

ORIGINAL RESEARCH

Open access

A Two-Stage Optimization Framework for EV Charging Deployment in Urban Distribution Networks

Noah Clark^{1*}, Amelia Green², Ethan Brooks¹

Abstract

This paper presents a two-stage approach that leverages energy savings from optimal network reconductoring to determine the appropriate sizing and placement of electric vehicle (EV) charging loads in residential areas of urban distribution networks. In the initial stage, the Flower Pollination Algorithm (FPA) was used to reduce annual energy losses in the radial distribution system through optimal reconductoring. A multi-objective function was created to simultaneously minimize the investment cost, peak power loss, and annual energy loss cost across various load factors. Outcomes from the flower pollination algorithm were benchmarked against those from the particle swarm optimization algorithm. In the subsequent stage, a straightforward heuristic was introduced to allocate and size the EV charging demand at each node, using a share of the annual energy savings realized from the optimal reconductoring. The quantity of electric cars, electric bikes, and electric scooters that could be supported at individual nodes was calculated without violating voltage or branch current limits. The proposed method was tested through simulations on the 123-bus and 51-bus radial distribution networks to confirm its validity and performance.

Keywords Electric vehicles, Flower pollination algorithm, Radial distribution system, Particle swarm optimization, Reconductoring

*Correspondence:

Noah Clark
noah.clark@imperial.ac.uk

¹ Department of Intelligent Grid Systems, Faculty of Engineering, Imperial College London, London, United Kingdom

² Department of Energy Analytics and AI, Faculty of Engineering, University College London, London, United Kingdom

Introduction

Electric vehicles (EVs) are steadily integrating into urban distribution systems to address the worldwide energy shortage resulting from dwindling fossil fuel reserves and to reduce overall pollution. Random, uncoordinated charging of EVs at residential parking facilities can overload distribution feeders and transformers, leading to poorer voltage conditions across the network. To address these challenges, multiple techniques have been explored for effectively managing EV charging demand in residential settings.

Network reconductoring is the process of selecting the most suitable conductor sizes for the different branches in a radial distribution system to reduce both costs and energy losses. The resulting efficiency gains from reconductoring enable utilities to handle additional EV loads without compromising system performance. A wide range of approaches for reconductoring radial distribution networks has been reported in the literature. Wang *et al.* [1] introduced a heuristic index that accounts for non-uniform loading patterns in reconductoring decisions. Mandal and Pahwa [2] proposed a conductor selection strategy based on defined load ranges, accounting for various technical and economic considerations. Ranjan *et al.* [3] outlined an evolutionary programming technique to identify optimal conductors by balancing annualized loss costs with capital expenditure. Satyanarayana *et al.* [4] put forward a basic heuristic to enhance the current-carrying

capability of distribution networks. Kaur and Sharma [5] developed an algorithm for conductor optimization that incorporates energy and power costs, anticipated load growth, and load factor. Rao et al. [6] applied a harmony search algorithm to achieve optimal conductor sizing. Franco et al. [7] formulated a mixed-integer linear programming model for reconductoring radial distribution systems. Abul'Wafa [8] described a sequential procedure for selecting optimal conductors in distribution networks. Samal et al. [9] presented a differential evolution planning framework for simultaneous capacitor placement and conductor sizing in unbalanced radial systems. Abdelaziz and Fathy [10] employed a crow search algorithm, while Ismael et al. [11] utilized the Salp Swarm Optimization (SSO) algorithm for conductor selection. Gampa et al. [12] introduced a Pareto-based FPA method for reconductoring distribution networks that include solar photovoltaic generation. Burgio et al. [13] proposed a heuristic method for sizing residential photovoltaic battery systems in distribution networks to deliver grid-support services. In the present study, the Flower Pollination Algorithm (FPA) was chosen for network reconfiguration due to its superior convergence characteristics and ability to consistently reach the global optimum, compared with widely used swarm and population-based methods such as PSO and the genetic algorithm (GA).

Developing a precise model of EV load is essential when evaluating how EV charging affects the distribution network. The effects of growing EV adoption on distribution systems have been extensively examined in the literature. Garcia and Vlachogiannis [14] developed PQ models of EV charging demand suitable for load-flow analysis, with charging time modeled using queuing theory. Shireen and Patel [15] examined the influence of EV chargers on distribution networks and recommended several mitigation strategies. Van den Berg et al. [16] introduced a method to forecast charging needs for future EV fleets in office environments and to evaluate the associated demand flexibility. Brinkel et al. [17] proposed a strategy to alleviate congestion in low-voltage grids by using shared electric vehicles. Iria et al. [18] and Nick et al. [19, 20] advocated the deployment of energy storage, network reconfiguration, and voltage regulation devices to alleviate congestion caused by EVs in distribution systems. Marra et al. [21] investigated the behavior of the demand profile under various EV battery charging scenarios. Guo et al. [22] assessed the consequences of high EV penetration levels on power grids. Zhang et al. [23] formulated EV charging load models incorporating customer demographics, travel likelihoods, charging habits, and energy usage rates. Hecht et al. [24] evaluated the need for different charger types based on vehicle parking duration at charging facilities.

The rapid increase in EVs produced by different manufacturers compels utility companies to identify the best sites for installing charging infrastructure. Extensive research has already been conducted on determining suitable locations for EV charging stations. Sachan and Kishor [25] calculated voltage-sensitivity indices using the inverse Jacobian matrix obtained from the Newton–Raphson load flow method to pinpoint optimal locations for EV charging. Gampa et al. [26] introduced a grasshopper optimization algorithm that employs a two-stage fuzzy multi-objective framework for the optimal placement of EVs, Distributed Generators (DGs), and Shunt Capacitors (SCs). Luo et al. [27] formulated an elaborate model to optimize the allocation of DGs and EV charging stations to minimize annualized costs. Li et al. [28] adopted a chance-constrained programming approach to schedule charging and discharging activities at an EV charging station. Bayram et al. [29] presented a probabilistic planning strategy for handling peak loads in distribution networks that include PEV charging facilities by optimally positioning energy storage systems. Fan et al. [30] designed a multi-objective mixed-integer nonlinear programming structure for distribution system expansion planning that accounts for the stochastic behavior of renewable energy sources and electric vehicles. Mehrjerdi and Hemmati [31] developed a stochastic approach for electric vehicle charging stations that are coupled with energy storage systems and wind power generation. Rahmani et al. [32] investigated planning and operational issues related to EV parking lots while incorporating traffic flow and driver behavior models. Parastvand et al. [33] proposed a graph-theory-based technique for positioning and sizing EV charging stations, accounting for traffic conditions to control vehicle waiting times at the stations. Suresh et al. [34] developed a hybrid optimization tool based on ant colony optimization to determine the placement of EV charging stations within a microgrid. Richardson et al. [35] evaluated how locally controlled versus centrally controlled EV battery charging strategies influence low-voltage distribution networks. Fachrizal and Munkhammar [36] proposed both distributed and centralized intelligent charging methods for EVs located in residential buildings to reduce net load variations by leveraging photovoltaic power generation.

Reducing the negative effects of EVs on the distribution network calls for robust load management strategies. Techniques for managing and scheduling EV loads have received considerable coverage in published studies. Coffman *et al.* [37] examined how residential solar PV systems can supply power for electric vehicle charging while simultaneously cutting greenhouse gas emissions. Khalkhali [38] proposed a stochastic mixed-integer linear programming model to harness EVs parked in residential areas to support regulatory objectives. Ayyadi *et al.* [39] introduced a linear programming method to reduce EV charging costs while accounting for uncertainties in arrival and departure schedules. Gong and Ionel [40] advocated deploying energy storage systems powered by rooftop PVs in smart homes to balance EV demand during evening peak periods. Ahmadi *et al.* [41] applied the JAYA algorithm to schedule EV charging and discharging operations to minimize daily load fluctuations. Limmer and Rodemann [42] developed a scheduling model for EV charging that leverages time-varying price signals to reduce peak demand and improve the financial performance of charging stations. Haes Alhelou *et al.* [43] presented an innovative mixed-complementary programming technique for determining the optimal generation mix while accounting for demand response programs, energy storage systems, and electric vehicles. Progress in Lithium-ion battery technology has been documented by Wang *et al.* [44], Yasin *et al.* [45], and Mehtab *et al.* [46]. Hou *et al.* [47] proposed a scrapping rule based on battery efficiency to prolong battery life and enhance peak shaving and demand response capabilities. Dixon and Bell [48] discussed the consequences of EVs on distribution systems by considering charger capacities along with demographic details of vehicle owners. Das *et al.* [49] delivered a detailed overview of the current EV landscape and stressed the need for more sophisticated charging infrastructure to maximize the combined benefits of EVs and DGs.

From the literature review outlined so far, it is evident that the bulk of existing studies on integrating EVs with the power grid have primarily addressed optimal location and capacity planning for EV charging stations, as well as various load management approaches. The growing adoption of EVs will necessitate major reinforcements to distribution system components such as overhead lines and distribution transformers. Because most users charge their vehicles at home overnight, it is crucial to determine the maximum EV charging demand that residential areas can safely handle. However, relatively few studies have explored economical upgrades to the distribution network specifically designed to support the expected large-scale arrival of EVs. The present work seeks to bridge this gap in the literature by implementing optimal network reconductoring and strategically allocating EV charging loads at residential sites, capitalizing on the energy savings from the network enhancement.

Several researchers have proposed optimal charging rates for EV batteries based on state of charge, availability of residential parking spots, and prevailing network conditions, using both local and centralized charging control methods. The primary drawback of these methods is that they depend on a reliable communication infrastructure and involve varying charging rates, which tend to reduce battery lifespan [35]. In recent years, numerous studies have introduced approaches that rely on rooftop photovoltaic (PV) systems to manage EV loads. Nevertheless, solar PV generation is unavailable during early morning and nighttime hours and remains unpredictable during rainy and winter periods. The mismatch between PV output and EV charging patterns across seasons necessitates the use of costly battery energy storage systems. In addition, the variability inherent in renewable energy sources may fail to meet home charging needs consistently throughout the year. Since most customers are away from home during midday, when solar generation peaks, they are largely limited to charging EVs only on weekends [27, 37]. For residential users who arrive home in the evening, it proves more practical to charge their vehicles directly from standard power outlets, as maintaining extra backup EV batteries is not cost-effective. Moreover, wind power is typically fed into the transmission network, with very limited opportunities for integration into urban distribution systems [50, 51]. Smart grid features such as demand response programs primarily benefit users who can flexibly adjust their consumption in response to utility-set electricity prices [52]. Although voltage regulators can help raise voltage levels, they do not provide a long-term solution. Because EV charging is most beneficial during off-peak periods and battery energy storage systems (BESS) remain expensive for individual households, utility providers must be prepared to deliver the necessary EV charging power. When renewable energy sources combined with smart grid solutions prove inadequate to handle high levels of EV penetration, distribution networks need to be strengthened through measures like network reconductoring to deliver power from substations while respecting all technical limits. Optimal network reconductoring not only boosts the current-carrying capacity of lines but

also reduces real power losses and yields notable energy savings, particularly during peak demand periods. The energy savings achieved during peak times can then be effectively redirected to support EV charging during off-peak hours.

Given the limitations of EV load management strategies that rely on PV systems and energy storage, this paper introduces a two-stage design framework for the optimal allocation of EV loads at individual nodes in residential distribution networks. In the first stage, optimal reconductoring of the radial distribution network is performed using the Flower Pollination Algorithm (FPA). In the second stage, a straightforward heuristic design approach is proposed to determine the maximum allowable EV load at each node by leveraging the energy savings from optimal network reconductoring. In this study, the additional EV load is assumed to be supplied directly from the utility grid to the upgraded distribution network, with EV charging occurring during both evening peak and off-peak hours. Additionally, the potential role of PV systems in improving distribution system performance during peak periods was examined. The main contributions of this study can be summarized as:

- The Flower Pollination Algorithm (FPA) was employed to reconstruct the distribution network while ensuring compliance with voltage and current limits.
- A heuristic-based methodology was created to assign EV charging loads at every node in a residential distribution network without breaching any operational constraints.
- The performance of the suggested algorithms was validated through multiple case studies conducted on the 51-bus and 123-bus test systems.
- The approach developed in this work serves as a useful resource for power engineers involved in distribution utility operations to manage EV charging load allocation efficiently.

Problem Formulation

In recent years, the Flower Pollination Algorithm (FPA) has demonstrated strong performance in addressing various power system optimization challenges, owing to its superior convergence speed compared to other metaheuristic methods, such as GA and PSO, particularly when dealing with a large number of optimization variables [53]. The quantity of branches involved in optimal reconductoring grows with the scale of the distribution system and requires evaluation across a wider range of conductor options. Furthermore, several researchers have successfully used FPA to address various power and energy-related issues [12, 54]. Therefore, this study first develops an FPA-based technique for optimal reconductoring of radial distribution networks. In the subsequent stage, a simple heuristic design procedure is formulated to allocate EV loads at residential sites, leveraging the energy savings achieved through network reconductoring. The objective of network reconductoring is to minimize annual energy losses across varying load factors, reduce conductor investment costs, and lower the cost of peak load losses.

Objective Function

The objective function for the reconductoring task in radial distribution networks was formulated to account for upfront capital expenditure on new conductors, annual expenses associated with energy losses across multiple load factors, and the financial impact of peak load losses. This total cost objective function (J_F) can be written in mathematical form as follows:

$$J_F = \gamma \sum_{l=1}^{NB} C_l L_l + K_e \sum_{LF=1}^3 \sum_{j=1}^{NB} I_{j,LF}^2 R_j T_{LF} + K_P RPL_{peak} \quad (1)$$

Where γ denotes the annual interest and depreciation rate, C_i is the per-unit cost of the conductor installed in the i th branch, L_i denotes the length of branch i in km, and K_e represents the unit cost of energy losses in Rs./kWh , $I_{j,LF}$ refers to the current flowing in branch j corresponding to load factor LF , R_j is the resistance value of the j th branch, TLF denotes the total annual hours at load factor LF , KP is the cost per unit of peak losses in Rs./kW , and RPL_{peak} corresponds to the peak load level in the original base case configuration.

Voltage and current constraints

The constraints on bus voltages and branch current capacities in the suggested method are defined by the following set of equations.

The voltage limit at each bus is stated as

$$V_{min} \leq |V_b| \leq V_{max} \quad (2)$$

Where V_{min} and V_{max} define the lower and upper permissible voltage boundaries, and $|V_b|$ signifies the voltage magnitude measured at node ' b '. For the present analysis, the limits were fixed at $V_{min} = 0.95$ pu and $V_{max} = 1.05$ pu.

