energies

MDPI

Article

Electric Vehicle and Soft Open Points Co-Planning for Active Distribution Grid Flexibility Enhancement

Jie Fang [1,*], Wenwu Li [1,2] and Dunchu Chen [1]

[1] College of Electrical Engineering and New Energy, China Three Gorges University, Yichang 443002, China
[2] Hubei Key Laboratory of Cascaded Hydropower Stations Operation and Control, China Three Gorges University, Yichang 443002, China
* Correspondence: 202208580121038@ctgu.edu.cn

Abstract: With the increasing penetration of distributed generation (DG), the supply–demand imbalance and voltage overruns in the distribution network have intensified, and there is an urgent need to introduce flexibility resources for regulation. This paper proposes co-planning of electric vehicles (EVs) and soft opening points (SOPs) to improve the flexibility of the active distribution network, thereby improving the economics and flexibility of the distribution network. Firstly, this paper establishes a charging pile day-ahead dispatchable prediction model and a real-time dispatchable potential assessment model through Monte Carlo sampling simulation. It replaces the traditional energy storage model with this model and then solves the EV and SOP collaborative planning model using a second-order conical planning algorithm with the objective function of minimizing the annual integrated cost. At the same time, the flexibility of the distribution network is analyzed by two indicators: power supply and demand balance and branch load margin. Finally, the optimization method proposed in this paper is analyzed and validated on an improved IEEE 33-node distribution system. Example results show that the planning method proposed in this paper can effectively reduce the annual comprehensive operating cost of distribution networks, meet the flexibility index, and be conducive to improving the economy and flexibility of distribution network operation.

Keywords: distributed generation; soft open point; electric vehicle; Monte Carlo sampling; second-order cone programming

check for updates

Academic Editor: Michael Negnevitsky

Received: 27 December 2024
Revised: 27 January 2025
Accepted: 31 January 2025
Published: 3 February 2025

Citation: Fang, J.; Li, W.; Chen, D. Electric Vehicle and Soft Open Points Co-Planning for Active Distribution Grid Flexibility Enhancement. *Energies* **2025**, *18*, 694. https://doi.org/10.3390/en18030694

1. Introduction

In response to the national goals of 'carbon peaking' and 'carbon neutrality', building a new type of power system dominated by new energy sources, and promoting widespread access to clean energy, China is actively promoting the transformation and upgrading of its power system. However, the uncertainty of DG generation brings problems such as voltage overruns and power overloads to the distribution network, which increases the difficulty of stable operation of the distribution network [1]. EVs, as mobile energy storage devices, have a huge load storage potential as their residence time at charging stations far exceeds the charging time, which is often overlooked. Studies have shown that rational management of EV charging and discharging through charging stations can provide spare capacity for the grid [2,3]. Meanwhile, SOPs, as flexible interconnected power electronic devices, can provide the ability to distribute tidal currents on a spatial scale [4], but their energy storage capacity is small, while the energy storage system, although effective in solving this problem, is difficult to promote on a large scale due to its own high cost. Therefore, considering the dispatchable potential of EV clusters and aggregating them into charging stations instead of energy storage systems through SOP collaborative planning is important to improve the economy and flexibility of the distribution system.

At present, scholars have carried out a number of studies on the flexibility caused by the high penetration of DG in the distribution network. Ref. [5] proposes an optimal configuration scheme of the distribution network considering the operation strategy and investment benefits, analyzes and determines the installation location of the energy storage device by establishing a comprehensive node voltage sensitivity index, and uses an improved particle swarm optimization algorithm to solve the optimal configuration model of double-layer multi-objective energy storage, so as to improve the voltage quality and economy of the distribution network. Ref. [6] proposes an active distribution network voltage optimization method to optimize the distribution network voltage distribution and improve system stability and efficiency through coordinated source-network-load-storage interaction. In ref. [7], a stochastic programming model is proposed to evaluate and optimize smart grid technology options in distribution networks to deal with network constraint violations caused by the increasing penetration of distributed generation. Ref. [8] proposes a hierarchical zoning planning method incorporating quantum genetic algorithms; Ref. [9] proposes a local control strategy based on SOP to suppress the voltage fluctuations and irregularities caused by high-permeability distributed generation in the distribution network, and realizes fast voltage regulation independent of communication by flexibly interconnecting the end nodes of multiple distribution station areas (DSAs); and ref. [10] proposes a genetic algorithm (GA)-based optimization technique to determine the optimal location and capacity of DG systems in distribution networks to reduce network losses, regulate voltage levels, and improve the impact of high permeability DG on network operations. In reference [11], by optimizing the location and capacity of distributed photovoltaic power generation and network reconfiguration, the real-time power loss is reduced and the voltage curve is improved. In the above literature, most of the planning is carried out on an existing basis and only a few papers introduce new resources to improve the flexibility and reliability of the distribution network.

The core of electric vehicles as load-side flexibility resources lies in the schedulable potential of their clusters, which are able to utilize their dispatch potential by participating in demand response based on the amount of energy required for future driving, using the storage capacity and charging and discharging capabilities of the vehicle's batteries. Ref. [12] focuses on the simulation of EV usage patterns and uncertainty analysis of the impact of EV charging on the grid. Ref. [13] proposes a two-stage voltage control strategy based on deep reinforcement learning to alleviate the problem of voltage violations in the distribution network caused by electric vehicle charging. Ref. [14] proposes a two-layer collaborative optimal scheduling method for electric vehicles and distribution networks considering demand response and carbon quota benefits, so as to reduce the total operating cost of the distribution network, reduce network loss, and improve the economy and low-carbon performance of the system. Ref. [15] mainly studies the planning model of EV charging facilities based on the spatial and temporal characteristics of charging demand, including charging load forecasting and the number and layout optimization of charging facilities. Ref. [16] studies how to improve the frequency stability of isolated microgrids through the orderly charging and discharging of electric vehicles, and designs an electric vehicle-based power control strategy (EVPC) to manage the process of electric vehicles participating in frequency control in microgrids. Although this literature regards electric vehicles as a flexible resource, most of it lacks detailed modeling of electric vehicle capacity and charging and discharging power.

