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Article

Optimization Model of Electric Vehicles Charging and Discharging Strategy Considering the Safe Operation of Distribution Network

Mengjiao Zou [1,*], Ye Yang [2], Mingguang Liu [1], Wen Wang [2], Heping Jia [1], Xiaofeng Peng [2], Shu Su [2] and Dunnan Liu [1]

[1] School of Economics and Management, North China Electric Power University, Beijing 102206, China; mingguangliu@163.com (M.L.); jiaheping@ncepu.edu.cn (H.J.); wsnwdrzou@163.com (D.L.)
[2] State Grid Electric Vehicle Service Company, Beijing 100053, China; yeyang.neo@live.com (Y.Y.); 120202206134@163.com (W.W.); pengxiaofeng@163.com (X.P.); bawei_95@163.com (S.S.)
* Correspondence: zoumengjiao_98@163.com; Tel.: +86-159-7427-0480

Abstract: Against the background of carbon neutrality, the power dispatching operation mode has undergone great changes. It not only gradually realizes the coordinated control of source–grid–load–storage, but also strives to realize the multi-level coordination of the transmission network, distribution network and microgrid. Disorderly charging and discharging of large-scale electric vehicles (EVs) will have a great negative impact on the distribution network, but aggregating EVs and guiding them to charge and discharge in an orderly manner will play a positive role in delaying investment in the distribution network. Therefore, it is urgent to adopt an effective scheduling control strategy for electric vehicle charging and discharging. First, a variety of indexes were set to analyze the influence of EVs access on distribution network and the correlation between the indexes. Then, by defining the EVs penetration rate and the load simultaneous rate, the charging load planning of EVs was calculated. Based on the simultaneous load rate, the regional electricity load plan was calculated, and a configuration model of distribution capacity suitable for charging loads in different regions was constructed. Finally, an optimal dispatch model for electric vehicles considering the safety of distribution network was proposed and the distribution transformer capacity allocation model was used as the optimization target constraint. Compared with most optimized dispatch models used to maximize aggregator revenues and reduce peak-to-valley differences and load fluctuations in distribution networks, this model could effectively reduce unnecessary investment while meeting regional distribution transformer needs and maintaining distribution network security. Taking the improved IEEE 34-bus systems as an example, the simulation analysis was carried out and the investment demand of distribution network under the condition of disordered and orderly charge and discharge was compared. The results show that the proposed optimal scheduling method can effectively reduce the load fluctuation of distribution network, keep the voltage offset within the allowable voltage deviation range, and can effectively delay the investment of distribution network.

Keywords: electric vehicles; distribution network; charge and discharge strategy; multi-objective optimization

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1. Introduction

Achieving the "30·60" double carbon target is an important direction for China's future development. At present, the energy, industry, and transportation sectors are the main sources of carbon emissions, accounting for more than 80% of China's total carbon dioxide emissions. Achieving the goal of carbon neutrality requires the coordinated development of low carbon by multiple industries [1,2]. China aims to raise its global competitiveness in the transport sector by setting up transport networks with wider coverage and higher speed. Terminal energy in China's transportation sector is becoming increasingly electrified, and the charging load of electric vehicles will become one of the largest loads in future grids. Since 2015, the number of electric vehicles in various provinces and cities in China has increased significantly. In 2016, the number of electric vehicles in China was about 240,000, and in 2021, it exceeded 5.41 million, with a year-by-year growth rate of 78.32% in the latest year. The growth of electric vehicle ownership between China's seven major administrative geographical divisions varies greatly. From 2016 to 2021, the ownership and changing trend of electric vehicles in China are shown in Figure 1. China's electric vehicle sales account for 50.32% of the global electric vehicle market sales, as shown in Figure 2.

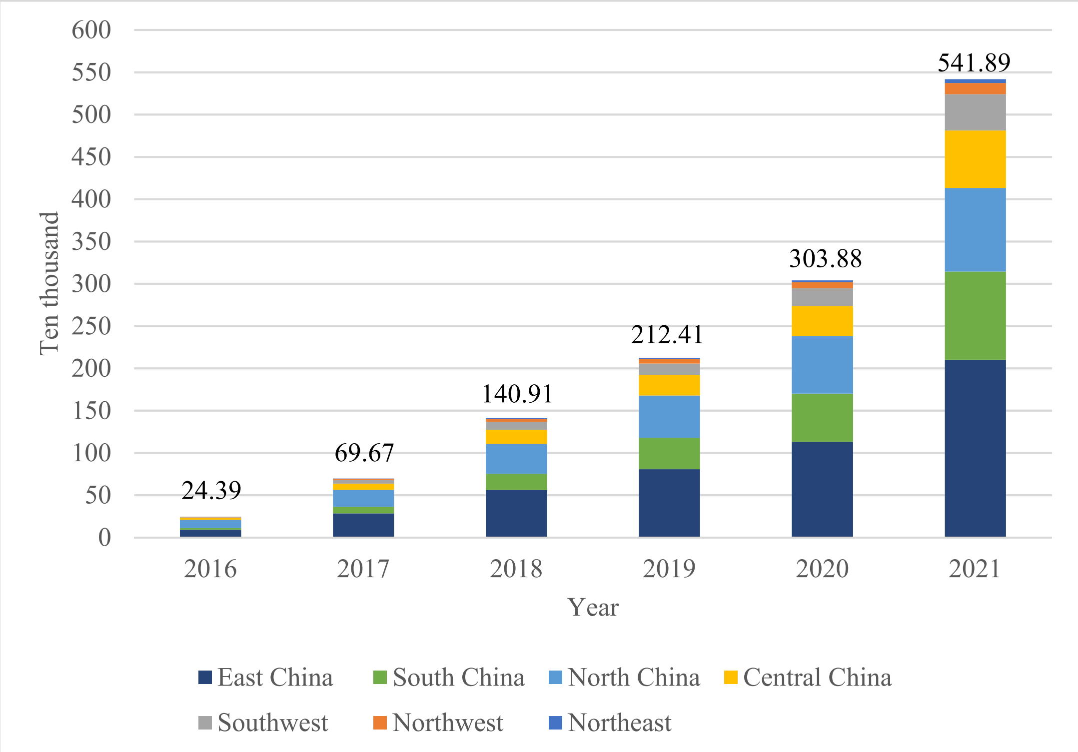

Figure 1. Electric vehicle ownership and changing trends in China (2016–2021).

