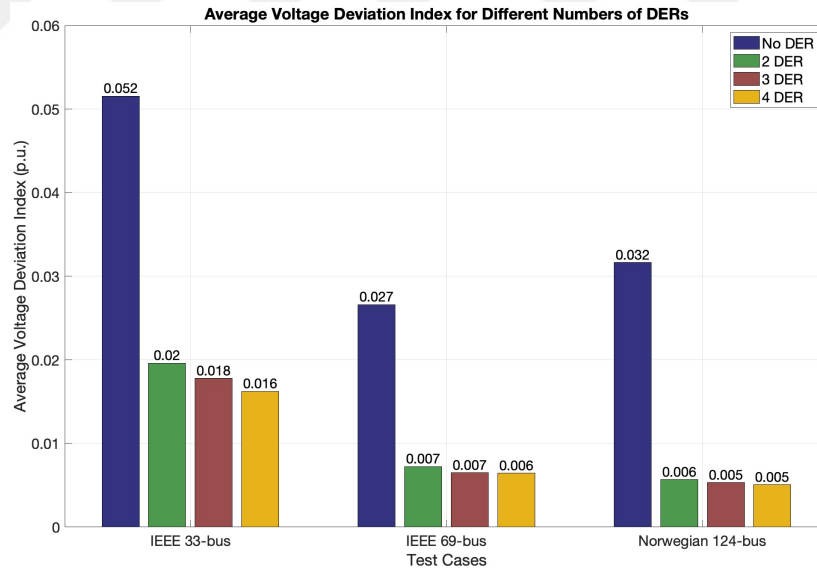


Figure 40: VDI Results

and 91% for IEEE33, IEEE69, and Norwegian, respectively. With 3 DER units, the reductions were 65%, 69%, and 92%, and with 4 DER units, they were 67%, 70%, and 93%. The Norwegian system benefited the most, achieving the highest percentage reduction in power losses. These results highlight the substantial impact

of DER integration on reducing power losses and improving system efficiency.

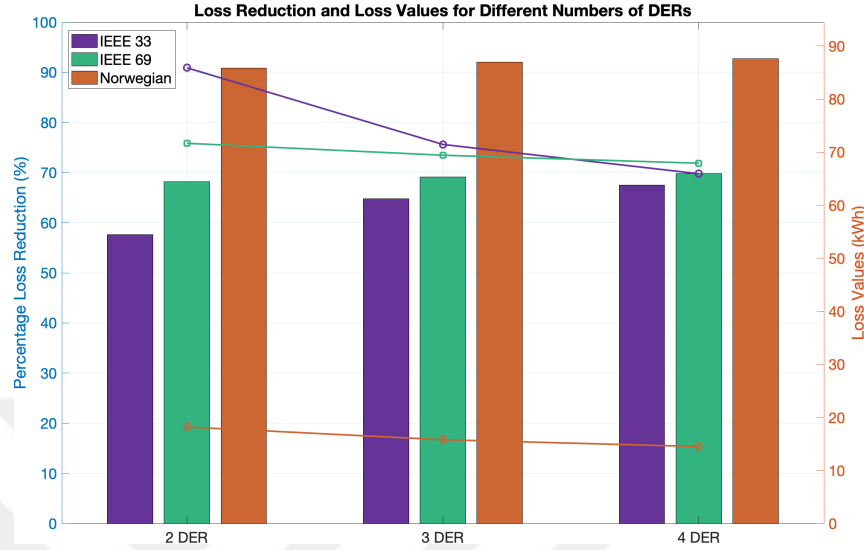


Figure 41: Active Power Loss Comparison

5.8 Conclusion

This chapter introduces a novel power system-oriented Particle Swarm Optimization approach, named PS-TVPSO, designed to minimize active power loss in distribution networks. The proposed approach optimizes both continuous and integer control variables simultaneously, addressing the sizing and allocation of DERs respectively. The innovative algorithms integrated into this approach, namely Connectivity-Driven Intensification Algorithm, Resistivity-Driven Intensification Algorithm, and High Demand Driven Algorithm significantly enhance the PSO search process and prevent it from falling into local optima. These complementary algorithms ensure a balanced search process, enhancing both local searches and exploration of underutilized areas. The proposed PS-TVPSO approach has been tested on IEEE 33, IEEE 69 systems, and the Norwegian 124 bus system. The results highlight the effectiveness of PS-TVPSO in solving optimal DER planning problem. Notably, as the number of DERs increases, the computational complexity rises, necessitating enhanced methods for improved performance. The trend of decreasing objective value's mean and median

values with additional DERs indicates improved optimization outcomes. Furthermore, PS-TVPSO shows significantly reduced variability, emphasizing its stability and consistent performance. It achieves lower mean and median values across all DER scenarios, suggesting superior optimization quality compared to the base TVPSO. In the Norwegian case, PS-TVPSO demonstrated its capability in navigating complex optimization landscapes, with closer convergence of all runs. This underscores the method's effectiveness in real-world scenarios.



CHAPTER VI

DIVERSIFIED RENEWABLE RESOURCES AND ESS PLANNING: A BILEVEL APPROACH WITH NETWORK-ORIENTED PSO

Modern power systems are facing various technical, environmental, and economic issues. Traditional power plants are not emission-free and create environmental pollution, leading to health problems and other global concerns. Therefore, the necessity of integrating renewable energy sources naturally emerges. Power system planners have been looking to distributed generation units as a solution to serve the distribution system's needs. Small-scale generators built near load centers are distributed generation (DG) or distributed energy resource (DER) units. DER units are dispersed throughout a utility's distribution system to reduce distribution losses and voltage disturbances [108]. This shift toward decentralized energy is also a trend in research because it helps create more reliable and sustainable energy systems. It is not just about being green; optimally sizing and allocating resources within distribution systems holds significance for several reasons. It is about making the energy system more reliable, adaptable, and self-sufficient. The optimal sizing and placement of these resources have become increasingly crucial to mitigating grid issues and reducing costs. Particle Swarm Optimization (PSO) is widely used to address such problems but faces computational inefficiency due to its numerical convergence behavior. This limits its effectiveness, especially for power system problems, because the numerical distance between two nodes in power systems might be different from the actual electrical distance. In this chapter, a scalable bilevel optimization problem with network oriented PSO method is proposed to optimize the diversified renewable

and storage DER integration into radial distribution networks. the connectivity algorithm prioritizes actual physical neighbors during the search to prevent local optima traps while resistivity method direct the search towards lower resistivity areas. The tests of the algorithms on the IEEE 33-bus, the 69-bus and Norwegian networks show significant reductions in power losses (up to 74 percent for PV, wind, and storage) and improved voltage stability (a 21 percent reduction in mean voltage deviation index) with respect to the results of classical PSO. The proposed network- oriented PSO outperforms classical PSO by achieving a 2.84 percent reduction in the average fitness value for the IEEE 69-bus case with PV, wind, and storage deployment. The Norwegian case study affirms the effectiveness of the proposed approach in real-world applications through significant improvements in loss reduction and voltage stability.

6.1 *Related Work*

Numerous studies have examined various optimization algorithms for the sizing and allocation of distributed generators (DGs) in radial networks, all aiming to enhance distribution system performance. Among these methods, Particle Swarm Optimization (PSO) emerges as the dominant approach, as evidenced by its repeated utilization across multiple investigations. While some focus on minimizing total costs [109], power losses [109],[76],[82],[86],[87],[110],[111],[88], and voltage disturbances [83], [84], [111], [112], others explore the flexibility of PSO through variant analyses [19], [105], as well as its hybridization with complementary algorithms [84], [111], [89]. Concurrently, strategies to enhance power factor correction have garnered abention, especially while addressing seasonal load fluctuations and overall system efficiency improvement [113]. DER types could be both conventional and renewable. Furthermore, emerging applications of PSO extend beyond traditional DG planning contexts, encompassing renewable resource planning in microgrid systems [114], [77], electric vehicle charging station (EVCS) integration [88]. Some researchers have studied planning

for storage systems [78], and virtual power plants [115]. Hybrid techniques, such as the KHO-GWO Algorithm [115], aim to enhance network resilience during floods and earthquakes while achieving economic and operational improvements. Moreover, the Comprehensive Teaching–Learning-Based Optimization (CTLBO) Algorithm [116] and the Shuffled Frog Leap Algorithm with the Ant Lion Optimizer (SFLA-ALO) [112] can be used to address the simultaneous sizing and siting of DERs and energy storage systems. Bilevel Optimization and Unscented Transformation (UT) methods have been proposed to enable optimal siting and sizing of flexi-renewable virtual power plants (FRVPPs) in distribution systems while minimizing expected energy not supplied [115]. Additionally, the Artificial Electric Field Algorithm (MOAEFA) consistently demonstrates superior performance in achieving optimal wind turbine placements [117]. Finally, the Hybrid Soccer League Competition–Pabern Search (SLC-PS) Algorithm is used to size and site the DGs, EVCSs, and ESSs within the distribution system [118].

6.2 Contribution

The existing literature on the sizing and allocation of DER units limits discussions on integrated distributed resources, particularly Diversified renewables (solar, wind, etc.) and storage, which hinders the leveraging of their integrated sustainability and reliability benefits for the grid. Moreover, research often overlooks dynamic seasonal demand and generation scenarios. On the other hand, common metaheuristic optimization methods have limitations in addressing crucial electrical network characteristics due to their numerical bias. This limits their effectiveness because the numerical distance between two nodes in power systems might be different from the actual electrical distance. A bilevel optimization module is proposed to fill the existing literature gap. First, the ‘Sizing module’ contributes by incorporating energy storage to handle variations in renewables, providing storage dispatch, and operating

as an integrated DER unit. This Diversified system can be extended to accommodate additional renewable units, making the proposed framework adaptable and scalable for evolving power system requirements. Second, the proposed framework applies two innovative algorithms to enhance PSO's efficiency in addressing power system challenges: The Connectivity-Driven Neighbor Generator and the Resistivity-Driven Candidate Generator. The Connectivity-Driven Neighbor Generator analyzes electrical connectivity among nodes, generating solution candidates aligned with the grid's physical topology. This ensures that the PSO explores spaces aligned with the electrical structure, prioritizing actual physical neighbors over numerical ones during the search. This approach avoids getting stuck at the local optima, especially in later iterations where the step size is smaller. Additionally, the Resistivity-Driven Candidate Generator strategically targets low-resistive regions, addressing resource allocation challenges and guiding the PSO toward regions that allows energy exchange locally with minimum power losses.