At this stage, there have been some studies on SOP planning. Ref. [17] proposes a distribution network optimization scheduling method considering the demand response and carbon quota income of electric vehicles, and uses a two-layer co-optimization model to determine the optimal location and size of the SOP to improve the economics and low-carbon performance of the distribution network. Ref. [18] proposes a strategy for optimal allocation of SOPs in a flexible interconnected distribution network by determining the optimal installation location of SOPs through improved sensitivity analysis and optimizing the SOP capacity using second-order cone planning in order to reduce the annual operating cost of the distribution network. Ref. [19] proposes a DC distribution network co-optimization method based on EV charging, discharging, and SOP topology reconfiguration to optimize the EV discharge power and SOP access configuration through a two-layer optimization model in order to reduce the system losses and voltage deviations, and to improve the economy and reliability of the system. Ref. [20] proposes a two-layer co-optimization planning model for distributed energy resources (DERs) including SOP in active distribution networks (ADNs), which aims to reduce the total investment and operating costs of the system by optimizing the location and capacity of DER and SOP, as well as coordinating the operation of DER, SOP, and voltage/reactive power control equipment, while improving system reliability and reducing carbon emissions. Ref. [21] proposes an optimal SOP allocation method considering DG stochasticity and volatility. Ref. [22] proposes a SOP allocation method that takes into account the risk of loss of critical customer loads. Ref. [23] proposes a flexible distribution network optimization method based on multiterminal SOP, which optimizes the layout and operation of distributed energy resources and reduces the investment and operating costs of the system by transforming the nonconvex nonlinear programming problem into a mixed integer second-order cone programming (MISOCP) model. The above literature is not sufficiently refined in modeling EVs and does not fully consider the dynamic characteristics of their capacity and charging/discharging power, leading to insufficient exploitation of the potential of EV flexibility resources, while the planning of SOPs is mostly focused on siting and capacity determination, and lacks synergistic planning with other flexibility resources, such as EVs, which makes it difficult to give full play to the comprehensive benefits of EVs in terms of enhancing the flexibility and economy of the power distribution network.

Based on the above background, this paper proposes a collaborative planning method for EVs and SOPs for active distribution network flexibility enhancement. The main contributions are as follows:

(1) The dispatchable potential of EVs is analyzed through Monte Carlo simulation and clusters of EVs are aggregated into a broad energy storage device centered on charging piles to replace traditional energy storage systems. This approach makes full use of the energy storage potential of EVs and avoids the limitation of the high cost of traditional energy storage systems, providing a new way of resource utilization to improve the flexibility of the distribution network.

(2) A collaborative planning method for EVs and smart soft opening points (SOPs) oriented to the flexibility enhancement of active distribution networks is proposed. With the objective function of minimizing the annual comprehensive operating cost, a second-order cone planning algorithm is used to solve the siting and capacity-setting planning model of SOPs, and the optimal allocation of EVs and SOPs is realized. The method significantly improves the flexibility and reliability of the distribution network while optimizing the economy.

(3) A supply–demand balance flexibility index and a branch load margin flexibility index are constructed for comprehensively assessing the flexibility of distribution networks. The validation results show that the proposed collaborative planning method can effectively reduce the annual comprehensive operating cost of the distribution network and significantly improve the flexibility index of the system, which provides a new

technical idea for the distribution network planning under the high penetration of distributed power sources.

Currently, research on EVs as flexibility resources has made some progress, but most of the existing research focuses on the assessment of EV dispatch potential and lacks refined modeling of charging and discharging power and capacity. Meanwhile, although planning research into smart SOPs has been carried out, it is mostly for the siting and capacity determination of a single device, and lacks synergistic planning with flexibility resources such as EVs. The synergistic planning method proposed in this paper fills this research gap and provides a new technical idea for the flexibility enhancement of active distribution networks.

2. Considering EV Dispatch Potential Characterization Models

2.1. EV Dispatchable Potential Modeling Analysis

The charging modes of EVs are mainly categorized as fast charging and slow charging. In fast charging mode, EVs are charged at the maximum rate with a fixed charging power and can therefore be categorized as regular loads. In slow charging mode, EVs stop much longer than the time required for charging, and charging stations can regulate the charging and discharging power of EVs to achieve load shifting and reverse power supply, thus improving the flexibility of the distribution network and making it an adjustable and flexible load [24].

2.2. Modeling of Generalised Energy Storage Devices

If EVs are modeled individually, on the one hand, too many variables will be introduced, increasing the complexity of the model; on the other hand, it is difficult to predict the driving characteristics of each EV in the day-ahead phase. The charging station, as a centralized manager of EVs, can be used as an adjustable load resource for distribution network planning by regulating the charging and discharging process of EVs in the charging station.

Since there are some differences in the definition domains of EVs due to their different grid connection times, it is necessary to extend these different definition domains into a unified scheduling timeframe in order to construct the model shown in Equation (1).

$$\begin{cases} 0 \leq P_{j,t}^{ch} \leq P_{j,t}^{ch,\max} & \forall t \in T \\ 0 \leq P_{j,t}^{dis} \leq P_{j,t}^{dis,\max} & \forall t \in T \\ S_{j,t} = S_{j,t-1} + \Delta S_{j,t} + \eta^{ch} p_{j,t}^{ch} \Delta t - \frac{\eta^{ref} p_{j,t}^{dis} \Delta t}{\eta^{dis}} \\ S_{j,t}^{\min} \leq S_{j,t} \leq S_{j,t}^{\max} \end{cases} \tag{1}$$

where $P_{j,t}^{ch,\max}$ and $P_{j,t}^{dis,\max}$ are the sum of the maximum charging and discharging power of charging station j in time period t, respectively; $P_{j,t}^{ch}$ and $P_{j,t}^{dis}$ are the sum of the actual charging and discharging power of charging station j in time period t, respectively; $S_{j,t}$ is the actual power of charging station j at time t; $S_{j,t-1}$ is the actual power of charging station j at time $t-1$; $S_{j,t}^{\max}$ and $S_{j,t}^{\min}$ are the upper and lower limits of EV battery capacity, respectively; $\Delta S_{j,t}$ is the change in power consumption of the charging station as a result of the EV being on or off the grid during the time slot; Δt is the time interval of change; η^{ch} and η^{dis} are EV charging and discharging efficiencies, respectively; and η^{ref} is the discharge compensation factor.

2.3. Calculation Model of Dispatchable Capacity Before EV Day

In the day-ahead phase, the charging station makes a forecast of its dispatchable potential based on past data. In the case of a particular charging station, for example, historical operational data are first determined as follows.

$$\Omega_v = \{E_{V1}, E_{V2}, \cdots, E_{Vn}, \cdots, E_{VN_v}\} \tag{2}$$

where Ω_v is the EV data; N_v is the number of EVs; and E_{Vn} is the historical data of electric vehicle charging at charging stations.