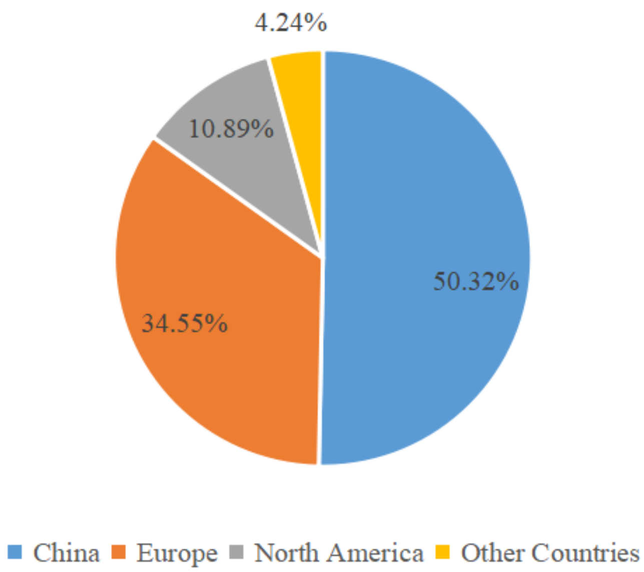

Figure 2. Distribution of electric vehicle sales in major global markets in 2021.

With the continuous acceleration of the construction of new power system, the source–grid–load–storage control business has developed rapidly [3,4]. "The industry development plan of new energy vehicles (2021–2035)" proposes that by 2025, the sales of new energy vehicles will reach about 20% of the total sales of new vehicles. As an important bridge connecting the power generation end and the load end, a large number of charging loads are connected to the distribution network, which will have a negative impact on the safe and stable operation of the urban distribution system [5]. Therefore, guiding electric vehicle users to participate in the optimal scheduling of the distribution system is the key to the regulation of distributed energy on the distribution side of the new power system [6,7].

Large-scale access of electric vehicles to the distribution network has become a trend, and the on-board charging technology of electric vehicles has also widely responded to usage [8]. Electric vehicles charging and discharging has randomness and uncertainty in time and space, and the literature [9–11] discusses the impact of electric vehicle charge and discharge system grid connections on the distribution network from the aspects of distribution network operation reliability (load peak-to-valley difference) and power quality (effect of network loss, power grid harmonics, grid voltage sag, three-phase imbalance). The literature [12] reveals the influencing factors and variations of low-voltage distribution networks on the carrying capacity of electric vehicles charging load. Reference [13] proposed a comprehensive evaluation method of distribution network operation characteristics based on piecewise linear probabilistic power flow and characteristic weighting and entropy weight method, which is used to comprehensively and accurately reflect the impact of the randomness of electric vehicles charging load on the operation characteristics of distribution network.

In order to alleviate the impact of electric vehicles load on distribution network, it is urgent to adopt effective dispatching control strategy to guide the charging and discharging behavior of electric vehicle users [14,15]. In this paper, an optimal dispatch model for electric vehicles considering distribution network safety is proposed. By calculating the penetration rate and simultaneous rate of electric vehicles, the charging load planning of electric vehicles is calculated. The regional electricity load plan is calculated based on the load stacking rate and obtains the distribution transformer capacity configuration model. Using the distribution transformer capacity configuration model as a constraint, compared with most optimized dispatch models used to maximize aggregator revenue, reduce peak-to-valley differences, and load fluctuations in distribution networks, it can effectively reduce unnecessary investments while meeting regional distribution transformer needs and maintaining distribution network security. For the sake of clarity, the major contributions of this paper are summarized below:

(1) Summarize the impact of EV access on the indicators of the distribution network and the correlation between the impacts.
(2) According to the power load planning of a certain area, combined with the distribution planning margin and the load power factor, the distribution capacity configuration model can be obtained. Calculating the distribution transformer requirements of each region under different charging modes can effectively reduce unnecessary investment.
(3) Establish a multi-objective optimization function that considers the load peak, load volatility, and voltage offset of each node of the power grid. Using the distribution transformer capacity configuration model as the optimization target constraint, the improved IEEE 34-bus systems is simulated as an example, and the investment requirements of the distribution network are analyzed and compared under disorderly and orderly charging and discharging.

The remains of this paper are organized as follows. Section 2 details a brief literature review, considering the current research methodology. Section 3 analyzes the impact of electric vehicle access to the grid regarding the indicators of the distribution network. Section 4 analyzes the transformer transformation of distribution network in disordered charging mode and constructs a distribution transformer capacity configuration model. Section 5 establishes an optimization model of electric vehicle charge–discharge strategy and provides the solution steps of multi-objective particle swarm algorithm. Section 6 uses an improved IEEE 34-bus systems as an example for simulation analysis. Section 7 outlines the summary of the overall paper.

2. Literature Review

In order to combat climate change and support the Sustainable Development Goals, electrification, networking, and intelligence sharing are becoming the development trend of the automotive industry. A new round of global scientific and technological revolution and industrial transformation is booming. The new energy automobile industry is developing rapidly on a global scale. There has been some literature on the development of electric vehicle technology and the optimal scheduling of electric vehicles loads. An hybrid electric vehicle (HEV) concept based on renewable energy resources (RERs) was introduced by Mamun et al. [16]. The proposed HEV design utilizes solar photovoltaic energy, wind energy, fuel cells, and a supercapacitor (PV + WE + FC + SC), which generates electrical energy via a proton exchange membrane (PEM) and an SC to cater for strong torque requirements. This paper discusses a DC isolated nanogrid layout for the integration of renewable generators, battery energy storage, demand response activities, and electric vehicle charging infrastructures. A DC isolated nanogrid layout for the integration of renewable generators, battery energy storage, demand response activities, and electric vehicle charging infrastructures was discussed by Habeeb et al. [17]. Ortiz et al. [18] presented a strategy based on a mixed-integer linear programing (MILP) model to improve the resilience in electric distribution systems (EDSs). Fan et al. [19] proposed an integrated expansion planning framework based on a multiobjective mixed-integer nonlinear program. The aim was to minimize the net present value of investments considering feeder routing, substation alterations, and construction while maximizing the utilization of proposed charging stations. In the literature [20], a hybrid approach was proposed for an electric vehicle-based grid connected to the distribution generation (DG). The major aspiration of this study was to minimize the peak power cutoff, voltage regulation, and spin reserve for making the optimization mode ideally convex and accurate second-order conic relaxations. In the work [21], with the goal of reducing losses, improving voltage distribution, and maximizing the benefits of energy storage or electric vehicle aggregators, an optimization model for energy storage and electric vehicles operation scheduling in distribution networks containing renewable energy power sources was proposed. Study [22] calculates the regulation amount of reactive power resources near the node when the voltage of regional key nodes exceeds the limit and achieves the goal of improving regional node voltage by adjusting the charging power of cluster electric vehicles when the regulation capacity is insufficient. The study [23] proposed two optimal scheduling control strategies: controlling the charging power of electric vehicles and controlling the initial charging time, so as to reduce the peak valley difference and load fluctuation of distribution network. The research conducted in [24] proposed the user behavior tendency function of electric vehicles and classified electric vehicles and established a multi-objective optimization function considering matching degree between wind power and load, distribution network loss and load variance to carry out the rolling scheduling of classified electric vehicles. Study [25] constructs the source–grid–load–storage interaction model to reduce the system operation cost, network loss rate, and voltage deviation and effectively improve the photovoltaic consumption level.