6.3 Methodology

The methodology employed in this study consists of two main modules: the Diversified DER Sizing and the Diversified DER Sitting modules. The former utilizes a Mixed Integer Linear Program (MILP) to determine the optimal size of renewable resources and BESS, while the latter employs PSO to find the best locations for these resources within the distribution network.

6.3.1 Diversified DER Sizing Module

The Diversified DER Sizing Module aims to determine the optimal size for renewables and storage. The mathematical model is a Mixed-Integer Linear Program (MILP). The Solar PV System has the following set of constraints.

Constraint (85) defines the generated power at time t using the solar profile and sizing decision variable. Constraint (86) ensures that the solar generation can feed

the load, be used to charge the battery, or be curtailed. Constraints (87) and (88) set a maximum limit for each task. Constraint (89) restricts the curtailed solar power at time t to be within a fraction, γ , of the generated solar energy. Adjusting γ to 1 allows for the curtailment of the whole solar generation; however, changing it to 0 prevents curtailment. Thus, γ should be adjusted based on simulation preference.

$$P_t^{\text{pv,gen}} = P_t^{\text{pv,profile}} \cdot S^{\text{cap}} \quad \forall t \in T \quad (85)$$

$$P_t^{\text{pv,gen}} = P_t^{\text{pv,load}} + P_t^{\text{pv,ch}} + P_t^{\text{pv,curtailed}} \quad \forall t \in T \quad (86)$$

$$P_t^{\text{pv,load}} \leq P_t^{\text{demand}} \quad \forall t \in T \quad (87)$$

$$P_t^{\text{pv,ch}} \leq P_t^{\text{pv,gen}} \quad \forall t \in T \quad (88)$$

$$P_t^{\text{pv,curtailed}} \leq \gamma \cdot P_t^{\text{pv,gen}} \quad \forall t \in T \quad (89)$$

The Wind Energy System has the following set of constraints. Constraint (90) is similar to (85) and defines the generated power at time t using the known wind profile for the location and the sizing decision variable. Constraint (91) ensures that the wind generation can feed the load, be used to charge the battery, or be curtailed. Constraints (92) and (93) set a maximum limit for each task. Constraint (94) restrains curtailed wind power at time t to be within a fraction, γ , of the total generated wind power. Adjusting γ to 1 allows curtailment of the whole wind generation; however, changing it to 0 prevents curtailment. Thus, γ should be adjusted based on simulation preference.

$$P_t^{\text{w,gen}} = P_t^{\text{w,profile}} \cdot W^{\text{cap}} \quad \forall t \in T \quad (90)$$

$$P_t^{\text{w,gen}} = P_t^{\text{w,load}} + P_t^{\text{w,ch}} + P_t^{\text{w,curtailed}} \quad \forall t \in T \quad (91)$$

$$P_t^{\text{w,load}} \leq P_t^{\text{demand}} \quad \forall t \in T \quad (92)$$

$$P_t^{\text{w,ch}} \leq P_t^{\text{w,gen}} \quad \forall t \in T \quad (93)$$

$$P_t^{\text{w,curtailed}} \leq \gamma \cdot P_t^{\text{w,gen}} \quad \forall t \in T \quad (94)$$

The Battery Energy Storage System (BESS) plays a role in managing temporal supply and demand balance. Firstly, Constraint (95) tracks the state of energy (SOE) at time t by considering the previous state and the charging and discharging power, incorporating efficiencies μ_c and μ_d . The state of energy here is different from the state of charge. It tracks the amount of energy stored in the BESS. By doing so, the sizing of the BESS in MWh becomes a decision variable reflected as the maximum energy capacity, E^{cap} , in Constraint (96). The depth of discharge can also be modeled as the minimum limit for the state of energy. Constraint (97) limits the charging power by the available energy capacity in the ESS, while Constraint (98) models the C-rate of the BESS by introducing a maximum limit on charging power. For example, an LFP-type BESS has a C-rate of 1, where the maximum charging power can be as much as E^{cap} ; however, a flow battery storage has a C-rate of $\frac{1}{4}$, where the maximum charging power is at most one-fourth of E^{cap} . Constraints (99) and (100) are similar to (96) and (97) but from the perspective of discharging action. Constraints (101) and (102) prevent the simultaneous charging and discharging event at time t by introducing a binary decision variable, u_t . Lastly, the model assumes that the BESS can only be charged from either the solar PV or the wind, as given in Constraint (103).

$$\text{soe}_t = \text{soe}_{t-1} + \mu_c P_t^{\text{ch}} \Delta t - \frac{1}{\mu_d} P_t^{\text{dch}} \Delta t \quad \forall t \in T \quad (95)$$

$$\alpha_{\min} E^{\text{cap}} \leq \text{soe}_t \leq E^{\text{cap}} \quad \forall t \in T \quad (96)$$

$$P_t^{\text{ch}} \leq E^{\text{cap}} - \text{soe}_{t-1} \quad \forall t \in T \quad (97)$$

$$P_t^{\text{ch}} \leq \beta E^{\text{cap}} \quad \forall t \in T \quad (98)$$

$$P_t^{\text{dch}} \leq \text{soe}_{t-1} \quad \forall t \in T \quad (99)$$

$$P_t^{\text{dch}} \leq \beta E^{\text{cap}} \quad \forall t \in T \quad (100)$$

$$P_t^{\text{ch}} \leq M u_t \quad \forall t \in T \quad (101)$$

$$P_t^{\text{dch}} \leq M(1 - u_t) \quad \forall t \in T \quad (102)$$

$$P_t^{\text{ch}} = P_t^{\text{PV,ch}} + P_t^{\text{w,ch}} \quad \forall t \in T \quad (103)$$

After the asset modeling, the next step is maintaining the supply and demand balance at each time step. The supply side includes power from the grid, solar generation, wind generation, and BESS discharge. Meanwhile, the demand side consists of the hourly demand, BESS charging from solar and wind, and curtailments of solar and wind. These constraints contribute to a comprehensive formulation defining the demand components, including solar to load, wind to load, grid power, and BESS hourly discharge. This systematic approach ensures a balance, guiding the system towards optimal resource utilization.

$$\begin{aligned} P_t^{\text{grid}} + P_t^{\text{pv,gen}} + P_t^{\text{w,gen}} + P_t^{\text{dch}} &= P_t^{\text{demand}} + P_t^{\text{pv,ch}} + P_t^{\text{w,ch}} \\ &\quad + P_t^{\text{pv,curtailed}} + P_t^{\text{w,curtailed}} \quad \forall t \in T \end{aligned} \quad (104)$$

$$P_t^{\text{demand}} = P_t^{\text{pv,load}} + P_t^{\text{w,load}} + P_t^{\text{grid}} + P_t^{\text{dch}} \quad \forall t \in T \quad (105)$$

The model's objective function minimizes the potential investment's combined

capital expenditure (CAPEX) and operational expenditure (OPEX). Operational expenditure (OPEX), in (107), is calculated as the sum of the grid power consumption P_t^{grid} multiplied by the corresponding coefficient a_t^1 for each time period t within the optimization horizon T . The coefficient a_t^1 accounts for the cost associated with grid power consumption at each time period.

Capital expenditure (CAPEX), in (108), is the sum of the initial investment costs related to the solar, energy storage, and wind systems. The overnight costs C^S , C^E , and C^W represent the upfront capital costs for installing each system type. These costs are then multiplied by the installed capacity of each system ($S^{\text{cap}}(MW)$, $E^{\text{cap}}(MWh)$, and $W^{\text{cap}}(MW)$) and the scaled lifetime coefficient L associated with each system type. The time factor is incorporated by considering the number of days (Δd) in the 1-year optimization period (365 days). This enables the simulations to be performed in a shorter time, for computational simplicity, especially when introducing representative days for the whole 1-year horizon.

$$\text{Minimize} \quad \text{OPEX} + \text{CAPEX} \quad (106)$$

$$\text{OPEX} = \sum_{t \in T} a_t^1 P_t^{\text{grid}} \quad \forall t \in T \quad (107)$$

$$\text{CAPEX} = \left(\frac{\Delta d}{365} \right) (C^S S^{\text{cap}} L^S + C^E E^{\text{cap}} L^E + C^W W^{\text{cap}} L^W) \quad \forall t \in T \quad (108)$$

6.3.2 Diversified DER Sitting Module

PSO represents an optimization method in DER allocation problem. This technique operates on a swarm intelligence principle, where individuals (particles) iteratively navigate a solution space, guided by their own best positions and the collective best positions found by the swarm. PSO's strength lies in its simplicity and ability to explore large solution spaces efficiently. The method's working mechanism involves particles adjusting their positions based on their own historical best positions and