The current in every branch must stay within the maximum current-carrying rating of the conductor type assigned to that branch. This requirement is formulated as

$$I_{jk} \leq I_{max,k} \quad (3)$$

Where I_{jk} denotes the current in branch j when conductor type k is selected, and $I_{max,k}$ gives the highest allowable current for conductor type k .

FPA for Network Reconductoring

The flower pollination algorithm [53] is a nature-inspired metaheuristic technique. At its essence, a flower exists to propagate its species by means of pollination, which involves moving pollen grains between different locations with the support of pollinating agents.

Two fundamental categories of pollination exist: biotic (cross-pollination) and abiotic (self-pollination). Biotic pollination depends on living agents such as birds, insects, and other animals that frequently cover substantial distances; their movements can be effectively replicated using Levy flight patterns. Abiotic pollination, by comparison, operates independently of any external agents and can be described mathematically via the Levy distribution function given below.

$$x_i^{t+1} = x_i^t + \gamma L(\lambda) (g_{best} - x_i^t) \quad (4)$$

Where x_i^t represents the vector of conductor type decisions for the branches at iteration t , γL serves as a parameter that adjusts the step size, g_{best} indicates the best-known solution found up to the current generation, and (λ) expresses the pollination intensity, which is sampled randomly from a Levy distribution.

$$L(\lambda) \sim \frac{\lambda \Gamma(\lambda) \sin\left(\frac{\pi\lambda}{2}\right)}{\pi s^{\lambda+1}} \quad (5)$$

Where the parameter λ is fixed at 1.5 to promote faster and more stable convergence; $\Gamma(\lambda)$ denotes the conventional gamma function, and s remains positive to ensure adequately large steps. A highly efficient contemporary approach for producing fine step sizes that match Levy distribution characteristics is the Mantegna algorithm (M), expressed through the following relation.

$$M(\omega) = \frac{X}{|Y|^{1/\omega}}, X \sim (0, \sigma^2), Y \sim (0, 1) \quad (6)$$

Where $X \sim (0, \sigma^2)$ signifies random draws from a standard normal distribution having zero mean, and σ^2 is the associated variance. The variance σ^2 itself is determined mathematically as:

$$\sigma^2 = \left[\frac{\Gamma(1 + \omega) \sin\left(\frac{\pi\omega}{2}\right)}{\Gamma\left(\frac{1+\omega}{2}\right) \omega 2^{\frac{(\omega-1)}{2}}}\right]^{1/\omega} \quad (7)$$

The biological reproduction mechanisms of biotic and abiotic pollination lend themselves well to solving the optimal reconductoring problem in distribution networks. The biotic pollination step can be mathematically modeled using the Mantegna algorithm, as shown in the equation below.

$$x_i^{t+1} = x_i^t + \gamma_M M(\omega) (g_{best} - x_i^t) \quad (8)$$

The abiotic or self-pollination step can be formulated mathematically as

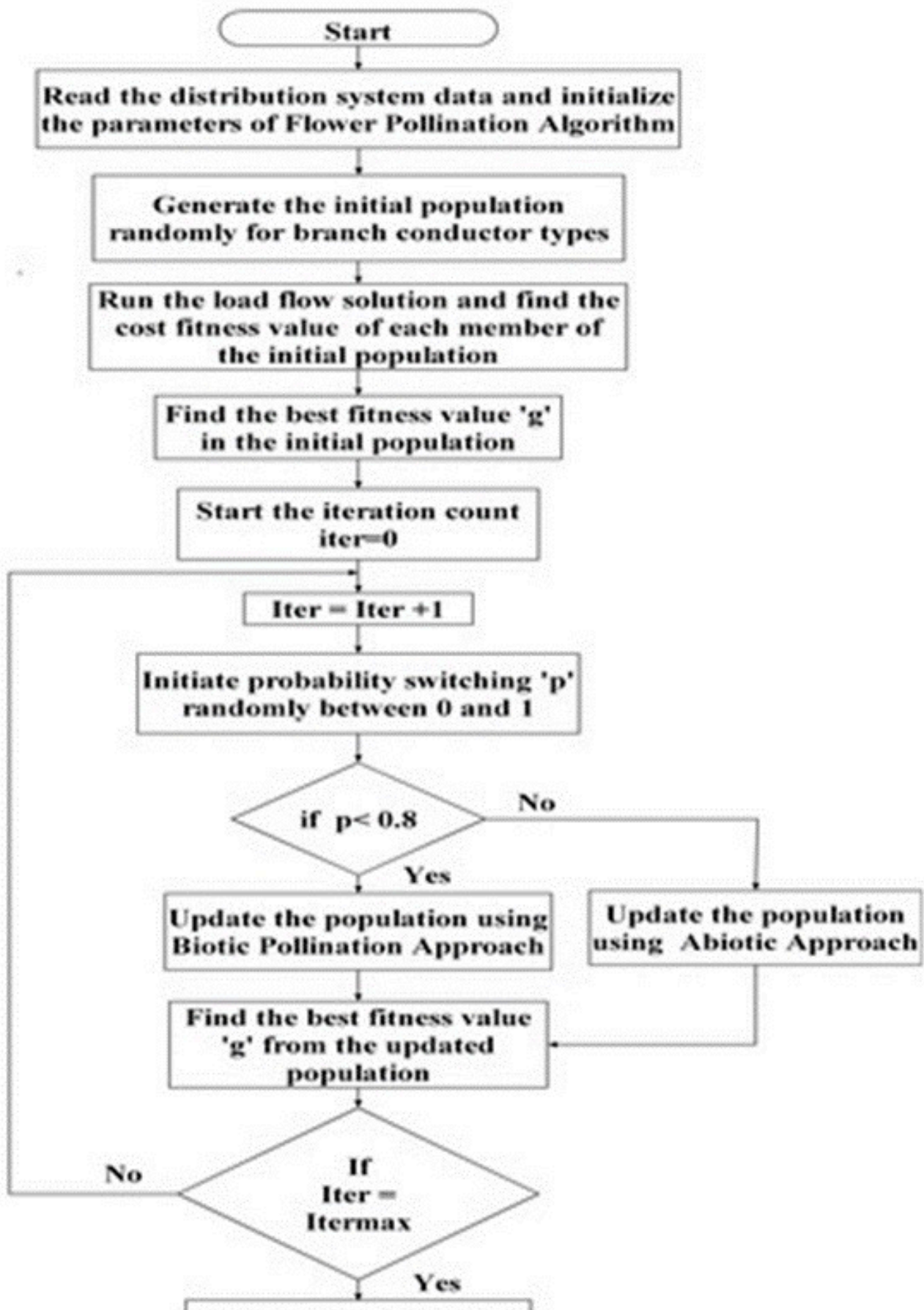
$$x_i^{t+1} = x_i^t + \varepsilon (x_j^t - x_k^t) \quad (9)$$

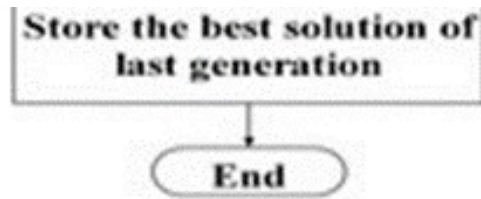
Where x_{tj} and x_{tk} represent two randomly picked candidate solutions from generation or iteration t , and ε indicates a random value drawn uniformly from the interval $[0, 1]$. ω is a fixed real constant set to 1.5.

Selection between biotic and abiotic pollination modes in each iteration is governed by a switching probability “ p ” that is generated randomly. The flowchart for applying the Flower Pollination Algorithm (FPA) to reconstruct the radial distribution network is shown in **Figure 1**, and **Algorithm 1** is listed below.

- 1:
Read the distribution system line and load data, and initialize the parameters of the flower pollination algorithm.
- 2:
Read the resistance/km and reactance/km data for the selected conductors for optimal network reconductoring.
- 3:
Generate a randomly distributed initial population for the distribution system network configuration using different types of branch conductors.
- 4:
Run the load flow and determine the cost objective function for each member of the population using Equation (1).
- 5:
Find the best fitness value of the initial population.
- 6:
Set the iteration count, $iter = 0$.
- 7:
Increment the iteration count by 1, i.e., $iter = iter + 1$.
- 8:
Find the probability switching value “p” randomly between 0 and 1.
- 9:
If the probability switching value $p < 0.8$, Go To Step 10, Go To Step 11.
- 10:
Update the population using the biotic pollination method from Equation (8), then Go To Step 12.
- 11:
Update the population using the abiotic pollination method by Equation (9).
- 12:
Find the best fitness value from the updated population.
- 13:
If the $iter < iterMax$, Go To Step 7; Go To Step 14.
- 14:
Store the best solution from the last iteration.

Algorithm 1. Step-by-Step Algorithm for Reconstructing using FPA





Reconductoring

Financial gains from optimal network reconductoring are assessed by weighing the annual repayment obligations on the capital spent to acquire new conductor materials against the monetary benefits from reduced energy losses.

The annual installment payment cost (*AIP*) corresponding to the loan taken for purchasing reconductoring materials across the distribution system is determined by the equation:

$$AIP = \left(\frac{I_{rate}(I_{rate} + 1)^N}{(I_{rate} + 1)^N - 1} \right) \sum_{t=1}^{NB} C_t L_t \quad (10)$$

Where *I_{rate}* denotes the interest rate, and *N* specifies the total duration in years for completing the installment payments. Annual economic savings are computed with the help of the following relations:

$$AESC = K_e \sum_{LF=1}^3 (RPL_{LF}^{Base} - RPL_{LF}^{RC}) T_{LF} \quad (11)$$

$$APLC = K_p (RPL_{peak}^{Base} - RPL_{peak}^{RC}) \quad (12)$$

Where *AESC* signifies the annual cost savings from reduced energy losses, and *APLC* stands for the annual cost savings from reduced peak losses. *K_e* represents the cost per unit of energy loss in Rs./kWh. *RPL_{LF}^{Base}* gives the total power loss at load factor *LF* in the original unmodified system, whereas *RPL_{LF}^{RC}* gives the total power loss at the same load factor *LF* once reconductoring has been implemented. *RPL_{peak}^{Base}* is the peak power loss recorded in the base case, and *RPL_{peak}^{RC}* is the peak power loss observed in the distribution system after reconductoring.

$$AECONS = AESC + APLC - AIP \quad (13)$$

The aggregate Annual Economic Savings cost (AECONS) is finally calculated using this equation:

Modeling of EV Charging Load Demand

Substantial integration of EV charging demand into distribution networks results in heightened losses and worsened voltage conditions. Consequently, suitable EV charging load representations for performing load flow analysis can be derived from the actual power uptake behavior of EV batteries during charging, as this behavior stems from electrochemical reactions within the battery cells. An exponential model was employed. Lithium-ion batteries remain the dominant choice for electric vehicles owing to their superior efficiency, and the exponential nature of their charging under constant-power and constant-voltage regimes can be captured by the equations presented next.

When charging commences from a low initial state of charge, the power equation takes the form:

$$PEV(t) = PEV^{max} (1 - e^{(-t/T)}) + PEV^0 e^{(-t/T)} \text{ for } 0 < t < T \quad (14)$$

Where PEV^0 corresponds to the starting charging power, and PEV^{max} denotes the upper limit of charging power for the EV battery. The technique outlined in this paper explicitly incorporates both constant-power and constant-voltage charging phases. Representative charging profiles for lithium-ion batteries are displayed in **Figure 2**. The following expressions describe the EV charging power requirements in the constant-power and constant-voltage phases.

$$PEV^{CP}(t) = PEV^{max} \text{ for } T_1 \leq t \leq T_2 \quad (15)$$

$$PEV^{CV}(t) = PEV^{max} \left(\frac{T_{max} - t}{T_{max} - T_2} \right) \text{ for } T_2 < t \leq T_{max} \quad (16)$$

Where $PEV(t)$ and $PEV^{CV}(t)$ denote the power drawn by EVs while operating in constant power mode and constant voltage mode, respectively. **Figure 2** illustrates the state of charge (SOC) progression from the start to full capacity. Battery size is normally specified by its energy storage capacity ((t)) measured in kWh, and the amount of energy stored in the battery throughout the charging process can be described with these equations.

$$BES(t+1) = BES(t) + PEV(t)\Delta(t) \quad (17)$$

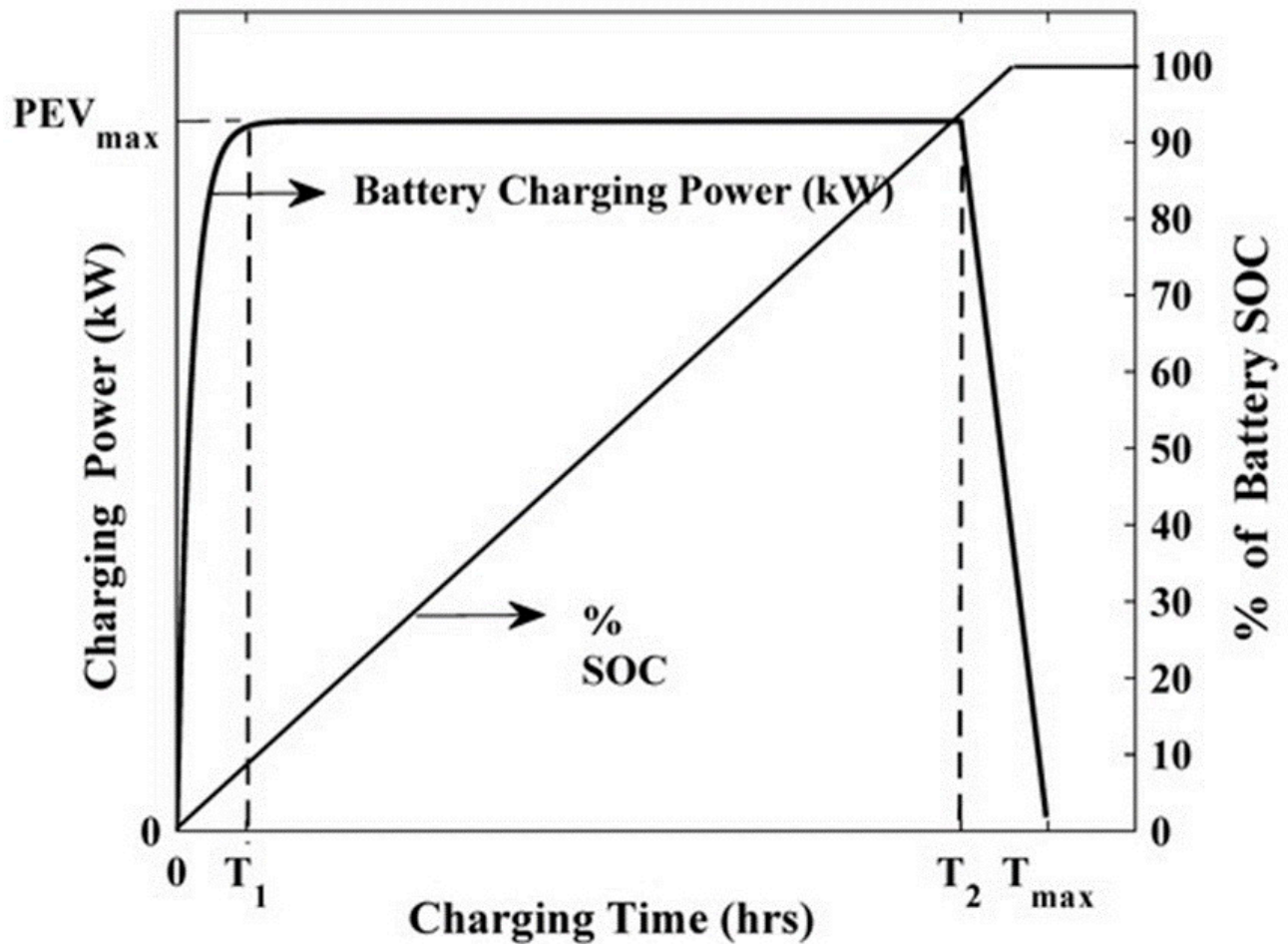


Figure 2. EV battery charging characteristics.

