

Maximizing Coverage and Reliability: Optimal EV Charging Station and DG Placement in Distribution Networks

¹Marwa Alee Hammad*

¹Faculty of Electrical and Computer Engineering, Hakim Sabzevari University, Sabzevar-Iran

*e-mail: mrwtaly10@gmail.com

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Abstract

Distributed generation (DG) and rapid growth in electric vehicles (EVs) necessitate the need for coordinated planning of the charging infrastructure and distributed energy resources (DERs) within distribution networks. Most of the existing studies focus on optimizing the placement of EV charging stations or optimization of DG allocation separately, and some studies have focused on losses of cost or power without jointly considering losses of services coverage and network reliability. Furthermore, the one network topology assessment may not be sufficient to represent radial, meshed and mixed distribution systems. This study suggests a constrained multi-objective framework for simultaneous placement of EV charging stations (EVCSs) and DG units to overcome these drawbacks. The model minimizes total deployment cost, while maximizing the geographical service coverage and network reliability. We use 50 particles and 100 generations of Differential Evolution (DE) using the mutation strategy DE/rand/1, binomial crossover and greedy selection. Geographical siting limits, facility-count constraint, voltage limits, line-loading limits, DG generation limits, EV charging capacity, and power-demand requirements are considered in evaluating candidate solutions. The framework is validated on a 25-node distribution network in radial, mesh and mixed topologies and contrasted to base case and randomly generated deployment solutions. The chosen compromise solution is 75.0% service coverage, 92.0% network reliability with an overall investment cost of US\$660,000, comprised of three EV charging stations and two DG units. The objective value achieved was best 0.3940 and 92.0% success rate was reported. The results show the feasibility of coordinated EVCS–DG planning to achieve economic, service and reliability goals in various network configurations.

Keywords: coverage optimization, differential evolution, distributed generation, distribution networks, electric vehicle charging stations, infrastructure planning, multi-objective optimization, reliability analysis, smart grid.

1 Introduction

Global shift towards sustainable energy and low carbon mobility has gained momentum and electric vehicles (EVs) and distributed energy resources are gaining momentum. Governments and utilities are spending billions of dollars on clean transportation. Clean transportation infrastructure costs billions of dollars in both governments and utilities. The proliferation of EVs has created a need for convenient and dependable charging stations, which has emerged as one of the key challenges in modern power systems [1]. Concurrently, Distributed Generation (DG), comprising renewable energy sources like solar photovoltaic, wind, and energy storage systems, has become a viable approach to enhance the resilience of the electricity grid, minimize transmission losses, and help manage decentralized electricity generation. The implementation of these technologies offers significant environmental and economic advantages, but they also raise novel operational and planning issues, which demand innovative optimization techniques [2].

The traditional distribution network is designed for the flow of power in one direction, from power generation plants to consumers, via transmission and distribution networks. This model is changing with the growth of EVs, as charging stations are becoming highly dynamic and localized, which will impact the way they operate. At the same time, DG units can also supply power at various points in the network, leading to bi-directional flow which can impact voltage stability, power quality, system losses and overall network reliability [3]. If not planned well, unmanaged EV charging station deployment can lead to transformer overloading, feeder congestion, voltage violations, and operational cost increases. Similarly, DG units not installed in the correct location can be causing

reverse power flows or failing to deliver the maximum technical and economic benefits. Thus, the problem of determining the best location of EVCSs and DG units is a major research challenge for the smart grid planning in modern times [4].

These are multiple conflicting objectives for EV station and DG station infrastructure planning. An economic goal of the utilities is to reduce installation, operating and maintenance costs and maximize the use of infrastructure. Technically, planners want to ensure network reliability, maximize service and minimize losses of power throughout the network, as well as maintain reasonable voltage profiles. The goals are sometimes conflicting as a higher number of charging stations or DG units will generally provide more coverage and reliability, but also lead to higher investments. The planning problem is thus a complicated problem of multi-objective optimization with nonlinear objective functions and many operational constraints, naturally [5].

There are a number of optimization methods that have been suggested to solve the facility placement problem in power systems. Relatively small systems can be solved optimally with classical mathematical programming techniques, such as linear programming, nonlinear programming, and mixed-integer optimization; however, these techniques generally fail to deal with large-scale nonlinear programming problems due to computational complexity and multiple local optima [6]. In this context, the flexibility, robustness, and capability to solve highly nonlinear engineering problems without relying on gradient information have made the metaheuristic optimization algorithms a subject of much interest. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and Differential Evolution (DE) are some of the most effective algorithms that have been applied to solve problems related to power systems [7].

Due to its simplicity, strong ability to perform global search, and fast convergence, DE becomes more popular in solving continuous optimization problems. Mutation, crossover, and selection operations of the algorithm result in new solutions that allow searching effectively in large and complex search space and maintaining diversity of populations. The DE approach is not so much dependent on the number of control parameters compared to other population-based algorithms, and in all cases, the results of the optimizations are very competitive. All these factors contribute to the suitability of DE for solving the co-allocation problem of EV charging stations and DG units in real distribution networks [8].

Though there has been significant research in the area of infrastructural planning, there still remain a few problems with the current literature. The current literature does not consider the joint interaction between the planning of EV charging stations and DG planning while optimizing each one separately. In addition, most of the methodologies try to minimize the cost or minimize power losses but give little importance to coverage and reliability of service delivery, which are crucial in meeting the growing demands of EV charging services. In addition, the majority of the existing frameworks are analyzed in one particular topology, which is not practical in the real world where networks may have radial, meshed or hybrid topology [9].

Although a substantial amount of research has been conducted on EVCS and distributed generation (DG) planning, there are some limitations. The placement of EVCS and the allocation of distributed generation have been explored in the literature many times as separate optimization problems and may neglect accounting for interactions among charging demand, distributed generation, network operating conditions and infrastructure utilization. Most of the other approaches have been based on economic goals, loss reduction or voltage improvement, with relatively less attention given to coverage or reliability. In addition, there are numerous optimization tools that have been tested with one type of distribution network topology, which does not optimize for other network topologies with varying characteristics like radial, meshed, or mixed. Optimized distribution-system planning based on Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO) is shown to be effective but there is a need for more research in the coordinated placement of EVCS and DG with multiple economic, spatial and technical objectives.

Considering these limitations, the following study proposes a constrained multi-objective optimization approach for simultaneous deployment of EVCSs and DG units. The proposed approach takes into account the total deployment cost, geographical service coverage and network reliability including practical engineering limitations such as voltage limits, line-loading limits, DG generation limits, EV charging capacity and power-demand requirements. DE is used to find appropriate

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deployment settings in 25 node distribution-networks of various topologies, among which radial, meshed and hybrid networks.

This study makes the following main contributions: (1) coordinated optimization of EVCS and DG placement in a single planning problem, (2) consideration of both economic and coverage objectives as well as reliability objectives simultaneously, (3) evaluation on various distribution-network topologies, and (4) comparison of optimized and randomly generated deployment solutions. These contributions enhance the basis for assessing EV charging and DG deployment strategies in real distribution network operating conditions.

2 Related Works

Farrokhifar et al. [10] proposed an energy management framework to optimize the use of BESSs and EVs to take advantage of the fluctuations of electricity prices and load demand over a longer time horizon. The framework proposed takes into account uncertainties related to renewable energy generation, especially solar PV and wind resources, in addition to market uncertainty in electricity prices. The hybrid energy system with solar panels, wind turbines and battery storage has been designed to increase the use of energy and the flexibility of operation. To find the optimal capacities of the renewable energy sources and storage devices, the optimization problem was formulated as a Mixed-Integer Linear Programming (MILP) model. The simulation results showed that coordinated planning of EVs, renewable energy sources, and batteries can achieve significant efficiency improvement for the system and lower operating costs in uncertain market conditions.

Dogan et al. [11] concentrated on issues associated with an increasing proportion of electric vehicles in electricity distribution systems. This research was aimed at studying various EV charging techniques with a view to minimizing the adverse consequences of EV charging under peak load conditions. Various types of charging were considered in order to estimate their influence on the performance of distribution systems like the voltage profile and loading of the system. A residential distribution system was selected as the basis for simulation of charging situations. It can be seen from the outcomes that with increasing the EV penetration rate, appropriate charging management can become a good remedy for congestion reduction and improving the operation of utilities' distribution systems.

In study [12] According to Ponnamm & Swarnasri, an optimal design of EV charging stations (EVCSs) and distributed generation (DG) in the Radial Distribution System (RDSs) was considered for the mitigation of negative consequences of EV integration. Their optimization process was based on the reduction of active power losses along with improvement of voltage regulation through decreasing the Average Voltage Deviation Index (AVDI). The researchers noted that there were many technical issues that needed to be considered when it comes to choosing the most appropriate locations for charging stations. It was revealed that coordination of EVCSs and DG led to better performance of the distribution network compared to the independent approach.