Some of the current research literature on the access of electric vehicles to the distribution network is summarized in Table 1.

Table 1. Summary of research literature on electric vehicles access to distribution network.

Ref.	Research Direction	Specific Research Content
[26–28]	Multi-objective optimization of electric vehicles access to distribution network	Evaluate the voltage security of the distribution networks in the presence of electric vehicles in the optimization framework, including the maximization of voltage security margin and minimization of operational cost as target optimization functions.
		An optimal scheduling model of the distribution network, considering the demand response side load is established, and the optimal scheduling problem is solved by using the firefly optimization algorithm.
		The economic cost of the distribution network and the unsatisfactory value of electric vehicle users are proposed as the optimization goals.
[29–31]	The impact of electric vehicle discharge behavior on the distribution network	Propose a distributed generation equivalent method based on the discharge behavior of electric vehicles.
		Analyze the impact of electric vehicle access on power quality in distribution networks.
		Study the demand characteristics of electric charging and the treatment method and model of access to the network. Analyze the impact on the distribution network load, the network loss, and voltage through different electric vehicles capacities.
[32]	evaluate the reliability of the distribution network incorporating electric vehicles	The effects of electric vehicles penetration, discharging threshold, and battery capacity on reliability of both distribution networks and electric vehicles are studied.
[33–35]	New technologies and Strategies	Propose an input–output methodology applied to a case study in a representative urban context.
		propose a distributed framework for vehicle grid integration taking into account the communication and physical networks.
		Propose a charging and discharging strategy along with two price-based and voltage-based load management programs to manage the penetration of electric vehicles for economic and technical purposes.

The current research mainly improves the power quality and power grid reliability by aggregating and guiding the charge and discharge of electric vehicles. The investment in the construction of the distribution network in the 14th five year plan will exceed CNY 1.2 trillion, accounting for more than 60% of the total investment in power grid construction [36]. In this paper, the impact of electric vehicle access on various indicators of the distribution network is analyzed and a distribution transformer capacity configuration model suitable for charging loads in different areas such as residential areas, commercial areas, and urban centralized charging stations is constructed. Through the optimal scheduling strategy to reduce the load fluctuation of the distribution network, control the voltage deviation, and compare the investment results of distribution network under the condition of disordered and orderly charge and discharge, the orderly charge and discharge will play a positive role in delaying the investment of distribution network.

3. Influence of Electric Vehicles Access on Distribution Network

According to the "Technical Guidelines for Distribution Network Planning and Design", Q/GDW 1738-2016, and the national standard "Guidelines for the Evaluation of Distribution Network Operation", the distribution network planning and operation indicators are analyzed. With the development of clean energy, the proportion of electric vehicle market will increase significantly. However, a large number of electric vehicle charging loads connected to the distribution network will have a great negative impact on the distribution network. The influence of electric vehicle charging loads on the power quality of the distribution network mainly includes harmonic, voltage offset, network loss, three-phase imbalances, and so on. The influence on the reliable operation of the power grid will be regarding of load rate, peak valley difference, and so on.

The load rate of distribution transformers is used to measure the residual capacity margin of distribution transformer, judge whether there is overload problem, and reflect the maximum load demand of distribution transformer over a period of time.

The impact of electric vehicle charging loads on various indicators of distribution network is interrelated (as shown in Figure 3). Disorderly charging of electric vehicles will cause heavy overloads, increase peak-on-peak, and enlarge the difference between peak-and-valley. At this point in time, the load rate will increase and the capacity load ratio will decrease. After the charging loads of electric vehicles are connected to the distribution network, the safety and stability of the system decreases, resulting in voltage offset. It is necessary to stabilize the voltage through reactive power compensation. The nonlinear effect of electric vehicle chargers will lead to harmonic pollution. In the case of disorderly access of large-scale electric vehicles, the three-phase load imbalance and current imbalance increase, and the line loss increment increases.

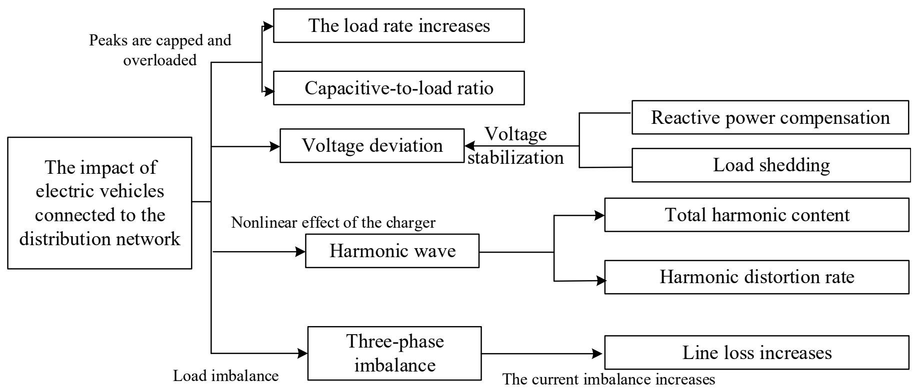

Figure 3. The impact of electric vehicle charging loads on various indicators of the distribution network.

4. Analysis of Transformer Transformation in Distribution Network under Disordered Charging Mode

4.1. Electric Vehicles Penetration Rate and Charging Load Simultaneous Rate

The base load refers to the user's daily basic electricity load in addition to the charging load of electric vehicles under the distribution change. When electric vehicles are connected to residential areas, commercial places, and urban centralized charging stations, the capacity of the original transformer may not be able to supply power normally, so the capacity of the transformer needs to be expanded.

Clarifying the ownership of electric vehicles is the first step in planning and calculating the charging load of electric vehicles. To this end, combined with the car ownership in certain areas, the penetration rate of electric vehicles in this area is defined as:

$$\alpha^{ev} = \frac{N^{EV}}{N^{R}} \tag{1}$$

where α^{ev} is the penetration rate of electric vehicles, N^{EV} is the number of electric vehicles, and N^{R} is the number of cars in the area.

