Post-print of Reactive Power Optimization in Distribution Networks Considering Electric Vehicles

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Abstract

After large-scale electric vehicle charging access to the power grid, the spatiotemporal uncertainty of charging poses new challenges to reactive power optimization in distribution networks. This paper investigates a reactive power optimization model for distribution networks incorporating electric vehicles, employing the charging power at each distribution network node, terminal voltage, tap positions of voltage regulators, and compensation capacity of reactive power compensation devices as control variables, with the objective of minimizing distribution network losses. Firstly, the uncoordinated charging load of electric vehicles is simulated; secondly, a mathematical model for reactive power optimization aimed at minimizing distribution network losses is established; finally, the effectiveness of the optimization model is verified using Matlab based on a 33-bus distribution network model. The results demonstrate that the optimization model can effectively reduce distribution network losses and improve voltage quality.

Full Text

Preamble

Reactive Power Optimization for Distribution Network with Electric Vehicles

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Abstract

The large-scale integration of electric vehicle (EV) charging introduces new challenges to reactive power optimization in distribution networks due to the temporal and spatial uncertainty of charging behavior. This paper investigates a reactive power optimization model for distribution networks that incorporates EVs, treating the charging power at each node, generator terminal voltage, tap positions of voltage regulators, and reactive power compensation capacity as control variables, with the objective of minimizing network losses. First, a Monte Carlo simulation is employed to model uncoordinated EV charging loads. Second, a mathematical model for reactive power optimization is established to minimize distribution network losses. Finally, the effectiveness of the proposed model is validated using MATLAB on a standard 33-node distribution network. The results demonstrate that the optimization model can effectively reduce network losses and improve voltage quality.

Keywords: Electric vehicle, distribution network, reactive power optimization, Monte Carlo

1 Introduction

As a critical component of China' s new energy vehicle strategy, electric vehicles have experienced rapid development in recent years. The government provides substantial subsidies and preferential policies for new energy vehicle purchases, with major cities further encouraging adoption by relaxing license plate quotas. This has significantly accelerated the growth of new energy vehicles in China. According to relevant statistics, pure electric vehicle sales in China reached 247,500 units in 2015, representing a 4.5-fold year-over-year increase. However, large-scale EV integration directly impacts power flow distribution and node voltage levels in distribution networks, thereby affecting reactive power optimization outcomes [1].

Previous research has addressed various aspects of this challenge. Studies [2-3] developed reactive power optimization models that minimize comprehensive distribution network operating costs by considering equipment operational costs such as transformer tap adjustment frequency and reactive compensation capacitor switching operations. Reference [4] investigated reactive power optimization models and algorithms for distribution networks with wind power, accounting for wind generation randomness and analyzing wind power' s role in reactive power regulation under different scenarios. Reference [5] proposed a dynamic reactive power optimization model for distribution networks with distributed generation, where capacitor banks operate according to preset schedules and DG reactive power output is optimized to derive optimal dispatch strategies. Reference [6] established a multi-objective reactive power optimization model for distribution networks with EV charging stations and wind power, validating the model across three typical time periods.

This paper employs Monte Carlo simulation to model uncoordinated EV charging loads and establishes a reactive power optimization model that minimizes distribution network losses while incorporating charging loads. Using the IEEE 33-node distribution network structure, the model is applied during the period of maximum EV charging load. The results confirm that the proposed model can effectively reduce distribution network losses.

2 Electric Vehicle Charging Power Demand Simulation

This study uses the performance parameters of the BAIC E150 electric vehicle as representative parameters for all EVs in the simulation. The parameters are listed in Table 1 .

Table 1. Simulation parameters of electric vehicle

Parameter	Value
Battery capacity Cn (kW • h)	[value]
Charging power Pn (kW)	[value]
Maximum driving range dm (km)	[value]

2.1 Start Charging Time and Daily Mileage

Private electric vehicles are primarily used for commuting, shopping, and other daily activities, typically returning home after work with relatively short daily travel distances. According to statistical data from the U.S. Department of Transportation on household vehicles, the probability density functions of start charging time Tc (h) and daily driving distance d (km) follow normal and log-normal distributions, respectively [8-10]. The probability density functions are:

fTc = !Tc 2! exp ! Tc !µTc

where Tc = 18 and Tc = 1.5.

d!d 2! exp ! ln d !µd

where d = 3.21 and d = 0.274.

2.2 Electric Vehicle Charging Power

The Monte Carlo method is used to sample the start charging time (assuming the return time equals the start charging time). The initial state of charge (SOC) can be calculated using Equation (3):

SOC = 1! (1! SOC)Cn

The charging power distribution for a single EV is then:

Pn Tc t Tc + t

The total active load at node 33 of the distribution network is 3,715 kW. The EV penetration rate is defined as the ratio of charging load demand to total active load. Assuming an EV penetration rate of 40%, the network accommodates approximately 371 vehicles. Monte Carlo simulation is employed to model the charging power demand of all EVs, with 10,000 simulation iterations. The simulation flowchart is shown in Figure 1 [Figure 1: see original paper].

The resulting EV charging power demand curve is presented in Figure 2 [Figure 2: see original paper].