Injeti & Thunuguntla [13] focused on the effects of plug-in electric vehicles (PEVs) on radial distribution networks and explored the use of distributed generation to reduce the impacts of charging power losses and voltage deviations. A multi-objective optimization model was designed to reduce active power and voltage variations with a 24-hour operating period. The suggested framework used both Particle Swarm Optimization (PSO) and Butterfly Optimization Algorithm (BOA) for locating the optimum DG locations and optimum operating condition. The network analysis technique used was backward-forward load flow. The results showed that effective integration of DG resources yields good voltage profiles and mitigates the negative impact of EV charging on the distribution system.

Aggarwal & Singh [14] provided an advanced method of planning that aimed at finding out the optimal placement and capacity of the distributed generation facilities for the provision of electric vehicle charging facilities. It was noted that the improper management of the process of charging of the electric vehicles could lead to increased losses in the distribution grid. The main aim of the developed optimization approach was to minimize the losses in the system while providing sufficient charging stations. The results of the simulation proved that the optimal placement of DGs contributes to reduced losses and improved performance of the EV charging system.

Battapothula et al. [15] developed an optimized model that considers both the sizing and allocation of FCS and DG in the distribution system at various penetration levels of EVs. An MINLP

model was developed to consider the investment costs, distribution power losses, and quality of charging services. The number of EVs in each geographical region was set as a working constraint since it was mandatory in providing realistic results for the planning process. It can be said that the suggested model has proved to be a good balance between the economic and technical aspects, thus, enabling an integrated approach in increasing charging infrastructure and DERs.

Masoumian et al. [16] explored the coordinated control of EVs at charging stations, distributed generation (DG) resources, and the power grid under different electricity price and EV charging demand scenarios. Simplified mathematical models such as two-point estimate method were utilized to assess the uncertainties in the system and to assess different DG technologies and EV charging facility contribution. The Novel Symbiotic Biogeography-Based Search Algorithm (NSBSA) was used to achieve the optimal participation of charging stations and wind based DG units in the distribution system, to maximize operational benefits. The findings showed that optimized scheduling of renewable generation and EV charging facilities not only improves the performance of the grid but also boosts economic outcomes.

Raja et al. [17] suggested a coordinated strategy for simultaneous installation of Renewable Distributed Generation (RDG) units and Vehicle Charging Stations (VCSs) to reduce the amount of Energy Not Supplied (ENS) in the DGs. A hybrid optimization method based on Nelder–Mead method and Cuckoo Search algorithm was developed to find the optimal installation location. The proposed method took advantage of the complementary benefits of renewables and charging stations to enhance supply reliability. The simulation results showed that the hybrid optimization algorithm was able to achieve better results in terms of reduced ENS and improved reliability and operational efficiency of the distribution network.

Zeb et al. [18] proposed a framework for optimizing designs of electric vehicle charging infrastructure (EVCI) with a combination of various types of EV chargers and solar PV generation. The first aim was to minimize electricity consumption and increase the charging efficiency under stochastic operating conditions. The optimization problem was represented as a constrained stochastic optimization model, and solved by Particle Swarm Optimization (PSO) algorithm. The proposed approach was able to determine optimally the combination of charging technologies and the role of solar energy to minimize dependency on the grid. The findings revealed that the synergy between the types of chargers and renewable energies can significantly enhance the charging efficiency and overall system performance.

Domínguez-Navarro et al. [19] study was undertaken in an attempt to make the electric vehicle fast-charging station more profitable by reducing the use of unnecessary energy through the installation of distributed generation and energy storage from renewable sources. In this regard, the authors of the study applied the Monte Carlo Simulation (MCS) technique in analysing the uncertainties associated with demands for charging and the generation of renewable energy, while the Genetic Algorithm (GA) technique was used in the optimization of the configuration and management of the charging station. Optimization was aimed at maximizing the Net Present Value (NPV) through the optimal configuration of the charging station.

Golla et al. [20] analyzed the demand for electric vehicle charging in residential and public EV charging stations by using real data and Monte Carlo Simulation (MCS). In the model proposed by the authors, the amount of energy necessary for EV charging was estimated based on various charging behaviors and patterns. The results of simulations have proved that the redistribution of the demand for EV charging from residential to public charging stations could contribute to a decrease in peak electricity demand while having no effect on the demand for charging.

Subudhi [21] a complete review of Wireless Charging Technologies for Electric Vehicle (EV) has been presented, covering static and dynamic charging technologies. The paper introduced the principle, design, and circuit configuration of the wireless charging system and compared their pros and cons. Focus was on the static wireless charging architectures, like circuit design and performance evaluation. The review found that while there is great potential for wireless charging to enhance user convenience and facilitate wide EV adoption, further enhancements are needed in efficiency and infrastructure cost.

Akıl et al. [22] proposed a coordinated charging strategy for EVs using the State of Charge (SOC) of EVs in the existing power grid. The proposed framework applied real world charging profiles to schedule EV charging in a flexible way, without unnecessary loading of the distribution

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network. The approach accounted for the state of charge (SOC) of the batteries and user charging needs, thereby optimally meeting the demand of the grid and charging availability. The coordinated charging was found to greatly enhance the flexibility of the power system while decreasing the peak load and keeping the user comfortable.

3 Methodology

The paper proposes a systematic six-phase methodology to find the optimum deployment strategy for Electric Vehicle (EV) charging station and Distributed Generation (DG) unit into power distribution network. It combines the analysis of the power system, mathematical optimization and evolutionary computing to simultaneously enhance the performance of the power system, the accessibility of charging service and economic efficiency. The results of the previous phase are used for the next phase, allowing the optimization to proceed in a systematic and sound way. The methodology starts with ****data acquisition and system modelling**** which consists of collecting the distribution network topology, bus parameters, line impedances, load profiles and operational constraints and modelling them. Data pertaining to EV charging demand, traffic distribution, potential EV charging station locations, renewable energy resources, and DG technologies are also integrated to create a realistic planning environment.

The second step is called problem formulation, in which the optimization goals and operational requirements are mathematically formulated. The target function takes into account several performance indicators such as minimizing network power loss, voltage deviation, minimizing installation and operating costs, maximizing coverage for EV charging and improving the overall reliability of the system. Limits of voltage, line loading, DG generation limits, charging station capacity, and power requirement are added as constraints to ensure technically viable solutions. The third stage is the encoding of solutions and their evolution optimization. Chromosomes are used to represent candidate solutions, with each chromosome representing a specific solution to the problem by holding the number, locations, and capacities of the EV charging stations and DG units. Optimization algorithms based on evolution are used to efficiently search the solution space by creating, evaluating and evolving populations of candidate solutions, until a convergence state is reached.

In the fourth phase, power flow and fitness evaluation are carried out. The operating conditions of the network including bus voltages, branch currents, active power losses and the loading of the system are analyzed for each candidate solution by conducting load-flow calculations. Electrical performance indices are then derived from the obtained results and merged with economic and coverage indices to get the overall fitness value of each solution. The fifth phase is the optimization and convergence analysis, which involves the production of successive generations until some prespecified stopping conditions are met. The algorithms perform a trade-off between exploration and exploitation to prevent getting stuck in local optima and continuously strive to better the solutions during the optimization cycle. Algorithms are monitored for convergence characteristics and computational performance to assure stability and efficiency of the algorithms.

The last step of phase six consists of the validation and comparison of the performance results. The optimal placement scheme is selected under several operation modes and compared to the base case for evaluation of enhancements achieved in voltage level improvement, reduction in power losses, charging availability, reliability, and the total cost of investments. Sensitivity analyses may be carried out to evaluate the validity of the suggested methodology under different load requirements, vehicle penetration rates, and renewable energy sources scenarios. The six-phased methodology is capable of providing a comprehensive methodology, where the modeling of the distribution network, multi-objective optimization, and evolutionary computation are integrated into one unified decision-making process. The systematic approach helps to find the most feasible and economically advantageous location of electric vehicles and distributed generation units in order to keep the reliability and security of the power distribution system intact.