For the study of electric vehicle charging loads, in addition to their distribution over time, it is more important to characterize the size of the peak charging load and its relationship with the scale of electric vehicles.

Peak charging load is not a simple superposition of charging power for all electric vehicles. To achieve this the simultaneous rate of electric vehicle charging load β^{ev} within this area are defined as:

$$\beta^{ev} = \frac{\underset{t=1,\ldots,24}{Max}(P_t^{EV})}{P_{EV} \cdot N_{EV}} \beta^{ev} \in [1, 0] \tag{2}$$

In the formula, P_{EV}^t and P_{EV} are the total charging load (kW) of the electric vehicles at the t-time and the rated charging power (kW) of the single-amount electric vehicle.

4.2. The Superposition Rate of Electric vehicles Charging Load and Grid Base Load

The most intuitive feature of the interaction between electric vehicles and the power grid is the superposition of the charging load and the basic load of the power grid. In order to characterize the degree of superposition of the charging load of electric vehicles and the base load of the grid, the charging load superposition rate is defined as:

$$\gamma^{ev} = \frac{\underset{t=1,\ldots,24}{Max} P(t)}{\underset{t=1,\ldots,24}{Max} P_t^{EV} + \underset{t=1,\ldots,24}{Max} P_t^{Base}} \tag{3}$$

where $P(t)$ is the total load of the t-time zone (kW); $\underset{t=1,\ldots,24}{Max} P(t)$ is the maximum value when the base load is superimposed with the electric vehicle load; and P_t^{Base} is the base load (kW) of the t-time zone.

4.3. Model of Electric Vehicle Charging Load Planning Calculation

Combining the simultaneity rate and permeability, the model of electric vehicle charging load planning and calculation can be obtained, as shown in the formula:

$$S^{ev} = \frac{P_{EV} \cdot \alpha^{ev} \cdot N^R \cdot \beta^{ev}}{\eta^{ev}} \tag{4}$$

where S^{ev} is the planned capacity of electric vehicles charging load in a region (kw) and η^{ev} is the charging efficiency of a regional charging facility.

4.4. Calculation Model of Power Load Planning

This paper will take residential areas, commercial areas, and urban centralized charging stations as examples. The analysis of transformer transformation in different areas will have slight differences in Formula (5).

The calculation model of regional power load planning is:

$$P^R = P^J \xi^R \delta^R \tag{5}$$

where P^R is the regional electricity planning calculation load (kW); P^J is the regional user planning load (kW); ξ^R is the regional planning load demand coefficient; and δ^R is the residential electricity load simultaneous rate.

Among them, the planning load of households in residential areas:

$$P^J = P^J_{\text{residential}} \cdot N^R_{\text{residential}} \tag{6}$$

In this formula, $P^J_{\text{residential}}$ is the planning load (kW/ set) of the unit household in the community and $N^R_{\text{residential}}$ is the number of residents in the community.

4.5. Distribution Transformer Capacity Configuration Model

According to the power load planning of a certain area, combined with the distribution planning margin and load power factor, the distribution transformer capacity configuration model can be obtained, as shown in Equation (7):

$$S^R = \frac{P^R}{\varphi^R \cos\phi} \tag{7}$$

where S^R is the planned calculated capacity of transformer (kVA); φ^R is the distribution planning margin; and $\cos\phi$ is the load power factor.

Considering the seriality of capacity settings of distribution transformer manufacturers, the rated capacity of distribution transformer shall be selected according to Formula (8):

$$\begin{cases} S^R \leq \sum\limits_m S_m^U \\ S^U \cos\phi \geq (\underset{t=1,\cdots,24}{Max} P_t^{EV} + \underset{t=1,\cdots,24}{Max} P_t^{Base})\gamma^{ev} \end{cases} \tag{8}$$

$$\sum_m S_m^U = S^U \tag{9}$$

where S_m^U is the rated capacity of a single standard distribution transformer suitable for a certain area and m is the number of distribution transformers running side by side.

5. Optimization Model of Charging and Discharging Strategy for Electric Vehicles

5.1. Objective Function

According to the analysis of the second subsection of the article, the load fluctuation of electric vehicles will have an impact on multiple indicators such as voltage offset, network loss, three-phase imbalance, load rate, peak-to-valley difference, and so on. In the case of limited reactive power regulation, the node voltage can be adjusted by adjusting the active power of the node load [15]. Therefore, the load peak, load fluctuation, and voltage offset of each node should be reduced as much as possible, and the objective function should be constructed as follows:

$$f_1 = \min\sum_{t=1}^{T} (P_t^{Base} + P_t^{EV} - \overline{P})^2 \tag{10}$$

$$f_2 = \min(\max\{P(t)\} - \min\{P(t)\}) \tag{11}$$

$$f_3 = \min(\sum_{t=1}^{T} |U_{j,t} - U_{j,0}|),\ j = 1, 2, \ldots\ldots, J \tag{12}$$

$$P_t^{EV} = \sum_{i=1}^{N} P_{ev,i}^t \cdot \kappa_{i,t}^1 - P_{ev,i}^t \cdot \kappa_{i,t}^2,\ t = 1, 2, \ldots\ldots, T \tag{13}$$

$$F(x) = \{\min f_1, \min f_2, \min f_3\} \tag{14}$$

where $F(x)$ is the multi-objective optimization objective function and f_1, f_2, and f_3 are used to represent the minimization of load fluctuations, the minimization of load peaks, and the minimization of voltage offsets, respectively. $\overline{P}$ is the mean load (kW) and P_t^{EV} is the total charging load of electric vehicle users at t time. $P_{ev,i}^t$ is the charging power of the electric vehicle user i; J represents the number of nodes in the distribution network; and $U_{j,t}$, $U_{j,0}$ represent the actual voltage and rated voltage of node j at the t moment, respectively. $\kappa_{i,t}^1$ and $\kappa_{i,t}^2$ are used to determine the charging and discharging status of the ith electric vehicle at the t-time, $\kappa_{i,t}^1 = 0$, $\kappa_{i,t}^2 = 0$ means that the electric vehicle is idle, $\kappa_{i,t}^1 = 1$ means that the electric vehicle is charged, and $\kappa_{i,t}^2 = 1$ means that the electric vehicle is in a discharged state.