The charging station records daily data on the EVs it serves, covering the moments of EV entry and exit, the battery power at the time of entry and exit, and the model of the EV (which involves the upper limits of battery capacity and charging and discharging power), as follows:

$$E_{Vn} = \left\{ \begin{array}{l} T_n^{arr}, T_n^{lea}, s_{n,arr}, s_{n,lea}, \\ s_n^{\min}, s_n^{\max}, p_{n,\max}^{ch}, p_{n,\max}^{dis} \end{array} \right\} \tag{3}$$

where T_n^{arr} and T_n^{lea} are the moments when the electric car enters and leaves the charging station; $s_{n,arr}$ and $s_{n,lea}$ are the battery levels of the electric vehicle as it enters and exits the charging station; $s_n^{\max}$ and $s_n^{\min}$ are the upper and lower limits of battery capacity for electric vehicles, respectively; and $p_{n,\max}^{ch}$ and $p_{n,\max}^{dis}$ are the upper limits of charging and discharging power for electric vehicles, respectively.

The derivation of the generalized energy storage parameters of the charging station is given in reference [2], and the parameters are derived as shown in Equation (5). Equation (6) reflects the EV cluster's dispatchable potential.

$$X_{n,t} = \begin{cases} 0 & \forall t \notin [T_n^{arr}, T_n^{lea}] \\ 1 & \forall t \in [T_n^{arr}, T_n^{lea}] \end{cases} \tag{4}$$

$$\begin{cases} p_{j,t}^{ch,\max} = \sum\limits_{n \in N_j^{EV}} p_{n,\max}^{ch} X_{n,t} \\ p_{j,t}^{dis,\max} = \sum\limits_{n \in N_j^{EV}} p_{n,\max}^{dis} X_{n,t} \\ S_{j,t}^{\min} = \sum\limits_{n \in N_j^{EV}} s_n^{\min} X_{n,t} \\ S_{j,t}^{\max} = \sum\limits_{n \in N_j^{EV}} s_n^{\max} X_{n,t} \\ \Delta S_{j,t} = \sum\limits_{n \in N_j^{EV}} \begin{array}{l} (s_{n,arr} X_{n,t}(X_{n,t} - X_{n,t-1}) - \\ s_{n,lea} X_{n,t-1}(X_{n,t-1} - X_{n,t})) \end{array} \end{cases} \tag{5}$$

$$\Lambda_v = \left\{ p_{j,t}^{ch,\max}, p_{j,t}^{dis,\max}, \Delta S_{j.t}, S_{j,t}^{\min}, S_{j,t}^{\max} \right\} \tag{6}$$

where $X_{n,t}$ denotes the state of EV n at time t; $X_{n,t-1}$ denotes the state of EV n at time $t-1$; $X_{n,t} = 1$ denotes that EV n is on-grid at time t; and $X_{n,t} = 0$ denotes that EV n is off-grid at time t. Λ_v is an ensemble consisting of the charging and discharging power upper limit, power upper and lower limits, and power variation of the EV cluster, and also represents the dispatchable potential of the EV cluster.

2.4. Methodology for Forecasting Day-Ahead Dispatchable Potential

In real-time operation, the charging station evaluates the EV scheduling capability through actual monitoring data. In this study, it is assumed that EV users are willing to share their car schedules and power demand with the charging station; otherwise, it is treated as maximum charging power. The charging station evaluates the dispatchable potential of EVs based on real-time data from the station, as shown in Equation (5). As time progresses, the charging station refreshes its dispatchability assessment but only implements schedules within a consecutive time window in the dispatch operation.

3. SOP Principles and Optimized Configuration Models

3.1. SOP Operation Principle

The Figure 1 shows the standard structure of an SOP, which consists of two symmetrical VSCs and an energy storage system. The operation of an SOP is mainly affected by the control mode of the VSCs, and PQ-VQ droop control is usually adopted to control the current of the distribution network. During normal operation, the two converters (VSCs) are operated in rectifier and inverter states, respectively, the electrical connection between the two systems is realized through the AC-DC-AC conversion process, and the energy is exchanged. Capacitors are connected on the DC side to the energy storage system to stabilize the DC voltage, ensure bi-directional consistency of the energy transfer, and increase the resistance to transient disturbances. In addition, the energy storage system can be used for new energy storage and consumption, giving the SOP the ability to regulate electric energy in time and space [25].

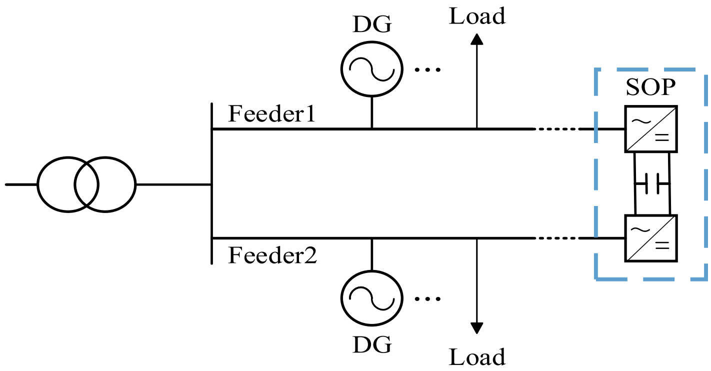

Figure 1. SOP schematic.

The SOP can accurately control the active and reactive power of the feeder to which it is connected, thus using the active and reactive power outputs of the two converters as decision variables. Despite the high operating efficiency of the B2B VSC, the two converters inevitably incur losses during large-scale active power transfers. Therefore, the converter loss coefficients are taken into account in the optimization model. Due to the isolation of the DC, the reactive power outputs of the two converters are independent of each other and only need to satisfy their respective capacity constraints. $PQ - V_{dc}Q$ control is chosen as the SOP control mode [26].

The operational constraints are as follows [21]:

$$P_{a,t}^{SOP} + P_{b,t}^{SOP} + P_{ab,t}^{SOP} = 0 \tag{7}$$

$$P_{ab,t}^{SOP} = A_{SOP,a}\left|P_{a,t}^{SOP}\right| + A_{SOP,b}\left|P_{b,t}^{SOP}\right| \tag{8}$$

$$\sqrt{(P_{a,t}^{SOP})^2 + (Q_{a,t}^{SOP})^2} \leq S_{a,t}^{SOP} \tag{9}$$

$$\sqrt{(P_{b,t}^{SOP})^2 + (Q_{b,t}^{SOP})^2} \leq S_{b,t}^{SOP} \tag{10}$$

where $P_{a,t}^{SOP}$, $P_{b,t}^{SOP}$ and $Q_{a,t}^{SOP}$, $Q_{b,t}^{SOP}$ are the active and reactive powers flowing into the moment converter a and b, respectively; $P_{ab,t}^{SOP}$ is the transmission loss at time t; $A_{SOP,a}$ and

$A_{SOP,b}$ are the energy consumption coefficients for inflow of converter a and b, respectively; and $S_{a,t}^{SOP}$ and $S_{b,t}^{SOP}$ are the capacities of the two converters, which are usually equal.