The following relation gives the battery's state of charge.

$$SOC(t) = \frac{BES(t)}{BES_{max}} \times 100 \quad (18)$$

EV batteries are typically charged from 20% to 90% SOC during periods of high demand [26]. Today, nearly all battery chargers function at a lagging power factor of 0.95. Once the battery reaches 100% SOC, charging is automatically stopped to prevent overheating, helping preserve the battery's lifespan and cycle life.

Energy Savings Division for EV Load Allocation among Charging Slots

A share of the energy savings produced by optimal network reconductoring can be used to integrate EV charging demand into the distribution network without violating voltage or current limits. This section outlines how those savings are allocated across various charging time windows. It begins by defining the feasible charging slots and then explains the procedure for distributing the savings among them to accommodate EV loads.

EV load charging slots division

This study evaluated the distribution system under three widely encountered load factor values: 0.4, 0.7, and 1.0. Each load factor was assumed to apply for 8 hours every day. Load levels are usually minimal from 12:00 a.m. to 8:00 a.m., so a load factor of 0.4 was assigned to that interval. The system typically experiences its highest demand in the afternoon, resulting in a load factor of 1.0 between 8:00 a.m. and 4:00 p.m. Evening hours see moderate consumption, leading to an average load factor of 0.7 from 4:00 p.m. to 12:00 a.m. Annually, 2920 hours were allocated to each load factor.

Most electric vehicles rely on lithium-ion batteries. Charging a typical medium-range EV battery from 20% SOC to 90% SOC generally takes about 4 hours. Residential parking availability for charging usually falls between 4:00 p.m. and 12:00 a.m. Because a minimum of 4 hours is required for a full session, 4 separate charging slots were established. The arrangement of distribution load factors and corresponding charging slots is depicted in **Figure 3**. Slots one and two fall within the 12:00 a.m. to 8:00 a.m. window under the 0.4 load factor. Slots three and four occur from 4:00 p.m. to 12:00 a.m. under the 0.7 load factor.

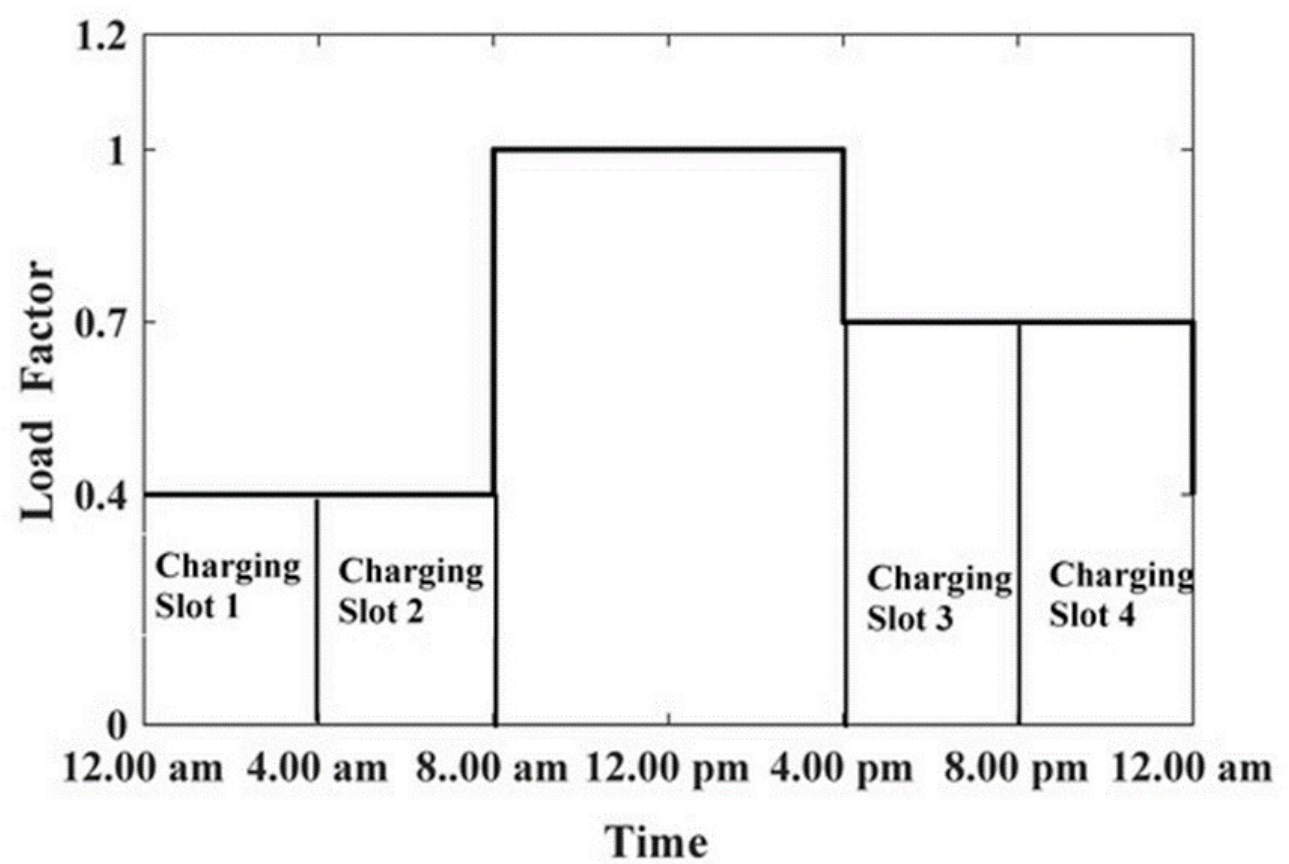


Figure 3. EV battery charging slots.

Energy savings division among the charging slots

The maximum EV load supported in any given charging slot is determined by the amount of available energy savings that can be applied during that time period. This section first determines the total daily energy savings that may be dedicated to EV charging (derived from the daily savings generated by optimal network reconductoring) and then apportions them

across the four defined slots. The daily portion of energy savings (E_{SEV}) available for EV load support is obtained from the expression below.

$$E_{SEV} = \frac{\alpha \left(\sum_{LF=1}^3 (RPL_{LF}^{Base} - RPL_{LF}^{RC}) T_{LF} \right)}{365} \quad (19)$$

Where α is the share (ranging between 0 and 1) of the energy savings achieved through FPA-based network reconductoring, E_{SEV} represents the daily energy savings reserved for EV charging, RPL_{BaseLF} is the base-case real power loss at load factor LF , and T_{LF} stands for the annual operating hours at that load factor.

The flow diagram in **Figure 4** illustrates the allocation of energy savings to the four charging slots.

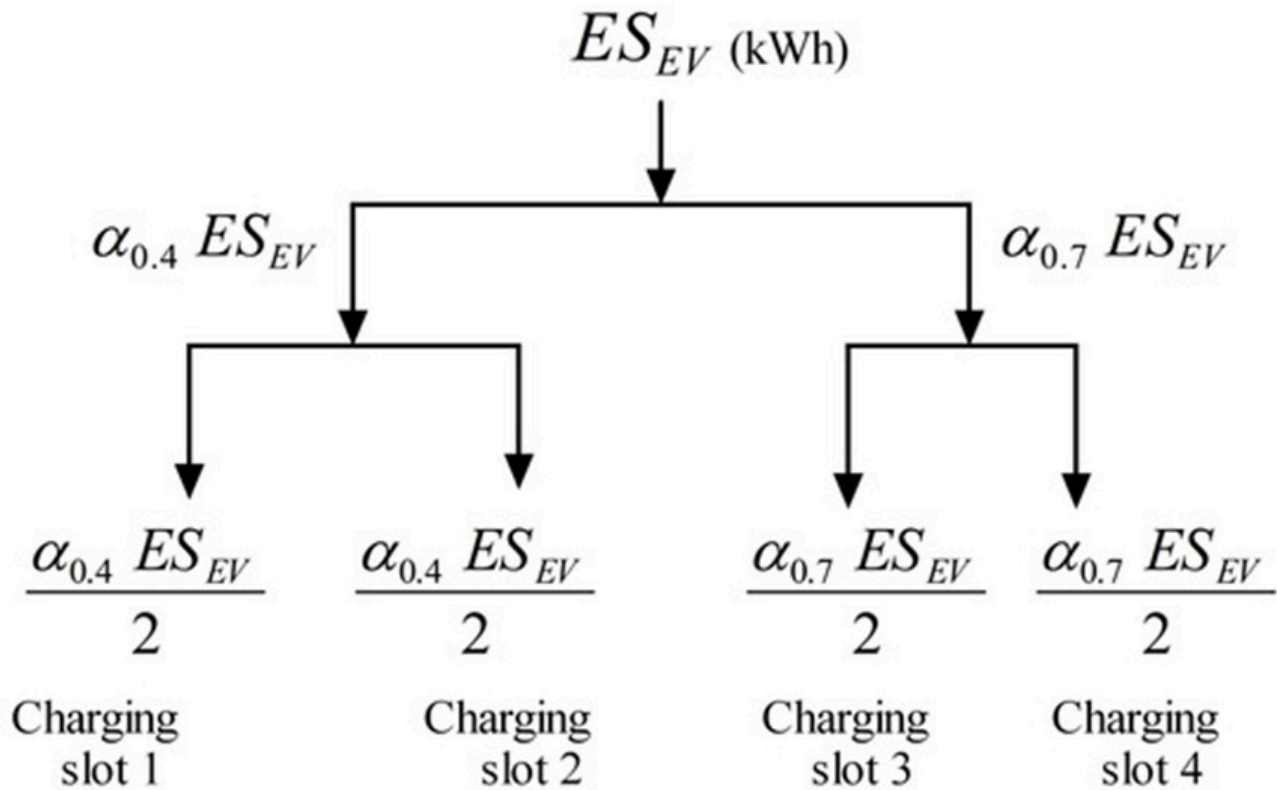


Figure 4. Energy savings division among charging slots.

From **Figure 4**, it is clear that the usable energy savings are split between the two applicable load factors of 0.4 and 0.7. Here, $\alpha_{0.4}$ and $\alpha_{0.7}$ indicate the portions of total savings assigned for EV charging at each load factor, and their combined value equals one. The diagram further shows that the savings assigned to each load factor are shared equally between its two associated charging slots.

The maximum extra power loss the distribution system can tolerate when EV load is introduced at a specific load factor, written as RPL_{LF}^{EVmax} , is calculated using the equation below:

$$RPL_{LF}^{EVmax} = \frac{\alpha_{LF} E_{SEV}}{N_{EV} T_{EV}} \quad (20)$$

Where NEV is the total number of charging slots, TEV is the duration allocated for EV charging, and αLF is the fraction of savings available at the given load factor.

Energy Savings-Based Heuristic Approach for EV Load Sizing and Allocation

The allocation of EV charging load across the distribution network can be performed by allowing an additional amount of real power loss, determined by the energy savings realized during the EV charging timeframe. The upper limit of real power loss during the charging interval—accounting for both the original distribution system demand and the added EV charging demand—can be described by the equation given below.

$$RPL_{LF}^{EVRC} = RPL_{LF}^{RC} + RPL_{LF}^{EVmax} \quad (21)$$

Where RPL_{LF}^{EVRC} represents the combined real power loss resulting from the distribution system load together with the acceptable EV load at load factor LF on the reconductored network.

Under the developed approach, EV charging load is examined at every node within the distribution system. The EV load is then gradually incorporated and controlled so that real power losses are permitted to rise only to the threshold set by the calculated energy savings. The present study proposes a straightforward heuristic to determine the maximum EV load at each node in the distribution system. Given that the majority of current EV chargers operate at a 0.95 power factor and that real power loss is affected by both active and reactive power, the analysis assumed a base-level EV load operating at 0.95 power factor at each node.

In the opening phase of this heuristic procedure, the minimum active power PEV_{min}^{EV} and the minimum reactive power QEV_{min}^{EV} drawn by the EV load were introduced concurrently at all nodes until the resulting real power loss exceeded the allowed threshold. In the subsequent phase, all node voltages were ordered from lowest to highest, with rankings assigned starting from the node exhibiting the smallest voltage. Following this ordering, the minimum EV load was progressively reduced at each node according to its ranking until the overall real power loss of the distribution system was brought back to an acceptable level. The flowchart depicting the suggested heuristic method is shown in [Figure 5](#), and [Algorithm 2](#) is presented below.