5.2. Constraint Condition

5.2.1. Battery Capacity and User Travel Constraints

Considering that the electric vehicle may be stored for a long time, 10% of the power "bottom redundancy" shall be reserved in the battery as the minimum. A margin of 5% is reserved to prevent battery damage caused by "overcharge", so set $SOC \in [0.1, 0.95]$.

$$0.1 \leq SOC_{i,start} + \frac{\sum\limits_{t=t_{in,i}}^{t_{off,i}} (P_{ev,i}^{t} \cdot \kappa_{i,t}^{1} \cdot \eta_{c} - P_{ev,i}^{t} \cdot \kappa_{i,t}^{2} / \eta_{d}) \times \Delta t_{i}}{S_{i}} \leq 0.95 \tag{15}$$

$$SOC_{\min,i} \leq SOC_{i,start} + \frac{\sum\limits_{t=t_{in,i}}^{t_{off,i}} (P_{ev,i}^{t} \cdot \kappa_{i,t}^{1} \cdot \eta_{c} - P_{ev,i}^{t} \cdot \kappa_{i,t}^{2} / \eta_{d}) \times \Delta t_{i}}{S_{i}} \leq 0.95 \tag{16}$$

$$\Delta t_{i} = t_{off,i} - t_{in,i} \tag{17}$$

where i is the number of the charging electric vehicle; t is the time period number; S_i is the battery capacity of the electric vehicle; $SOC_{i,start}$ is the initial charging state of the electric vehicle when it is connected to the charging device; $SOC_{\min,i}$ is the minimum state of charge set by the electric vehicle user to meet the travel requirements; Δt is the length of the time period; and η_c and η_d are the charging efficiency coefficient and discharge efficiency coefficient of the electric vehicle, respectively. Since the charging and discharging of electric vehicles cannot be carried out at the same time, $\kappa_{i,t}^{1} \cdot \kappa_{i,t}^{2} = 0$.

5.2.2. Network Trend Constraints

See Equation

$$\begin{cases} P_{j} = V_{j} \sum\limits_{h \in j} V_{h} (G_{jh} \cos \theta_{jh} + B_{jh} \sin \theta_{jh}) \\ Q_{j} = V_{j} \sum\limits_{h \in j} V_{h} (G_{jh} \sin \theta_{jh} + B_{jh} \cos \theta_{jh}) \end{cases} \tag{18}$$

where P_j and Q_j are the active and reactive power of node j; V_j and V_h are the voltage amplitudes of node j and node h; G_{jh} and B_{jh} are the conductance and acceptance of the branch jh; and θ_{jh} is the voltage angular difference between node j and node h.

5.2.3. Node Voltage Constraints

See Equation

$$U_{j,\min} \leq U_{j,t} \leq U_{j,\max} \tag{19}$$

where $U_{j,\min}$ is the lower limit of the node j voltage and $U_{j,\max}$ is the upper limit of the node j voltage.

5.2.4. Distribution Capacity Constraints

See Equation

$$(\underset{t=1,\cdots,24}{Max} P_{t}^{EV} + \underset{t=1,\cdots,24}{Max} P_{t}^{Base})\gamma^{ev} \leq S_{j} \cos \phi \tag{20}$$

where the left side of the inequality represents the maximum charging load of the branch j and S_j represents the distribution capacity of the branch j.

5.3. Multi-Objective Particle Swarm Algorithm Solving

Particle swarm optimization (PSO) has the advantages of fast update speeds, wide application range, and uncomplicated programming and is widely used in the solutions of multi-objective optimization problems. The multi-objective particle swarm algorithm (MOPSO) is conducive to increasing the effect of local search [37]. The mathematical description of MOPSO is as follows:

There are N particles in a D-dimensional space, each in the position:

$$x_i = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{iD}),\ i = 1, 2, 3, \ldots, N \quad (21)$$

The velocity of the particle is:

$$v_i = (v_{i1}, v_{i2}, v_{i3}, \ldots, v_{iD}),\ i = 1, 2, 3, \ldots, N \quad (22)$$

The individual optimal value (pbest) is:

$$p_i = (p_{i1}, p_{i2}, p_{i3}, \ldots, p_{iD}),\ i = 1, 2, 3, \ldots, N \quad (23)$$

The global optimal value (gbest) is:

$$p_g = (p_{g1}, p_{g2}, p_{g3}, \ldots, p_{gD}),\ i = 1, 2, 3, \ldots, N \quad (24)$$

During the update process, both the speed and position of the particles need to meet the range constraints, and if the range is exceeded, the boundary value is used instead of the out-of-bounds value. During iteration, the velocity and position update formulas for particle i are:

$$v_{id}(t+1) = \omega v_{id}(t) + c_1 r_1 (p_{id}(t) - x_{id}(t)) + c_2 r_2 (p_{gi}(t) - x_{id}(t)) \quad (25)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (26)$$

In the formula, $i \in [1, N]$; $d \in [1, D]$; t is the number of iterations ($t > 0$); c_1, c_2 are learning factors and $c_1, c_2 \in [0, 2]$; and r_1 and r_2 take the random number between (0, 1). Inertia weight ω is an important factor affecting the convergence of particle swarm optimization algorithm.

The particle swarm algorithm with constant inertia weights has a fast convergence rate, but because there is no close connection between electric vehicle users, the randomness is large and it is easy to fall into local optimization. A varying ω is used for this issue:

$$\omega_j = (\omega_{start} - \omega_{end})(\frac{t_{\max} - k}{t_{\max}}) + \omega_{end} \quad (27)$$

In this equation, ω_{start} is the initial weight; ω_{end} is the last weight; k is the current number of iterations; and $t_{\max}$ is the maximum number of iterations.

In this paper, the multi-objective particle swarm algorithm is used to solve the problem, and the specific steps are as follows:

1. Set the population number and maximum number of iterations, initial population, initialization parameters.
2. To achieve the fitness value calculation, calculate the objective function of each particle to find the individual value of each particle and the current optimal solution of the particle swarm.
3. Use the Pareto domination principle to select dominant particles (Pareto optimal solution) and update the individual optimal position of each particle, select the guide particles from the external archive, and generate a new population.
4. Recalculate the fitness degree, update the individual optimal particle position and the global optimal particle position according to the fitness degree, determine whether to update the particle position, and record the global optimality.
5. Iterate the maximum number of iterations set, constantly update the external archive, and finally obtain the Pareto optimal solution set and a set of optimal solutions in the solution set.

6. Calculation Example

6.1. Parameter Settings

In this paper, the modified IEEE 34-bus network is used for simulation analysis, the IEEE 34-bus network distribution is shown in Figure 4, and the node data is shown in Appendix A, Tables A1–A7. The voltage level of the distribution network is 10 kV and the reference power is 10 kW. The rated power of the AC charging pile in the residential area is 7 kW; the power of the AC charging pile in the commercial area is 7 kW; the power of the DC charging pile in the commercial area is 120 kW; and the DC charging pile in the centralized charging station is rated at 120 kW. The battery capacity takes 25 kWh, and the charging efficiency of the charging facility is 0.95.