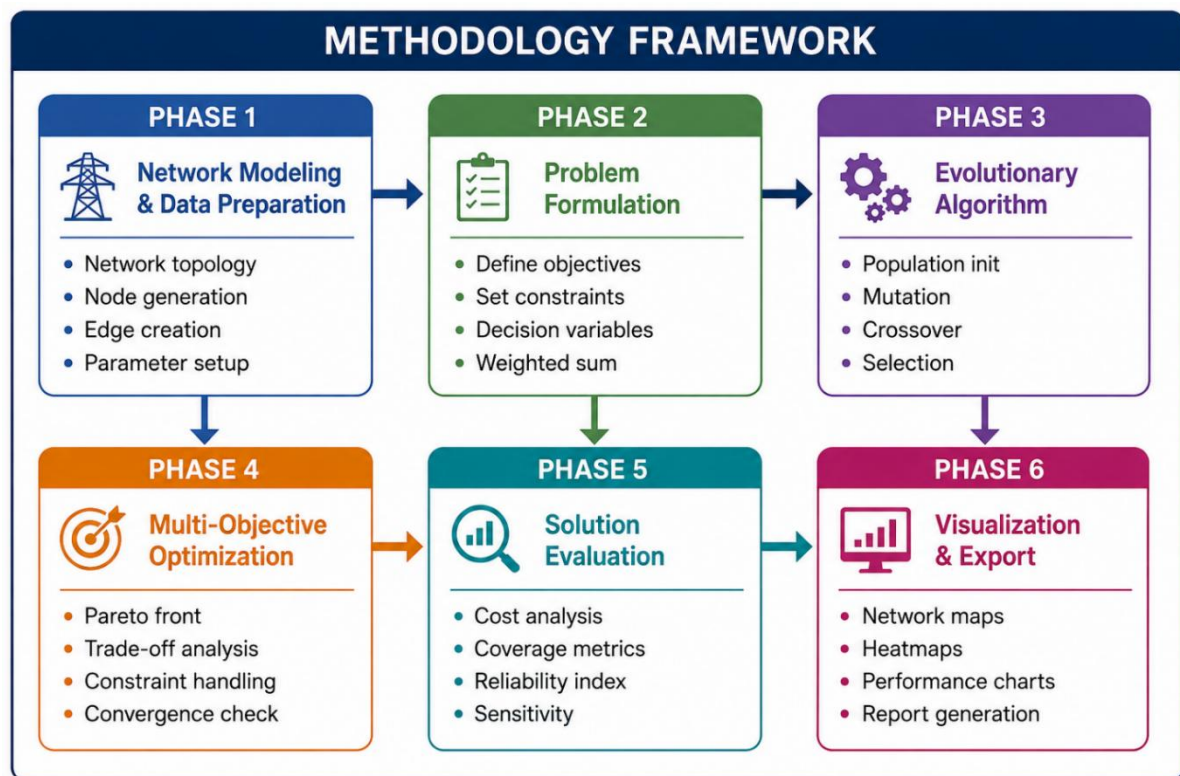


Figure 1 Comprehensive methodology framework

The methodology presented here represents a full methodology of how to make the most efficient planning of the charging stations of Electric Vehicles (EV) and DG units in the power distribution systems. In contrast to conventional methods, where these infrastructures are optimized separately, this methodology makes them optimized at the same time. This new methodology may help to make more efficient, reliable and sustainable power grid. This scientific research is a big step forward using the method of multi-objective optimization, which considers both technical and economic performance. The main goal of this methodology is minimizing the losses of power, voltage deviation, installation cost, increasing the charging coverage, reliability and usage of renewable energy sources. The methodology successfully solves the conflicts between these objectives and meets the requirements of the utility operators and EV customers.

Furthermore, the optimization algorithm used in the research work is the famous Differential Evolution (DE) algorithm, due to its simplicity, fast convergence, and strong global search ability. The DE algorithm is able to efficiently search the complex solution space of the problem of placement and sizing, providing high-quality solutions without being trapped in the local optima. Another important point is the use of interactive visualization tools which enable the users to analyze the output of the optimization process through network maps, convergence curves, and performance indices. Such graphic tools facilitate decision making and enable the comparison between different planning scenarios. In addition, the methodology allows an extensive documentation of the results, since the system can automatically produce professional reports, tables and charts and analytical reports in various formats.

3.1 Network Modeling and Data Preparation

In the first step of the proposed approach, a realistic model for the power distribution network is built, and all the input data needed for the optimization process is prepared. The correctness of the system representation is of paramount importance when it comes to optimizing results, so accurate network modeling is crucial. This stage establishes the electrical network topology, spatial dimensions, potential siting of Electric Vehicle (EV) charging stations and Distributed Generation (DG) units, as well as operational parameters that are relevant for optimization. The distribution

network is represented in a graph, where the buses are the nodes and the distribution lines are the edges that connect the nodes. This graph-based representation offers a flexible mathematical tool to analyze network connectivity, compute electrical distances, calculate coverage areas and optimize networks. Each node is also equipped with geographical coordinates that indicate their geographical position within the service area, so that an overall consideration of electrical performance and geographical accessibility is possible. Before optimization, all network parameters are set up, such as node location, substation position, network density, candidate installation locations, and coverage radius. These parameters are provided as input for the Differential Evolution optimization algorithm and are the same for all simulation scenarios except when explicitly changed for sensitivity analysis.

3.1.1 Distribution Network Representation

The distribution network is mathematically represented as an undirected graph:

$$G = (V, E) \quad (1)$$

where:

- $V = \{v_1, v_2, \dots, v_n\}$ denotes the set of network nodes (distribution buses).
- $E = \{e_1, e_2, \dots, e_m\}$ denotes the set of distribution lines connecting the buses.
- Each node (v_i) is associated with two-dimensional coordinates (x_i, y_i), representing its geographical position.
- Node v_0 represents the main distribution substation, which acts as the primary power source for the network.

The distribution system used in the proposed planning model is represented in the basic mathematical form in Equation (1). The set (N) represents the locations where distributed generation (DG) units and electric vehicle (EV) charging stations can be installed, and the set (L) represents the electrical connections that allow power to be sent from the network nodes. Each node has associated geographical coordinates that are evaluated during charging-service optimization to assess spatial relationships and charging-service coverage. Thus, Equation (1) defines the network structure which is used for the subsequent optimization, topology analysis and deployment decisions.

The electrical and geographical attributes of the distribution system can be efficiently described using graph theory. Connectivity defines the available power flow paths and spatial coordinates can be used to calculate distances between EV charging stations, DG units, and the location of consumers. This dual representation enables the optimization algorithm to take into account both electrical constraints and geographical coverage during optimization. The nodes in the network can be residential, commercial, industrial or mixed load demand centers. From these nodes, candidate stations and locations for DG units are identified to obtain optimal locations for installation of the stations and DG units based on technical and economic performance indicators. The network model also includes service coverage areas where each charging station or DG unit is assumed to be able to serve customers within a specific service radius. In this representation, it is possible to assess charging accessibility, as well as energy use from renewables, while keeping the electrical operating conditions acceptable all the way through the distribution system.

3.1.2 Network Parameters

Several parameters are set to describe the distribution network and to set up the operating conditions for the optimization process. The size of the network, geographical layout, connectivity level and coverage capability are determined by these parameters. They also serve as a means to assess various planning scenarios and compare optimization results. The methodology can be applied to small and medium-sized distribution systems: from 10 to 50 network nodes. The coordinates of nodes are randomly chosen in a service area of 10 km × 10 km, whereas the main substation is placed at the center of the network for a balanced power supply configuration. The density of the network is

a parameter that determines the number of inter-connections between the buses and therefore affects both the power flow properties and the reliability of the network.

The adopted service coverage radius is 3 km for both EV charging stations and DG units, thus allowing the users who are within this radius can access the respective EV charging station and DG unit. In addition, all of the service area is subdivided into a 10 x 10 computational grid to provide a realistic estimate of charging coverage, accessibility and service availability while optimizing. A summary of the various parameters of the principal networks used throughout this research is presented in Table 1.

Table 1 Network parameters

Parameter	Symbol	Value Range	Description
Number of Nodes	N	10–50	Total buses in the distribution network
Node Coordinates	(x, y)	$[0,10] \times [0,10]$ km	Geographical position of each node
Substation Location	(x ₀ , y ₀)	(5,5) km	Fixed location of the main substation
Network Density	ρ	0.1–0.4	Connectivity ratio between nodes
Coverage Radius	r	3.0 km	Maximum service distance of EV charging stations and DG units
Grid Resolution	g	10 × 10	Computational grid used for coverage analysis

3.1.3 Network Topology Generation

The optimization framework that is proposed starts with developing a realistic distribution network model that accurately reflects the electrical infrastructure and geographical distribution of the service area. This is the basic step as the efficacy of the optimization process relies on the quality of the network representation and the accuracy of the input data. The distribution system is represented as an undirected graph, which consists of a set of nodes (V), the distribution buses, and a set of edges (E), the distribution lines between the buses. These two-dimensional geographical coordinates are assigned to each node and the main substation is located at a fixed point in the service area as the main power source. Realistic simulation scenarios are created by setting network parameters such as: number of nodes, network density, coverage radius and computational grid resolution that simulate practical distribution systems. Three representative distribution network topologies are generated to assess the robustness and applicability of the method based on DE optimization. The radial topology is similar to traditional distribution systems, which have a single power flow path from the substation to each load, and is simple to operate, but it is not fault tolerant. The meshed topology offers better reliability, load sharing capabilities and there are alternative power flow paths suitable for dense urban environments. The mixed topology utilizes the strengths of both a radial topology and a meshed topology as the majority of the topology is radial, with the addition of some redundant connections that provide additional operational flexibility and system resilience. In topology generation, the electrical connections are created throughout the service area while the nodes forming the network are distributed in space, and ensuring full network connectivity. This graph-based approach allows for electrical performance, geographical accessibility, EV charging coverage and DG placement to be analyzed simultaneously, which will provide a realistic and scalable basis for the next stage of multi-objective optimization.