3.2. SOP Configuration Mode

The configuration costs of SOPs are categorized into investment costs, operation and maintenance (OM) costs, and power supply loss costs:

$$W_{SOP} = W_{SOP}^{TZ} + W_{SOP}^{YW} + W_{SOP}^{LOSS} \tag{11}$$

$$W_{SOP}^{TZ} = \sum_{i=1}^{n} \sum_{j \in \Omega_i} \frac{w_{SOP} S_{SOP,ij}}{y_{SOP}} \tag{12}$$

$$W_{SOP}^{YW} = \eta \sum_{i=1}^{n} \sum_{j \in \Omega_i} \frac{w_{SOP} S_{SOP,ij}}{y_{SOP}} \tag{13}$$

$$W_{SOP}^{LOSS} = 365\lambda \sum_{i=1}^{n} \sum_{t=1}^{T_t} (P_{i,t} + P_{SOP,i,t}^{LOSS})\Delta t \tag{14}$$

where W_{SOP} is the average annual configuration cost of the SOP; W_{SOP}^{TZ} is the average annual investment cost of the SOP; W_{SOP}^{YW} is the average annual OM cost of the SOP; W_{SOP}^{LOSS} is the average annual cost of power supply losses for the SOP; Ω_i is the set of all nodes adjacent and connected to node i; w_{SOP} is the investment cost per unit of capacity of the SOP; y_{SOP} is the service life of the SOP; $S_{SOP,ij}$ is the size of the SOP capacity installed between nodes i and j; η is the SOP annual OM cost factor; λ is the annual cost factor for power supply losses in the distribution network; T_t is the total number of time periods; Δt is the size of the interval for each time period; $P_{i,t}$ is the amount of active power injected at the node i during time period t; and $P_{SOP,i,t}^{LOSS}$ is the active loss of the SOP at node i at time period t.

4. Planning Models and Solution Algorithms and Processes for Distribution Networks

4.1. Distribution Network Planning Models

4.1.1. Economic Indicators

The planning model uses the annual integrated minimum cost as the objective function, which is calculated as follows:

$$\min F_J = W_{SOP} + C_{PC} + C_{NLC} \tag{15}$$

$$C_{PC} = 365 \sum_{t=1}^{T} c_g P_t^{MG} \tag{16}$$

$$C_{NLC} = 365 \sum_{t=1}^{T} c_{loss} P_{ij,t}^{loss} \tag{17}$$

where F_J is the annual consolidated cost; C_{PC} is the annual cost of purchasing power from the higher-level grid; C_{NLC} is the annual cost of network loss; c_g denotes the unit price of the power purchased by the distribution grid from the main grid; c_{loss} denotes the cost of each unit of power loss in the distribution grid; P_t^{MG} denotes the magnitude of active power supplied to the distribution grid by the higher-level grid at time t; and $P_{ij,t}^{loss}$ denotes the grid loss power of the branch ij at time t.

4.1.2. Flexibility Indicators

Distribution network flexibility energy is often described in terms of the ability to regulate and transmit flexibility resources. The formulae for the calculation of its indicators are given in reference [22].

- Calculation of supply and demand balance indicators

The supply–demand balance of the distribution network is mainly reflected in the supply–demand side power balance. Therefore, this paper evaluates the supply–demand balance flexibility using the net load adaptation rate I_F. The larger the value of I_F, the greater the flexibility resources that can fully satisfy the flexibility demand of the load side.

$$I_F = \sum_{t=1}^{T} \frac{F_U^t - F_D^t}{T\left(P_{t+1}^{nl} - P_t^{nl}\right)} \tag{18}$$

$$\begin{cases} F_U^t = \sum\limits_{i \in \Omega_{EV}} F_{EV,i,t}^{up} + F_{MG,t}^{up} \\ F_D^t = \sum\limits_{i \in \Omega_{EV}} F_{EV,i,t}^{down} + F_{MG,t}^{down} \end{cases} \tag{19}$$

where F_U^t and F_D^t denote the upstream and downstream flexibility of the distribution network at time t, respectively; T is 24 h, i.e., the total dispatch cycle, with each cycle being 1 h; P_t^{nl} and P_{t+1}^{nl} are the net load power values of the distribution network at time periods t and $t+1$, respectively; $F_{EV,i,t}^{up}$ and $F_{EV,i,t}^{down}$ are the regulation capacities of the charging piles of the distribution network at time t, respectively; Ω_{EV} is the set of charging pile installation locations; and $F_{MG,t}^{up}$ and $F_{MG,t}^{down}$ are the regulation capacity of the superior grid on the distribution grid at time t, which is divided into forward and reverse.

- Calculation of load margin indicators

In order to achieve flexible matching of supply and demand in the distribution network, flexible matching at the network level is necessary. Given the unpredictable fluctuation of net load, branch circuits must have sufficient load margin. In this paper, the average load profile of the network is evaluated using the branch load margin I_{BF}. The smaller the value of I_{BF}, the more adequate the load margin of the branch, the more flexible the distribution network, and the more capable it is to cope with the changing demand.

$$I_{BF} = \frac{1}{T} \sum_{t=1}^{T} \sum_{ij \in \Omega_B} \frac{L_{ij,t}}{N_B} \tag{20}$$

where Ω_B is the set of all branches in the distribution network; N_B is the number of its branches; and $L_{ij,t}$ is the ratio of the actual value of the current in branch ij at t to the maximum value allowed for that branch.

In the planning process, the supply–demand balance flexibility index is combined with the feeder load adequacy flexibility index to jointly characterize the flexibility of the system, such that the optimal flexibility index function max$F$ is

$$\max F = I_F - I_{BF} \tag{21}$$

4.2. Solving Algorithm and Process

In this paper, sensitivity analysis is used to determine the potential installation locations of SOPs, and the specific calculation process is referred to in the literature [27]. Therefore, in the optimization model, the siting location of SOPs is regarded as a known parameter rather than a decision variable. Meanwhile, this paper divides EV clusters into four charging stations and includes them as energy storage systems in the distribution network planning, in which the storage capacity and charging and discharging power of EVs are treated as known parameters, and the charging and discharging power of charging stations are treated as a decision variables.