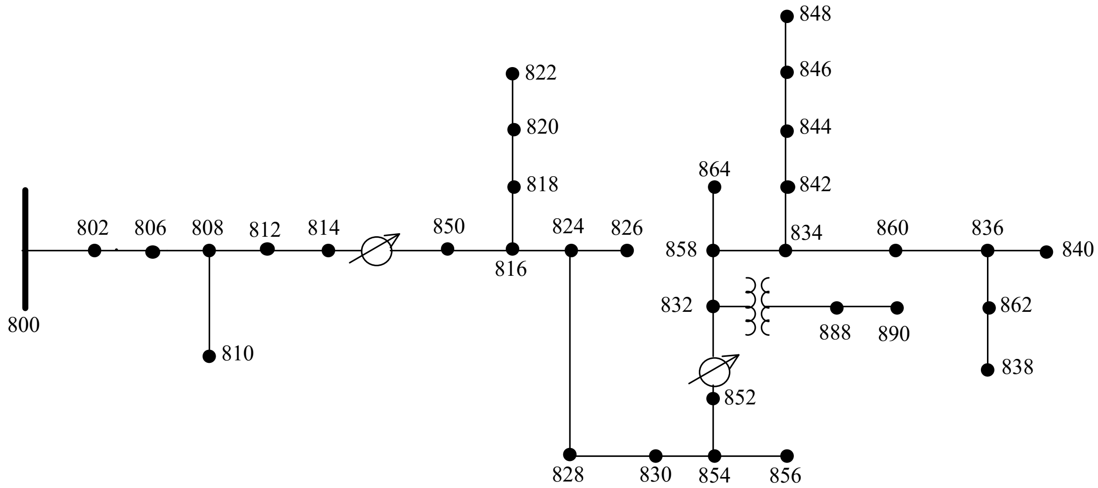

Figure 4. IEEE 34-bus network.

The distribution capacity of 2000 households in the residential area is about 9000 kVA, the electric vehicle ownership in the residential area is 1000, the penetration rate of electric vehicles is 0.5, the charging rate of electric vehicles is considered according to 0.6, the household planning load is 8 kW/set, the resident electricity load demand coefficient is 0.6, the residential electricity load power factor is 0.85, the residential electricity load planning margin is 0.8, and the total load of the residential area is connected to node 888. The commercial area has an underground parking lot with 1000 charging piles, and the simultaneous charging rate of electric vehicles is considered according to 0.4. The total load of the business district is connected to the node 822. The regional distribution network with a base load of about 40 MW has three centralized charging stations, which are connected to nodes 844, 846, and 848, respectively. There are 5000 charging piles in the area, the charging rate of electric vehicles is considered, according to 0.45. The S13 type transformer is selected, with a rated capacity of 1000 kVA.

6.2. Analysis of Results

The calculations in this paper were solved in a MATLAB environment on a computer with a processor of 11th Gen Intel(R) Core(TM) i7-1165G7 and a clock frequency of 2.7 GHz, and the maximum calculation time was 2 min. The maximum number of iterations in the solution process of the multi-objective optimized particle swarm algorithm was 300, the number of particle swarms was 60, the initial inertia weight was 0.85, and the acceleration constant was 1.25. Under the simulation conditions set in this paper, the load peak, load fluctuation, and voltage offset of each node of the distribution network were optimized. In the simulink simulation experiment, the voltage offset value in V2G mode is shown in Figure 5, and the voltage shift occurs at the moment of load access of the electric vehicle, and the maximum voltage offset of A phase is 1.75%, the maximum voltage offset of B phase is 5.19%, and the maximum voltage offset of C phase is 1.87%. The trend of three-phase voltage balance is shown in Figure 6. Because the load of electric vehicles entering the grid accounts for a small proportion of other loads in the power supply area, the voltage offset and three-phase voltage imbalance are within the allowable range.

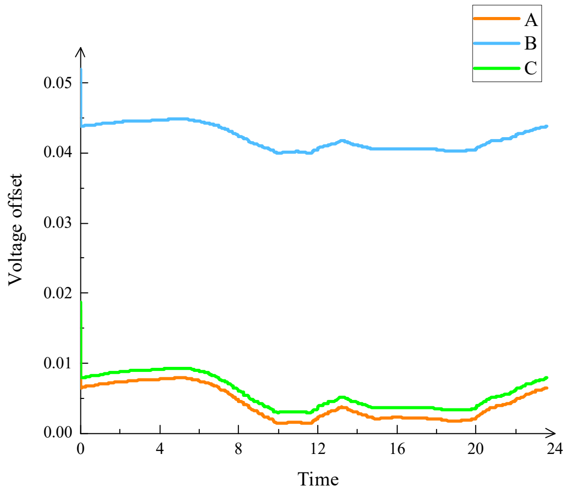

Figure 5. Three-phase voltage offset value in V2G mode.

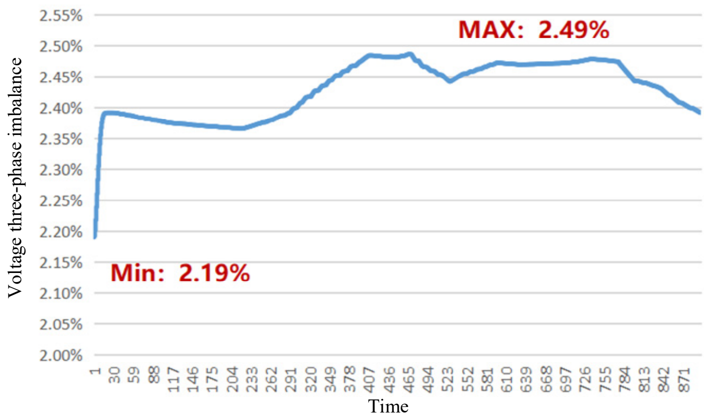

Figure 6. Three-phase voltage imbalance in the distribution network.

The larger the load standard deviation, the greater the burden of frequency regulation on the power grid, in which it is easy to cause frequency fluctuations and voltage fluctuations, affecting the power quality. The power supply quality of the distribution network can be reflected through the load standard deviation. According to the comparison of the distribution network evaluation indicators in the disordered charging mode and V2G mode in the residential area in Figure 7a and Table 2, the V2G mode of electric vehicles reduces the superposition rate of electricity load in the community compared with the disordered mode. According to the allocation capacity configuration model in Section 4.5, the number of distribution transformers in different charge and discharge modes is calculated, the V2G mode reduces the transformer transformation cost, and the investment in distribution capacity and related equipment is CNY 1.75 million per 1000 kVA [38], saving CNY 5.25 million. Compared with the disordered charging mode, the load standard deviation in V2G mode is reduced by 705.31 kW, and the peak-to-valley difference is reduced by 42.66%, which greatly enhances the power quality of the distribution network.