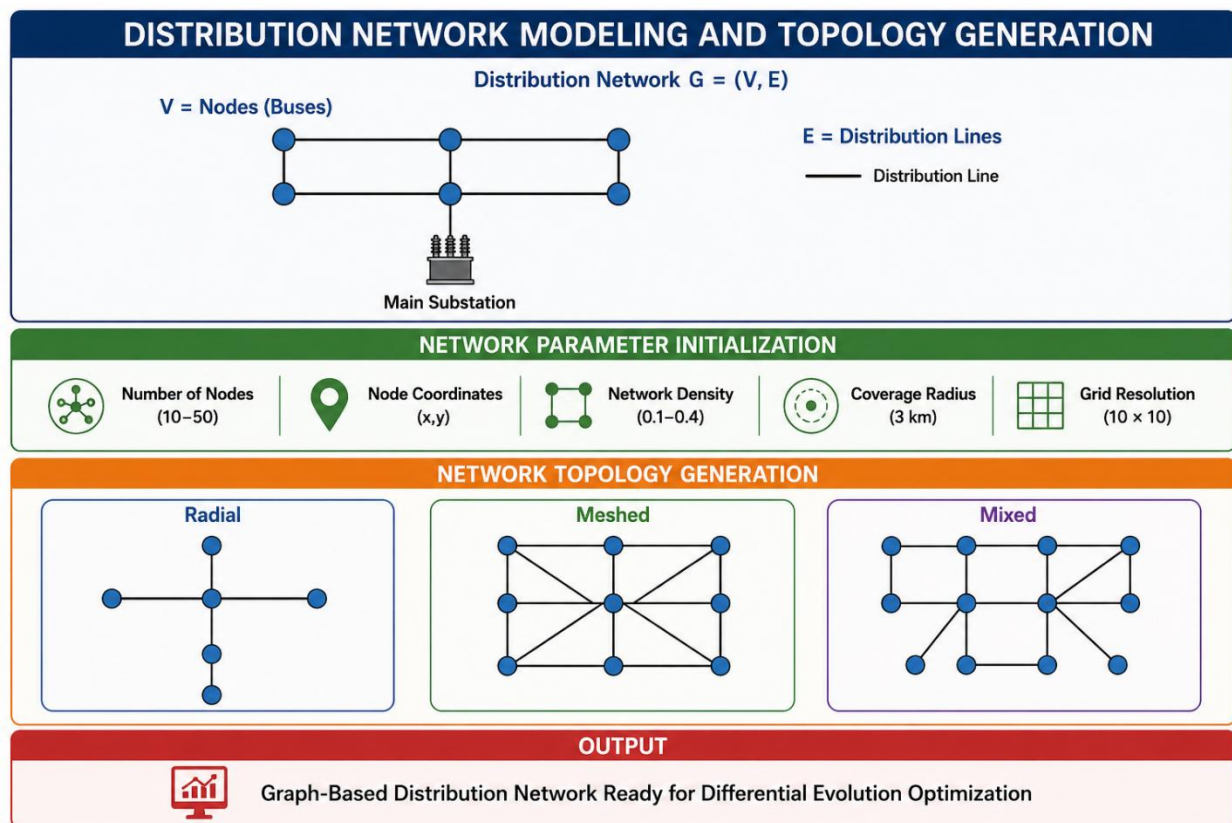


Figure 2 Distribution network modeling and topology generation

The distribution network is indicated by its structure and geographical representation in Figure 2. The network is represented as a graph with nodes (distribution buses) and edges (distribution lines), with each node being a possible location in the distribution system. Geographical coordinates assigned to the nodes refer to the actual locations of these nodes and can be used to assess the spatial relationships between the different components of the network and potential placement of EV charging stations and distributed generation (DG). The primary source of electrical power is represented by the main distribution substation, and the rest of the buses are represented by the distribution lines with which they are connected, creating the network topology. The interconnection among the buses determines the electrical and geographical structure of the distribution system shown in Figure 2. The type of topology becomes significant for the optimization process because the characteristics of the power flow, service coverage, and network reliability can vary, depending on the position and connection of the charging station or DG unit. Hence, Figure 2 is a visual depiction of the mathematical model in Equation (1) of the network structure, and clarity is provided on how the network nodes, distribution lines and geographical locations are represented in the proposed planning model.

3.2 Network Metrics and Analysis

After setting up the topology for the distribution network, a detailed network analysis is carried out to analyze the structural characteristics of the network and determine its suitability for the optimization process. Before EV charging stations and Distributed Generation (DG) units are placed in the system, network metrics can be used to quantify the electrical and topological properties, which can be used to compare network configurations in a meaningful way. These metrics also help to understand the impact of network structure on power distribution, service access and overall system reliability.

The node degree distribution, or the number of distribution lines connected to a network node, is one of the primary metrics considered. The node degree is a measure of the local connectivity of the network and its importance of individual buses in the distribution system. Those networks are called

radial networks, in which the majority of nodes have a degree of one or two since each load is connected to it via only one electricity path. Meshed networks have higher average node degrees because there are multiple interconnections between adjacent buses, while mixed networks are with a combination of radial structures and some redundant interconnections have a level of connectivity in between. Balanced node degree distribution helps to make the power flow more flexible and increases the power network's resilience against line failures.

The **edge length distribution** is also a significant metric, and a concept concerning the physical distance between nodes that are connected together. Each node has a geographical coordinate, so the Euclidean distance between adjacent buses can be calculated, which can be used to estimate the length of each distribution line. The more edge length, the more the construction cost, electrical resistance, voltage drop, and power loss. Longer lines tend to result in more losses and lower voltage stability, while shorter lines tend to be more efficient and cost less. Therefore, the optimization model takes both the electrical performance and geographical distances into account when determining the installation locations. The overall level of interconnection in the distribution system is also assessed, by calculating the network connectivity density. The number of existing edges in the graph divided by the maximum number of edges possible in the graph is called Connectivity density and it is expressed as

$$\rho = \frac{|E|}{|V|(|V|-1)} \quad (2)$$

Where $|V|$ is the number of nodes and $|E|$ is the number of distribution lines. A low density is associated with a sparse network with a few branches while a high density is associated with a highly interconnected network with many branches. The average density of radial networks is usually between 0.08 and 0.12, while the average density of meshed networks is usually between 0.20 and 0.30, and the average density of mixed networks is usually between 0.12 and 0.18. These values can be used to quantify network redundancy and reliability. The node degree distribution, edge length distribution and connectivity density as a whole give a complete picture of the topology of the network generated. These provide a check that the distribution systems being created in the simulation are representative of actual electrical distribution systems and provide a solid base for the subsequent Differential Evolution optimization process. The proposed methodology considers both topological and spatial attributes to ensure that the decisions for the placement of an EV charging station and DG are realistic and reflect the actual network condition, and that the power can be delivered efficiently, there will be an adequate service coverage and high system reliability.

Network density, as shown in equation (2), depends on the number of distribution lines as well as on the number of buses. It is a very useful parameter for comparison of network topologies because it provides an equal measure of how connected these topologies are regardless of the number of nodes. Network density, as defined in the proposed planning analysis, captures the structural properties of the distribution network, and it is used to investigate the influence of network topology on the location of EV charging stations and distributed generation (DG) units. Therefore, equation (2) has a direct relationship with the topology model in equation (1) where the distribution network is represented by nodes and connecting edges.

3.3 Problem Formulation

This study proposes the optimal siting of electric vehicle (EV) charging stations and distributed generation (DG) units as a constrained multi-objective problem. The goal is to identify the best number and spatial placement of EV charging stations and DG to create an economically efficient, well-covered, and highly reliable charging network. The optimization takes into account three conflicting objectives: (i) minimize the total system cost, (ii) maximize geographical service coverage and (iii) maximize network reliability. Each objective is competing with each other – in order to increase charging station count, coverage may be reduced, for instance, and vice versa – so a multi-objective optimization is applied to achieve best possible compromise between competing requirements. The optimization is done over a two-dimensional topographical representation of the study area where the placement of candidate charging stations and DG units are allowed within prescribed geographical limits. One candidate solution returned by the optimization algorithm is a full deployment plan: the number of charging stations, the number of DG units and their respective

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installation coordinates. The fitness of every solution is assessed mathematically through objective functions and based on practical engineering constraints. The decision variables are represented by the solution vector as indicated in Equation (3).

$$X = [n_s, n_d, x_{s1}, y_{s1}, x_{s2}, y_{s2}, \dots, x_{sn_s}, y_{sn_s}, x_{d1}, y_{d1}, x_{d2}, y_{d2}, \dots, x_{dn_d}, y_{dn_d}] \quad (3)$$

where

- n_s denotes the number of EV charging stations.
- n_d denotes the number of distributed generation units.
- x_{si}, y_{si} represents the location of the i^{th} charging station.
- x_{di}, y_{di} represents the location of the i^{th} DG unit.