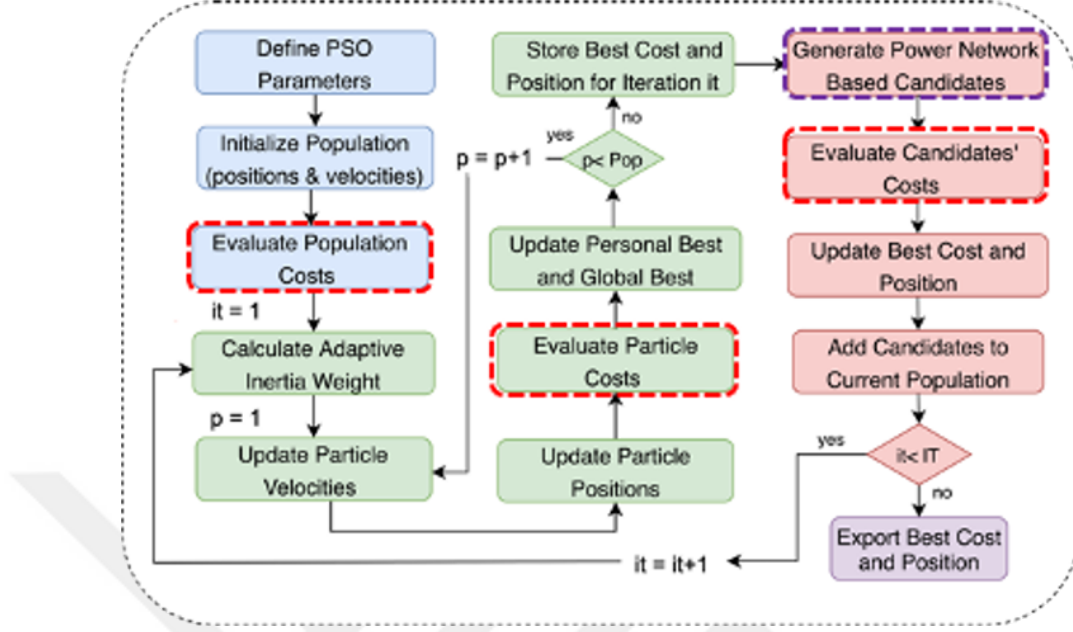


Figure 42: Proposed PSO Algorithm

the global best position found by the swarm, allowing for efficient convergence toward optimal solutions. The improved, electrical based Particle Swarm Optimization algorithm is illustrated in Fig. 42. A population of potential solutions, is initialized randomly including their positions and velocities. This population comprise renewable units and BESS allocation within the distribution network.

For each initialized particle, fitness function value is evaluated, indicating its overall quality with respect to the optimization objective. A network validation and cost function module as described in detail in later is developed to evaluate power loss cost, and costs related to power flow operational limits. The particles then undergo iterative updates. Each particle adjusts its position within the solution space based on its previous best position and the best position found by any particle in the population. The PSO algorithm proceeds through multiple iterations, seeking to converge toward a solution that balances the trade-offs between costs, constraints, and the allocation of DER components across the network. Convergence behaviour is shaped

by adaptive parameter, inertia weight, which determines the trade-off between exploration and exploitation, and, crucially, the diversity among the solutions. The parameter k in the adaptive weight equation is crucial in PSO, determining the rate of weight reduction during optimization. A higher k promotes exploration, while a lower k emphasizes exploitation. Choosing the right k balance is essential for efficient convergence and problem-specific optimization.

Equation (109) defines the position x_p of each particle p within the search space of the PSO algorithm. Each particle p is represented as a vector containing the location of the hybrid resources S_p^{location} , W_p^{location} , and E_p^{location} .

Equation (110) calculates the inertia weight w_{it} at iteration it in the PSO algorithm. This inertia weight is adjusted exponentially over the iterations based on the initial inertia weight w_{ini} , the final inertia weight w_{fin} , a decay rate k , and the current iteration it out of a total of IT iterations.

The particle velocities $v_{p,it}$ for particles p at iteration it are updated using the newly calculated w_{it} , $c_{1,it}$, and $c_{2,it}$, as shown in (111). This update also incorporates randomness by introducing rand , a random value between 0 and 1. Following this, the position $x_{p,it}$ of particle p at iteration it is updated based on its current position and the newly computed velocity $v_{p,it}$, as depicted in (112).

$$x_p = [S_p^{\text{location}}, W_p^{\text{location}}, E_p^{\text{location}}] \quad (109)$$

$$w_{it} = \max \left(w_{\text{fin}}, w_{\text{ini}} \cdot \exp \left(-k \left(\frac{it}{IT} \right) \right) \right) \quad (110)$$

$$v_{p,it} = w_{it} \cdot v_{p,it} + c_{1,it} \cdot \text{rand} \cdot (x_{p,\text{best}} - x_{p,it}) + c_{2,it} \cdot \text{rand} \cdot (x_{G,\text{best}} - x_{p,it}) \quad (111)$$

$$x_{p,it} = x_{p,it-1} + v_{p,it} \quad (112)$$

Utilizing PSO in power and energy system planning presents inherent limitations. The conventional application of PSO in these contexts tends to exhibit specific drawbacks. Firstly, it often showcases a numerical bias, it is emphasizing numerical

optimization over crucial electrical aspects intrinsic to the power grid. This narrow focus might lead to solutions that need more efficiency in complex electrical systems. Moreover, the innate inability of basic PSO to capture the dynamics inherent in power networks, such as ignoring the impact of network topology or connectivity on optimal solutions, remains a substantial limitation. When confronted with large-scale problems, PSO encounters scalability challenges, impeding computational efficiency and hindering its applicability in real-world scenarios. Therefore, key algorithms within the the proposed PSO method are the Connectivity-Driven Neighbour Generator and the Resistivity-Driven Neighbour Generator.

6.3.2.1 Connectivity-Driven Neighbour Generator

The Connectivity-Driven Neighbour Generator, a core algorithm in the proposed framework, operates by delving into the electrical connectivity among nodes in the power grid. This algorithm essentially functions by comprehensively analysing the network topology, allowing for the generation of solution candidates that align with the physical structure of the grid. What sets this approach apart is its consideration of the interconnections among nodes. Doing so ensures that the PSO algorithm explores solution spaces that are inherently aligned with the grid’s electrical structure. This addresses a critical limitation of traditional PSO, which tends to overlook the profound impact of node connections. As a result, this algorithm significantly enhances the PSO’s efficiency in navigating the search space, enabling it to yield better solutions.

6.3.2.2 Resistivity-Driven Neighbour Generator

The Resistivity-Driven Candidate Generation algorithm addresses resource allocation challenges by targeting areas with lower resistivity, indicative of optimal opportunities within the power grid. This algorithm initially identifies the least resistive lines, focusing on the lowest 25 percent based on resistivity values, and extracts unique

Algorithm 6 Connectivity-Driven Neighbor Generator

```
1: Import branch data from MATPOWER Library and extract from-node and to-node information
2: Initialize ConnectivityMatrix with dimensions (NumberNodes, NumberNodes)
3: for each branch  $b$  in the power network do
4:   Assign ConnectivityMatrix(from( $b$ ), to( $b$ )) = 1
5:   Assign ConnectivityMatrix(to( $b$ ), from( $b$ )) = 1
6: end for
7: Call ChosenNeighborCandidates = GetNeighborsByConnectivity(CurrentSolution, NumberCandidates)
8: Initialize NeighborCandidates matrix with dimensions (NumberCandidates, length(solution))
9: for each candidate  $k$  in NumberCandidates do
10:   Initialize an empty array Neighbor
11:   for each node  $n$  in the solution do
12:     Find ConnectedNodes = nodes connected to solution( $n$ ) in ConnectivityMatrix
13:     Choose a random node from ConnectedNodes and store it as Neighbor( $n$ )
14:   end for
15:   Store Neighbor array in the  $k$ -th row of NeighborCandidates
16: end for
17: Return ChosenNeighborCandidates = unique rows (NeighborCandidates)
```

nodes associated with these lines. When generating multiple candidate solutions, the algorithm randomly selects nodes from this subset, promoting diversification while concentrating on areas favourable for optimal resource deployment. By introducing nodes from low-resistivity areas into the candidate solutions, the algorithm guides the PSO towards regions where the electrical properties suggest better potential for resource allocation. This strategy aligns to address PSO's limitations related to purely numerical optimizations, providing a more directed and contextually informed search within the power network.

Algorithm 7 Resistivity-Driven Candidate Generator

```
1: Import branch data from MATPOWER Library and extract resistance, from-node, and to-node information
2: Sort resistance values in ascending order to get sorted_indices
3: Select indices representing the least resistive lines: selected_indices
4: Extract unique_nodes connected to the selected lines
5: Call Chosen_Candidates = CandidatesByResistivity(current_sol, num_candidates)
6: Initialize new_Candidates matrix with dimensions (num_candidates, length(current_sol))
7: Generate new solutions based on resistivity criteria:
8: for each candidate  $k$  in num_candidates do
9:   Choose from unique_nodes connected to selected least resistive lines
10:   new_sol[nodes_to_change] = replace values of current_sol with the chosen unique_nodes
11:   Assign new_Candidates[ $k$ ] = new_sol
12: end for
13: Return Chosen_Candidates = UniqueRows(new_Candidates)
```