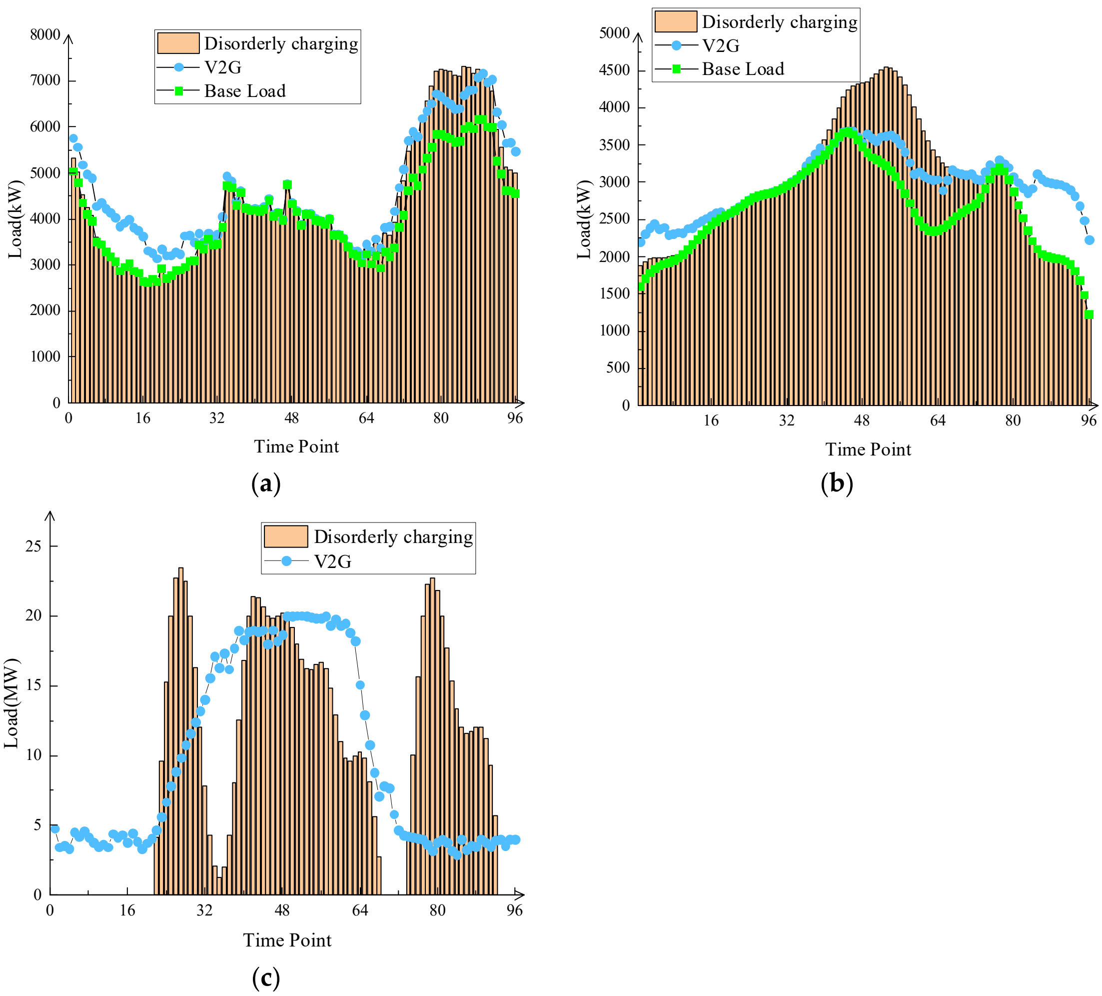

Figure 7. Load curves of disordered charging mode and V2G mode in various regions. (**a**) Load curves in residential areas; (**b**) the load curves of the business district; (**c**) charging station load curves.

Table 2. Comparison of distribution network evaluation indicators in the disordered charging mode and V2G mode in residential area.

Evaluation Indicators	Disordered Charging	V2G
Load overlay rate	0.96	0.82
Number of distribution transformers (units)	9	12
Maximum load rate	81.38%	59.71%
Peak-to-valley difference (kW)	4693.6	2691.2
Load standard deviation (kW)	1409.46	704.09

According to the comparison of the distribution network evaluation indicators in the commercial area of Figure 7b and Table 3, the V2G mode of electric vehicles reduces the simultaneous rate of electricity consumption in commercial areas and saves CNY 1.75 million in transformer transformation costs. In the case of disorderly charging, due to the large number of electric vehicles driving into the business district during the day, the charging load is mostly concentrated during the times from 9:00 a.m. to noon, which is superimposed with the original morning peak load, resulting in a load spike. In the V2G mode, the maximum load rate is reduced by 3.7% and the peak-to-valley difference is reduced by 54.89%.

Table 3. Comparison of distribution network evaluation indicators in the disordered charging mode and V2G mode in commercial area.

Evaluation Indicators	Disordered Charging	V2G
Load overlay rate	0.88	0.79
Number of distribution transformers (units)	7	6
Maximum load rate	72.16%	68.46%
Peak-to-valley difference (kW)	3318.02	1496.6
Load standard deviation (kW)	838.41	403.95

According to the comparison of the evaluation indicators of the distribution network of the charging station in Figure 7c and Table 4, the peak-to-valley difference is reduced from 23.47 MW to 17.15 MW using the V2G mode. The load standard deviation in V2G mode is reduced by 1.47 MW compared with the disordered charging mode, and the peak-to-valley difference is reduced by 26.93%, which greatly enhances the power quality of the distribution network.

Table 4. Comparison of distribution network evaluation indicators in disordered charging mode and V2G mode in charging station.