- 1: Read the distribution system line data and load data, and initialize real and reactive powers at each node to their base values at the considered load factor.
- 2: The lowest possible EV charging load real power $PEVEV_{min}$ and reactive power $QEVEV_{min}$ are selected.
- 3: Add the minimum real and reactive powers of EV charging load to the real and reactive power loads of the distribution system at every node at the charging slot considered.
- 4: Run the load flow and obtain the real power loss and node voltages.
- 5: If the constraints on node voltage limits, branch current limits, and maximum permitted loss with EV charging load allocation $RPLEVRCLF$ are satisfied, Go To Step 3; otherwise, Go To Step 6.
- 6: Run the load flow and assign rankings to the nodes, starting with the node with the minimum voltage.
- 7: Set the Rank $R = 0$.
- 8: Increment the Rank count by one, i.e., $R = R + 1$.
- 9: Deduct the minimum real and reactive powers of EV charging load from the real and reactive powers of R th rank node at the charging slot considered.
- 10: Run the load flow and obtain the real power loss and node voltages.
- 11: If the constraints on node voltage limits, branch current limits, and maximum permitted real power loss with EV charging load allocation $RPLEVRCLF$ are not satisfied, Go To Step 8; otherwise, Go To Step 12.
- 12: Calculate the EV charging load at each node in the distribution system by subtracting the base loads from the total load.
- 13: Store the results.

Algorithm 2. Step-by-Step Algorithm for the Proposed Heuristic Approach for EV Charging Load Allocation

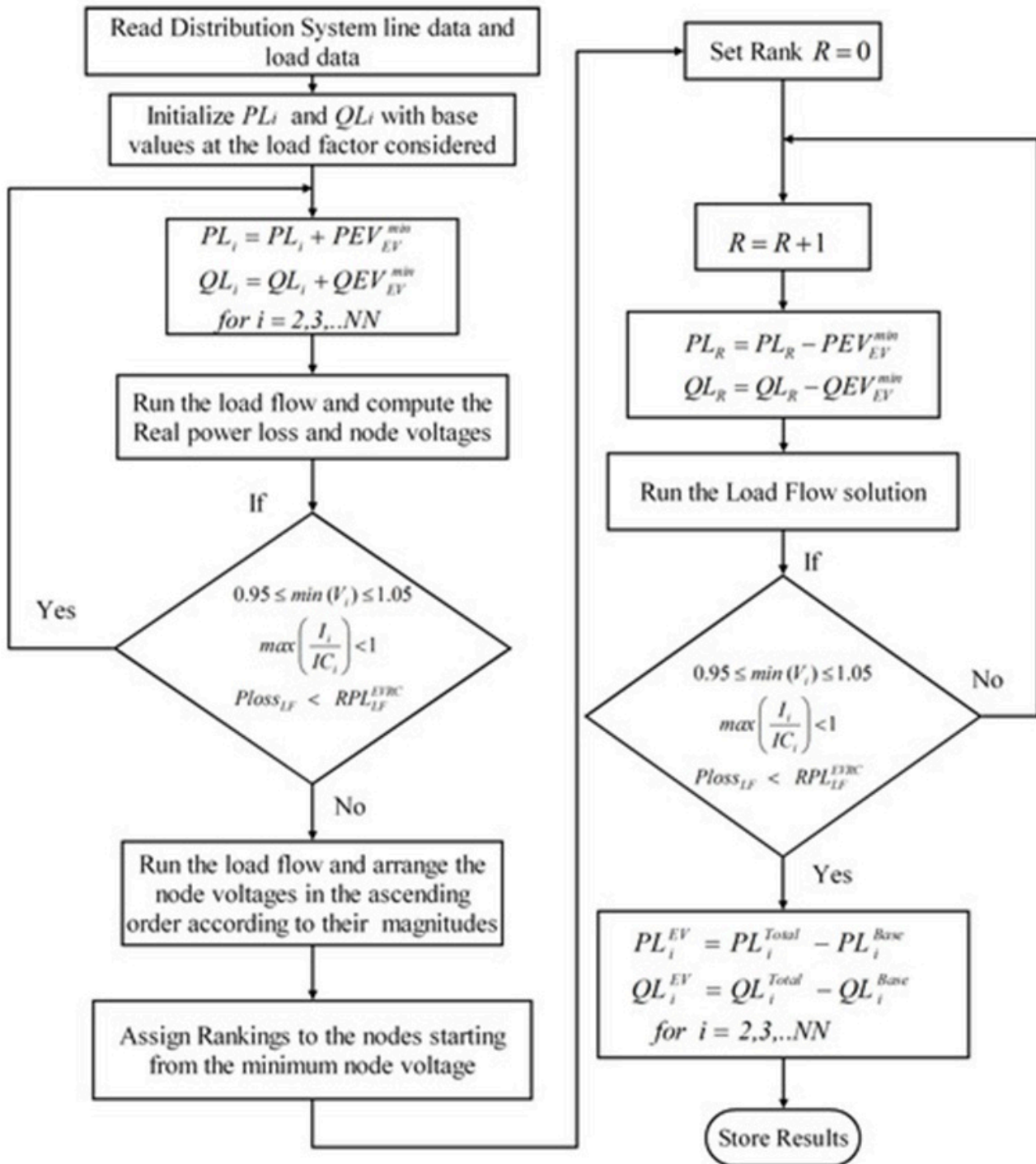


Figure 5. Heuristic approach for EV load allocation.

The actual absorbed power and reactive power at each node can be determined by subtracting the base-case load values from the final total load values, as shown in the equations below.

$$PL_i^{EV} = PL_i^{Total} - PL_i^{Base} \quad (22)$$

$$QL_i^{EV} = QL_i^{Total} - QL_i^{Base} \quad (23)$$

Where PL_i^{EV} and QL_i^{EV} denote the active and reactive power that the system can support at each node of the distribution network, associated with the EV loads. PL_i^{Base} and QL_i^{Base} correspond to the original base-case active and reactive power demands of the distribution system. PL_i^{Total} and QL_i^{Total} represent the active and reactive power demands after the proposed EV load allocation is applied at each node.

In residential distribution systems, the most common electric vehicles for transportation are electric cars, electric bikes, and electric scooters. Consequently, the number of EVs that can be hosted at each node is determined based on their individual battery charging capacities.

EVs are prioritized by battery capacity to deliver the greatest possible fuel savings. Electric cars receive the highest priority, electric bikes the next, and electric scooters the lowest. At any distribution system node, the aggregate EV load must not exceed the maximum EV load limit determined by the heuristic procedure. This constraint is expressed mathematically in the following equation.

$$N_i^{Car} PEV_{Car}^{max} + N_i^{Bike} PEV_{Bike}^{max} + N_i^{Scooter} PEV_{Scooter}^{max} \leq PL_i^{EV} \quad (24)$$

where PEV_{Car}^{max} , PEV_{Bike}^{max} , and $PEV_{Scooter}^{max}$ denote the maximum power drawn during constant-power charging mode by the batteries of electric cars, bikes, and scooters, respectively.

The largest number of electric cars that can be accommodated at the i th node is computed using the expression below.

$$N_i^{Car} \approx \frac{PL_i^{EV}}{PEV_{Car}^{max}} \quad (25)$$

Where N_i^{Car} is the integer portion of the value produced by the power ratio in the equation above. After placing the maximum feasible number of electric cars, the following option considered is electric bikes, which serve transportation needs and possess moderately smaller battery capacities than those of electric cars.

The maximum number of electric bikes that can be hosted is determined by subtracting the already-assigned electric car load from the overall allowable EV load.

$$N_i^{Bike} \approx \frac{PL_i^{EV} - N_i^{Car} PEV_{Car}^{max}}{PEV_{Bike}^{max}} \quad (26)$$

Where N_i^{Bike} represents the whole number part of the figure calculated using the power ratio in the equation shown above. Similarly, the number of scooters ($N_i^{Scooter}$) is calculated from the remaining EV load capacity after cars and bikes have been placed.

$$N_i^{Scooter} \approx \frac{PL_i^{EV} - N_i^{Car} PEV_{Car}^{max} - N_i^{Bike} PEV_{Bike}^{max}}{PEV_{Scooter}^{max}} \quad (27)$$

Results and Discussion

This paper presents a two-stage framework for determining the maximum EV load that can be accommodated in residential areas within urban distribution networks, leveraging energy savings from optimal reconductoring.

Optimal network reconstructing using flower pollination algorithm

In the first stage, the best possible reconductoring solution for the radial distribution network was obtained using the flower pollination algorithm. The fitness function used in the algorithm included the combined investment cost of the selected optimal conductors, the annual cost of energy losses in the distribution system evaluated across load factors 0.4, 0.7, and 1.0, and the cost related to losses at peak load. For each of these three load factors, an identical load duration (T) equal to 2920 hours per year was applied. Details of the conductor types and their parameters [55] appear in [Table 1](#).

Table 1. Conductor data.

Conductor number	Conductor type	Area (mm ²)	Reactance (Ω/km)	Resistance (Ω/km)	Weight (kg/km)	Maximum current capacity (A)
1	Squirrel	20.71	0.355	1.374	85	115
2	Gopher	25.91	0.349	1.09	106	133
3	Weasel	31.21	0.345	0.9116	128	150
4	Ferret	41.84	0.339	0.672	171	181
5	Rabbit	52.21	0.335	0.5449	214	208
6	Mink	62.32	0.333	0.4565	255	234
7	Beaver	74.07	0.33	0.3906	303	261
8	Raccoon	77.83	0.329	0.3656	318	270
9	Cat	94.21	0.327	0.315	385	305
10	Dog	103.6	0.315	0.2745	394	324
11	Tiger	128.1	0.282	0.2221	604	382
12	Bear	258.1	0.25	0.1102	1229	595

The suggested FPA-based procedure was run on two test systems: an 11 kV, 123-bus network [5] and an 11 kV, 51-bus network [12]. Outcomes were measured against those from the PSO algorithm. Both systems used a nominal voltage of 11 kV. The cost function parameters were fixed at $K_p = 2500$ Rs./kW, $K_e = 3.0$ Rs./kWh, and $\gamma = 0.1$. Conductor cost was approximated at 120 Rs./Kg [55].

Network layouts for the 123 and 51 radial distribution systems are shown in [Figures 6 and 7](#), respectively.

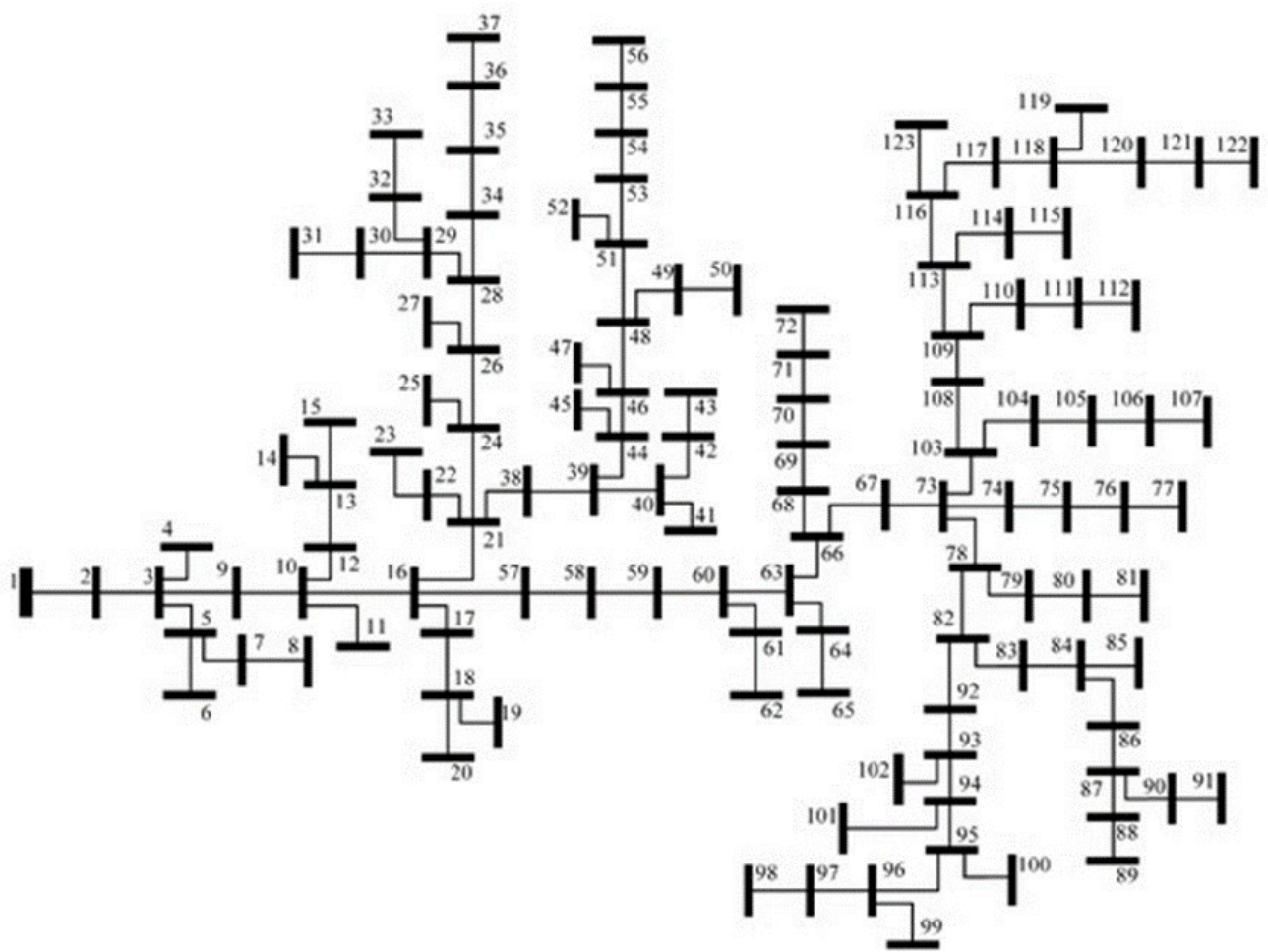


Figure 6. 123 bus radial distribution system.