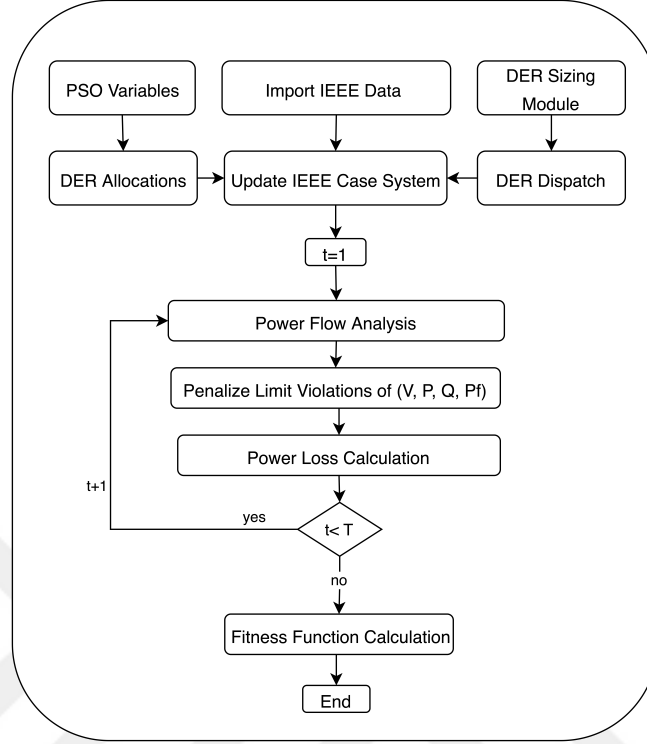


Figure 43: Network Validation and Fitness Function Flowchart

6.3.2.3 Network Validation and Cost Function

The intermittent nature of renewable generation and the varying charging and discharging patterns of batteries can introduce fluctuations and imbalance in the system. Network Validation module and Cost Function Calculation is necessary when allocating battery and renewable systems to ensure operational safety, optimize hybrid system placement, maintain grid stability, and comply with regulatory standards. It enables the effective integration of Diversified system technologies while preserving the reliability and performance of the distribution grid. Distribution systems have physical and operational limitations that must be considered to ensure safe and reliable operation. These constraints include voltage limits, thermal limits of power lines and transformers, and power flow balance requirements. The detailed process of this module is shown in Fig. 43.

Given the PSO control variables, which encompass the allocation decisions, load

data and results from the sizing module, the function dynamically configures the IEEE network parameters for each time step. It updates the generator allocation for renewable units and storage, demand data, then performs power flow simulations to assess the network's behaviour. Notably, it calculates penalty factors for violations such as slack bus power, bus voltage, reactive power generation, and line capacity. These penalties are used to evaluate the quality of the allocation solutions. Finally, Network Validation accumulates penalties across all time steps, providing a comprehensive measure of the network's performance. The resulting fitness value and other vital information are then used to guide the optimization process, ensuring that the proposed methods lead to efficient and reliable hybrid DER integration.

- **Power Flow Analysis**

Power flow analysis is a vital component of this distribution-level hybrid system planning. It's integral to the Network Validation and Cost Function Calculation, optimizing renewable and BESS units' allocation. Power flow ensures technical reliability, economic viability, and network constraint compliance throughout the evaluation. Power flow analysis yields insights into voltage, power, and constraint respect. Violations trigger penalties to quantify their impact. It also calculates power losses to minimize them, enhancing system efficiency. MATPOWER [119] is used to execute power flow equations.

$$\text{Min } P_{\text{loss}} \quad (113)$$

Subject to:

$$P_{\text{loss},t} = \sum_i P_{i,t}^{\text{utility}} + \sum_i (P_{i,t}^{\text{PV}} + P_{i,t}^{\text{W}} + P_{i,t}^{\text{dch}}) - \sum_i (\text{PL}_{i,t} + P_{i,t}^{\text{ch}}) \quad (114)$$

$$P_{i,t}^{\text{utility}} + P_{i,t}^{\text{PV}} + P_{i,t}^{\text{W}} + P_{i,t}^{\text{dch}} - \text{PL}_{i,t} - P_{i,t}^{\text{ch}} = V_{i,t} \sum_{j=1}^N V_{j,t} (G_{ij} \cos \theta_{ij,t} + B_{ij} \sin \theta_{ij,t}) \quad (115)$$

$$Q_{i,t}^{\text{utility}} - Q_{i,t} = V_{i,t} \sum_{j=1}^N V_{j,t} (G_{ij} \sin \theta_{ij,t} - B_{ij} \cos \theta_{ij,t}) \quad (116)$$

$$V_{i,t}^{\min} \leq |V_{i,t}| \leq V_{i,t}^{\max} \quad (117)$$

$$\theta_{ij,t}^{\min} \leq \theta_{ij,t} \leq \theta_{ij,t}^{\max} \quad (118)$$

Equation (114) defines the power loss $P_{\text{loss},t}$ as the difference between the total power supplied by the utility and distributed energy resources (DERs) including solar PV ($P_{i,t}^{\text{PV}}$), wind ($P_{i,t}^{\text{W}}$), and BESS discharging ($P_{i,t}^{\text{dch}}$), and the total power consumed by the loads and the charging power of the storage system ($\text{PL}_{i,t} + P_{i,t}^{\text{ch}}$) at time t . The power balance equations (115) and (116) ensure that the active and reactive power injections from the utility, DERs, and the loads, as well as the storage system charging, satisfy Kirchhoff's voltage law at each node for every time period. Here, $P_{i,t}^{\text{DER}}$ is split into $P_{i,t}^{\text{PV}}$, $P_{i,t}^{\text{W}}$, and $P_{i,t}^{\text{dch}}$ representing the power generated by solar PV, wind, and other DERs respectively. Constraints (117) and (118) impose limits on the voltage magnitudes and phase angle differences at each node, ensuring they remain within specified bounds to maintain system stability and efficient operation.

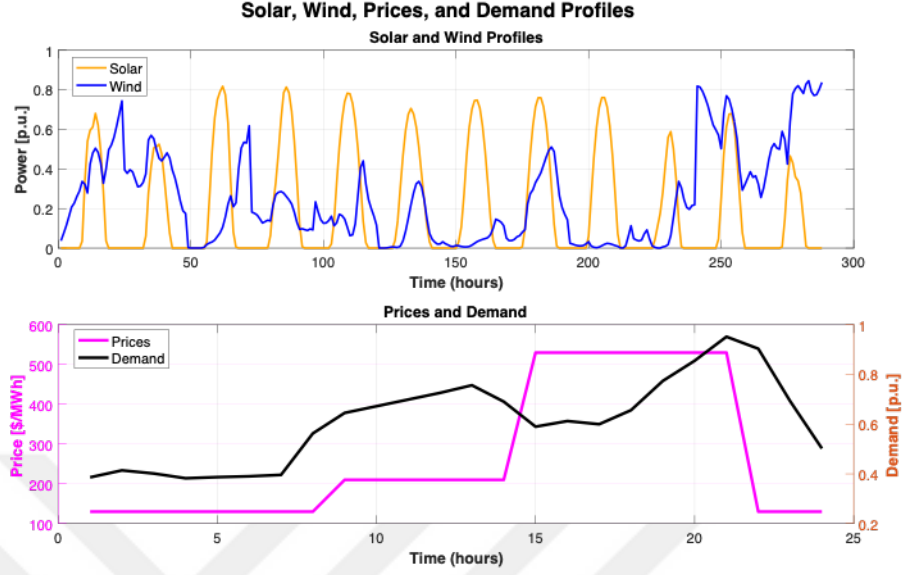


Figure 44: Time Series Input Data

6.4 Case Study

The simulations utilized a comprehensive dataset of 12 representative days of a year to validate the methods proposed in previous sections. Fig. 44. illustrates the time series input data used in the case studies. The data includes time series electricity prices, specifically Time of Use (TOU) prices, which are crucial for capturing dynamic price variations throughout the day. Additionally, an hourly demand profile expressed in per unit is incorporated as illustrated in the simulations. This demand profile has been scaled by the nodal peak demand values provided by IEEE cases, enabling a time-varying demand representation. The hourly solar PV and wind profiles, expressed in per units, for the specific site were utilized. These renewable generation profiles were employed to identify the optimal sizes of solar PV and wind systems in MW based on the mathematical model proposed in previous sections.

Financial and technical assumptions extracted from [120] are incorporated and given in to Table 19 ensure the feasibility and applicability of the methods in real-world scenarios. These assumptions encompassed overnight capital costs, lifetimes,

and technical details of renewable systems and BESS.

Table 19: Technical and Financial Assumptions

Definition	Value	Unit
Solar PV Overnight Cost	1.29 million	\$ / MW
Solar PV Lifetime	25	Years
Wind System Overnight Cost	1.25 million	\$ / MW
Wind System Lifetime	20	Years
BESS Overnight Cost	500 thousand	\$ / MWh
BESS Lifetime	15	Years
BESS Duration	4	Hours
BESS Charging Efficiency	0.9	p.u
BESS Discharging Efficiency	0.9	p.u
BESS Depth of Discharge (DoD)	20	Percent

Three different networks, IEEE 33-bus, IEEE 69-bus [119], and the Norwegian medium voltage distribution network [102] are used for assessing the practicality and effectiveness of the proposed planning and allocation strategies in previous sections. Utilizing data from these networks, different case studies have been implemented and simulated in MATLAB to assess the effectiveness strategy utilizing network oriented PSO configurations. The detailed parameters of the designed cases are employed and summarized in Table 20 .

