FOREX Publication
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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 3 | Pages 788-793 | e-ISSN: 2347-470X

Addressing Power Loss and Voltage Profile Issues in Electrical Distribution Systems: A Novel Approach Using Polar Bear Gradient-Based Optimization

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ABSTRACT- Energy is an essential commodity for everyone, with electrical energy being the most preferred form. Unfortunately, non-renewable energy resources are gradually depleting, and renewable energy sources take several years to establish. To mitigate this problem, technology has shifted from non-renewable energy sources to electrical devices and machines, including household appliances like washing machines and air conditioners. However, the generation of electricity is still inadequate to meet the growing demand. This leads to two major problems: high power loss and poor voltage profile, making it difficult for power distribution companies to ensure a consistent and reliable power supply. This paper aims to address the reduction and minimization of power losses by adjusting distribution side transformer tap settings using the polar bear gradient-based optimization. The proposed approach uses the 14-bus system as a reference and calculates losses for this system using the backward-forward sweeping technique. The results are compared with standard PSO algorithm; the proposed strategy shows superior results.

Keywords: Capacitor Banks, Distribution Network, Electric Vehicles (EVs), Gradient-Based Optimization, Load Demand Curve, Power Losses, Power Distribution, Power Factor, Radial Distribution System (RDS), Reactive Power Compensation, Voltage Dependent Load Modeling, Voltage Profiles.

ARTICLE INFORMATION
Author(s): Dr. M. Rama Prasad Reddy, Chodagam Srinivas, Bireddi Eswararao, Rajendraprasad Kuriti and Dr. M. Koteswara Rao;
Received: 03/07/2023; **Accepted**: 03/09/2023; **Published**: 23/09/2023;
e-ISSN: 2347-470X;
Paper Id: IJEER 0307-01;
Citation: 10.37391/IJEER.110323
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-11/ijeer-110323.html

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1. INTRODUCTION

Due to the uncertainty of load, the process and regulation of a distribution arrangement is also complicated fields. The actual density is extremely high, and the load varies from time to time. The power disappearance in a distribution grid is not the same; it varies due to loads. This changing of load causes a poor voltage profile. An average of 13% of generated power by the synchronous generator is approximately wasted in the distribution system in the form of losses. To tackle this challenge, there are several methods, one of which is the installation of shunt capacitors. Shunt capacitors serve a vital role in the operation of the distribution network, facilitating improvements in power factor and voltage profile, as well as reducing power loss through reactive power compensation [1].

However, it should be noted that the load demand varies during the day, and thus capacitors with different optimal sizes should be installed in the grid. The capacitor allocation is classified into six different approaches to clear the capacitor placing disarrangement in the distribution network. The authors have suggested the particle swarm optimization algorithm to solve the capacitor appropriation trouble [2].

A two-stage methodology is presented to identify "the ideal capacity and placement of the capacitor, aiming to minimize energy loss and enhance voltage profile" [3].

In the first stage, the capacitor locations are determined, and in the second stage, the capacitor size is optimized. Previous research has addressed the capacitor allocation problem in unbalanced networks to minimize energy loss in the distribution system [2, 3].

The allocation problem of shunt capacitors in radial distribution systems aims to compensate for reactive power and is addressed using a hybrid evolutionary approach incorporating particle swarm optimization algorithms [4].

A new heuristic algorithm called the grasshopper optimization algorithm is employed to get the optimal allocation problem of switchable capacitors in the spreading scheme.

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2. PROPOSED METHODOLOGY

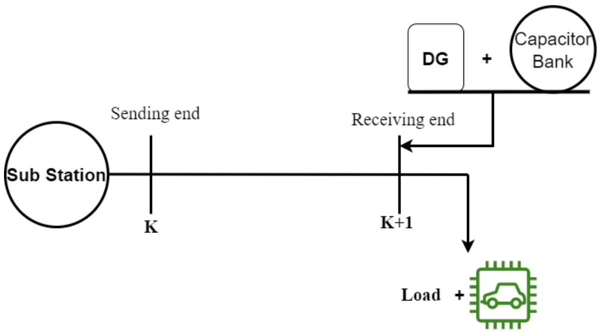

Fig. 1: Modified radial distribution system.