The optimization problem is divided into two phases: in the first phase, the objective is to minimize the annual integrated operating cost of the distribution network, and the optimization decision variables are the capacity size of the SOP and the charging and discharging power of the charging station; in the second phase, the optimization objective is to maximize the flexibility of the operation of the distribution network, subject to the satisfaction of the voltage constraints. The solution flow of the model is shown in Figure 2.

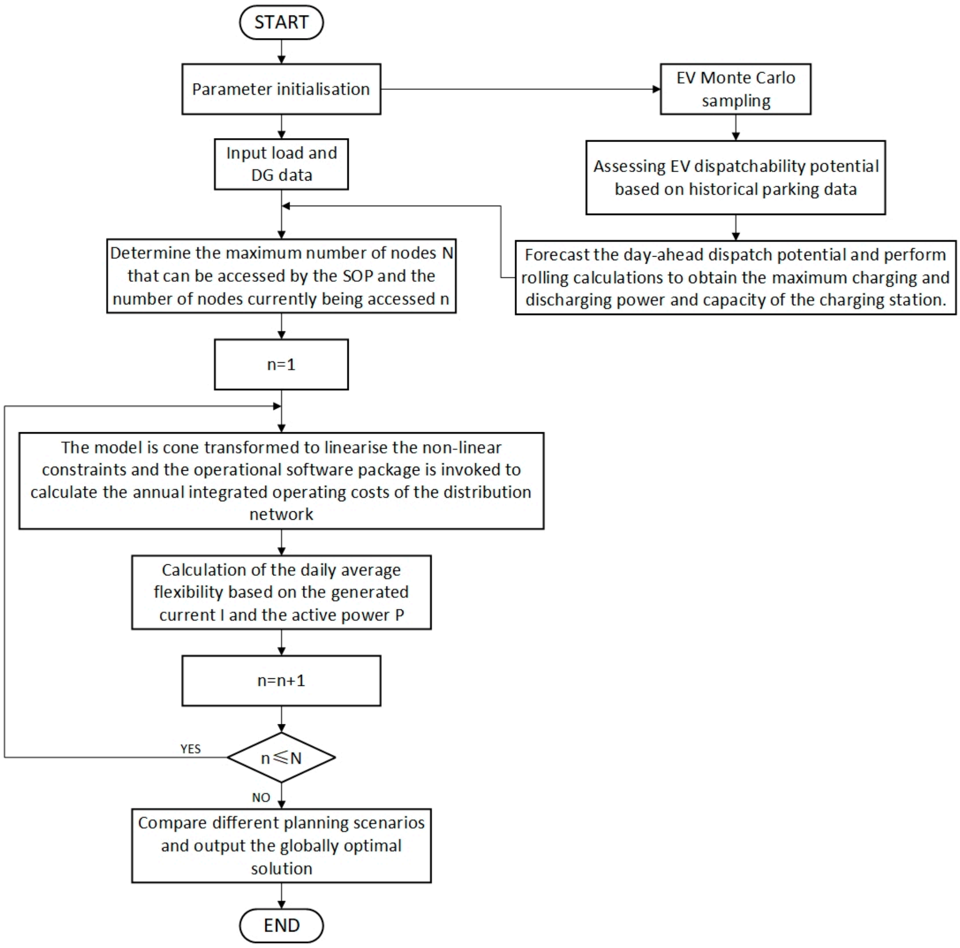

Figure 2. Algorithm flow chart.

In the above optimization problem, the uncertainty mainly comes from the charging and discharging behavior of EVs and the output power of DG. The charging and discharging behaviors of EVs are affected by the user's travel plan and charging demand, while the output of distributed power sources is affected by factors such as weather conditions. In this paper, we simulate the charging and discharging behaviors of EVs through Monte Carlo sampling to predict the dispatchable potential of EVs, and we introduce a flexibility index to assess the adaptive capability of the distribution network, while solving the optimization model using a second-order cone planning algorithm. Together, these methods enable the optimization model to find the optimal planning solution in terms of economy and flexibility, taking into account the uncertainties of EVs and distributed power sources.

5. Calculus Analysis

In this paper, the effectiveness of the proposed collaborative planning approach is verified using a modified IEEE 33-node power distribution network, the structure of which is shown in Figure 3, with specific data referenced from the literature [28].

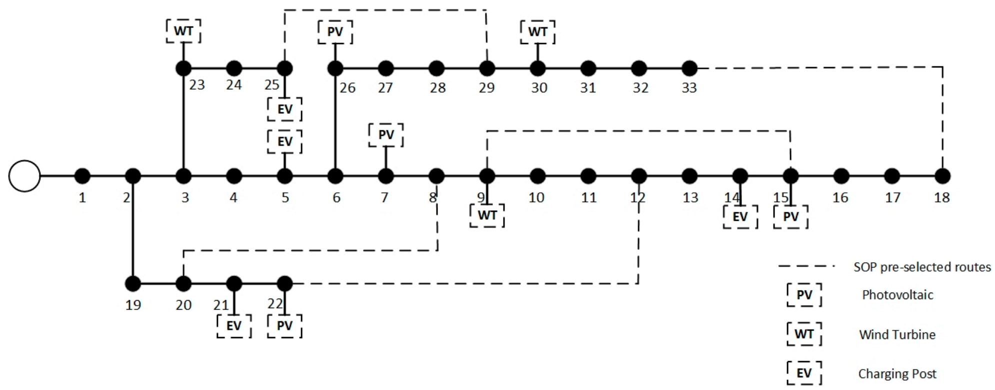

Figure 3. IEEE 33-node distribution system diagram.

In order to investigate the impact of high DG penetration on the distribution network, four photovoltaic (PV) generators and three wind turbine (WT) generators were integrated into the distribution network in this study. The PV units were installed at nodes 7, 15, 22, and 26 with installed capacities of 800, 800, 500, and 400 kW, respectively, and the wind turbine units were installed at nodes 9, 23, and 30 with installed capacities of 800, 500, and 300 kW, respectively. The daily load operating curves of the system were obtained in hourly steps through load forecasting techniques, as shown in Figure 4, and the output of the DG was also processed by this method. When power was purchased from the superior grid, peak and valley time-sharing tariffs were adopted, with peak tariffs from 09:00–11:00 and 14:00–18:00; level tariffs from 06:00–08:00, 12:00–13:00, and 19:00–22:00; and valley tariffs from 23:00–5:00. Other relevant parameters are shown in Table 1.