Table 20: Simulated Case Study Parameters

Case	Swarm Size	Maximum Iteration	c1	c2	w_ini	w_fin	k
IEEE 33 Solar + BESS	25	50	2	2	1	0.05	2
IEEE 33 Solar + BESS + Wind	50	75	2	2	1	0.05	2
IEEE 69 Solar + BESS	25	50	2	2	1	0.05	2
IEEE 69 Solar + BESS + Wind	50	75	2	2	1	0.05	2
Norwegian Solar + BESS + Wind	50	100	2	2	1	0.05	2

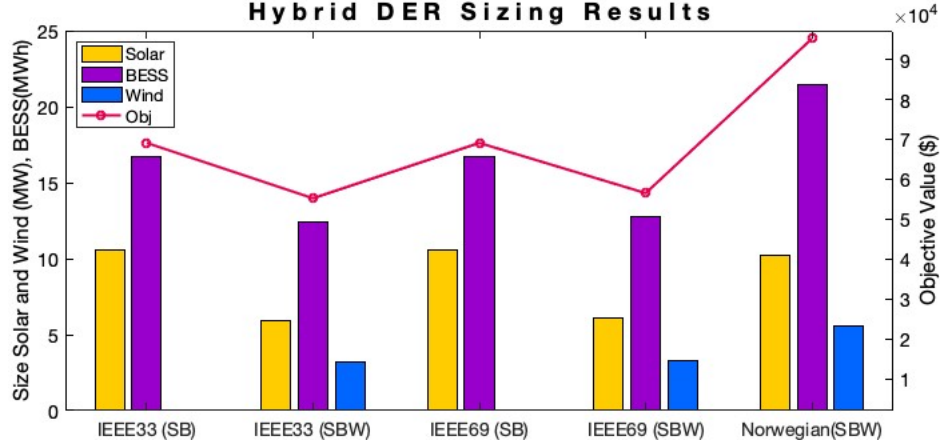


Figure 45: Diversified DER Sizing Results across Case Studies

6.5 Simulation Results and Discussion

6.5.1 Diversified DER Sizing Simulations

In evaluating DER sizing across the different case studies, IEEE33, IEEE69 and the Norwegian distribution system, significant findings are highlighted in Fig. 45. The Solar+Battery case yields an objective function of \$69,089 in both IEEE33 and IEEE69 systems, indicating an optimal sizing with a 10.56 MWp PV system and a 16.68 MWh (4hr) BESS. In contrast, the Solar+Wind+BESS case demonstrates a reduced objective function value of \$55,209 in IEEE 33 and \$56,504 in IEEE 69, with optimal sizes of 6.06 MWp PV array, 3.32 MWp wind system, and a 12.73 MWh (4hr) BESS. In the Norwegian scenario, the Solar+Wind+BESS case achieves an objective function value of \$95,218.30 with DER sizes of 10.22 MW, 5.6 MW, and 21.45 MWh for Solar, Wind and BESS respectively. Therefore, the more diversified resources with BESS demonstrate superior economic efficiency.

6.5.1.1 Self Sufficiency Ratio

The Self Sufficiency Ratio (SSR) [34] quantifies the extent to which a system relies on locally generated renewable energy and stored energy reserves to meet its energy demand through the system's time horizon. Comprising Solar PV, wind and battery

discharge, the SSR encapsulates the collective impact of DER sources on reducing dependence of the load on the grid. Mathematically, SSR is calculated as the ratio of the sum of renewables, and battery discharge energies to the total energy demand over the simulation horizon. The SSR formula is expressed as in (119):

$$SSR = \frac{\sum_t (P_t^{\text{pv,load}} + P_t^{\text{w,load}} + P_t^{\text{dch}})}{\sum_t \sum_i PL_{i,t}} \times 100 \quad (119)$$

As illustrated in Table 21, despite a 68.60% SSR, the optimal size of assets exhibits a renewable curtailment of 159 MWh. This solution achieves a lower renewable curtailment than the previous case with 62 MWh per the simulation horizon (12 days). Lower curtailment also increases the SSR to 78.59% for the latter case. Thus, diversified renewables with BESS enhanced self-sufficiency and optimized renewable energy utilization.

Table 21: SSR and Renewable Curtailment - IEEE69

Feature	Solar + BESS	Solar + Wind + BESS	Unit
Renewable Curtailment	159.01	61.89	MWh
SSR	68.60	78.59	Percent

Fig. 46-(a) shows how the total load is satisfied at each time step. The supply side includes solar, wind, BESS discharge, and power grid contributions. Generally, the BESS is used when there is less renewable availability. Furthermore, the grid imports exist when there is a need for more local resources such as renewables and BESS discharge. Fig. 46-(b) illustrates the BESS dispatch and state of energy.

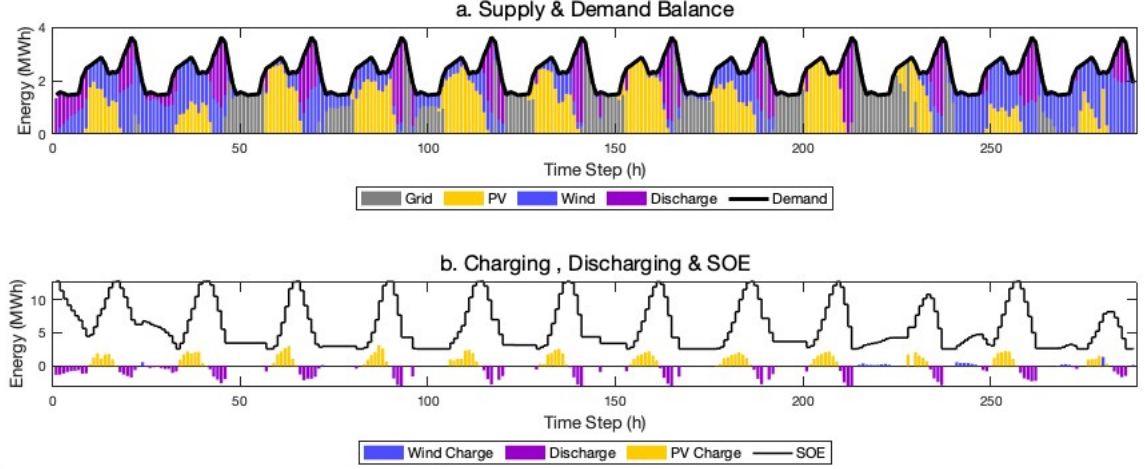


Figure 46: Supply-Demand Balance and BESS Dispatch - IEEE69

6.5.2 Diversified DER Sitting Simulations

6.5.2.1 Computational Performance of PSO

Ten simulations are presented in this section, including IEEE33, IEEE69, and the Norwegian 124 bus systems. In Fig. 47-a, the PSO without network-oriented algorithms is applied to the IEEE33 bus case for solar PV and BESS, resulting in different convergence values for some runs. The average final fitness value across the 20 runs is USD 5410.4. Fig. 47-b introduces network-oriented algorithms, showing improved convergence as all runs reach the same fitness value. The average fitness value for these runs is USD 5274.5. Comparing the two cases highlights that incorporating electrical-related methods leads to a global optimal solution with a lower average fitness value, emphasizing the significance of integrating domain-specific knowledge in enhancing PSO efficiency for complex power optimization tasks. The fitness value results from Fig. 47-c show the optimization performance of a basic PSO algorithm and an enhanced version incorporating network-oriented algorithms in the IEEE33 bus case with three distributed resources, solar PV, wind, and BESS. The basic PSO algorithm without electrical methods faces challenges in terms of the increased complexity, resulting in different convergence values with an average final fitness value of USD 4,365.4 after 75 iterations. In contrast, Fig. 47-d illustrates that considering the

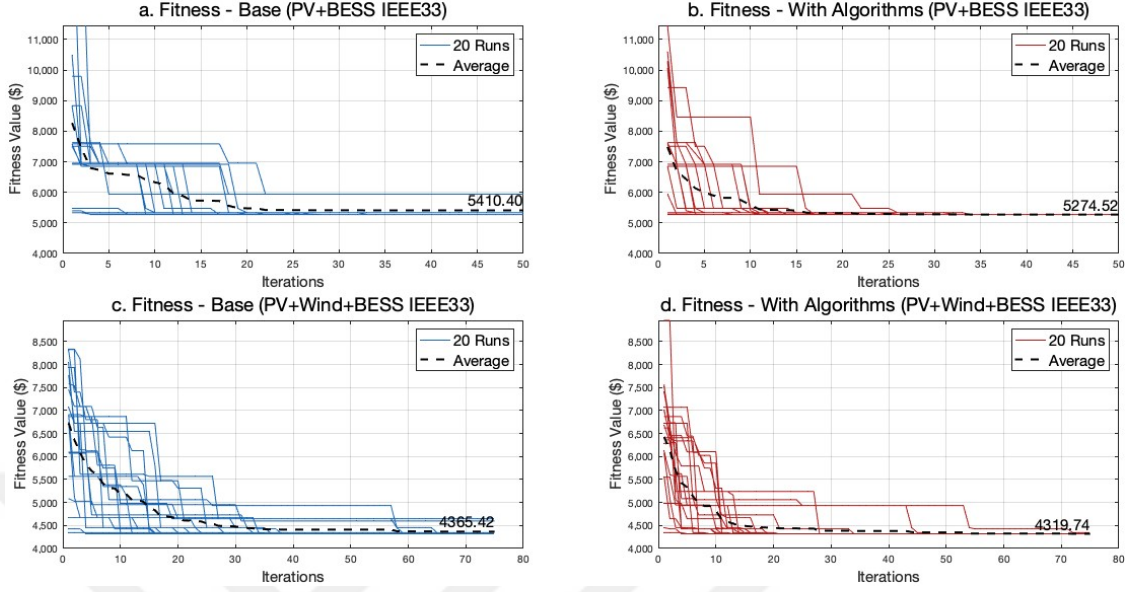


Figure 47: Algorithm Performance Comparison – IEEE33

network-oriented algorithms in the PSO searching process facilitates consistent convergence of all 20 runs to the same fitness value. It ensures improved exploration and convergence in the face of increased complexity. The average fitness value for these runs is notably lower at USD 4,319.7. This comparison underscores the significance of power-related algorithms in enhancing PSO efficiency, particularly in scenarios involving multiple distributed resources, leading to reduced power losses and achieving optimal solutions in complex power system optimization.