The optimization process explores the problem space through a continuous change in the values of these decision variables to find the optimum configuration of infrastructure. The first criterion is to minimize the economic cost of building and running the charging infrastructure. The total economic cost includes the cost of installing the charging stations and distributed generators (DG), along with their maintenance costs during the planning period. The cost function is expressed in Equation (4) as:

$$C = \frac{C_n n_s + C_d n_d + (M_s n_s + M_d n_d) T}{10^6} \quad (4)$$

Where:

- C_n is the installation cost of one EV charging station,
- C_d is the installation cost of one DG unit,
- M_s is the annual maintenance cost of a charging station,
- M_d is the annual maintenance cost of a DG unit, and
- T represents the project lifetime.

In light of this, while taking into account the costs of capital expenditure and operation, optimization helps in arriving at an economic design rather than just minimizing the costs related to construction. The second objective of the model is to maximize the coverage for the charging stations. By coverage, we mean the coverage ratio which means the proportion of the geographic coverage area that lies under the effective service coverage of either the single charging station or DG charging station. This region is segmented into finite grids and the coverage ratio is determined based on the distance between each of the grids and the nearest charging station. The coverage relation given in Equation (6) as:

$$Coverage = \frac{|\{(x,y) \in G : \exists f, d((x,y)f) \leq r\}|}{|G|} \quad (5)$$

Where (G) is the set of all grid nodes, (r) is the service radius, and $d((x,y)f)$ is the Euclidean distance from grid node (x,y) to facility (f). Optimizing this objective would mean having the highest possible level of access to the charging services for the maximum number of EV users through minimum distances traveled. The third objective is meant to maximize the reliability of the charging infrastructure system. Reliability refers to the ability of the charging network to provide its services notwithstanding any breakdowns in equipment, maintenance work, or changes in electricity demands. The more charging stations and DG stations added to the network, the higher the redundancy and reliability of the system. The reliability model used in this paper can be described in Equation (6) as:

$$R = \min(0.85 + 0.05\min(n_s, 5) + 0.04\min(n_d, 5), 0.99) \quad (6)$$

with a base reliability value of 0.85, with an increment of reliability of 0.05 per each charging station, 0.04 for each DG unit, but the upper bound on the attainable reliability value being limited at 0.99 considering engineering practicalities. Since the units of all three objective functions are different, they have been integrated using a weighted sum methodology. The resulting objective function given in Equation (7) as:

$$F = \omega_1 C + \omega_2 (1 - Coverage) + \omega_3 (1 - R) \quad (7)$$

where ω_1 , ω_2 , and ω_3 denote the weighting coefficients assigned to cost, coverage, and reliability, respectively, with $\omega_1 + \omega_2 + \omega_3 = 1$

By using such a metaheuristic optimization algorithm, the multi-objective optimization problem can be effectively and efficiently solved by converting it to a single objective optimization function, using the weighted objective. The weighting factors allow the planner to adjust the relative importance of the three factors of economic performance, charging accessibility, and system reliability, in accordance with the priority given in the planning process. There are a number of engineering and operating restrictions to the optimization. The charging stations and DG units should not be installed in excess of the practical investment limit. All facilities should be established within the geographical range (coordinates) of the study area; all the coordinates should fall within the geographical network limits of the defined study area. To avoid clustering and to spread out charging stations in the network, a minimum separation distance is enforced. Furthermore, reliability and coverage are added as minimum requirements, thus meaning that all the potential solutions will provide to the end-user an acceptable service quality before being evaluated by the optimization algorithm.

Each iteration of the optimization, the candidate solution is first evaluated for all constraints. The cost, coverage and reliability objective is evaluated and normalised, if possible. The fitness function of the optimization algorithm is then calculated as the weighted objective value and used for the optimization. Each iteration, the candidate solutions with the greater fitness values are kept and tweaked until they converge or the stopping criterion is met.

The relation between the decision variables and objective functions is shown in each figure, as is the optimization model after incorporating the weights and the engineering constraints, and the resultant optimal deployment of EV charging stations and distributed generation units. It gives a general idea of the mathematical formulation used in all of this study and serves as a basis for the application of optimization algorithms described in the following sections.

3.4 Evolutionary Algorithm Implementation

Differential Evolution (DE) is an evolutionary-based optimization technique commonly used in the solution of non-linear optimization problems. Due to its easy implementation, fast convergence, and powerful ability to search globally, DE has been recognized as one of the best meta-heuristic optimization techniques. Contrary to traditional optimization techniques which are based on gradient computations, DE finds optimal solutions by evolving the population of candidate solutions through mutation, crossover, and selection procedures. In DE, an optimization process starts by generating an initial population of (NP) candidate solutions in a pre-specified search range. An individual in the population represents a vector whose components relate to the decision variables of the problem under consideration. Then the fitness value of each candidate is computed using the objective function. After the generation of an initial population, DE applies mutation procedure to generate a mutant vector for each target solution through the combination of three random individuals from the current population. With DE/rand/1, the mutant vector is generated as indicated in Equation (8):

$$V_i = X_{r1} + F(X_{r2} - X_{r3}) \quad (8)$$

where (F) is the mutation factor controlling the amplification of the differential vector, while X_{r1} , X_{r2} , and X_{r3} are distinct randomly selected population members. The crossover operator is subsequently applied to increase population diversity by combining the target vector and the mutant vector. A trial vector in Equation (9) is generated according to the binomial crossover mechanism,

$$U_{ij} = \begin{cases} V_{ij} & \text{if } \text{rand}(0,1) \leq CR \text{ or } j = j_{rand} \\ X_{ij} & \text{otherwise} \end{cases} \quad (9)$$

where (CR) refers to the crossover probability and j_{rand} ensures that there is inheritance of at least one dimension from the mutant vector. The last step is the selection where the fitness values of both the target vector and the trial vector are compared. If the trial vector performs better than the target vector, the former takes its place in the next iteration; otherwise, the target vector remains the same. This is because the greedy selection strategy ensures that the quality of the population will always improve with time. These evolutionary operations continue iteratively until the specified

number of generations is attained. In this paper, Differential Evolution is used to solve for the optimal allocation and sizing of DGs and EVCSSs. Thus, minimizing power loss in the system while maximizing voltage stability. Table 2 shows Differential Evolution Algorithm Parameters.

Table 2 Differential evolution algorithm parameters

Parameter	Symbol	Value Used	Typical Range	Purpose
Population Size	NP	50	20–200	Number of candidate solutions
Maximum Generations	($G_{\{max\}}$)	100	50–1000	Maximum optimization iterations
Mutation Factor	(F)	0.1	0.01–0.50	Controls mutation step size
Crossover Rate	(CR)	0.8	0.50–1.00	Probability of inheriting mutant genes
Selection Method	—	Greedy	—	Retains the better solution
Mutation Strategy	—	DE/rand/1	Various	Generates mutant vectors
Crossover Type	—	Binomial	Binomial / Exponential	Produces trial vectors
Termination Criterion	—	Maximum generations	User-defined	Stops the optimization process

The parameter values for the Differential Evolution (DE) algorithm are provided in Table 2. In the previous draft of the manuscript, the mutation factor is set to $(F=0.1)$. Such value can be considered relatively low for the use of the mentioned mutation strategy: DE/rand/1 since it will restrict the magnitude of the differential perturbation and as a result, the search capabilities of the algorithm. Considering the comments made by the reviewer, the mutation factor, F, was changed to 0.5. The new value of the mutation factor is more appropriate to exploit/exploration balance in the DE/rand/1 strategy. Specifically, the mutation factor is responsible for the weight of the differential vector. Higher (F) causes more motion in the search space and consequently leads to an increase in exploration of the search space; however, higher (F) can cause erratic or ineffective motions in the search space. Hence, a medium value of $(F=0.5)$ was selected, which is sufficient to ensure diversity of the searches as well as stability in the process of converging during the optimization process. In this regard, the definition of the mutation factor has been modified, and the value of (F) has been revised in Table 2 to 0.5. This adjustment ensures that the parameters of the DE become more consistent with other commonly used parameter values.