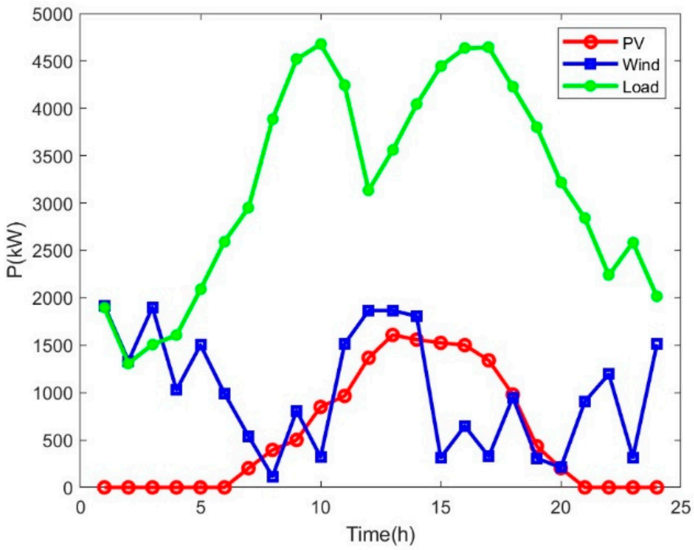

Figure 4. DG and load 24 h power diagram.

Table 1. System parameters.

SOP Parameters	Discount Rate	Investment Cost per Unit of Capacity/(RMB/KV-A)	Loss Factor	Years of Use/Year	Purchased Power Tariffs from Higher-Level Grids
value	0.08	1000	0.98	20	Higher: 0.6; equal: 0.4; lower: 0.3
EV parameters	**Rated charge/discharge power/kW**	**Rated capacity/kW-h**	**Charge and Discharge Efficiency**	**SOC limits**	**Aggregate energy storage power variation range/MW**
value	6.6	32	0.95	[0.15, 0.9]	[−5, 5]

At the same time, a total of 2000 EVs were Monte Carlo sampled in this paper. Firstly, the EV clusters were classified into three categories of private cars, net cars, and commuter cars, and classified according to different charging time periods. The time of arriving and leaving the charging station during the charging time of different types of cars varied, and the article dealt with this by normal distribution. The battery power when arriving at the charging station varied slightly, and the article dealt with this by uniform distribution. Sampling at uniform, different EVs arriving at and leaving the charging station and the battery capacity at the time of arrival are shown in Table 2, and the specific data for each EV are shown in Table 3.

Table 2. EV sampling parameters.

Parameter Distribution of EVs	T_n^{arr}	T_n^{lea}	$s_{n,arr}$
Type I vehicle	$N(18,4)$	$N(8,4)$	$U(0.2s_B, 0.4s_B)$
Type II vehicle	$N(21,1)$	$N(7,1)$	$U(0.4s_B, 0.6s_B)$
Type III vehicle	$N(9,2)$	$N(17,2)$	$U(0.4s_B, 0.6s_B)$

$N(\mu, \sigma^2)$: A normal distribution with mathematical expectation μ and standard deviation σ; $U(a, b)$: The uniform distribution of the interval [a, b]; s_B: The rated capacity of EV batteries. This paper assumes that EVs have uniform specifications.

Table 3. Charging station sampling parameters.

Number of EVs	Type I Vehicle	Type II Vehicle	Type III Vehicle
Charging station 1	M (180, 220)	M (190, 210)	0
Charging station 2	M (180, 220)	M (80, 120)	M (380, 420)
Charging station 3	0	M (900, 110)	M (380, 420)
Charging station 4	M (380, 420)	0	0

5.1. Comparison of the Economics of Different Programmes

In order to verify the economics of EV and SOP collaborative planning, this paper sets up the following four planning scenarios for accessing the traditional distribution system of distributed power IEEE nodes:

- Plan 1: Traditional active distribution network.
- Plan 2: Active distribution network considering only SOP optimization planning.
- Plan 3: Active distribution grid with conventional energy storage and SOP co-planning.
- Plan 4: Active distribution grid for EV and SOP co-planning.

For each of the above four scenarios, the planning costs and economic benefits were calculated. The results of the SOP co-planning are shown in Table 4, and the charging and discharging scenarios for the charging station are shown in Figure 5. The average annual investment costs in the table cover the commissioning costs of the SOP and the economic comparison of the various planning scenarios are shown in Table 5.

Table 4. SOP planning results. (∗ means multiply).

Plan	SOP Planning Result/Node Number (Capacity (kV-A))	Consolidated Cost/∗10^4 RMB	Economic Benefits/∗10^4 RMB
1	/	1644.0	0
2	12–22 (210), 25–29 (310), 8–21 (380)	1434.5	209.5
3	12–22 (190), 25–29 (310), 8–21 (340)	1331.2	312.8
4	12–22 (190), 8–21 (380), 25–29 (500)	1255.7	388.3