In Fig. 47-a,b, showing PSO applied to the IEEE69 case with PV and BESS, the convergence led to a fitness value of USD 6,597.9 in both cases. Extending the analysis to Fig. 47-c,d with the inclusion of PV, wind, and BESS in the IEEE69 case, (c), under basic PSO, shows instances where runs are trapped in local optima, concluding with a final average fitness value of USD 6,500.35. Conversely, integrating developed algorithms in (d) guarantees convergence to the same fitness value for all runs, achieving a significantly lower average fitness value of USD 6,409.15. This analysis underscores the crucial impact of network-oriented algorithms in optimizing PSO search for DER planning problems, especially in scenarios with multiple distributed

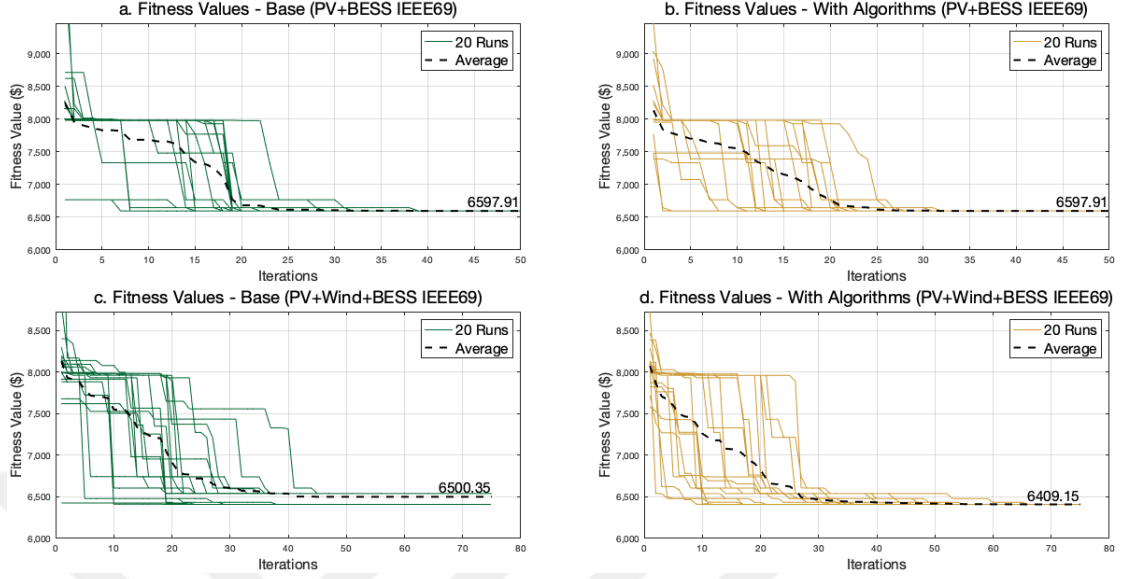


Figure 48: Algorithm Performance Comparison – IEEE69

resources, with all runs achieving a significantly lower average fitness value of USD 6,409.15. This analysis underscores the crucial impact of network-oriented algorithms in optimizing PSO search for DER planning problems, especially in scenarios with multiple distributed resources.

In the results for the Norwegian case study, illustrated in Fig. 49, the integration of network-oriented algorithms yielded promising PSO performance. Specifically, these algorithms led to a reduction in the average fitness value from USD 5,303.1 to USD 5,218.2 compared to the scenario without their use, indicating improved solution quality. Moreover, it appears that the proposed algorithms facilitated faster convergence, with most runs converging around iteration 50. These findings underscore the importance of the proposed algorithms for distributed energy resource planning and their validation in real-world networks.

6.5.2.2 Active Power Loss

Table 22 reveals the outcomes of power loss reduction and other aspects through PSO simulations with proposed algorithms for the IEEE 33 bus, the IEEE 69 bus,

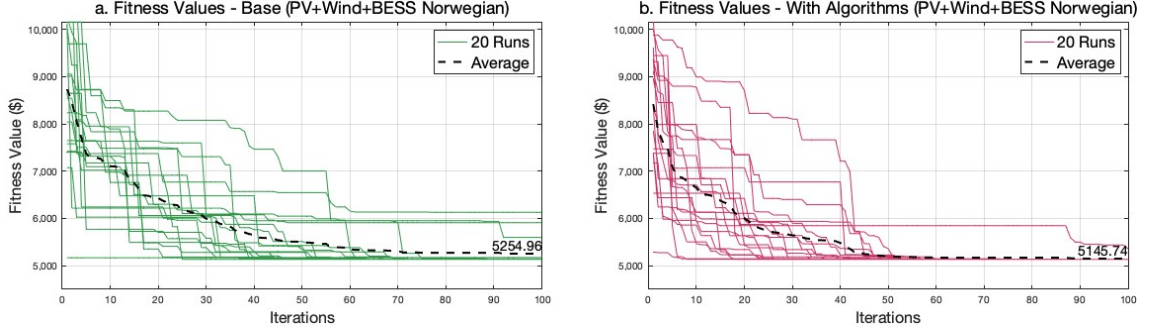


Figure 49: Algorithm Performance Comparison – Norwegian

and the Norwegian 124 bus cases. In the IEEE 33 bus case, the PV + BESS configuration results in a substantial 69% reduction, while adding wind resources in the PV + Wind + BESS scenario achieves a 74% reduction. Moving to the IEEE 69 bus case, PV + BESS yields a 65% reduction, and the integration of the PV + Wind + BESS scenario achieves a 66% reduction in power losses. The analysis underscores the effectiveness of these diversified distributed resources in mitigating power losses. However, it is notable that introducing multiple resources adds complexity, leading to slightly increased computational times, emphasizing the need for computational efficiency in optimizing DER planning. The Norwegian case, where PV + Wind + BESS reduces losses by 58%, further confirms the practical success of the proposed method in optimizing distributed resource deployment and reducing power losses.

Table 22: Diversified DER Sitting Results

Case	Power Loss (MWh)	Power Loss Reduction (%)	PV Site	Wind Site	BESS Site	Time (s)
IEEE 33 PV + BESS	10.55	69	6	-	6	801
IEEE 33 PV + Wind + BESS	8.64	74	7	19	7	2907
IEEE 69 PV + BESS	13.2	65	9	-	9	824
IEEE 69 PV + Wind + BESS	12.82	66	55	2	55	3416
Norwegian PV + Wind + BESS	10.27	58	47	12	47	9200

6.5.2.3 Voltage Stability ad VDI

The voltage distribution analysis across 288 time steps in the IEEE33 distribution system shown in Fig. 50 compares two scenarios: solar and BESS and solar, wind,

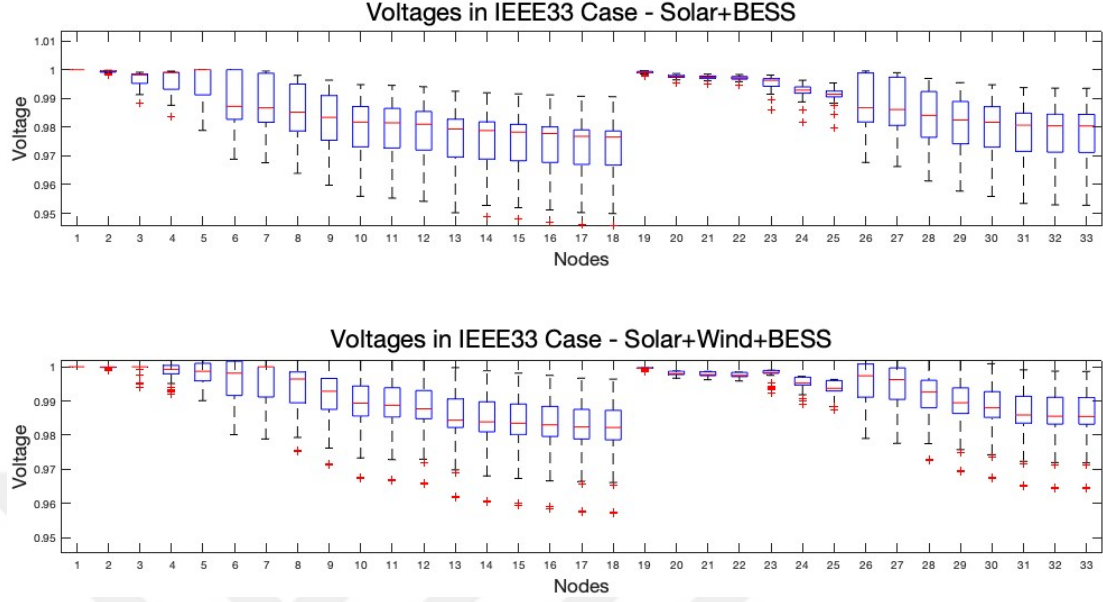


Figure 50: Algorithm Voltage Distribution Results – IEEE33

and BESS. For the solar and BESS cases, voltage levels range from 0.946 to 1.000, averaging 0.986. In the solar, wind, and BESS cases, the distribution spans 0.957 to 1.013, indicating a stable voltage profile. The incorporation of three integrated resources improves the profile, reflected in the higher average (0.992), median (0.994), and maximum (1.013) values. This analysis highlights voltage levels' enhanced stability and reliability when integrating solar, wind, and BESSs, contributing to an optimized power distribution system.