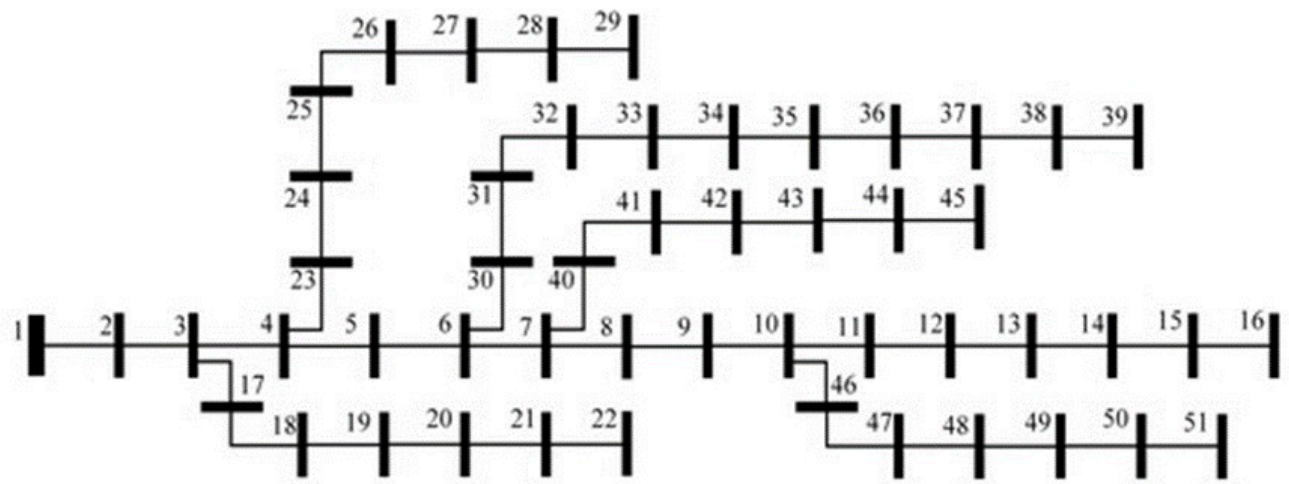


Figure 7. 51 bus radial distribution system.

All simulations of the 123 bus and 51 bus test systems were executed in MATLAB R2017a. The optimal conductor choices provided by the proposed Flower Pollination Algorithm (FPA) are listed in [Table 2](#) for the 123-bus system and in [Table 3](#) for the 51-bus system.

Table 2. Optimum conductor selection for the 123 bus system.

Branch number	Conductor type (base case)	Conductor type (PSO)	Conductor type (FPA)	Branch number	Conductor type (base case)	Conductor type (PSO)	Conductor type (FPA)
1	Bear	Bear	Bear	62	Tiger	Bear	Bear
2	Bear	Bear	Bear	63	Squirrel	Bear	Squirrel
3	Squirrel	Bear	Squirrel	64	Squirrel	Squirrel	Bear
4	Squirrel	Squirrel	Squirrel	65	Dog	Bear	Bear
5	Squirrel	Bear	Beaver	66	Cat	Bear	Bear
6	Squirrel	Squirrel	Raccoon	67	Squirrel	Bear	Weasel
7	Squirrel	Squirrel	Squirrel	68	Squirrel	Bear	Bear
8	Bear	Bear	Bear	69	Squirrel	Squirrel	Bear
9	Bear	Bear	Bear	70	Squirrel	Squirrel	Rabbit
10	Squirrel	Bear	Cat	71	Squirrel	Bear	Squirrel
11	Squirrel	Bear	Weasel	72	Cat	Bear	Bear
12	Squirrel	Squirrel	Squirrel	73	Squirrel	Bear	Bear
13	Squirrel	Bear	Gopher	74	Squirrel	Squirrel	Tiger
14	Squirrel	Squirrel	Beaver	75	Squirrel	Squirrel	Bear
15	Bear	Bear	Bear	76	Squirrel	Squirrel	Ferret
16	Squirrel	Squirrel	Weasel	77	Weasel	Bear	Bear
17	Squirrel	Squirrel	Mink	78	Squirrel	Bear	Bear
18	Squirrel	Squirrel	Bear	79	Squirrel	Squirrel	Squirrel
19	Squirrel	Squirrel	Weasel	80	Squirrel	Squirrel	Gopher
20	Ferret	Bear	Bear	81	Squirrel	Bear	Bear
21	Squirrel	Bear	Raccoon	82	Squirrel	Squirrel	Mink
22	Squirrel	Ferret	Gopher	83	Squirrel	Squirrel	Bear
23	Squirrel	Squirrel	Dog	84	Squirrel	Squirrel	Rabbit
24	Squirrel	Squirrel	Squirrel	85	Squirrel	Squirrel	Squirrel
25	Squirrel	Bear	Mink	86	Squirrel	Bear	Rabbit
26	Squirrel	Squirrel	Beaver	87	Squirrel	Squirrel	Squirrel
27	Squirrel	Squirrel	Squirrel	88	Squirrel	Squirrel	Rabbit
28	Squirrel	Squirrel	Weasel	89	Squirrel	Squirrel	Squirrel
29	Squirrel	Squirrel	Mink	90	Squirrel	Squirrel	Raccoon

30	Squirrel	Squirrel	Squirrel	91	Squirrel	Squirrel	Bear
31	Squirrel	Squirrel	Weasel	92	Squirrel	Squirrel	Dog
32	Squirrel	Squirrel	Squirrel	93	Squirrel	Bear	Dog
33	Squirrel	Squirrel	Squirrel	94	Squirrel	Squirrel	Beaver
34	Squirrel	Bear	Rabbit	95	Squirrel	Squirrel	Raccoon
35	Squirrel	Bear	Gopher	96	Squirrel	Squirrel	Bear
36	Squirrel	Squirrel	Cat	97	Squirrel	Bear	Squirrel
37	Squirrel	Squirrel	Bear	98	Squirrel	Squirrel	Squirrel
38	Squirrel	Bear	Bear	99	Squirrel	Squirrel	Squirrel
39	Squirrel	Squirrel	Mink	100	Squirrel	Squirrel	Beaver
40	Squirrel	Squirrel	Squirrel	101	Squirrel	Squirrel	Bear
41	Squirrel	Gopher	Bear	102	Gopher	Bear	Bear
42	Squirrel	Squirrel	Bear	103	Squirrel	Squirrel	Tiger
43	Squirrel	Bear	Bear	104	Squirrel	Squirrel	Squirrel
44	Squirrel	Bear	Bear	105	Squirrel	Bear	Squirrel
45	Squirrel	Squirrel	Bear	106	Squirrel	Bear	Weasel
46	Squirrel	Bear	Beaver	107	Squirrel	Bear	Tiger
47	Squirrel	Bear	Bear	108	Squirrel	Bear	Bear
48	Squirrel	Bear	Mink	109	Squirrel	Squirrel	Rabbit
49	Squirrel	Bear	Squirrel	110	Squirrel	Squirrel	Bear
50	Squirrel	Squirrel	Ferret	111	Squirrel	Bear	Weasel
51	Squirrel	Squirrel	Ferret	112	Squirrel	Bear	Bear
52	Squirrel	Squirrel	Bear	113	Squirrel	Ferret	Squirrel
53	Squirrel	Bear	Squirrel	114	Squirrel	Squirrel	Squirrel
54	Squirrel	Squirrel	Squirrel	115	Squirrel	Bear	Tiger
55	Squirrel	Bear	Squirrel	116	Squirrel	Bear	Raccoon
56	Tiger	Bear	Bear	117	Squirrel	Squirrel	Squirrel
57	Tiger	Bear	Bear	118	Squirrel	Squirrel	Squirrel
58	Tiger	Bear	Bear	119	Squirrel	Bear	Cat
59	Tiger	Bear	Bear	120	Squirrel	Bear	Bear
60	Squirrel	Squirrel	Bear	121	Squirrel	Squirrel	Squirrel
61	Squirrel	Bear	Squirrel	122	Squirrel	Squirrel	Squirrel

Table 3. Optimum conductor selection for the 51 bus system.

Branch number	Conductor type (base case)	Conductor type (PSO)	Conductor type (FPA)	Branch number	Conductor type (base case)	Conductor type (PSO)	Conductor type (FPA)
1	Dog	Bear	Bear	26	Squirrel	Ferret	Beaver
2	Dog	Bear	Bear	27	Squirrel	Squirrel	Squirrel
3	Dog	Bear	Bear	28	Squirrel	Bear	Ferret
4	Dog	Bear	Bear	29	Rabbit	Squirrel	Tiger
5	Mink	Bear	Bear	30	Rabbit	Dog	Dog
6	Mink	Bear	Bear	31	Rabbit	Dog	Cat
7	Mink	Bear	Bear	32	Rabbit	Raccoon	Beaver
8	Mink	Bear	Bear	33	Rabbit	Dog	Raccoon
9	Squirrel	Dog	Dog	34	Rabbit	Mink	Squirrel
10	Squirrel	Bear	Dog	35	Rabbit	Bear	Beaver
11	Squirrel	Dog	Raccoon	36	Rabbit	Squirrel	Squirrel
12	Squirrel	Dog	Rabbit	37	Rabbit	Weasel	Gopher
13	Squirrel	Squirrel	Dog	38	Rabbit	Squirrel	Gopher
14	Squirrel	Mink	Raccoon	39	Squirrel	Bear	Dog
15	Squirrel	Squirrel	Squirrel	40	Squirrel	Dog	Dog
16	Squirrel	Dog	Dog	41	Squirrel	Dog	Rabbit
17	Squirrel	Bear	Rabbit	42	Squirrel	Mink	Mink
18	Squirrel	Dog	Cat	43	Squirrel	Ferret	Rabbit
19	Squirrel	Mink	Ferret	44	Squirrel	Squirrel	Ferret
20	Squirrel	Ferret	Squirrel	45	Squirrel	Dog	Dog
21	Squirrel	Squirrel	Rabbit	46	Squirrel	Squirrel	Ferret
22	Squirrel	Dog	Tiger	47	Squirrel	Mink	Rabbit
23	Squirrel	Dog	Beaver	48	Squirrel	Rabbit	Squirrel
24	Squirrel	Mink	Squirrel	49	Squirrel	Bear	Ferret
25	Squirrel	Squirrel	Mink	50	Squirrel	Squirrel	Squirrel

Comparative performance results for FPA and PSO in the two distribution systems are presented in [Tables 4 and 5](#). These tables clearly demonstrate that the FPA method delivered considerably greater reductions in real power loss and

better improvements in minimum voltage levels than the PSO method. In addition, **Table 6** shows that the FPA approach achieved substantially lower reconductoring expenses while producing higher annual energy savings and improved economic returns across both test systems.

Table 4. Comparison of voltage min (p.u).

Method	51 Bus			123 Bus		
Load Factor	0.4	0.7	1.0	0.4	0.7	1.0
Base Case	0.9659	0.9390	0.9107	0.9930	0.9877	0.9824
PSO	0.9851	0.9737	0.9621	0.9949	0.9911	0.9872
FPA	0.9852	0.9739	0.9623	0.9956	0.9923	0.9890

Table 5. Comparison of real power losses (kW).

Method	51 Bus			123 Bus		
Load Factor	0.4	0.7	1.0	0.4	0.7	1.0
Base Case	19.20	61.07	129.81	7.83	24.17	49.73
PSO	6.38	19.88	41.31	4.28	13.19	27.08
FPA	6.26	19.51	40.52	3.91	12.04	24.71

Table 6. Annual savings comparison.

Metric	51 bus system		123 bus system	
	PSO	FPA	PSO	FPA
Conductor Cost (Rs)	4,344,009	3,664,850	1,482,368	1,339,892
Annual Energy Savings (kWh)	416,129	419,867	108,566	119,924
Energy Savings per Day (kWh)	1,140.08	1,150.32	297.44	328.56
Annual Economic Savings (Rs)	959,392	1,052,353	208,204	264,940

Daily and per-slot breakdowns of energy savings available for EV charging on the 123 bus and 51 bus test systems are summarized in **Tables 7 and 8**. Two separate case studies were created for assigning the EV charging load. In Case-1, 25% of the total available energy savings are used at the 0.4 load factor, with the balance assigned at the 0.7 load factor. In Case 2, the available energy savings are split evenly between the 0.4 and 0.7 load factors. Since most EV batteries take roughly 8 hours to charge from 20% to 90% state of charge, every charging slot (TEV) was set at 4 hours. The extra real power loss caused by EV load ($RPLEV_{maxLF}$) and the overall allowable real power loss including EV load ($RPLEVRCLF$) were computed using the method explained previously.

Table 7. Energy savings allocation with EV load for 123 bus.

123 Bus	Case-2 (50%–50%)		Case-1 (25%–75%)	
Load Factor	0.4	0.7	0.4	0.7
Energy Savings Available per Day (kWh)	82.14	82.14	41.07	123.21
Energy Savings Available per Slot (kWh)	41.07	41.07	20.535	61.605
Additional Real Power Loss with EV Load (kW)	10.26	10.26	5.13	15.4
Real Power Loss without EV Load (kW)	3.91	12.04	3.91	12.04
Total Loss Permitted with EV Load (kW)	14.17	22.3	9.04	27.44
Actual Loss with EV Load (kW)	14.17	22.3	9.04	27.44
Minimum Voltage (p.u.)	0.9924	0.9901	0.9938	0.9891

Table 8. Energy savings allocation with EV load for 51 buses.

51 Bus	Case-2 (50%–50%)		Case-1 (25%–75%)	
Load Factor	0.4	0.7	0.4	0.7
Energy Savings Available per Day (kWh)	287.58	287.58	143.79	431.37
Energy Savings Available per Slot (kWh)	143.79	143.79	71.895	215.685
Additional Real Power Loss with EV Load (kW)	35.94	35.94	17.97	53.92
Real Power Loss without EV Load (kW)	6.26	19.51	6.26	19.51
Total Loss Permitted with EV Load (kW)	42.2	54.45	24.23	73.43
Actual Loss with EV Load (kW)	42.2	54.45	24.23	73.43
Minimum Voltage (p.u.)	0.966	0.9594	0.9736	0.9536

For this research, the smallest considered EV battery size was 1 kWh. Charging the battery fully in 4 hours required an active power draw of 0.25 kW. Because typical EV chargers operate at a power factor of 0.95, they also draw 0.082 kVAr of reactive power during charging. The distribution of EV charging load under both cases is illustrated in [Figures 8-11](#). The maximum allowable EV charging load at individual nodes was established using the permissible power-loss figures from [Tables 7 and 8](#), combined with the heuristic procedure.