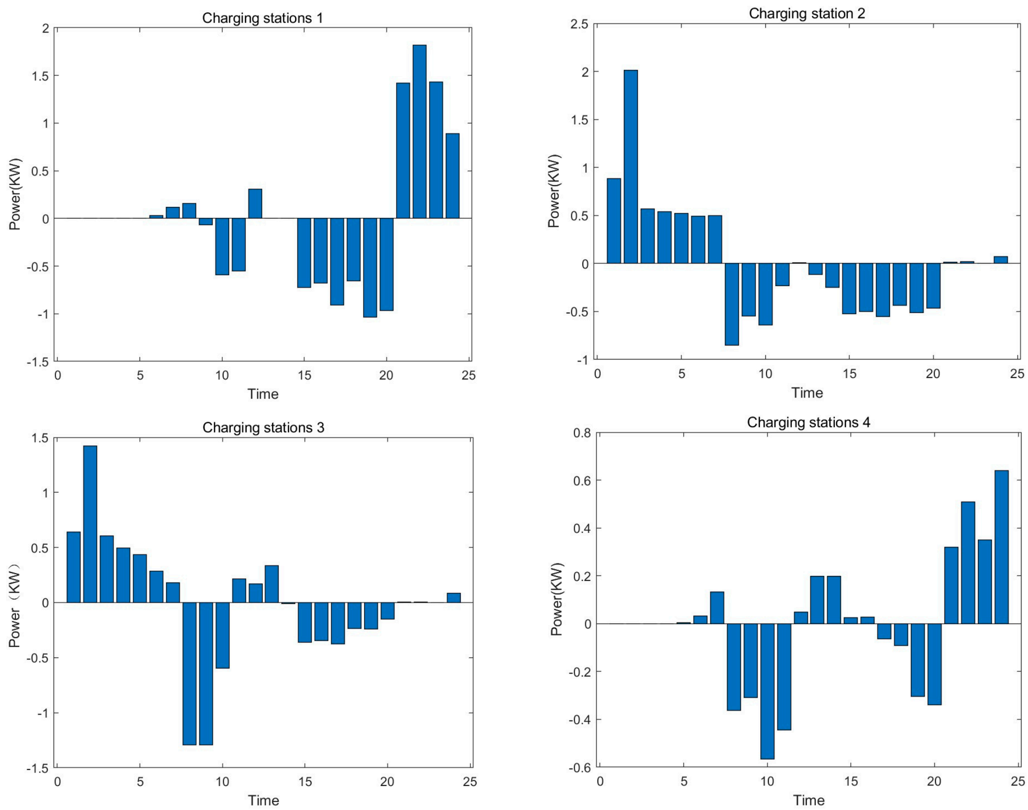

Figure 5. Charging and discharging power diagram of charging stations.

Table 5. Economy comparison.

Plan	C_{SI}/∗10^4 RMB	C_{OMS}/∗10^4 RMB	C_{PC}/∗10^4 RMB	C_{NLC}/∗10^4 RMB
1	0	0	1615.7	28.3
2	11.6	2.3	1399.5	21.0
3	16.2	1.74	1287.1	26.2
4	11.5	2.7	1214.2	27.8

From the economic comparison of the four scenarios in Table 4, it can be seen that planning the SOP with EV dispatchable potential is the most economically efficient, thus verifying the advantage of considering EV dispatchable potential when planning the SOP.

The data in Table 5 show that Option 4 is the most effective in terms of improving economic efficiency. Although the deployment of ESS and SOP requires some upfront investment, they also significantly reduce the OM costs of the distribution network, and considering the dispatchable potential of EVs, the investment in energy storage can be further scaled down, which in turn increases the revenue of the distribution network accordingly.

5.2. Comparison of the Flexibility of Different Programmes

As shown in Table 6, compared to Scenario 1, Scenarios 2, 3, and 4 all have smaller branch flexibility adequacy metrics. This is due to the fact that Scenarios 2, 3, and 4 are equipped with SOPs, which optimize the distribution system's power allocation and improve the system's ability to adapt to demand fluctuations, thereby reducing network losses and the cost of purchasing power from the higher grid. The branch circuit flexibility margin indicator increases for Options 3 and 4 compared to Option 2. This is due to the fact that with the addition of energy storage, balancing the load also increases the power transfer on the line, resulting in a decrease in the margin.

Table 6. Flexibility comparison.

Plan	I_F	I_{BF}	Max F
1	1.091	0.471	0.620
2	3.283	0.211	3.072
3	4.631	0.324	4.307
4	11.046	0.341	10.705

6. Conclusions

In this paper, an innovative EV and SOP cooperative planning method is proposed, aiming to improve the operational efficiency and economy of the active distribution network (ADN). By capturing the uncertainty of EV charging behavior and renewable energy output through Monte Carlo simulation and combining it with a second-order cone planning algorithm, this study successfully achieved the optimal configuration of EV clusters and SOPs. Compared with the traditional active distribution model, the optimal planning model proposed in this paper reduces the operating cost by about 24.8% in terms of economics, which improves the overall system efficiency and return on investment, while in terms of flexibility, the flexibility index of the model proposed in this paper is much higher than that of the traditional model, which indicates that it can better adapt to the uncertainty brought by the high penetration of distributed power sources.

The model in this paper takes into account the practical constraints and uncertainties of EV charging behavior and renewable energy output, making it more suitable for practical applications. Through Monte Carlo simulation and the introduction of flexibility metrics, the model is able to better adapt to complex grid operating environments, providing grid operators with a more effective tool to manage the growing EV charging demand. Future research will delve into the feasibility of applying the model to a wider range of real-world grid environments, including grids of different regions, sizes, and structures. This will help to better understand the complexity of EV–grid interactions and provide grid operators with more effective tools to manage the growing demand for EV charging.

Author Contributions: Conceptualization, W.L.; methodology, J.F.; investigation, D.C.; resources, W.L.; data curation, J.F.; writing—original draft preparation, J.F.; writing—review and editing, J.F.; visualization, D.C.; supervision, W.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data are contained within the article. The data presented in this study are available in the cited references.