2.1 Forward/Backward Sweep Technique

To further analyze the actual system and quantify the losses, it is necessary to employ measurement techniques for classification purposes. The system losses in this study are calculated using the Forward/Backward Sweep technique. This technique is a well-known method used in power system analysis to evaluate the power flow and losses in a distribution network. By employing this technique, the study can accurately determine the system losses by considering the characteristics and parameters of the network components. The Forward/Backward Sweep technique involves iteratively calculating the power flow and losses in each branch of the network, starting from the source, and propagating towards the load nodes. This comprehensive approach enables a thorough assessment of the system losses, aiding in the analysis and optimization of the distribution network.

Here both AC & DC type-2 and type-3 EV charging stations are placed in the RDS on random choices at the buses. The uncertainty arising from EV charging terminals contributes to increased losses in the Radial Distribution System (RDS) and disrupts the unity of the load demand curve. *Table 1 & 2* provides information on the types, ratings, and locations of EV charging stations within the RDS.

To enhance the voltage profile within the integrated RDS, real and reactive power compensation is achieved by incorporating Photovoltaic (PV) systems (DG) with suitable penetration levels and capacitor banks. Additionally, this paper introduces voltage-dependent load modeling. *Table 3* presents the PV penetration levels, percentage of compensation by capacitor banks (CB), and their corresponding locations within the RDS. *Equations (1)-(3)* represent the calculated values for voltage at the receiving end, as well as the real and reactive power losses after evaluating the impact of the undefined DG with capacitor banks.

$$|V_{k+1}| = \frac{|V_k| + \left(|V_k|^2 - 4\left(\left(P_{int}^2 + Q_{int}^2\right)^{1/2}\right)\left(R^2 + X^2\right)\right)^{1/2}}{2} \tag{1}$$

$$P_{Loss(k,k+1)}^{DG} = \frac{\left((P_{k+1} - P_{int})^2 + (Q_{k+1} - Q_{int})^2\right)}{|V_{k+1}|^2} * R \tag{2}$$

$$Q_{Loss(k,k+1)}^{DG} = \frac{\left((P_{k+1} - P_{int})^2 + (Q_{k+1} - Q_{int})^2\right)}{|V_{k+1}|^2} * X \tag{3}$$

To detect shadow in each image we first tried to find out the shadow pixels using histogram analysis followed by seed point and region growing method. The detected shadow points are reconfirmed as shadow region using artificial intelligence method.

TABLE 1: DC EV Charging Stations [5]

Parameters/ Levels	Level 1	Level 2	Level 3
Supply Ratings	36 KW, 200-450V, 80A	96 KW,200-450V, 210A	200 KW, 200-600V, 210A
Location	-	6, 7	4

TABLE 2: AC EV Charging Stations [5]

Parameters/ Levels	Level 1	Level 2	Level 3
Supply Ratings	1.9 KW, 120V, 16A	19.2 KW, 208-240V, 80A	43.5 KW, 240V, 180A
Location	-	9, 11, 13, 15	3

TABLE 3: Compensation & Penetration of PV, Capacitor Banks [6-8]

DG/Capacitor	% Penetration Compensation	Bus Location
PV	0-75	5
	0-75	7
	0-25	9
	0-25	10
	0-25	12
	0-25	14
	0-25	15
Wind	0-50	2
Capacitor Bank	30	5
	50	6
	50	7
	20	8

2.1.1 Nonpartisan activity

Here the single detached objective to abbreviate the power losses, i.e., real & reactive power losses. The objective function is characterized as follows.

$$\min F(x) = \frac{1}{f(x)}; f(x) \neq 0$$

In this study, the design variables considered are edge present, integrate service, and transformer tap settings. These variables play a crucial role in optimizing the performance of the system. It is important to note that the tap settings have specified minimum and maximum limitations, which are set at 0.9 and 1.10 per unit (P.U.), respectively. These limits ensure that the tap settings remain within a feasible range during the optimization process. By incorporating these design variables and constraints, the study aims to achieve an optimal solution for the system under consideration.