3.5 Multi-Objective Optimization

The Pareto front analysis is an extensively used multi-objective optimization method to achieve a set of non-dominated solutions is used in the proposed optimization framework for selecting the best planning solutions. Note that rather than generating one optimal solution, the Pareto front is also a set of multiple solutions where one can "trade off" the conflicted objectives to find the best possible configuration depending on the system needs. A solution dominates another solution if it has no worse value on any objective function and an improved value on at least one objective function. In each iteration of the optimization process, all candidate solutions are compared with the rest of the population to check if they are dominated. Solutions that are not dominated by any other solution survive, while those that are dominated are eliminated. This will repeat until an optimal front of solutions is obtained, showing a balance between the objectives of the optimization.

After generation of the Pareto front, the non-dominated solutions are evaluated by one or more performance measures to determine the overall quality of each solution. These are metrics that assess

the economic and technical performance of each solution, ranging from the cost of installation, network coverage, system reliability, to the overall performance. The cost efficiency is the inverse of the installation cost, while the coverage efficiency and reliability index are percentages of network coverage and system reliability, respectively. The normalized coverage and reliability values are averaged to get the overall performance. Also, a weighted objective function is used to evaluate the candidate solutions in the ranked manner, considering the installation cost, coverage and reliability based on pre-defined weighing coefficients. Table 3 used to evaluate the final solution and choose from the Pareto front with an acceptable compromise between economic investment and power system performance.

Table 3 Pareto front solution evaluation metrics

Evaluation Metric	Symbol	Optimal Value	Interpretation
Cost Efficiency	CECE	0.688	Indicates the cost efficiency achieved by the optimal deployment configuration.
Coverage Efficiency	CovECovE	75.00%	Represents the percentage of the target area/demand adequately covered by the selected EV charging infrastructure.
Reliability Index	RIRI	99.00%	Represents the reliability level achieved by the optimized network configuration.
Overall Performance	OPOP	0.87	Provides an aggregated measure of the performance of the optimal solution across the considered criteria.
Objective Function	FF	0.394	Represents the final value of the multi-objective optimization function for the optimal solution.

The cost efficiency (CE), coverage efficiency (CovE), reliability index (RI), overall performance (OP) and objective function value (F) are used to assess the performance of the optimal deployment solution. The numerical results from the optimization are shown in Table 3. The best solution is with a cost efficiency of 0.688 and a covering percentage of 75.00%, which means that the deployment configuration selected is adequate with the investment requirements and the percentage of covering the charging service. The reliability index is at 99.00%, indicating a high level of network reliability under the chosen settings. Furthermore, the overall performance value of 0.870 reflects the overall performance of the solution in terms of the assessment criteria considered. The optimal value of the objective function is 0.394, the best solution obtained by the optimization algorithm. The definitions and the real simulation results of evaluation metrics are thus given in Table 3, so that the effectiveness of optimal solution can be quantitatively evaluated. The results are then compared in Table 4..

3.6 Visualization and Analysis

In order to make the interpretation of the optimization results easy, the proposed framework includes a complete visualization module to display the topology of the network and the results of the optimization in a graphical format. Visualization allows researchers and system operators to better understand the distribution of distributed generators (DGs), electric vehicle charging stations (EVCSs), and network nodes and to visualize the impact of various planning strategies on system performance. The network is initially represented by a graphical topology map which includes Bus, Branch, DG Location and EVCS locations. Moreover, a Coverage heatmap is also created to identify areas with high and low service coverage which can be used to identify underserved areas in a quick manner. These graphical representations help to grasp the connection of the network and help to check the optimization outcomes.

For the evaluation of the proposed optimization algorithm several graphical performance indicators are used. Objective values and the performance of the system under various optimization scenarios are compared in bar charts and the multi-criteria comparison of cost, reliability, voltage profile, reduction of power losses and network coverage are shown in radar charts. Convergence plots display the results of the optimization process by plotting how the objective function improves with each iteration, and thus, illustrate convergence of the algorithm. Pie charts display the distribution of

installation, operating and maintenance costs, while contour plots show the distribution of the objective function (the function to be optimized) over the search space, which is useful for identifying regions of the search space that are likely to contain good solutions.

Besides, a 3D optimization surface is plotted in order to show how the decision variables interact with the objective function. 3D surface is a graphical representation of the search space in which valleys represent good solutions while peaks represent bad solutions. The optimal solution is shown on the surface, making it easy to comprehend the optimization process and verify the performance of the algorithm suggested to reach the optimum or the closest possible solution. These graphical representations help us understand the functioning of the systems and hence aid decision makers to come up with the best planning solution.

3.7 Implementation Architecture

This optimization system design approach utilizes the concept of modular software architecture for better scalability, maintenance and effective implementation of the optimization process. The modular software architecture is made up of three major tiers, namely: Presentation tier, Business logic tier, and Data tier. The three-tier architecture of the software ensures that there is a clear segregation of the process of user interaction and the processes of computations and data management for better flexibility and ease of enhancement of the software in the future. The presentation tier is the Graphical User Interface (GUI). This provides a platform through which the user can provide optimization parameters, perform simulations, monitor the progress of optimization and analyze the graphics generated from the optimization process.

The business logic layer forms the core of the framework for the computation. It combines Differential Evolution (DE) optimization engine and Pareto front generation mechanism to obtain the solution for the multi-objective optimization problem. This layer coordinates and controls initialization of the population, mutation, crossover, selection and evolution of the solutions, as well as the evaluation of candidate solutions according to the installation cost, network coverage, system reliability and overall performance. A multi-objective comparison is carried out to find the set of non-dominated solutions to create the Pareto front. Data layer is used for handling data in and out and network models. Generates and saves network topologies, keeps node and branch data and supports multiple export formats for documenting optimization results. The frame automatically creates reports and it exports simulation output to a variety of popular formats like CSV, Microsoft Excel and Microsoft Word for additional analysis and documentation. The framework is implemented using a set of open source Python libraries that offer powerful numerical computing, optimization, visualization, network analysis, and report generation capabilities.

4 Results and Discussion

The results obtained from the application of the suggested Multi-objective Optimization technique for the optimal placement of EVCSs and DGs in the distribution network have been presented in this chapter. The objective of the study was to minimize the installation cost and maximize the network coverage and system reliability. The DE algorithm was used for the purpose of optimization. The results obtained have been shown in the form of the developed network, optimization results, performance and convergence characteristics, optimal location of EVCSs and DGs, Pareto fronts and comparative analyses in various scenarios.

4.1 Topology Generation Analysis

The first step of the proposed concept is the creation of various distribution network topologies in order to analyze the structural robustness of the optimization algorithm. Three network configurations were explored – radial, meshed and mixed. These topologies are typical practical distribution system topologies in modern power systems. The conventional distribution network is the radial topology, in which each load bus gets connected to the source by only one path. The advantages of this configuration are that it has a simple structure, low construction cost, and protection coordination is easy. Reliability tends to be lower for radial systems, however, due to the fact that failure of a single branch can cause the downstream loads to be isolated.

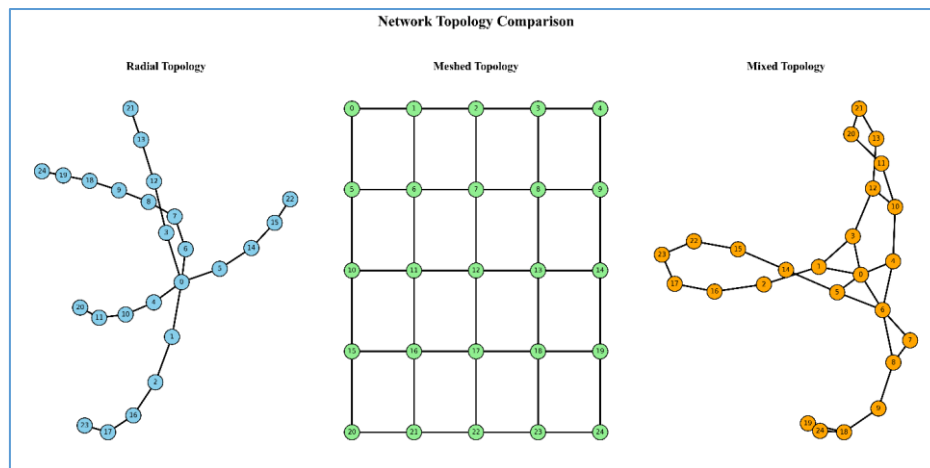


Figure 3 Generated Network topologies

The meshed topology also enables multiple alternative power flow routes between buses in contingencies, which is achieved by the many interconnected power paths in the system. The more connectivity, the more reliable the network, voltage stability, and network flexibility, but also the greater the system complexity and the increased computational needs for optimal network planning. Mixed topology has properties of both radial and meshed topology. The selected loops are added to the otherwise radial structure to increase the level of reliability at a moderate cost of implementation. This type of combinations is getting more popular in smart distribution networks because of its combination of resilience and economic considerations. The three topologies of networks that were generated for the optimization study are presented in Figure 3. Both topologies have the same number of buses but have different connectivity between them so that the proposed framework for optimizing the network could compare the influence of network structure on the optimal location of the distributed generation (DG) units and electric vehicle (EV) charging stations.