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

References

1. Yu, W.; You, R.; Zhou, J.; Li, X. Research on Operation Optimization of Active Distribution Networks Based on Multi-Port SOP Integrated Energy Storage System. In Proceedings of the 2021 6th International Conference on Power and Renewable Energy (ICPRE), Shanghai, China, 17–20 September 2021; IEEE: Shanghai, China, 2021; pp. 707–712.
2. Jun, Y.; Ting, Z.; Han, S.; Zhou, T.; Wu, F.Z.; Liu, S. Two-stage Market Bidding Strategy of Charging Station Considering Schedulable Potential Capacity of Electric Vehicle. *Autom. Electr. Power Syst. (AEPS)* **2021**, *45*, 86–96. [CrossRef]
3. Bauer, P. Future of EV Charging. In Proceedings of the 2019 International Aegean Conference on Electrical Machines and Power Electronics (ACEMP) & 2019 International Conference on Optimization of Electrical and Electronic Equipment (OPTIM), Istanbul, Turkey, 27–29 August 2019; pp. 8–9. [CrossRef]
4. Cao, W.; Wu, J.; Jenkins, N.; Wang, C.; Green, T. Operating Principle of Soft Open Points for Electrical Distribution Network Operation. *Appl. Energy* **2016**, *164*, 245–257. [CrossRef]
5. Fan, X.; Li, P.; Zuo, M. Optimal Allocation Strategy of Energy Storage to Improve the Voltage Quality of Distribution Network. *J. Phys. Conf. Ser.* **2022**, *2303*, 012065. [CrossRef]
6. Liang, J.; Zhou, J.; Yuan, X.; Huang, W.; Gong, X.; Zhang, G. An Active Distribution Network Voltage Optimization Method Based on Source-Network-Load-Storage Coordination and Interaction. *Energies* **2024**, *17*, 4645. [CrossRef]
7. Konstantelos, I.; Giannelos, S.; Strbac, G. Strategic Valuation of Smart Grid Technology Options in Distribution Networks. *IEEE Trans. Power Syst.* **2016**, *32*, 1293–1303. [CrossRef]
8. Liu, H.; Chen, Q.; Liu, Z.; Shao, Y.; Zeng, G. Hierarchical Zoning Planning Method for Large-scale Distributed Power Generation Access to Medium and Low voltage Distribution Network. *Microcomput. Appl. MA* **2024**, *40*, 149–152.
9. Yang, Z.; Yang, F.; Min, H.; Shen, Y.; Tang, X.; Hong, Y.; Qin, L. A Local Control Strategy for Voltage Fluctuation Suppression in a Flexible Interconnected Distribution Station Area Based on Soft Open Point. *Sustainability* **2023**, *15*, 4424. [CrossRef]
10. Alhamali, A.; Farrag, M.E.; Bevan, G.; Hepburn, D.M. Determination of optimal site and capacity of DG systems in distribution network based on genetic algorithm. In Proceedings of the 2017 52nd International Universities Power Engineering Conference (UPEC), Heraklion, Greece, 28–31 August 2017; pp. 1–6. [CrossRef]
11. Ismail, B.; Haifi, M.F.H.Y.; Rahman, N.H.A.; Kahar, N.H.A.; Alhamrouni, I.; Yahya, Y. Optimal Allocation of DG-PV and Network Reconfiguration for Power Loss Reduction and Voltage Profile Enhancement with Contingency Assessment. In Proceedings of the 2023 International Conference on Engineering Technology and Technopreneurship (ICE2T), Kuala Lumpur, Malaysia, 15–16 August 2023; pp. 51–56. [CrossRef]
12. Wang, Y.; Infield, D. Markov Chain Monte Carlo Simulation of Electric Vehicle Use for Network Integration Studies. *Int. J. Electr. Power Energy Syst.* **2018**, *99*, 85–94. [CrossRef]
13. Sun, X.; Qiu, J. A Customized Voltage Control Strategy for Electric Vehicles in Distribution Networks with Reinforcement Learning Method. *IEEE Trans. Ind. Inf.* **2021**, *17*, 6852–6863. [CrossRef]
14. Hai, C.; Hao, W.; Hong, D. Optimal Dispatch of Distribution Networks that Take into Account EV Demand Response and Carbon Allowance Earnings. *Power Syst. Technol.* **2024**, *12*, 1–12.
15. Liao, B.; Mao, J.; Li, L.; Li, B.; Yang, J.; Wen, F.; Salam, M.A. A Planning Model for Charging Facilities of Electric Vehicles Considering Spatial and Temporal Characteristics of Charging Demands. In Proceedings of the 2016 IEEE 2nd Annual Southern Power Electronics Conference (SPEC), Auckland, New Zealand, 5–8 December 2016; IEEE: Auckland, New Zealand, 2016; pp. 1–6.
16. Vahedipour-Dahraie, M.; Rashidizaheh-Kermani, H.; Najafi, H.; Anvari-Moghaddam, A.; Guerrero, J. Coordination of EVs Participation for Load Frequency Control in Isolated Microgrids. *Appl. Sci.* **2017**, *7*, 539. [CrossRef]
17. Jiang, X.; Zhou, Y.; Ming, W.; Yang, P.; Wu, J. An Overview of Soft Open Points in Electricity Distribution Networks. *IEEE Trans. Smart Grid* **2022**, *13*, 1899–1910. [CrossRef]
18. Cheng, Q.; Li, X.; Zhang, M.; Fei, F.; Shi, G. Optimal Configuration Strategy of Soft Open Point in Flexible Distribution Network Considering Reactive Power Sources. *Energies* **2025**, *18*, 529. [CrossRef]
19. Kang, Y.; Lu, G.; Chen, M.; Li, X.; Li, S. Collaborative Optimization of Direct Current Distribution Network Based on Scaled Electric Vehicles Charging and Discharging and Soft Open Points Topology Reconfiguration. *Energies* **2025**, *18*, 373. [CrossRef]
20. Pamshetti, V.B.; Singh, S.; Thakur, A.K.; Singh, S.P.; Babu, T.S.; Patnaik, N.; Krishna, G.H. Cooperative Operational Planning Model for Distributed Energy Resources with Soft Open Point in Active Distribution Network. *IEEE Trans. Ind. Appl.* **2023**, *59*, 2140–2151. [CrossRef]
21. Yang, X.; Zhou, Z.; Zhang, Y.; Liu, J.; Wen, J.; Wu, Q.; Cheng, S. Resilience-Oriented Co-Deployment of Remote-Controlled Switches and Soft Open Points in Distribution Networks. *IEEE Trans. Power Syst.* **2023**, *38*, 1350–1365. [CrossRef]
22. He, Y.; Yang, X.; Wu, H.; Qiu, R.; Xu, B.; Ding, M. Coordinated Planning of Soft Open Point and Energy Storage System for Flexibility Enhancement of New Distribution System. *Autom. Electr. Power Syst.* **2023**, *47*, 142–150. [CrossRef]

23. Ye, C.; Long, Z.; Lin, W. Optimization method for flexible distribution network operation based on multi-end SOP. In Proceedings of the 2024 3rd International Conference on Energy, Power and Electrical Technology (ICEPET), Chengdu, China, 17–19 May 2024; pp. 606–610. [CrossRef]
24. Heider, F.; Jahic, A.; Plenz, M.; Tröger, K.; Schulz, D. A generic EV charging model extracted from real charging behaviour. In Proceedings of the 2022 IEEE IAS Global Conference on Emerging Technologies (GlobConET), Arad, Romania, 20–22 May 2022; pp. 393–398. [CrossRef]
25. Yang, M.; Pei, X.; Li, Y. Multi-port Coordinated Control Strategy of SOP in Distribution Network. In Proceedings of the 2020 IEEE Applied Power Electronics Conference and Exposition (APEC), New Orleans, LA, USA, 15–19 March 2020; pp. 2333–2337. [CrossRef]
26. Flourentzou, N.; Agelidis, V.G.; Demetriades, G.D. VSC-Based HVDC Power Transmission Systems: An Overview. *IEEE Trans. Power Electron.* **2009**, *24*, 592–602. [CrossRef]
27. Zheng, X.; Tian, Z.; Lei, D. Optimal Allocation of Soft Open Point in Active Distribution Network Based on Improved Sensitivity Analysis. *Autom. Electr. Power Syst.* **2021**, *45*, 129–137. [CrossRef]
28. Baran, M.E.; Wu, F.F. Network Reconfiguration in Distribution Systems for Loss Reduction and Load Balancing. *IEEE Trans. Power Deliv.* **1989**, *4*, 1401–1407. [CrossRef]