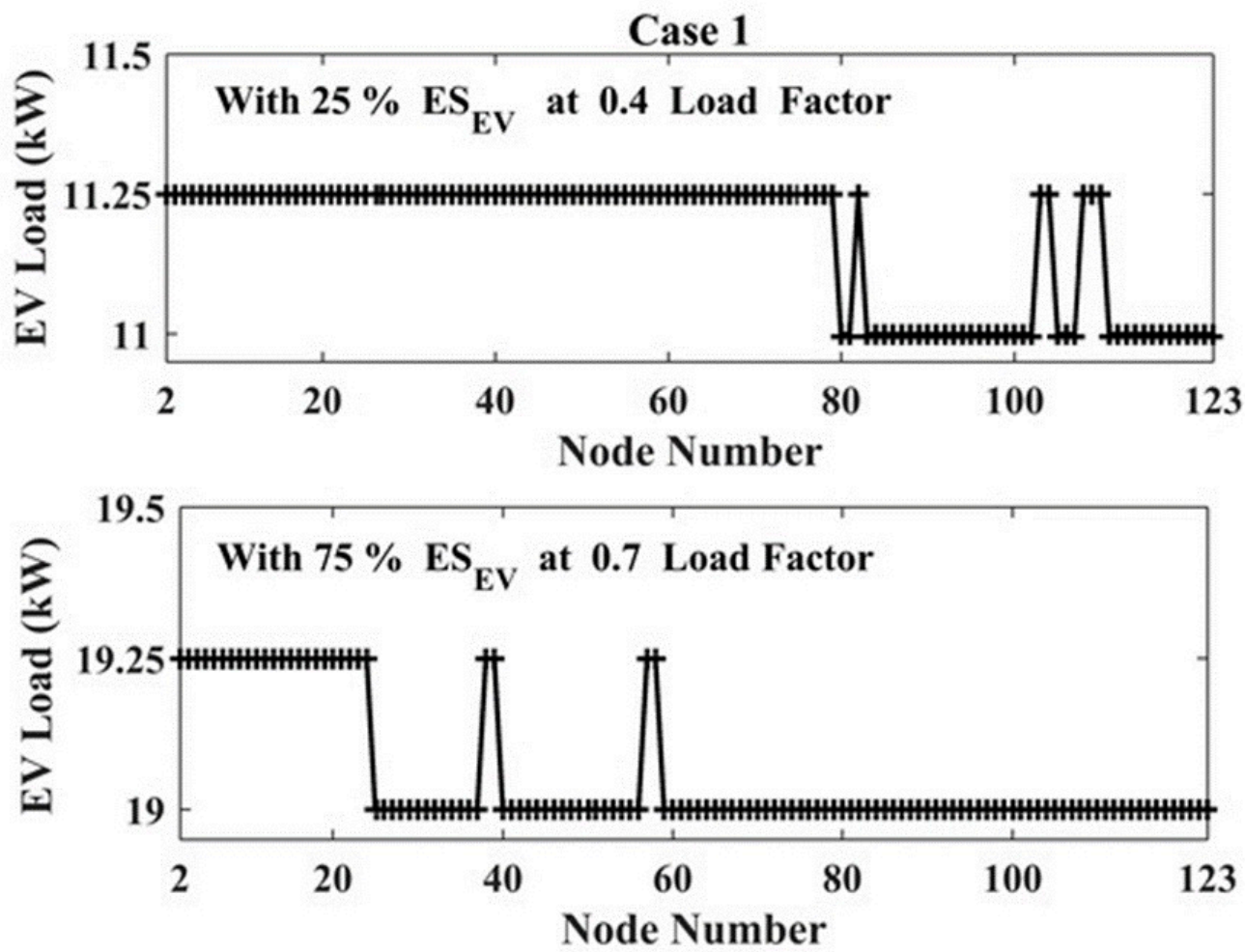


Figure 8. EV load allocation for the 123 bus system for Case-1.

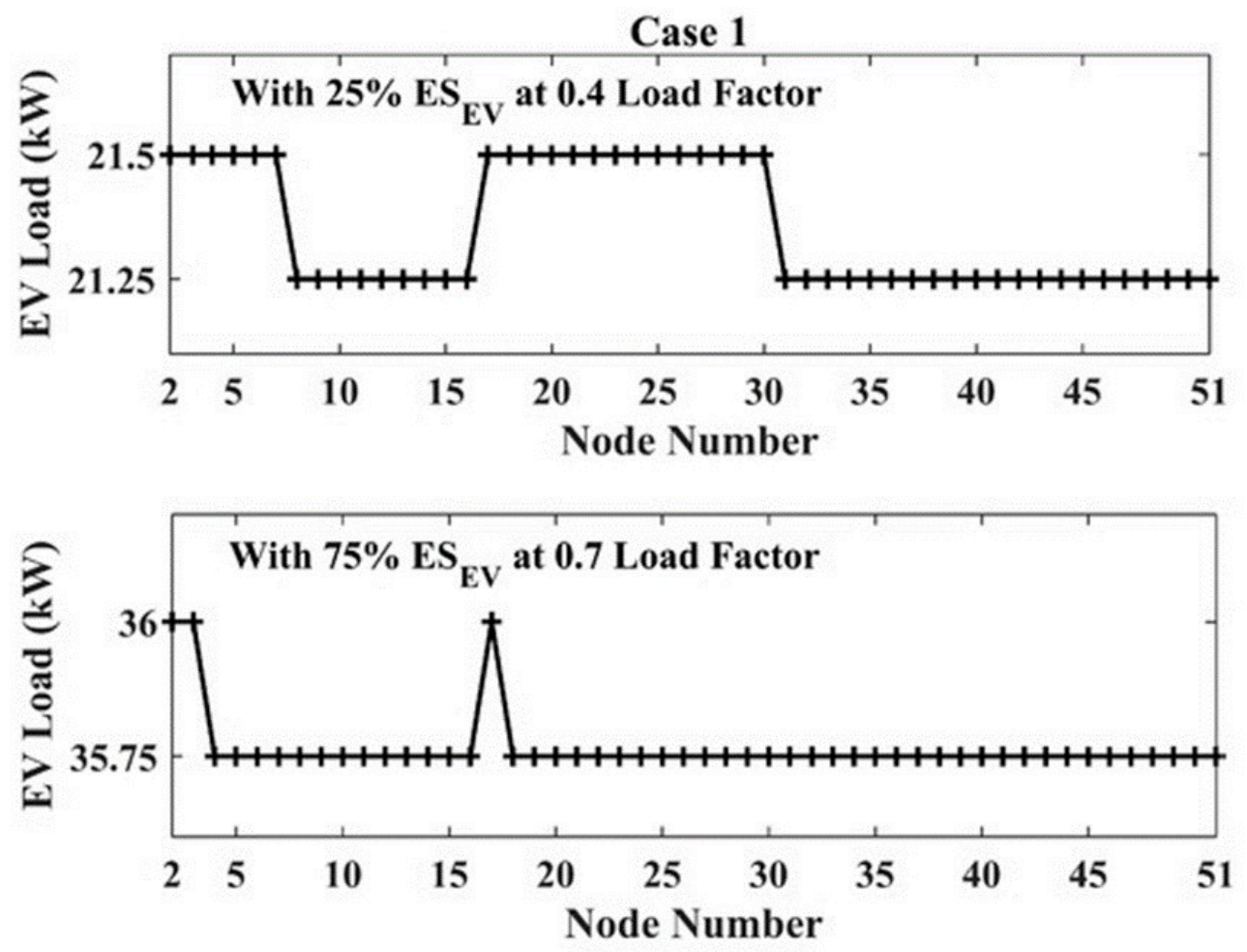


Figure 9. EV load allocation for the 51 bus system for Case-1.

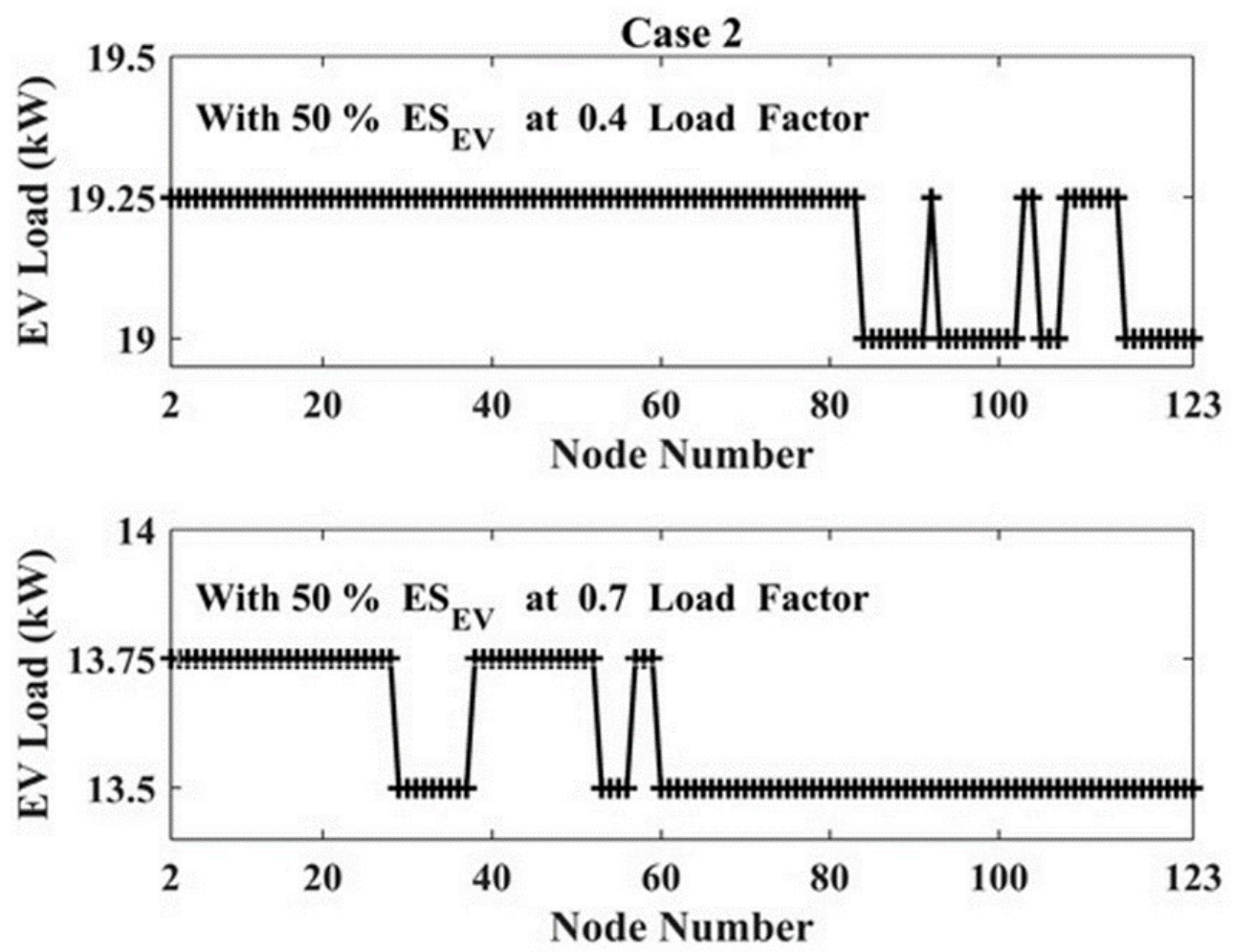


Figure 10. EV load allocation for the 123 bus system for Case-2.

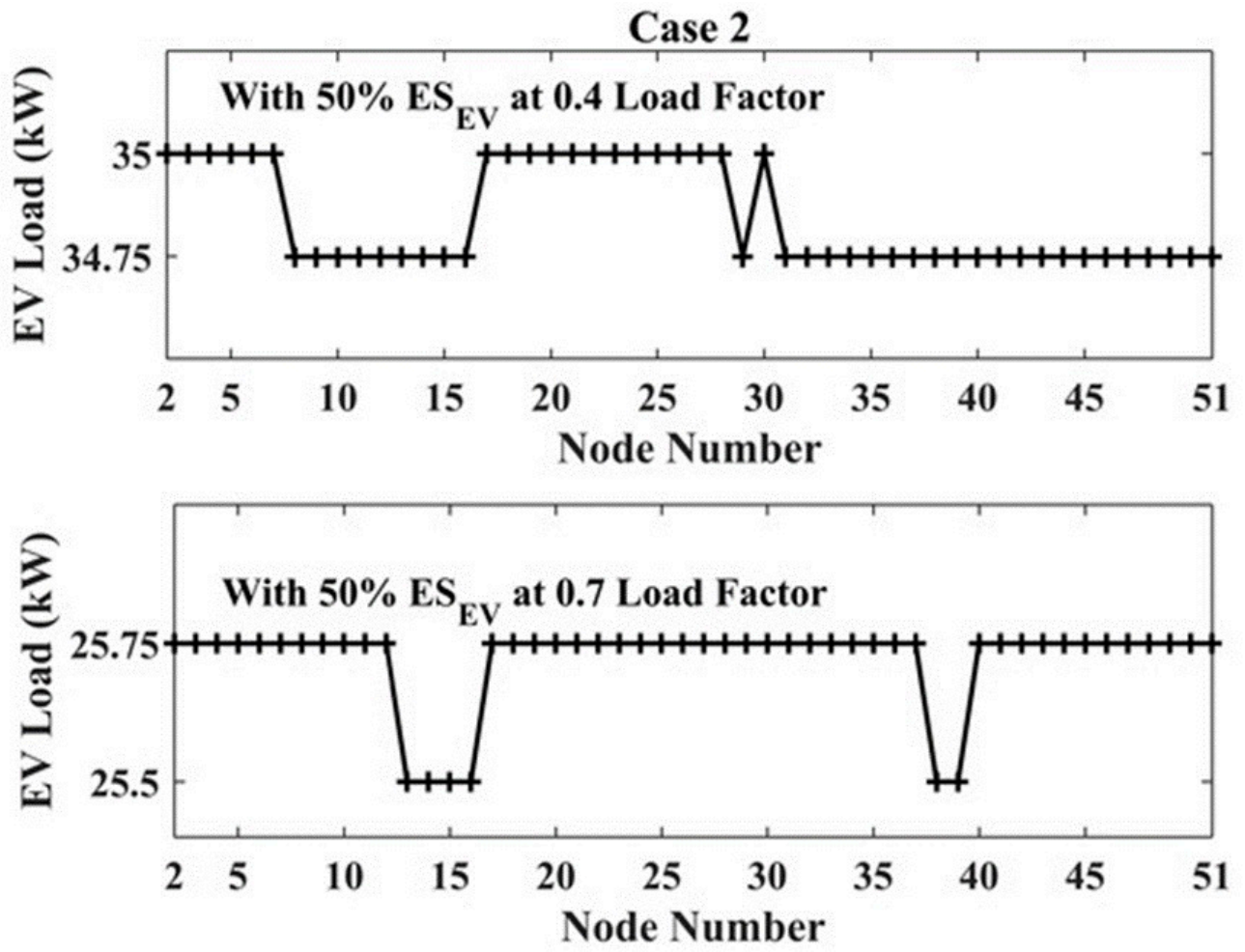


Figure 11. EV load allocation for the 51 bus system for Case-2.