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2.2 Polar Bear Optimization

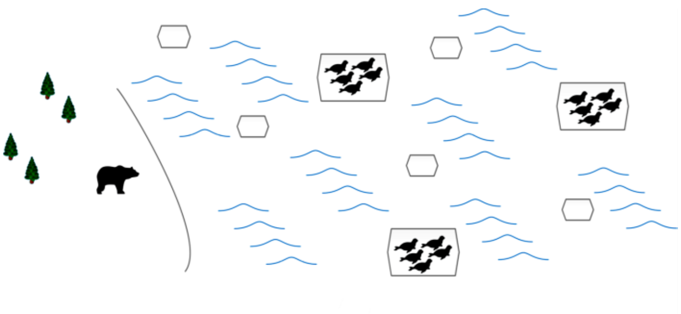
Polar Bear Optimization (PBO) is an optimization algorithm rooted in the natural hunting behavior of polar bears. Taking cues from how polar bears hunt and survive in icy environments, PBO leverages these strategies to solve complex optimization problems. By mimicking the adaptive and strategic behavior of polar bears, PBO offers a unique and effective approach to problem-solving. It was proposed by Abbaszadeh et al. in their research paper titled "Polar Bear Optimization: Algorithm and Applications" [9]. The algorithm imitates the foraging behavior of polar bears in the Arctic region to solve optimization problems efficiently.

The Polar Bear Optimization (PBO) algorithm, drawing inspiration from the hunting behavior of polar bears, has shown promising results in solving various optimization problems. However, like any optimization algorithm, PBO has certain limitations and drawbacks that need to be considered.

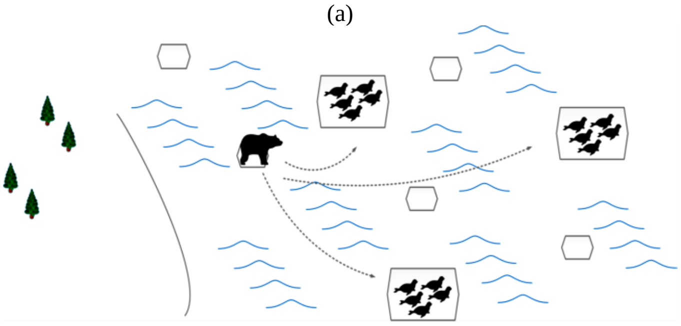
Here are a few drawbacks of PBO:
• *Premature Convergence*: PBO may suffer from premature convergence, where the algorithm settles into a suboptimal solution prematurely, without exploring the entire search space. This can result in suboptimal solutions and limit the algorithm's ability to find the global optimum.

• *Limited Exploration*: PBO's hunting behavior is based on the movement of polar bears on ice floes, which may limit the exploration capability of the algorithm. The search process may become constrained, leading to a reduced ability to discover diverse and globally optimal solutions.

• *Sensitivity to Parameters*: PBO requires setting several parameters, such as the step size and number of iterations, which can significantly impact the algorithm's performance. Inadequate parameter settings may lead to slower convergence or premature convergence.



(a)



(b)

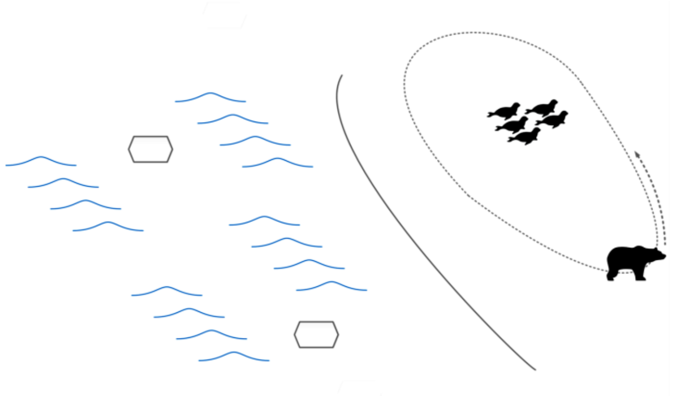


Figure 2: Polar Bear Hunting Behavior Modeled as an Optimization Strategy [9].

To address these limitations, here the paper developed a variant of PBO called Gradient-based Polar Bear Optimization (GB-PBO) and implemented it in your MATLAB code. GB-PBO incorporates gradient descent optimization within the PBO framework to enhance the algorithm's exploration and exploitation capabilities. Here's why you chose GB-PBO:

- *Enhanced Exploration*: By integrating gradient descent optimization, GB-PBO allows for more effective exploration of the search space. The gradient information guides the search towards promising regions, increasing the chances of discovering better solutions.