Evaluation Indicators	Disordered Charging	V2G
Load overlay rate	-	-
Number of distribution transformers (units)	26	23
Maximum load rate	90.28%	87.12%
Peak-to-valley difference (kW)	23.47	17.15
Load standard deviation (kW)	8.20	6.73

7. Conclusions and Future Works

In this paper, the influence of disordered charge and discharge of large-scale electric vehicles on various indicators of the distribution network is analyzed, and a multi-objective optimization function, considering the load peak, load fluctuation, and voltage offset of each node, is established, and the following conclusions are formed according to the results of the improved IEEE 34-bus simulation study:

1. The large-scale disorderly access of electric vehicles to the distribution network will exacerbate the peak-to-valley difference of the power grid, affecting the quality of power and the life of the transformers. According to the power load planning of a certain region, combined with the distribution planning margin, the load power factor can obtain the distribution capacity configuration model, calculate the distribution transformer demand of each region under different charging modes, and effectively reduce unnecessary investment.
2. The orderly charging and discharging of electric vehicles is conducive to reducing the load rate of the distribution network to delay the investment and construction of the distribution network, according to the estimation that the number of electric vehicles will reach 80 million in 2030, it is expected that by 2030, the cumulative investment in the distribution network can saved CNY 147 billion, and the V2G mode of electric vehicles is conducive to helping the construction of digital power grids and promoting the process of modernizing the power grid.
3. According to the simulation results, the V2G mode of electric vehicles reduces the load peak-to-valley difference of residential area by 42.66%, the load peak-to-valley difference of commercial area by 54.89%, and the load peak-to-valley difference of charging stations by 26.93%, keeping the three-phase voltage offset within the allowable range, effectively improving the power quality of the power grid and improving the reliable operation safety of the power grid.

Future works should focus on analyzing the charging and discharging strategies for electric vehicles, for which the proportion of different types of electric vehicle users (operating vehicles, non-operating vehicles) who are willing to participate in aggregation regulation under different compensation price incentives has to be considered.

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Abbreviations

The following abbreviations are used in this manuscript:

ACSR	Aluminum core steel reinforced aluminum overhead cable
DC	Direct current
AC	Alternating current
EVs	Electric vehicles
PV	Solar photovoltaic energy
WE	Wind energy
FC	Fuel cell
SC	Supercapacitor
HEV	Hybrid electric vehicles
RERs	renewable energy resources
PEM	proton exchange membrane
DG	Distribution generation
PSO	Particle swarm algorithm
MOPSO	Multi-objective particle swarm algorithm

Appendix A

Table A1. Transformer Data.

	kVA	kV-High	kV-Low	R-%	X-%
Substation:	2500	69-D	24.9-Gr. W	1	8
XFM-1	500	24.9-Gr.W	4.16-Gr. W	1.9	4.08

Table A2. Spot Loads.

Node	Load Model	Ph-1 (kW)	Ph-1 (kVAr)	Ph-2 (kW)	Ph-2 (kVAr)	Ph-3 (kW)	Ph-4 (kVAr)
860	Y-PQ	20	16	20	16	20	16
840	Y-I	9	7	9	7	9	7
844	Y-Z	135	105	135	105	135	105
848	D-PQ	20	16	20	16	20	16
890	D-I	150	75	150	75	150	75
830	D-Z	10	5	10	5	25	10
Total		344	224	344	224	359	229

Table A3. Regulator Data.

Regulator ID:	1			**Regulator ID:**	2		
Line Segment:	814–850			**Line Segment:**	852–832		
Location:	814			**Location:**	852		
Phases:	A-B-C			**Phases:**	A-B-C		
Connection:	3-Ph,LG			**Connection:**	3-Ph,LG		
Monitoring Phase:	A-B-C			**Monitoring Phase:**	A-B-C		
Bandwidth:	2.0 volts			**Bandwidth:**	2.0 volts		
PT Ratio:	120			**PT Ratio:**	120		
Primary CT Rating:	100			**Primary CT Rating:**	100		
Compensator Settings:	Ph-A	Ph-B	Ph-C	**Compensator Settings:**	Ph-A	Ph-B	Ph-C
R—Setting:	2.7	2.7	2.7	**R—Setting:**	2.5	2.5	2.5
X—Setting:	1.6	1.6	1.6	**X—Setting:**	1.5	1.5	1.5
Volltage Level:	122	122	122	**Volltage Level:**	124	124	124

Table A4. Regulator Data.

Node A	Node B	Length (ft.)	Config.
800	802	2580	300
802	806	1730	300
806	808	32,230	300
808	810	5804	303
808	812	37,500	300
812	814	29,730	300
814	850	10	301
816	818	1710	302
816	824	10,210	301
818	820	48,150	302
820	822	13,740	302
824	826	3030	303
824	828	840	301
828	830	20,440	301
830	854	520	301
832	858	4900	301
832	888	0	XFM-1
834	860	2020	301
834	842	280	301
836	840	860	301
836	862	280	301
842	844	1350	301
844	846	3640	301
846	848	530	301
850	816	310	301
852	832	10	301
854	856	23,330	303
854	852	36,830	301
858	864	1620	302
858	834	5830	301
860	836	2680	301
862	838	4860	304
888	890	10,560	300

Table A5. Distributed Loads.

Node (A)	Node (B)	Load Model	Ph-1 (kW)	Ph-1 (kVAr)	Ph-2 (kW)	Ph-2 (kVAr)	Ph-3 (kW)	Ph-3 (kVAr)
802	806	Y-PQ	0	0	30	15	25	14
808	810	Y-I	0	0	16	8	0	0
818	820	Y-Z	34	17	0	0	0	0
820	822	Y-PQ	135	70	0	0	0	0
816	824	D-I	0	0	5	2	0	0
824	826	Y-I	0	0	40	20	0	0
824	828	Y-PQ	0	0	0	0	4	2
828	830	Y-PQ	7	3	0	0	0	0
854	856	Y-PQ	0	0	4	2	0	0
832	858	D-Z	7	3	2	1	6	3
858	864	Y-PQ	2	1	0	0	0	0
858	834	D-PQ	4	2	15	8	13	7
834	860	D-Z	16	8	20	10	110	55
860	836	D-PQ	30	15	10	6	42	22
836	840	D-I	18	9	22	11	0	0
862	838	Y-PQ	0	0	28	14	0	0
842	844	Y-PQ	9	5	0	0	0	0
844	846	Y-PQ	0	0	25	12	20	11
846	848	Y-PQ	0	0	23	11	0	0
Total			262	133	240	120	220	114

Table A6. Overhead Line Configurations (Config.).

Config.	Phasing	Phase (ACSR)	Neutral (ACSR)	Spacing ID
300	B A C N	1/0	1/0	500
301	B A C N	#2 6/1	#2 6/1	500
302	A N	#4 6/1	#4 6/1	510
303	B N	#4 6/1	#4 6/1	510
304	B N	#2 6/1	#2 6/1	510

Table A7. Shunt Capacitors.

Node	Ph-A (kVAr)	Ph-B (kVAr)	Ph-C (kVAr)
844	100	100	100
848	150	150	150
Total	250	250	250

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