For example, under Case-1 at a 0.4 load factor on the 123 bus system, the EV charging load at individual nodes was increased stepwise by 0.25 kW, along with the corresponding reactive power at 0.95 power factor, until the overall real power loss just crossed 9.04 kW, as listed in [Table 7](#). The EV charging load at each node was then reduced in steps of 0.25 kW until the total real power loss matched 9.04 kW exactly. This pattern is visible in [Figure 8](#) at the 0.4 load factor, where the highest EV charging load per node is either 11.25 kW or 11 kW. The same stepwise variation of 0.25 kW in the maximum EV charging load per node is also evident in [Figures 9-11](#).

In the present study, the EV charging requirements at residential sites were examined by considering three popular types of electric vehicles used for daily transportation: the Mahindra e2oPlus Electric Car with a 10.08 kWh battery, the Revolt RV400 Electric Bike with a 3.24 kWh battery, and the Okinawa R30 Electric Scooter with a 1.25 kWh battery. All three vehicle types can be charged from 20% to 90% state of charge within 4 hours. [Tables 9 and 10](#) show that the number of EVs that can be accommodated at each node depends directly on the maximum allowable EV charging load per node, as shown in [Figures 8-11](#).

Table 9. Number of EVs charged per slot for 123 bus.

123 Bus	Load Factor	EV Load per Node (kW)	Number of Nodes	Scooters per Slot per Node	Bikes per Slot per Node	Cars per Slot per Node
Case-1	0.4	11.25	84	2	1	4

		11	38	1	1	4
	0.7	19.25	27	1	2	7
		19	95	0	2	7
Case-2	0.4	19.25	92	1	2	7
		19	30	0	2	7
	0.7	13.75	45	2	1	5
		13.5	77	1	1	5

Table 10. Number of EVs charged per slot for 51 buses.

51 Bus	Load Factor	EV Load per Node (kW)	Number of Nodes	Scooters per Slot per Node	Bikes per Slot per Node	Cars per Slot per Node
Case-1	0.4	21.5	20	0	2	8
		21.25	30	2	1	8
	0.7	36	3	1	1	14
		35.75	47	0	1	14
Case-2	0.4	35	19	0	0	14
		34.75	31	0	3	13
	0.7	25.75	44	0	1	10
		25.5	6	2	0	10

Tables 11 and 12 display the overall number of electric vehicles that can be charged daily across both test systems. An important point to note is that under Case-1, a larger number of electric vehicles can be charged during the 0.7 load factor period. This occurs because 75% of the available energy savings are assigned to the 0.7 load factor, which permits a greater rise in power losses and therefore supports a substantially higher EV charging load at every node. In contrast, Case 2 allows more electric vehicles to be charged during the 0.4 load factor period since the energy savings are shared equally between the two load factors.

Table 11. Number of EVs charged per day for the 123 bus.

Category	Item	Value 2	Value 1	Total
123 Bus	Load Factor	0.7	0.4	
Case-1	NCars/day	1708	976	2684
	NBikes/day	488	244	732

	NScooters/day	54	412	466
Case-2	NCars/day	1220	1708	2928
	NBikes/day	244	488	732
	NScooters/day	334	184	518

Table 12. Number of EVs charged per day for 51 buses.

Category	Item	Value 2	Value 1	Total
51 Bus	Load Factor	0.7	0.4	
Case-1	Ncars/day	1400	800	2200
	Nbikes/day	100	140	240
	Nscooters/day	6	120	126
Case-2	Ncars/day	1000	1338	2338
	Nbikes/day	88	186	274
	Nscooters/day	24	0	24

The total EV charging load added per slot under Cases 1 and 2 is summarized in **Tables 13 and 14** for the 123-bus and 51-bus systems, respectively. The tables indicate that in Case-1, the share of EV load injection is considerably higher during the 0.7 load factor period than during the 0.4 load factor period. In Case-2, however, the percentage of EV load injection is higher during the 0.4 load factor period compared with the 0.7 load factor period. Thus, by distributing 50% of the energy savings gained from reconductoring and permitting losses to increase accordingly, a substantial volume of EV charging load can be introduced into the distribution network without breaching the minimum voltage constraints in either test system.

Table 13. EV load charging capacity per day for 123 buses.

Category	123 Bus	Case-2		Case-1	
		0.4 Load Factor	0.7 Load Factor	0.4 Load Factor	0.7 Load Factor
EV load injection/slot (kW)		2341	1658.25	1363	2324.75
EV load injection/slot (%)		46.86	33.19	27.28	46.43
EV load charging capacity/day (kWh)		31,994		29,502	
EV load charging capacity/day (%)		38.12		35.15	

Table 14. EV load charging capacity per day for 51 buses.

Category	51 Bus	Case-2		Case-1	
		0.4 Load Factor	0.7 Load Factor	0.4 Load Factor	0.7 Load Factor
EV load injection/slot (kW)		1742.25	1286.00	1067.50	1788.25
EV load injection/slot (%)		70.74	52.21	43.34	72.61
EV load charging capacity/day (kWh)		24,226		22,846	
EV load charging capacity/day (%)		58.55		55.21	

From Tables 13 and 14, it is evident that the highest achievable daily EV charging load was 31,994 kWh for the 123-bus system and 24,226 kWh for the 51-bus system. Battery Energy Storage Systems (BESS) cost roughly Rs 22,000/kWh (\$300/kWh) [56] and would require a substantial capital outlay to handle daily EV load, making them impractical for this purpose. Furthermore, meeting the required energy solely through solar PV installations at residential sites is challenging. Hence, it proves more cost-effective to strengthen the distribution network via reconductoring and draw the necessary power directly from the substation.

Figure 12 shows the EV charging load at each node for both test systems when 100% of the available energy savings is assigned to a single load factor period. The figures reveal that allocating all savings to the 0.4 load factor enables considerably more EV load to be placed than allocating them to the 0.7 load factor.

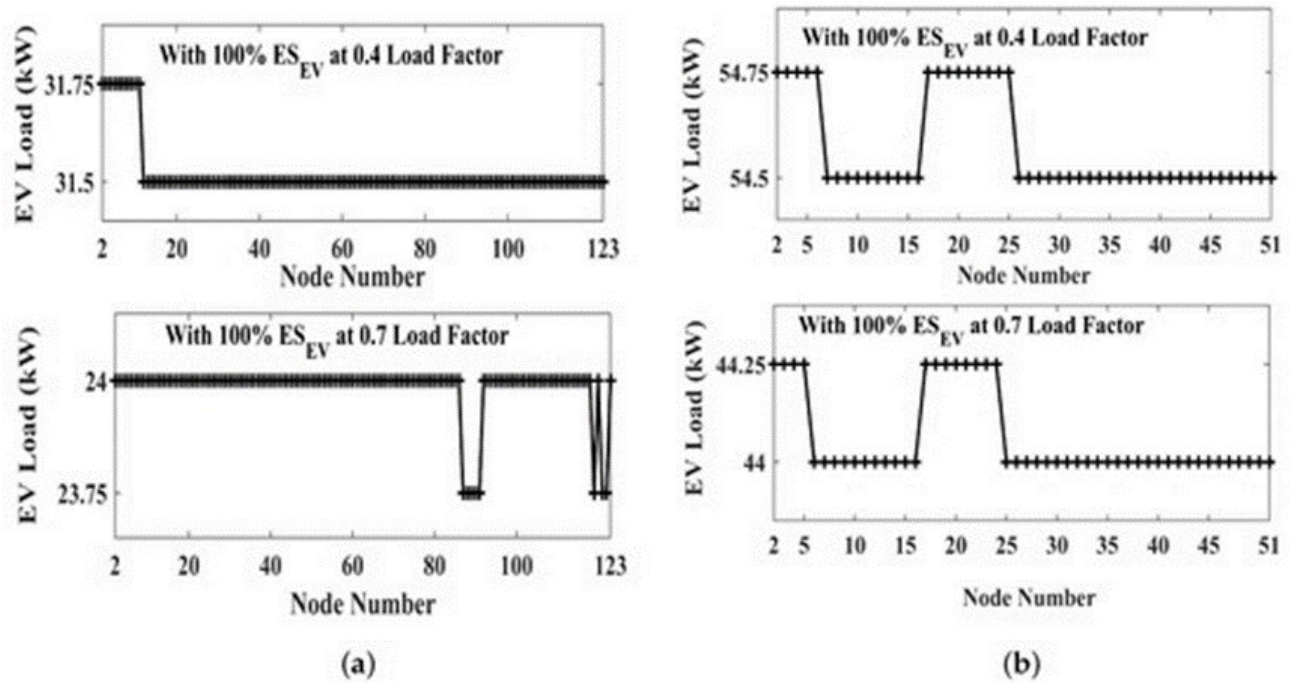


Figure 12. EV load with 100 % energy savings. (a) 123 bus system. (b) 51 bus system.

Maximum solar PV generation typically occurs in the afternoon and can help offset peak daytime demand. Figure 13 demonstrates that injecting solar PV power results in an improved minimum-voltage profile and lower real-power losses.

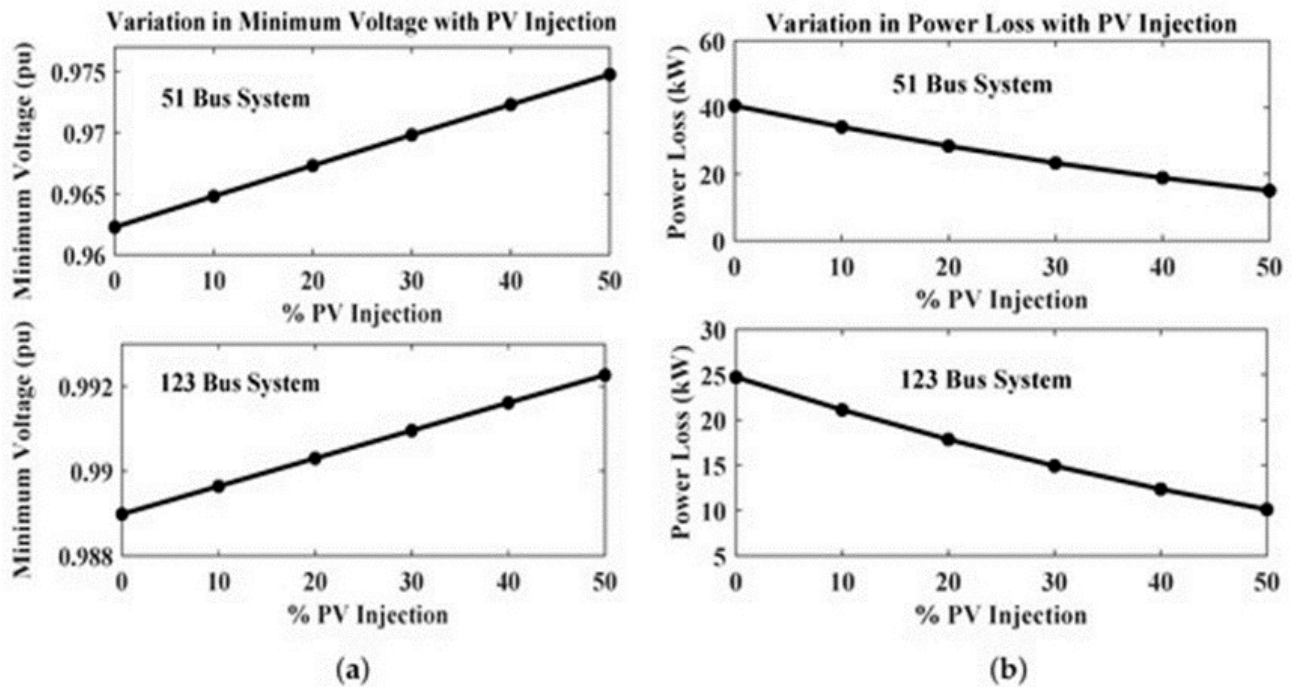


Figure 13. Performance with PV injection. (a) Minimum voltage. (b) Real power loss.

It should be highlighted that the substantial rise in EV load will require utilities to enhance the rating of distribution transformers. However, if upgrading transformers proves too costly, overload issues can be avoided by restricting the total substation load during off-peak hours to the original base-case peak value. The total substation load comprises both the regular distribution system demand and the added EV charging load. In this study, the authors assumed that distribution transformers would be upgraded as needed to handle the EV charging demand. Network reconfiguration methods can be combined with reconductoring to reduce real power losses further and prevent transformer overloading. Additionally, the stress on distribution transformers can be eased through the strategic placement of shunt capacitor banks and distributed generators in conjunction with reconductoring and reconfiguration strategies.

Conclusion

This paper introduces a two-stage framework for the optimal placement of EV chargers at residential sites, leveraging energy savings from optimal reconductoring of distribution networks. In the first stage, the Flower Pollination Algorithm (FPA)-based method was applied to perform optimal reconductoring of radial distribution systems, aiming to reduce annual energy losses while keeping conductor investment costs at an efficient level. The proposed FPA approach delivered noticeable improvements in the voltage profile and substantially lower real power losses than both the base case and the PSO-based method. In addition, the annual energy savings and economic benefits were markedly higher at the optimal conductor cost when using the suggested reconductoring strategy than those obtained with the PSO-based approach.

In the second stage, EV load allocation at each node was performed using a straightforward heuristic that used a portion of the total annual energy savings resulting from the network reconductoring. These annual energy savings were computed by considering the distribution system load at three load factors throughout the day. Simulation results indicate that the maximum EV load can be accommodated when available energy savings are divided equally between off-peak periods with lower load factors (morning and evening) rather than assigning a larger share to the evening peak hours. The maximum EV load that can be supported at each node while respecting voltage and current limits was found to be considerably higher when a lower load factor was used to achieve the same level of energy savings. The EV charging

demand was then distributed among the three most frequently used types of electric vehicles among residential consumers—cars, bikes, and scooters. The results clearly demonstrate that a strengthened distribution network, achieved through optimal reconductoring, can meet the charging needs of a large fleet of electric vehicles.