- *Improved Convergence*: The incorporation of gradient descent optimization in GB-PBO helps in refining by incorporating solutions and refining the search process, the Gradient-Based Polar Bear Optimization algorithm enhances convergence speed and solution quality, surpassing traditional PBO approaches. This advancement enables more efficient optimization and improved outcomes.

- *Reduced Premature Convergence*: GB-PBO's ability to perform local search using gradient descent optimization helps mitigate the issue of premature convergence. It allows the algorithm to escape local optima and continue exploring the search space, leading to better overall performance.

By integrating gradient-based optimization techniques, your MATLAB code utilizing GB-PBO aims to overcome the drawbacks of standard PBO by achieving a balance between exploration and exploitation. The combination of PBO's inspiration from polar bear behavior and gradient descent optimization's refinements can potentially result in improved performance and solution quality in solving optimization problems.

2.2.1 Gradient Based Polar Bear

Algorithm Steps:

- Initialize the problem parameters, including the number of particles (Npar), the benchmark function (FN), the function number (FunNumber), and the variable bounds (VarLow and VarHigh).

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- Set the number of PBO iterations (PBOIterations), the number of GD iterations (GDIterations), and the step size (StepSize).
- Set the initial best cost (BestCost) to infinity and the best solution (BestSolution) to an empty array.
- Initialize the population by randomly generating individuals within the variable bounds. Evaluate the cost of everyone using the benchmark function and update the best cost and best solution if necessary.
- Enter the main loop for PBOIterations iterations.
- For everyone in the population, perform GDIterations iterations of gradient descent optimization. Compute the gradient of the cost function using the compute Gradient function. Update the position of the individual using the step size and the gradient.
- Apply bounds to the updated position to ensure it stays within the variable bounds.
- Evaluate the cost of the updated position using the benchmark function.
- Update the personal best if the cost of the updated position is better than the current best cost.
- Repeat steps 6-9 for all individuals in the population.
- Repeat steps 5-10 for PBOIterations iterations.
- Output the final best cost (BestCost) and the corresponding best solution (BestSolution).

3. RESULTS & DISCUSSIONS

The initial stage of minimizing power losses involves the integration of voltage load modeling in the 15-bus Radial Distribution System (RDS). The resulting outcomes are subsequently compared with the outcomes obtained using constant power modeling, as depicted in *figure 4*.

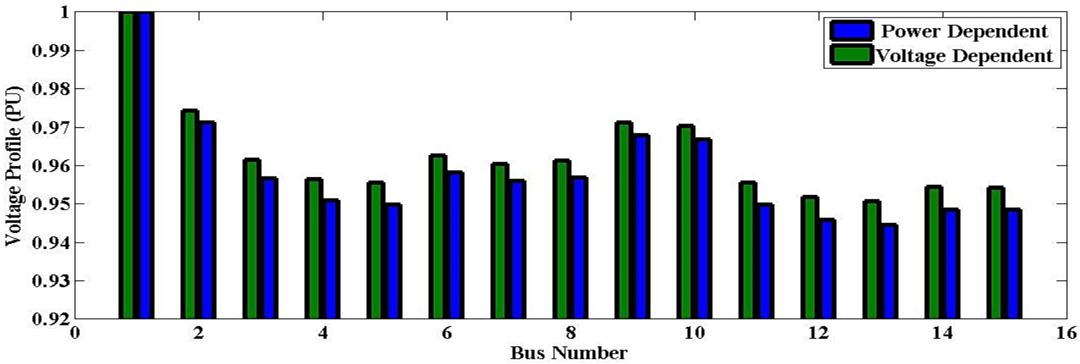

Fig. 4: Comparison of constraint power & Voltage load description voltage profile.