Fig. 51 shows analyses of the IEEE69 distribution system in two scenarios, one involving solar and BESS and the other incorporating solar, wind, and BESS, revealing notable insights into the voltage distribution. In the solar and BESS case, the main voltage distribution consistently exhibits values above 0.96 per unit (p.u.). However, in the solar, wind, and BESS scenario, the entire voltage distribution notably increases, with more buses recording values of 1.0 p.u. This observed enhancement underscores the positive impact of integrating multiple DER units on the voltage profile. The findings suggest that an increased number of integrated DERs, specifically solar, wind, and BESSs, contributes to a more significant improvement in the

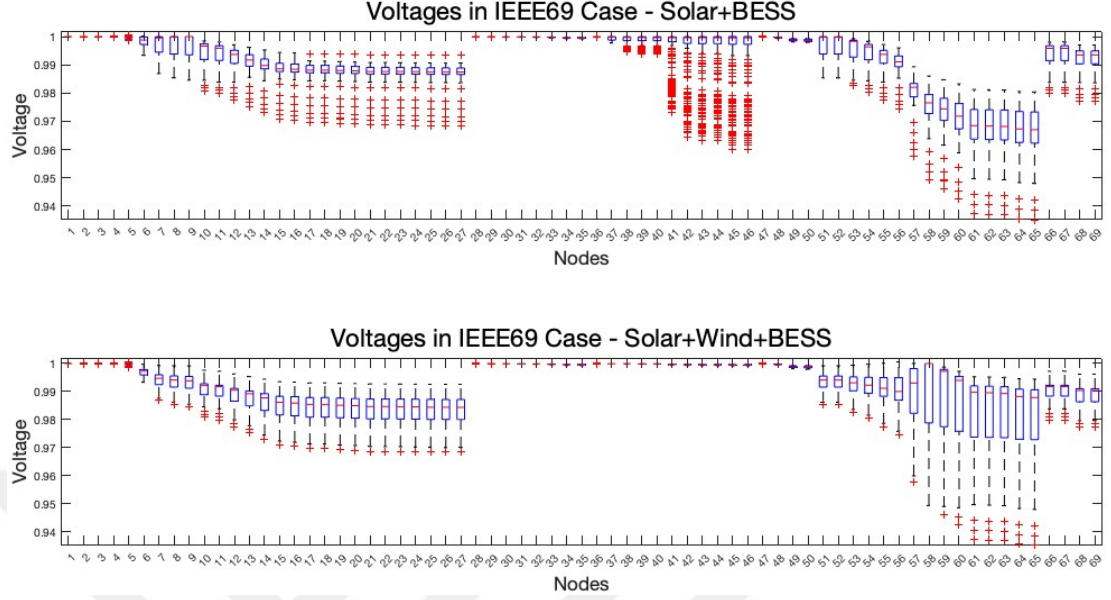


Figure 51: Algorithm Voltage Distribution Results – IEEE69

voltage profile. This leads to further enhancement of the stability and reliability of the distribution system.

Voltage Deviation index (VDI) quantifies the magnitude of voltage fluctuations within the distribution network, reflecting the system's voltage stability and quality. VDI is computed as the average deviation of bus voltages from their nominal values over a specified period [111], as given in (120). A low VDI indicates high stability on voltage, while the high VDI indicates low stability.

$$VDI_t = \frac{1}{N} \sum_{i=1}^N \left| \frac{V_{i,t} - V_{\text{nominal}}}{V_{\text{nominal}}} \right| \quad (120)$$

Fig. 52 illustrates the VDI distribution in the two distribution network cases: IEEE33 and IEEE69. Each subplot represents a specific scenario, including the base case and scenarios incorporating DERs, such as PV, wind, and BESSs. Blue bars depict the VDI value histogram, while a red line overlays the histogram, representing a theoretical normal distribution curve. In the base cases of both systems, the mean VDI values are 0.037 (IEEE33) and 0.0185 (IEEE69), with standard deviations of

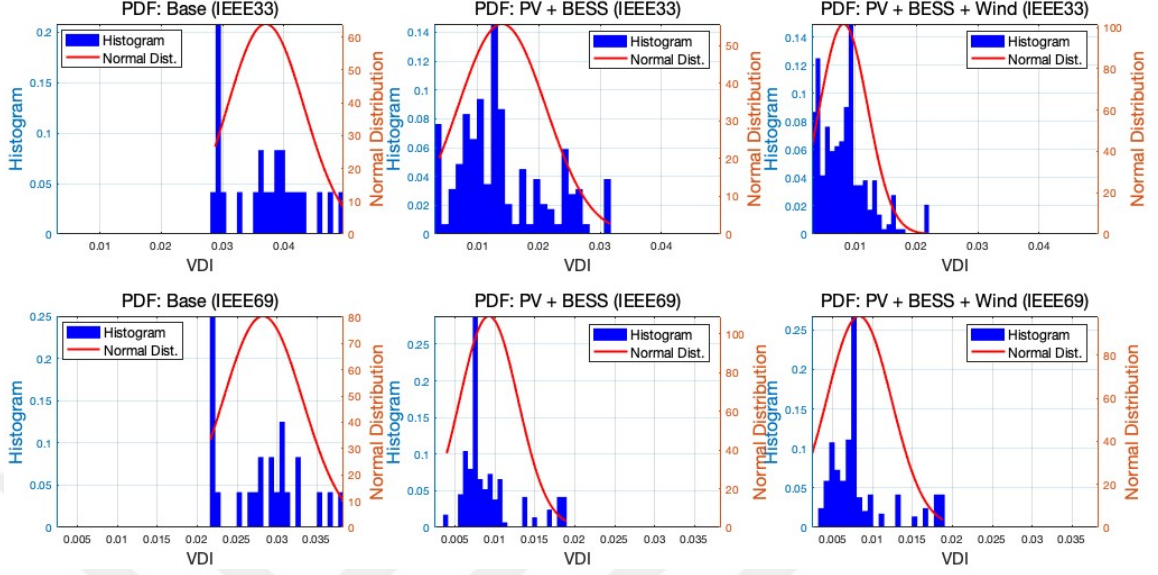


Figure 52: VDI Distribution with / without DERs — IEEE cases

0.0062 and 0.0035, respectively. Integrating PV and BESS reduces the mean VDI to 0.014 (IEEE33) and 0.0092 (IEEE69), with standard deviations of 0.0072 and 0.0037. Further integration of PV, wind, and BESS in IEEE33 results in a mean VDI decrease of 0.0081, with a standard deviation of 0.0039, while in IEEE69, the mean VDI decreases to 0.0083, with a standard deviation of 0.0041. This analysis demonstrates the impact of the diversification of distributed resources especially renewables and storage, on VDI, offering insights into enhancing system stability and reliability.

In the Norwegian case study, the distribution of VDIs shown in Fig. 53 notably shifts towards the y-axis following the integration of solar, wind, and BESS. This shift indicates a significant reduction in VDI values over the analyzed horizon, reflecting minimized voltage deviations. Specifically, the mean VDI values for the base case and the case with Solar + Wind + BESS integration are 0.0210 and 0.0040, respectively, indicating a substantial decrease. Similarly, the standard deviation values decrease from 0.0046 in the base case to 0.0033 in the Solar + Wind + BESS integration case, showing improved voltage stability.

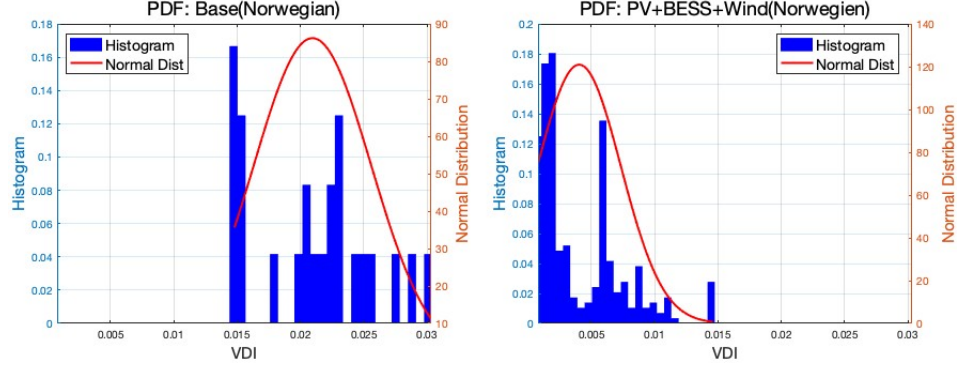


Figure 53: VDI Distribution with / without DERs - Norwegian

6.6 Conclusion

The distribution grid is more vulnerable than ever with the increased share of distributed energy resources. While the initial deployment of DERs shows no destructive impact on grid performance, the widespread deployment may negatively affect reliability. Therefore, finding the best capacity at the best location in the grid is becoming important now and will be more important soon. This study proposed a bilevel optimization framework for integrating diversified renewable resources and storage in distribution systems. The sizing module determines the optimal sizes of Diversified systems that effectively manage variations in renewable energy generation through energy storage deployment. The siting module searches for the best location for the Diversified system while ensuring technical reliability. One of the solution methods for such a problem is using the PSO algorithm; however, the numerical convergence methodology of PSO does not fit with the concept of electrical connectivity. The bus numbers in the power grid do not necessarily reflect the order of connection in the network; therefore, the two algorithms proposed in this chapter enhance PSO's computational efficiency by considering the electrical characteristics of power grids to optimize resource allocation. The Connectivity-Driven Neighbor Generator ensures the exploration of the solution space aligned with the grid's network topology and hence overcomes local optima challenges in PSO for such power system problems.

Secondly, the Resistivity-Driven Neighbor Generator strategically targets areas with lower resistivity. Simulations of IEEE 33-bus and IEEE 69-bus cases demonstrated reductions in power losses, with the integration of PV, wind, and BESS achieving a 74% loss reduction in the IEEE 33 bus case. Notably, the regular PSO in the IEEE69 case with PV and BESS demonstrated convergence to an average fitness value of USD 6,597, while the integration of network-oriented methods guaranteed convergence to a significantly lower average fitness value of USD 6,409 in a shorter computational time. Additionally, integrating renewables and storage systems reduces the VDI, thereby improving voltage profiles and enhancing system stability. The Norwegian case study further validated these findings, indicating major improvements in voltage stability and loss reduction, affirming the effectiveness of the proposed approach in real-world applications. These outcomes underscore the significance of the proposed methods in balancing technical reliability, economic viability, and computational efficiency in addressing the complexities of distributed resource planning. In future work, the scope of the proposed power network-based algorithms will be extended to assess their effectiveness across various evolutionary optimization methods. Additionally, efforts will focus on addressing uncertainties in renewable energy generation to optimize renewable distributed resource planning. This will involve exploring stochastic optimization techniques aimed at managing the variability and intermittency inherent in renewable energy sources, ultimately facilitating their sustainable integration into distribution grid.