Solar PV generation available at residential premises is inadequate to handle large-scale EV load integration. Furthermore, the substantial capital costs of deploying battery energy storage systems make them impractical for managing the extensive daily EV charging demand of residential users. Therefore, it is far more cost-effective to improve distribution system performance via network reconductoring and to supply the necessary EV load directly from the substation. Looking ahead, urban distribution networks will need to support considerable EV charging demand at residential locations. Consequently, these systems must be reinforced through network reconductoring and upgrades to distribution transformers to accommodate high levels of EV charging load reliably. Smart grid technologies can be effectively applied to commercial EV charging stations serving public and commercial transport, such as buses, trucks, taxis, and heavy-duty vehicles. Future research could include additional case studies that incorporate smart grid technologies to optimize the sizing and placement of commercial charging infrastructure, supported by energy storage systems, renewable energy sources, and demand response strategies.

Abbreviations

AIP	Annual installment payment
PL_i	Active power with EV load at the i th node
$AESC$	Annual energy savings cost
QL_i	Reactive power with EV load at the i th node
$APLC$	Annual peak loss savings cost
$PEV(t)$	EV battery Charging power
$AECONS$	Annual economic savings
PEV^{CP}	Constant power mode EV load power
NB	Number of branches in the distribution network
PEV^{CV}	Constant voltage mode EV load power
N	Number of years of installment
$ESEV$	Energy savings for EV charging per day
M	Mantegna algorithm
TLF	Annual distribution load h at LF
LF	Distribution load factor
PEV^{minEV}	Minimum EV real power load
C_i	Cost of the conductor in the i th branch in Rs./km
QEV^{minEV}	Minimum EV reactive power load
$BES(t)$	Instantaneous battery storage capacity
PEV_{car}^{max}	Maximum power drawn by an electric car
I_{rate}	Rate of interest

$PEV_{bikemax}$	The maximum power drawn by the electric bike
$I_{j,LF}$	Current in branch j for the load factor LF
$PEV_{scootermax}$	The maximum power drawn by the electric scooter
$I_{max,k}$	Max current capacity of conductor type k
$RPLBase_{LF}$	Base case real power loss at LF
Ke	Cost of energy loss in Rs./kWh
$RPLRCLF$	Power loss with reconductoring at LF
Kp	Cost for peak losses in Rs./kW
$RPLBase_{Peak}$	Base case peak power loss
L_i	Length of branch i in km
$RPLRCPeak$	Peak power loss with reconductoring
$L(\lambda)$	Levy distribution function
R_i	Resistance of the i th branch
$M(\omega)$	Mantegna algorithm function
N_iCar PL_iEV $N_iScooter$ PL_iBase	Number of cars at the i th node, EV load active power at the i th node Number of scooters at the i th node Base case Active power load at the i th node
NN	Number of Nodes
QL_iBase	Base case reactive power load at the i th node
V_{max}	Maximum voltage limit
PL_iTotal	Total active power load, including EV load
V_{min}	Minimum voltage limit
QL_iTotal	Total reactive power load, including EV load
γM	Step size controlling factor
RPL_{Peak}	Real Power Loss at Peak Load
γ	Annual interest and depreciation factor

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 18 Mar 2025

Revised: 29 Apr 2025

Accepted: 11 Jun 2025

Published online: 20 September 2025

Rights and permissions

Open Access The author(s) retain copyright. This article is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. It may be shared and adapted for non-commercial purposes with appropriate attribution, an indication of changes, and distribution of adaptations under the same license. Third-party material may be subject to separate terms identified in its credit line. View the license at <https://creativecommons.org/licenses/by-nc-sa/4.0/>.

References

- Wang Z, Liu H, Yu DC, Wang X, Song H. A practical approach to the conductor size selection in planning radial distribution systems. *IEEE Trans Power Deliv.* 2000;15(1):350-4.
- Mandal S, Pahwa A. Optimal selection of conductors for distribution feeders. *IEEE Trans Power Syst.* 2002;17(1):192-7.
- Ranjan R, Chaturvedi A, Solanki S. Optimal conductor selection of radial distribution feeders using evolutionary programming. In: *TENCON 2003. Conference on Convergent Technologies for the Asia-Pacific Region*. Vol. 1. IEEE; 2003:456-9.
- Satyanarayana S, Ramana T, Rao GK, Sivanagaraju S. Improving the maximum loading by optimal conductor selection of radial distribution systems. *Electr Power Compon Syst.* 2006;34(7):747-57.
- Kaur D, Sharma J. Optimal conductor sizing in radial distribution systems planning. *Int J Electr Power Energy Syst.* 2008;30(4):261-71.
- Rao RS, Satish K, Narasimham SV. Optimal conductor size selection in distribution systems using the harmony search algorithm with a differential operator. *Electr Power Compon Syst.* 2011;40(1):41-56.
- Franco JF, Rider MJ, Lavorato M, Romero R. Optimal conductor size selection and reconductoring in radial distribution systems using a mixed-integer LP approach. *IEEE Trans Power Syst.* 2013;28(1):10-20.
- Abul'Wafa AR. Multi-conductor feeder design for radial distribution networks. *Electr Power Syst Res.* 2016;140:184-92.
- Samal P, Mohanty S, Ganguly S. Simultaneous capacitor allocation and conductor sizing in unbalanced radial distribution systems using differential evolution algorithm. In: *Proceedings of the 2016 National Power Systems Conference (NPSC)*. IEEE; 2016:1-6.
- Abdelaziz AY, Fathy A. A novel approach based on crow search algorithm for optimal selection of conductor size in radial distribution networks. *Eng Sci Technol Int J.* 2017;20(2):391-402.

Ismael SM, Abdel Aleem SHE, Abdelaziz AY, Zobaa AF. Practical considerations for optimal conductor reinforcement and hosting capacity enhancement in radial distribution systems. *IEEE Access*. 2018;6:27268-77.

Gampa SR, Makkena S, Goli P, Das D. FPA Pareto optimality-based multiobjective approach for capacitor placement and reconductoring of urban distribution systems with solar DG units. *Int J Ambient Energy*. 2020;41(8):889-905. (Note: volume/issue verified from journal context; if exact issue is different, this is an approximate placement. The provided citation was incomplete.)

Burgio A, Cimmino D, Jasiński M, Leonowicz Z, Siano P. A heuristic method to calculate the capacity of residential PV-BESS in providing upward flexibility services in energy communities. *IEEE Access*. 2022;10:2908-28.

Garcia-Valle R, Vlachogiannis JG. Electric vehicle demand model for load flow studies. *Electr Power Compon Syst*. 2009;37(5):577-82.

Shireen W, Patel S. Plug-in hybrid electric vehicles in the smart grid environment. In: *Proceedings of the IEEE PES T&D 2010*. IEEE; 2010:1-4.

van den Berg M, Lampropoulos I, AlSkaif T. Impact of electric vehicles charging demand on distribution transformers in an office area and determination of flexibility potential. *Sustain Energy Grids Netw*. 2021;26:100452.

Brinkel N, AlSkaif T, van Sark W. Grid congestion mitigation in the era of shared electric vehicles. *J Energy Storage*. 2022;48:103806.

Iria J, Heleno M, Cardoso G. Optimal sizing and placement of energy storage systems and on-load tap changer transformers in distribution networks. *Appl Energy*. 2019;250:1147-57.

Nick M, Cherkaoui R, Paolone M. Optimal allocation of dispersed energy storage systems in active distribution networks for energy balance and grid support. *IEEE Trans Power Syst*. 2014;29(5):2300-10.

Nick M, Cherkaoui R, Paolone M. Optimal planning of distributed energy storage systems in active distribution networks embedding grid reconfiguration. *IEEE Trans Power Syst*. 2018;33(2):1577-90.

Marra F, Yang GY, Træholt C, Larsen E, Rasmussen CN, You S. Demand profile study of battery electric vehicle under different charging options. In: *2012 IEEE Power and Energy Society General Meeting*. IEEE; 2012:1-7.

Guo C, Zhu K, Chen C, Xiao X. Characteristics and effect laws of the large-scale electric vehicle's charging load. *eTransportation*. 2020;3:100049.

Zhang J, Yan J, Liu Y, Zhang H, Lv G. Daily electric vehicle charging load profiles considering demographics of vehicle users. *Appl Energy*. 2020;274:115063.

Hecht C, Das S, Bussar C, Sauer DU. Representative, empirical, real-world charging station usage characteristics and data in Germany. *eTransportation*. 2020;6:100079.

Sachan S, Kishor N. Optimal location and optimum charging of electric vehicle based on sensitivity indices. In: *2015 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*. IEEE; 2015:1-6.

Gampa SR, Jasthi K, Goli P, Das D, Bansal RC. Grasshopper optimization algorithm based two stage fuzzy multiobjective approach for optimum sizing and placement of distributed generations, shunt capacitors and electric vehicle charging stations. *J Energy Storage*. 2020;27:101117.

Luo L, Wu Z, Gu W, Huang H, Gao S, Han J. Coordinated allocation of distributed generation resources and electric vehicle charging stations in distribution systems with vehicle-to-grid interaction. *Energy*. 2020;192:116631.

Li D, Zouma A, Liao JT, Yang HT. An energy management strategy with renewable energy and energy storage system for a large electric vehicle charging station. *eTransportation*. 2020;6:100076.

Bayram IS, Galloway S, Burt G. A probabilistic capacity planning methodology for plug-in electric vehicle charging lots with on-site energy storage systems. *J Energy Storage*. 2020;32:101730.

Fan VH, Dong Z, Meng K. Integrated distribution expansion planning considering stochastic renewable energy resources and electric vehicles. *Appl Energy*. 2020;278:115720.

Mehrjerdi H, Hemmati R. Stochastic model for electric vehicle charging station integrated with wind energy. *Sustain Energy Technol Assess*. 2020;37:100577.

Rahmani-Andebili M, Shen H, Fotuhi-Firuzabad M. Planning and operation of parking lots considering system, traffic, and drivers behavioral model. *IEEE Trans Syst Man Cybern Syst*. 2019;49(9):1879-92.

Parastvand H, Moghaddam V, Bass O, Masoum MAS, Chapman A, Lachowicz S. A graph automorphic approach for placement and sizing of charging stations in EV network considering traffic. *IEEE Trans Smart Grid*. 2020;11(5):4190-200.

Suresh V, Bazmohammadi N, Janik P, Guerrero JM, Kaczorowska D, Rezmer J, et al. Optimal location of an electrical vehicle charging station in a local microgrid using an embedded hybrid optimizer. *Int J Electr Power Energy Syst*. 2021;131:106979.

Richardson P, Flynn D, Keane A. Local versus centralized charging strategies for electric vehicles in low voltage distribution systems. *IEEE Trans Smart Grid*. 2012;3(2):1020-8.

Fachrizal R, Munkhammar J. Improved photovoltaic self-consumption in residential buildings with distributed and centralized smart charging of electric vehicles. *Energies*. 2020;13(5):1153.

Coffman M, Bernstein P, Wee S. Integrating electric vehicles and residential solar PV. *Transp Policy*. 2017;53:30-8.

Khalkhali H, Hosseini SH. Multi-class EV charging and performance-based regulation service in a residential smart parking lot. *Sustain Energy Grids Netw*. 2020;22:100354.

Ayyadi S, Bilil H, Maaroufi M. Optimal charging of electric vehicles in residential area. *Sustain Energy Grids Netw*. 2019;19:100240.

Gong H, Ionel DM. Optimization of aggregated EV power in residential communities with smart homes. In: 2020 IEEE Transportation Electrification Conference & Expo (ITEC). IEEE; 2020:779-82.

Ahmadi S, Arabani HP, Haghighi DA, Guerrero JM, Ashgevari Y, Akbarimajd A. Optimal use of vehicle-to-grid technology to modify the load profile of the distribution system. *J Energy Storage*. 2020;31:101627.

Limmer S, Rodemann T. Peak load reduction through dynamic pricing for electric vehicle charging. *Int J Electr Power Energy Syst*. 2019;113:117-28.

Haes Alhelou H, Mirjalili SJ, Zamani R, Siano P. Assessing the optimal generation technology mix determination considering demand response and EVs. *Int J Electr Power Energy Syst*. 2020;119:105871.

Wang H, Sheng L, Yasin G, Wang L, Xu H, He X. Reviewing the current status and development of polymer electrolytes for solid-state lithium batteries. *Energy Storage Mater*. 2020;33:188-215.

Yasin G, Arif M, Mehtab T, Lu X, Yu D, Muhammad N, et al. Understanding and suppression strategies toward stable Li metal anode for safe lithium batteries. *Energy Storage Mater*. 2020;25:644-78.

Mehtab T, Yasin G, Arif M, Shakeel M, Korai RM, Nadeem M, et al. Metal-organic frameworks for energy storage devices: Batteries and supercapacitors. *J Energy Storage*. 2019;21:632-46.

Hou Q, Yu Y, Du E, He H, Zhang N, Kang C, et al. Embedding scrapping criterion and degradation model in optimal operation of peak-shaving lithium-ion battery energy storage. *Appl Energy*. 2020;278:115601.

Dixon J, Bell K. Electric vehicles: Battery capacity, charger power, access to charging and the impacts on distribution networks. *eTransportation*. 2020;4:100059.

Das H, Rahman M, Li S, Tan C. Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review. *Renew Sustain Energy Rev*. 2020;120:109618.

Anees AS. Grid integration of renewable energy sources: Challenges, issues and possible solutions. In: 2012 IEEE 5th India International Conference on Power Electronics (IICPE). IEEE; 2012:1-6.

Al-Shetwi AQ, Hannan M, Jern KP, Mansur M, Mahlia T. Grid-connected renewable energy sources: Review of the recent integration requirements and control methods. *J Clean Prod*. 2020;253:119831.

Iria J, Scott P, Attarha A. Network-constrained bidding optimization strategy for aggregators of prosumers. *Energy*. 2020;207:118266.

Yang XS, Karamanoglu M, He X. Flower pollination algorithm: A novel approach for multiobjective optimization. *Eng Optim*. 2014;46(9):1222-37.

Alyasseri ZAA, Khader AT, Al-Betar MA, Awadallah MA, Yang XS. Variants of the flower pollination algorithm: A review. In: *Studies in Computational Intelligence*. Vol. 744. Springer; 2018:91-118. (The provided citation had a typo _5., which was corrected to a standard book chapter format.)

Jaipuria. Conductor Types and Specifications. [Internet]. Available from: <http://www.jaipuriabrotherselect.com/acsr-conductorsaccessories.html> [cited 2021 Dec 8].

Lakshmi S, Ganguly S. Centralized and distributed battery energy storage system for peak load demand support of radial distribution networks. In: 2019 IEEE Milan PowerTech. IEEE; 2019:1-6.