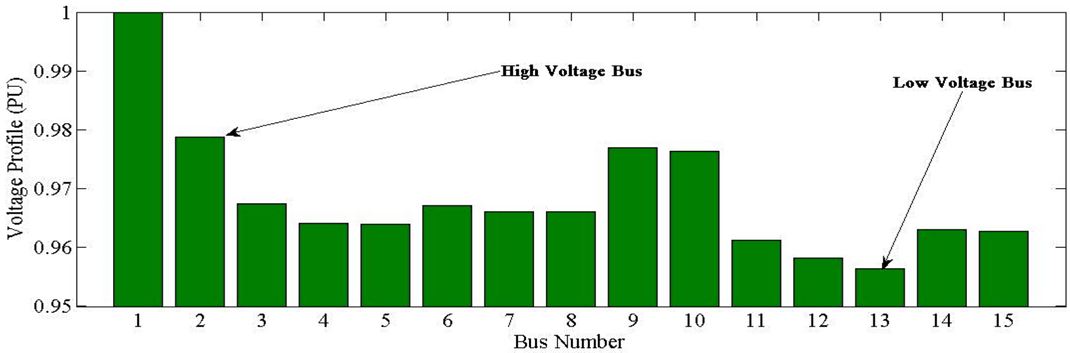

Fig. 5: Recovery of Distribution System Voltage Profile following the Implementation of EV Charging Stations

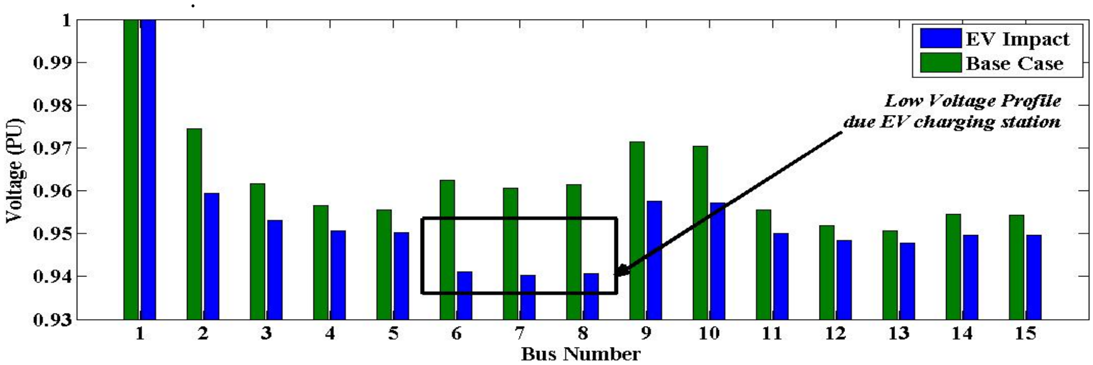

Fig. 6: Comparative Analysis of Voltage Profile in the Distribution System following the Integration of EV Charging Terminals.

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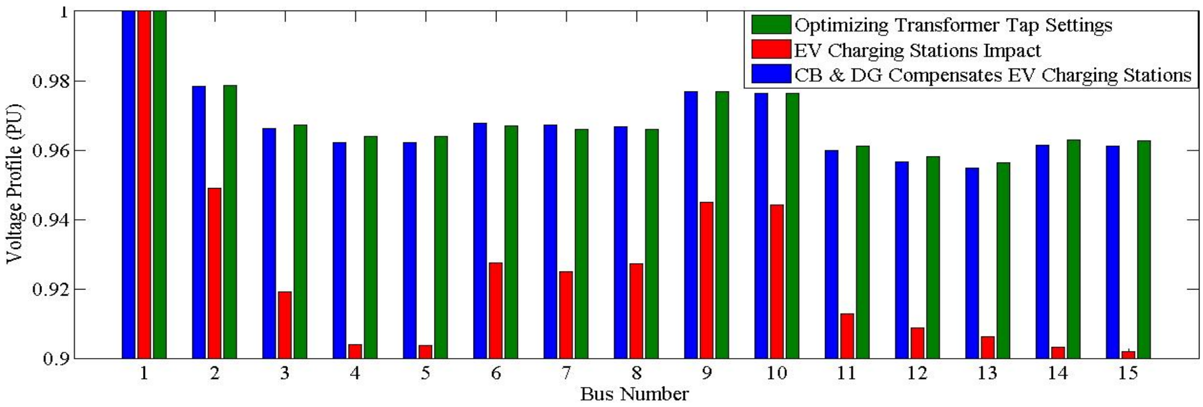

Fig. 7: Voltage Profile Response Considering Different Scenarios: With and Without Compensation, and Optimized Transformer Tap Settings.