CHAPTER VII

CONCLUSION

This dissertation has conducted extensive investigations into the optimization of distributed resources from nanogrid size to grid-scale systems, aiming to enhance cost effectiveness, reliability, efficiency, and sustainability. Through the proposal of innovative methodologies, validated by both test and realistic case studies, the research has yielded significant findings across various levels of DER integration.

Chapter 3 introduced an integrated framework for NG capacity planning of grid-connected nanogrids, which are small solar and energy storage systems that can provide kilowatt-level services to individual buildings. This multilevel optimization approach comprehensively evaluates the nanogrid's cost-effectiveness, sustainability, and reliability by employing a multi-faceted techno-enviro-economic assessment. The Planner module first identifies optimal asset sizing by considering a two-day look-ahead logic. Following this, the Operator module acts as a digital twin for the system, performing hourly calculations over a short-term horizon. Finally, the Evaluator module assesses the technical, environmental, and economic metrics for each solution, thus evaluating the effectiveness of the asset-sizing decisions. The proposed framework is scalable and adaptable, capable of being applied to larger microgrid capacities beyond the kilowatt range and under realistic conditions. Instead of providing a single best solution, the framework presents results for technical, environmental, and economic assessments for any potential NG solution, allowing decision-makers and planners to select the option that best meets their specific requirements. Notably, the optimal BESS energy capacity requirement escalates during summer months due to higher solar availability, which allows the BESS to charge more renewable energy

for later usage. Additionally, higher BESS and PV capacities correlate with greater grid independence (PGI) and reduced grid imports, leading to increased operating cost savings. The look-ahead logic enhances the model by considering not only the conditions of the current day but also anticipating general trends for the next two days. Moreover, the framework enables the shifting of renewable energy from high solar-low demand periods to low solar-high demand periods, resulting in more efficient RES utilization. It also allows the BESS to store excess PV generation and dispatch it during high-price periods, leading to significant cost savings.

The optimal planning and integration of large-scale DERs in distribution networks present a challenging task, particularly in extensive networks with multiple DERs. Simultaneous sizing and allocation are complex NP-hard problems, requiring innovative strategies to address load and generation variations over time. Chapter 4 compared two methods for optimizing the integration of Hybrid Distributed Resources into Radial Distribution Networks. The first method adopts a centralized approach, while the second employs a decentralized, bi-level framework. Both methods utilize APSO for optimization purposes. A comprehensive comparison was conducted on solution quality, computational efficiency, technical enhancements, and cost-effectiveness. The decentralized approach demonstrated a higher likelihood of attaining the global optimal solution, balancing computational efficiency and solution quality. It achieved better voltage stability, and greater reductions in power losses and total costs compared to the centralized method. Specifically, the decentralized method reduced power losses to 11.50 MWh, a 67.65 percent reduction, with a total cost of \$114,658, representing a 52.86 percent cost reduction. Additionally, the decentralized method revealed a slight edge in voltage stability compared to the centralized method, indicated by a lower mean Voltage Deviation Index (VDI). Sensitivity analysis highlighted the importance of parameter selection and configuration optimization

to achieve trade-offs between computational efficiency and solution quality. In the decentralized method, the 'pop35' configuration, with a population size of 35 particles, demonstrated superior optimization outcomes.

Chapter 5 introduced a novel power system-oriented Particle Swarm Optimization approach, named PS-TVPSO, developed to minimize real power loss in distribution networks. This method optimizes a mix of continuous and integer control variables simultaneously. The innovative algorithms integrated into PS-TVPSO significantly enhance the PSO search process, ensuring a balanced search and exploration of underutilized areas. The approach was tested on IEEE 33, IEEE 69 systems, and the Norwegian 124 bus system. A comprehensive comparison of the proposed approach with several variants of the PSO and other heuristic algorithms from the literature was conducted. The results demonstrated that PS-TVPSO outperforms conventional PSO and other heuristic methods in the literature in terms of solution quality and reduced convergence variability. PS-TVPSO showed significantly reduced convergence variability across several runs, emphasizing its stability and consistent performance. Additionally, PS-TVPSO achieved lower mean and median values across all DER scenarios compared, suggesting superior optimization quality compared to the conventional TVPSO. Results indicated a trend of decreasing active power loss values with increased DER integration. Voltage levels improved significantly with the integration of two DER units, although further additions did not yield substantial improvements.

Chapter 6 developed a bilevel optimization framework for integrating diversified renewable resources and storage in distribution systems. This framework includes a sizing module for determining the optimal sizes of diversified systems, effectively handling variations in renewable energy generation through energy storage integration. The siting module identifies the optimal site for the diversified system while ensuring technical reliability. Two domain-specific algorithms were integrated into PSO and applied to the siting problem to enhance the solution exploration process, avoiding

local optima traps, especially in later iterations where the step size is smaller. Simulations of IEEE 33-bus and IEEE 69-bus cases, as well as a Norwegian case study, demonstrated significant reductions in power losses, with the integration of PV, wind, and BESS achieving up to 74% loss reduction in the IEEE 33-bus case. In the IEEE 69-bus case, regular PSO with PV and BESS demonstrated convergence to an average fitness value of USD 6,597, while the integration of network-oriented methods guaranteed convergence to a significantly lower average fitness value of USD 6,409 in a shorter computational time. The Norwegian case study further validated these findings, indicating major improvements in voltage stability and loss reduction, affirming the effectiveness of the proposed approach in real-world applications. These outcomes highlight the significance of the proposed methods in balancing technical reliability, economic viability, and computational efficiency in addressing the complexities of distributed resource planning under real case scenarios.

Finally, this dissertation has made significant contributions to the field of DER planning and integration in distribution networks. The proposed methodologies have demonstrated their effectiveness in enhancing system cost effectiveness, reliability, efficiency, and sustainability.

A. NOMENCLATURE

Symbol	Description
β	BESS's minimum State of Energy (SoE) ratio
s_t	Hourly solar generation (kW)
l_t	Hourly demand load (kW)
μ_c, μ_d	Charging and discharging efficiencies
G	Maximum power drawn from the grid (kW)
γ	Charging and discharging maximum ratio
ρ_t	Hourly time of use energy prices
α^E	Per diem factors for BESS considering lifetime
α^S	Per diem factors for PV considering lifetime
OC^E	Total overnight cost for BESS
OC^S	Total overnight cost for PV
E	Energy storage size of Operator model (kWh)
S	Solar PV size of Planner Operator (kW)
L^s, L^w, L^e	Scaled lifetime of solar PV, wind, and BESS
T	Time steps (hour)
g_t	Hourly energy imported from the grid (kWh)
e_t	BESS state of energy (kWh)
d_t	Hourly BESS discharge power (kW)
c_t	Hourly BESS charge power (kW)
u_t	Binary variable, one if the battery is charging, and zero otherwise
E^p	Energy storage size for Planner model (kWh)
S^p	Solar PV size for Planner model (kW)
PL_i	Nodal active load (MW)
S^p, W^p, E^p	Solar PV, wind, and BESS sizes (MW), (MWh)

Symbol	Description
P_t^{grid}	Total hourly energy imports (MWh)
$OPEX$	Operational expenditure (USD)
$CAPEX$	Capital expenditure (USD)
PG_i, QG_i	Nodal active and reactive power generation (MWh)
$\overline{PG_i}, \underline{PG_i}$	Maximum and minimum reactive power generation (MVAR)
PG_{ij}, QG_{ij}	Active and reactive Power Flow from i to j
$\overline{S_{ij}}$	Apparent Power Limit (MVA)
$\underline{V_i}, \overline{V_i}$	Maximum and minimum allowable voltage magnitudes
$\underline{\theta_{ij}}, \overline{\theta_{ij}}$	Maximum and minimum allowable voltage angles
P_{loss}	Active power loss (MW)
PL_i	Active power consumed by nodal loads
$P_{i,t}^{utility}$	Hourly power supplied by the feeder (MW)
$P_{i,t}^{HDER}$	Hourly power supplied by hybrid distributed resource (MW)
P_i^{DER}	Power supplied by nodal distributed resource (MW)
N	Set of nodes
$S^{cap}, W^{cap}, E^{cap}$	Solar PV, wind, and BESS sizes (MW), (MWh)
$P_t^{pv,profile}, P_t^{w,profile}$	Solar and wind profiles (p.u.)
$P_t^{pv,gen}, P_t^{w,gen}$	Solar and wind power generation (MW)
P_t^{Demand}	Total hourly demand (MWh)
$P_t^{pv,load}, P_t^{w,load}$	Solar and wind to load power (MW)
γ	Allowed renewable curtailment ratio (p.u.)
$P_t^{pv,ch}, P_t^{w,ch}$	Solar and wind to charging power (MW)
μ_c	BESS charging efficiency (p.u.)
μ_d	BESS discharging efficiency (p.u.)
$P_t^{pv,curtailed}, P_t^{w,curtailed}$	Solar and wind curtailed power (MW)
soe_t	State of energy of BESS (MWh)

Symbol	Description
P_t^{dch}	Discharge power of BESS (MW)
P_t^{ch}	Charge power of BESS (MW)
α_{min}	BESS minimum ratio (p.u.)
M	A large value (big M)
Δt	Time granularity
β	Charging capability ratio from BESS (p.u.)
Δd	Representative days of simulation
C^s, C^w	Overnight capital cost of PV and Wind (USD/MW)
C^e	Overnight capital cost of BESS (USD/MWh)

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