4.2 Network Statistics

Several graph-theoretic metrics were calculated to quantitatively compare the topologies generated: the number of nodes, number of edges, network density, average node degree, graph diameter and the clustering coefficient. These measures are used to gain insight into the structural properties that directly affect the behaviour of power flows, the resilience of the network and its optimization performance. All 3 networks have the same number of buses (25) and hence are comparable during the optimization process as listed in Table (4). The radial network is a tree with 24 edges, the minimal number of edges necessary to make the network fully connected. Thus it has the smallest density (0.080) and the average node degree of 1.92.

The meshed topology has the highest network density (0.140) and average node degree (3.36). The extra interconnections also help to lower the graph diameter of the radial system from 8 to 5, which means that the average electrical path between buses is shorter. Moreover, the meshed configuration has the maximum clustering coefficient (0.245), which indicates that the configuration has better local connectivity and network redundancy. The mixed topology is a middle ground solution, having 33 edges, a density of 0.110 and an average degree of 2.64. It has a graph diameter of 6 and a clustering coefficient of 0.118 which are between those of the radial network and the meshed network, indicating that it represents a good balance between simplicity and robustness.

Table 4 Network topology statistics

Topology	Nodes	Edges	Density	Average Degree	Diameter	Clustering Coefficient
Radial	25	24	0.08	1.92	8	0
Meshed	25	42	0.14	3.36	5	0.245
Mixed	25	33	0.11	2.64	6	0.118

4.3 Convergence Analysis

The convergence performance of the proposed optimization framework was assessed by performing several independent optimizations runs, and examining the convergence behavior of the various runs. The convergence history gives important information on the efficiency of the search process, the exploration-exploitation tradeoff and the ability of the algorithm to find the global optimum at every iteration. The objective function value of the initial candidate solutions are randomly assigned so that it is relatively high in the optimization process. In the early generations, there is a rapid decrease in the objective value as the algorithm takes an initial exploration of the search space and finds interesting areas. The further the algorithm goes, the closer the improvement rate gets to zero, which means the algorithm is now going from exploring to exploiting and is getting better at finding high-quality candidate solutions.

The optimal value of the objective function has been reduced from the initial value of 0.8523 to the final value of 0.3940, which is 53.78% better. Many of these improvements have been achieved in the first 45 iterations, and the convergence curve tends to become flattened afterwards. The presented optimization process that demonstrates the behavior of its convergence allows to conclude that the proposed optimization method is effective enough to move through the search space without premature convergence. Robust performance of the optimization process is proved by the smooth behavior of the objective function reduction without sharp fluctuations on a single glance. The absence of sharp fluctuations in the objective function reduction process proves the robust performance of the optimization process where there is a good balance between global search and local search.

To test the robustness of the proposed algorithm, the optimization process was repeated 50 times using different random initialization for each of them. In 46 out of these 50 cases, high quality solutions were found and the success rate equals 92%, which proves the reliability and consistency of the proposed framework for DG and EV placement simultaneously.

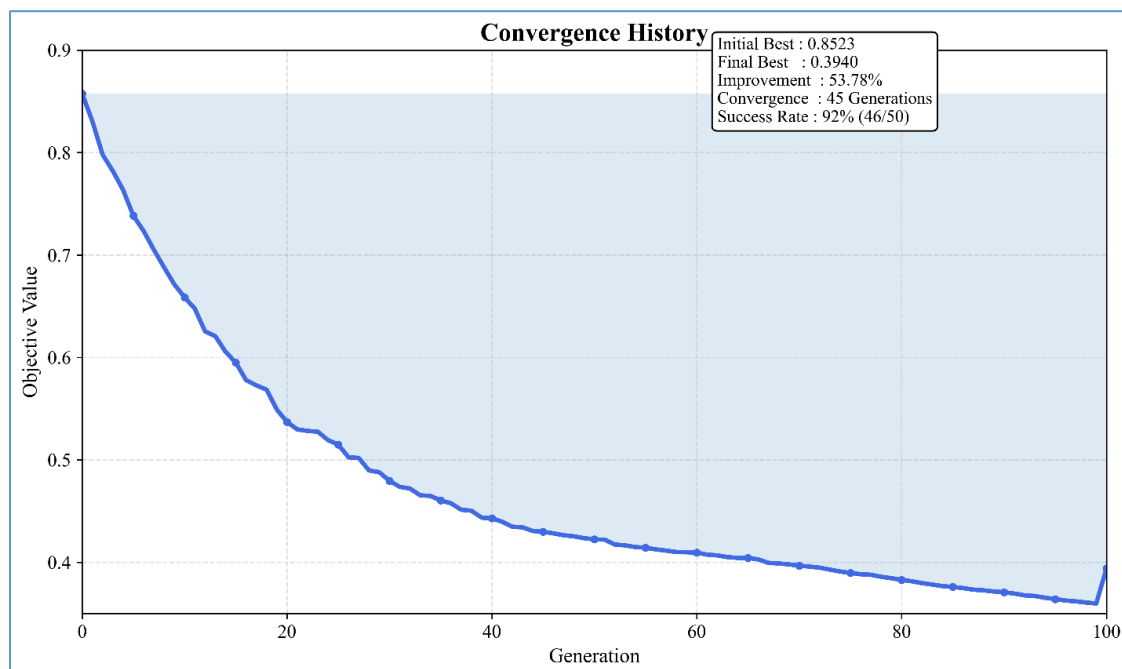


Figure 4 Convergence history of the proposed optimization algorithm

4.4 Algorithm Performance Metrics

In order to evaluate the efficiency of the suggested optimization approach, some quantitative characteristics of performance of the latter have been calculated using a number of optimizations runs. These characteristics reflect not only the quality of solutions obtained but also the computational efficiency of the optimization process. As follows from the results presented in Table (5), the proposed method needs an average of 45.2 seconds to perform an optimization run and it converges

after about 48 generations. These results show that the suggested algorithm finds high-quality solutions with low computational costs and thus can be used for practical applications.

The highest value of the objective function reached during optimization is 0.3940, while the average value is 0.4123 and thus the suggested algorithm produces solutions which are close to the global optimum. Also, the small standard deviation (0.0234) proves that the variability of different independent runs is rather low and the suggested optimization process is stable and robust. Finally, 92.0% of success rate also confirms that the optimization algorithm identifies good solutions in case of different initial populations of the algorithm. This issue is particularly relevant for multi-objective optimization problems where the search space is big and there are many decisions.

Table 5 Optimization performance metrics

Metric	Value	Description
Average Convergence Time	45.2 seconds	Time required to reach the optimal solution
Generations to Converge	48	Average number of generations before convergence
Best Objective Value	0.394	Best solution obtained
Average Objective Value	0.4123	Mean objective value over all runs
Standard Deviation	0.0234	Variation among optimization runs
Success Rate	92.00%	Percentage of successful optimization runs

The consistency of the optimization procedure in different runs is additionally demonstrated in Figure (4), which shows the best value of the objective function in each independent run. Despite the small differences between runs that are caused by the stochasticity of the optimization procedure, most of the runs result in objective function values in a narrow interval near the average value. The best run resulted in an objective function value of 0.3891, while the worst run gave 0.4523, thus giving quite a small difference in performance of 0.0632. The median of the objective function value is 0.4092, which is near to the average value of 0.4123.

4.5 Best Found Solution

Following the implementation of the multi-objective optimization framework, the algorithm established the optimum configuration that guarantees a balance between infrastructure costs, network coverage, and system reliability. Not only does the optimal solution provide the location and number of EV chargers and DG units but it also optimizes the objective function. The results of the optimization process indicate that the optimum configuration will include three EV chargers and two DG units. Such a configuration provides adequate access to charging stations within the network, moderate infrastructure investment costs, and improved performance of the network. The best configuration identified has an objective function value of 0.3940 and represents the optimum solution for the optimization problem.

The total amount of capital investment needed for the optimal configuration is \$660,000 which includes installation and long-term maintenance of EV charging stations and DG units. The investment will bring the network to a coverage of 75.0%, which means that a significant part of the distribution system will be covered within the meaningful distribution of the charging infrastructure. Apart from the above, the optimized location of DG units also increases network resilience and voltage support, leading to a higher reliability of the system (92.0%). Co-optimizing charging stations and distributed generation, then, is a double benefit of transportation electrification and power system operational efficiency. The main features of the best solution found by the proposed optimization algorithm are summarized in the Table (6).