Table 3: Comparative Analysis of Power Losses and Voltage Elevation in the Distribution Network

Case	Min. bus Voltage (PU) & Location	Max. bus Voltage (PU) & & Location	Real Power Losses (KW)	Reactive Power Losses (KVar)
Constant Power Model	0.9445 & Bus No. 13	0.97128 & Bus No. 2	61.7873	57.2905
Constant Voltage Model	0.94722 & Bus No. 13	0.97260 & Bus No. 2	56.0592	44.4975
EV Station Placement	0.90374 & Bus No. 15	0.95047 & Bus No. 2	327.90	309.64
Compensation by DG & CB	0.9570 & Bus No. 13	0.9759 & Bus No. 2	46.3221	33.5377
PBO-based Distribution Transformer Tap Settings	0.9550 & Bus No. 13	0.976 & Bus No. 2	48.5822	29.5225
GB-PBO-based Distribution Transformer Tap Settings	0.9570 & Bus No. 13	0.979 & Bus No. 2	43.1013	29.6452

Table 3 presents the outcomes of utilizing polar bear gradient-based optimization transformer tap settings in terms of reducing power loss and enhancing the voltage profile in the RDS. Notably, bus number 7 experiences a substantial voltage profile alteration due to the influence of the EV charging station, as indicated in *table 3* for the IEEE 15 bus system. However, through the implementation of compensation techniques and a strategy based on polar bear gradient-based optimization transformer tap settings, the voltage profiles were improved, including at bus numbers 13 and 7. Furthermore, the maximum voltage levels were increased, along with the enhancement of the voltage profiles at those specific bus numbers.

Table 4 provides a comprehensive comparison of different methodologies applied to assess real and reactive power losses as well as transformer tap settings. The table evaluates the performance of three algorithms: Particle Swarm Optimization (PSO), Polar Bear Optimization (PBO), and Gradient-Based Polar Bear Optimization (GB-PBO). The aim is to identify the most effective approach for minimizing power losses and optimizing transformer tap settings.

Table 4: Comparison of Methodologies for Real and Reactive Power Losses and Transformer Tap Settings

Methodology	Real Power Losses (KW)	Reactive Power Losses (KVar)	Transformer Taping (PU)
Without Optimization	46.3221	33.5377	1.0
PSO	44.1155	32.5346	0.9820
PBO	46.5334	30.6460	0.9276
GB-PBO	43.1013	29.6452	0.9

Upon analysis, it is observed that the GB-PSO algorithm yields the most favorable outcomes compared to PSO and PBO. The GB-PSO algorithm demonstrates superior performance in terms of minimizing real and reactive power losses. Furthermore, it achieves optimized transformer tap settings that contribute to enhanced system efficiency and voltage profile stability.

These findings indicate that the GB-PSO algorithm outperforms both PSO and PBO in terms of power loss reduction and optimal transformer tap settings. It showcases the effectiveness of integrating gradient-based techniques with the Polar Bear Optimization approach.

Overall, *table 4* highlights the advantages of employing the GB-PSO algorithm for addressing power losses and optimizing transformer tap settings in the distribution system. These findings offer valuable insights for researchers and practitioners aiming to optimize the efficiency and effectiveness of power distribution networks.

4. CONCLUSIONS

The study showcases the efficacy of polar bear gradient-based optimization in diminishing power losses and enhancing voltage profiles within radial distribution systems that incorporate EV charging stations. The results demonstrate that the proposed method, which involves the strategic placement and sizing of capacitor banks alongside polar bear gradient-based optimization-based transformer tap settings, can yield substantial reductions in real power loss while simultaneously improving voltage profiles throughout the distribution network. Additionally, the study emphasizes the significance of adequate compensation to effectively manage the impact of EV charging stations on the distribution system. These findings hold valuable insights for power distribution companies, aiding them in the design and optimization of distribution systems to accommodate the escalating penetration of EVs. Future research endeavors may explore alternative optimization techniques and investigate the influence of different types of EV charging stations on distribution networks.

Conflicts of Interest: The authors declare no conflict of interest.

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