3 Reactive Power Optimization Model for Distribution Network with Electric Vehicles

Reactive power optimization aims to alter power flow distribution in distribution networks by adjusting generator terminal voltages, transformer tap positions, and capacitor bank switching, thereby reducing network losses and improving voltage quality, given fixed network structure, generator capacity, and load distribution [1]. This paper investigates a reactive power optimization model for distribution networks incorporating EVs.

In distribution networks with EV integration, reactive power optimization can be achieved not only through traditional reactive power regulation methods but also by adjusting charging power at each node [11]. The control variables include: charging power at each node, generator terminal voltage, voltage regulator tap positions, and reactive power compensation capacity from shunt capacitors. The optimization model for minimizing distribution network losses is formulated as:

min Ploss = min ei Gije j ! Bij f j) + fi Gij f j + Bije j

where ei is the real part of node voltage, fi is the imaginary part of node voltage, Gij is the real part of the admittance matrix element, and Bij is the imaginary part of the admittance matrix element.

3.1 Objective Function

This study assumes that all nodes except the slack node (node 1) are equipped with EV charging piles. The control variables consist of charging power at each node, generator terminal voltage, voltage regulator tap positions, and reactive power compensation capacity. The objective is to minimize network losses. The system voltage base is 10 kV, and the capacity base is 10 MV•A. Node 1 includes a generator and a voltage regulating transformer, while node 18 contains a wind turbine and a shunt capacitor reactive power source, as shown in Figure 3 [Figure 3: see original paper].

3.2 Constraints

(1) Equality constraints. These primarily represent active and reactive power balance:

ei Gije j ! Bij f j) + fi Gij f j + Bije j fi Gije j ! Bij f j) ! ei Gij f j + Bije j

(2) Inequality constraints. These include constraints on control variables and state variables (node voltages). The specific inequality constraints are:

0 Pi^ev Pmax
Umin Ug Umax
Tmin T Tmax
Qmin Qc Qmax
Vmin Vi Vmax

where Pi^ev is the charging power at node i, Ug is the generator terminal voltage, T is the voltage regulator tap position, Qc is the shunt capacitor reactive power compensation capacity, and Vi is the voltage at node i (i = 1, 2, 3, ···, 33).

Node voltage constraints are incorporated into the objective function as penalty terms:

min F = min Ploss + V (Vi - Vmax) + (Vmin - Vi)

3.3 Model Solution

Distribution network reactive power optimization is essentially a nonlinear mixed-integer programming problem characterized by multiple states and constraints [12]. This paper employs a genetic algorithm to solve the optimization model:

1. **Initialization:** Set evolution generations, population size, and encoding parameters.
2. **Initial population creation:** Use binary encoding for control variables including charging power at each node, generator terminal voltage, voltage regulator tap positions, and capacitor compensation capacity.
3. **Selection, crossover, mutation, and fitness evaluation:** Perform power flow calculations to obtain objective function values. The crossover probability is 0.8, and the mutation probability is 0.02.
4. **Population update:** Eliminate inferior individuals and retain superior ones to generate a new offspring population.
5. **Repeat steps 3-4** until iteration termination criteria are met.

An elitist strategy is employed, where the best individual's genes are not mutated during each iteration. The solution flowchart is shown in Figure 4 [Figure 4: see original paper].

3.4 Case Study Results and Analysis

The voltage regulating transformer has 9 adjustable tap positions ranging from 0.9 to 1.1. The shunt capacitor reactive power is assumed continuously adjustable with a capacity of ±0.5 Mvar. The wind turbine excitation reactance xm is 188 Ω, and the leakage reactance x is 16.55 Ω.

This study investigates reactive power optimization during the period of maximum EV charging load. As shown in Figure 2, the peak charging load occurs at 19:00, reaching 735.45 kW. The charging load at all non-slack nodes is constrained between 0 and 30 kW.

The convergence curve is shown in Figure 5 [Figure 5: see original paper], and the optimization results are presented in Table 2 and Table 3 .

The genetic algorithm converges completely by generation 30, reducing network losses from 0.0258 pu to 0.0226 pu. Table 3 reveals that nodes closer to the distribution network end (e.g., nodes 32 and 33) have reduced charging loads after optimization. Since voltage levels are lower near network ends, reducing charging loads at these nodes improves voltage quality. The results show that nodes 18 and 17 have higher optimized charging power because node 18 is equipped with a wind turbine and reactive power compensation device, enabling local active and reactive power balance and reducing line losses.

Figure 6 [Figure 6: see original paper] compares node voltage profiles before and after reactive power optimization at 19:00. The optimization significantly improves voltage levels across all nodes, demonstrating that the proposed model can effectively enhance voltage quality, reduce voltage limit violations, and improve system stability.

4 Conclusion

This paper establishes a reactive power optimization model for distribution networks that incorporates EV charging loads. Building upon traditional reactive power regulation measures, the model treats node charging power, generator terminal voltage, voltage regulator tap positions, and reactive power compensation capacity as control variables. The results demonstrate that the proposed model effectively reduces distribution network losses and improves node voltage quality, offering positive implications for economic network operation. However, the optimization of node charging loads is relatively coarse-grained, lacking detailed optimization at individual charging pile level, which warrants further refinement.

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Note: Figure translations are in progress. See original paper for figures.