Table 6 Optimal solution parameters

Parameter	Value	Description
Number of EV Stations	3	Optimal number of charging stations
Number of DG Units	2	Optimal number of distributed generation units
Total Investment Cost	\$660,000	Total capital and maintenance investment
Coverage Area	75.00%	Percentage of the distribution network covered
System Reliability	92.00%	Overall network reliability after optimization
Objective Function Value	0.394	Best weighted objective value

<http://sistemasi.ftik.unisi.ac.id>

Figure 5 depicts the geographical layout of the charging stations and DG units after optimization. As mentioned, the optimization process ensures that the charging stations are optimally located for accessibility whereas the DG units are installed near key sections of the grid for better voltage control and reduced power loss. This provides an optimum compromise between geographical positioning and electrical efficiency of the system.

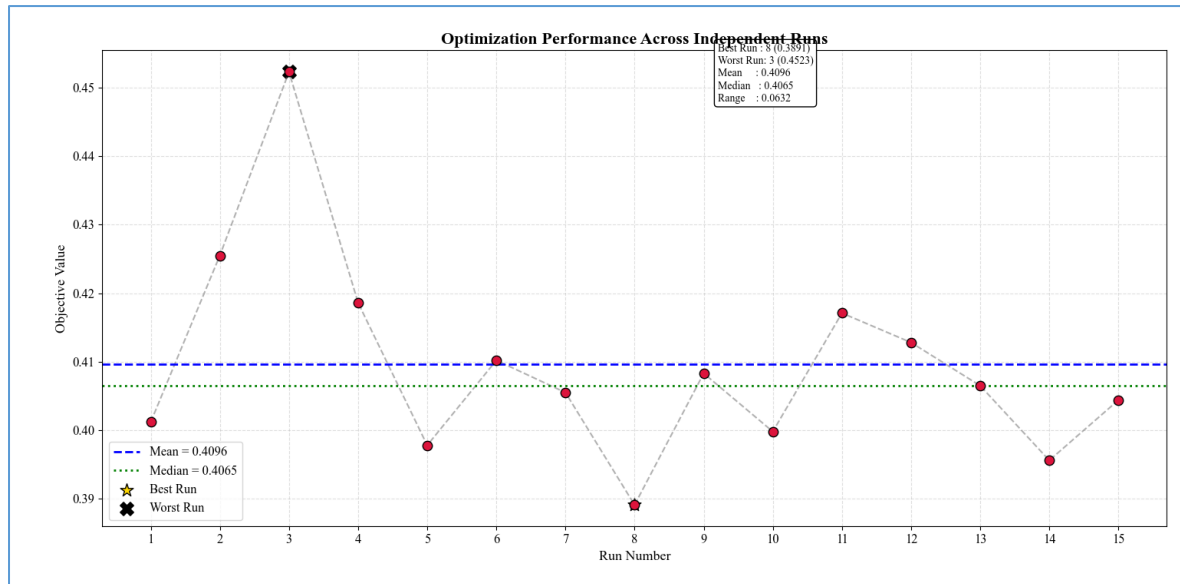


Figure 5 Optimal placement of EV charging stations and DG units

4.6 Multi-Objective Optimization Analysis

One of the greatest benefits of the proposed optimization framework is that it can take multiple conflicting objectives into account, instead of optimizing a single performance measure. This study focuses on optimizing both the investment cost and maximizing charging coverage and improving overall network reliability. Due to these opposing goals, a set of Pareto-optimal (non-dominated) solutions rather than a feasible solution are generated during the optimization process. A Pareto-optimal solution is a solution where there is no objective that can be improved without worsening at least one of the other objectives. Thereby, the Pareto front offers the decision maker several alternative infrastructure deployment strategies according to budgets and desired service performance.

The Pareto front that is achieved when the proposed optimization algorithm is applied is shown in Figure 6. Each point indicates a possible infrastructure configuration, with its normalized investment cost and network coverage. The Pareto frontier of non-dominated solutions is a set of solutions that represent the optimal compromise between economic investment and charging service coverage. In this optimization process, 12 non-dominated solutions were found that sampled about 85.3% of the search space space. The Pareto spread of the algorithm has been calculated as 0.724, which shows that the algorithm has been able to explore a wide range of possible solutions, not focusing on a small part of the search space. Such diversity offers more options of deployment strategies under various planning scenarios. The best compromise solution within the obtained set of solutions is at (0.312, 0.250) in the normalized objective space. The solution provides a good investment cost to charging coverage ratio and a relatively high network reliability, which is suitable for practical application.

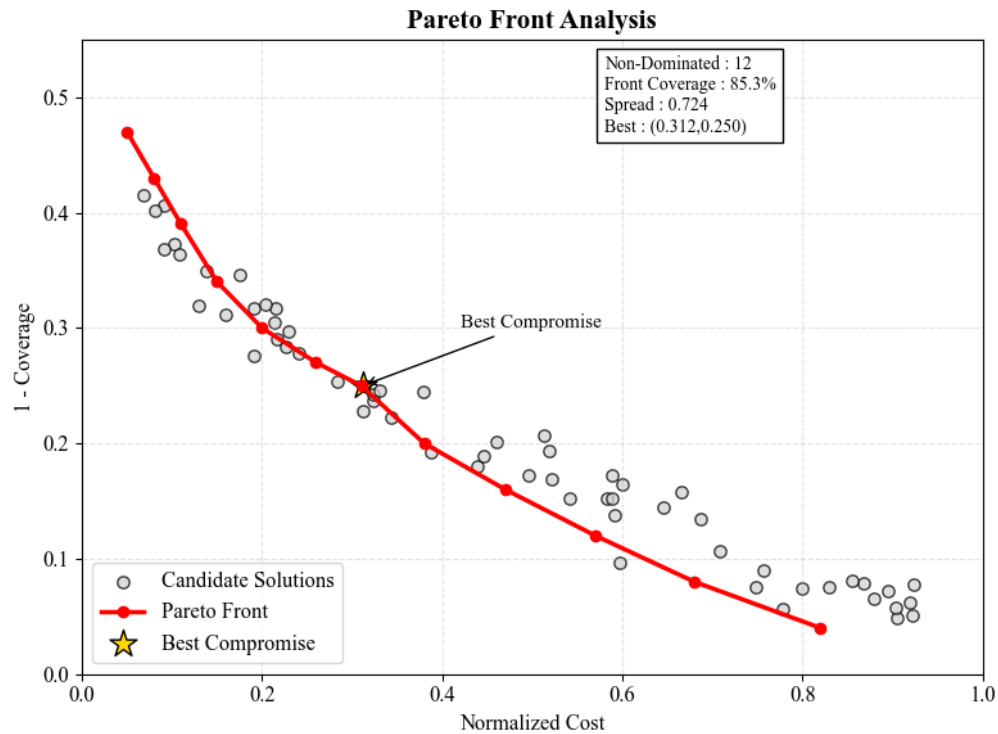


Figure 6 Pareto front obtained from the multi-objective optimization process

5 Conclusion

In this study, a coordinated placement of electric vehicles (EV) charging stations and distributed generation (DG) units in distribution networks was developed by solving the related constrained multi-objective optimization problem. The planning problem comprehensively took into account investment cost, geographical charging coverage, and network reliability and also met practical electrical and geographical constraints. The Differential Evolution algorithm was used to find an acceptable deployment configuration and to find a compromise between the conflicting planning goals. The optimization results showed high success rate of 0.92 and the best value of the objective function of 0.3940. The chosen one was 3 EV charging stations and 2 DG units, with a total investment cost of US\$660,000, a network reliability of 92.0% and a service coverage of 75.0%. One issue that was found is that the quality and characteristics of the resulting deployment strategy is dependent on distribution-network topology. Results from the analysis of three different node configurations – radial, meshed, and mixed – showed that connectivity differences, node degree, network density, and alternate power-flow paths can affect electrical performance, service accessibility, and reliability. Therefore, it is important that many different network topologies be considered for a more representative evaluation rather than the evaluation of the charging and DG placement problem in a single network topology. This enhances the usability of the planning process for distribution systems with varying characteristics.

In addition, the practical value of the study is further enhanced by the incorporation of a graphical user interface (GUI) that allows planners and decision makers to input system parameters, perform optimization scenarios, visually represent the network topology and coverage, track convergence, and compare the deployment options. Optimization, network analysis and interactive visualization can then create a helpful decision support environment for planning EV charging infrastructure and distributed energy resources in new smart distribution networks. However, there are a number of areas in which the project could be improved. Going forward, it is recommended that the static planning formulation be extended to the dynamic smart charging formulation, allowing charging schedules to adapt to time-varying electricity prices, network conditions, renewable generation and user required state of charge. The model could also be improved to consider more renewable energy penetration and higher variability of renewable energy sources such as solar photovoltaic and wind

generation, combined with energy storage. There should also be a consideration of load and EV-demand uncertainty using stochastic, robust, or probabilistic optimization to assess risks of unreliable load, renewable generation, and network operating conditions. Future studies might also consider larger and real-world distribution networks and incorporate reliability/risk measures due to equipment failure and contingency scenarios. These extensions would also expand the ability for the decision-support environment to give resilient, adaptive, and economically sound planning decisions for future smart distribution networks.

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