Post-Print of Reactive Power Optimization Method for Distribution Networks Considering Coordinated Operation of DG, DS, and EV

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Abstract

By comprehensively considering the coordinated operation of distributed generation, electric vehicle charging and discharging, and distributed energy storage, along with the collaborative control of reactive power output from different types of reactive power compensation devices, a multi-objective optimization model for distribution network reactive power optimization is established with the minimization of active power loss and voltage fluctuation in the distribution network as the objective function. Taking into account the probabilistic characteristics of wind speed, the uncertainty of solar irradiance, state of charge and charging/discharging characteristics, and operating efficiency, stochastic models are constructed for the output power of distributed wind turbines, photovoltaic power generation systems, electric vehicle charging/discharging power, and energy storage device charging/discharging power. The reactive power of DG, DS, and EV are selected as control variables, and the optimization problem is solved using a genetic algorithm. Simulation results demonstrate the adaptability of the reactive power optimization model constructed in this paper and the feasibility and effectiveness of the proposed algorithm.

Full Text

Reactive Power Optimization Method for Distribution Networks Considering Coordinated Operation of DG, DS, and EV

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Abstract: This paper presents a multi-objective reactive power optimization model for distribution networks that comprehensively considers the coordinated operation of distributed generation (DG), electric vehicle (EV) charging/discharging, and distributed storage (DS) systems, along with the collaborative control of reactive power output from different types of reactive power compensation devices. The objective function minimizes active power losses and voltage fluctuations in the distribution network. Considering the probabilistic characteristics of wind speed, uncertainty of solar irradiance, state of charge, charging/discharging characteristics, and operational efficiency, stochastic models are constructed for the output power of distributed wind turbines, photovoltaic generation systems, EV charging/discharging power, and energy storage device charging/discharging power. The reactive power from DG, DS, and EV is selected as control variables, and a genetic algorithm is employed to solve the optimization problem. Simulation results demonstrate the adaptability of the proposed reactive power optimization model and the feasibility and effectiveness of the algorithm.

Keywords: renewable energy distribution network, reactive power optimization, coordinated operation of DG, DS and EV, reactive power compensation devices

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2 Stochastic Probability Models for DG Output

Energy depletion and environmental degradation represent two major challenges facing the world today. Developing and utilizing renewable energy while reducing environmental pollution have become common concerns for all nations. In this context, distributed generation (DG) and electric vehicles (EV) will occupy important positions in future development plans for the power and automotive industries, with their penetration rates gradually increasing. However, large-scale, unplanned integration of DG and EV into the grid will impact traditional distribution networks [1-2].

The large-scale integration of distributed power sources, distributed storage devices (DS), and EV charging stations significantly affects distribution network operation. Current literature has conducted in-depth research on coordinated operation after DG and EV integration into distribution networks. Reference [3] introduces an orderly EV charging optimization scheme aimed at loss reduction. Reference [4] proposes a hierarchical control architecture for orderly charging that can integrate with traditional grid control frameworks to achieve coordinated control of EVs and distributed renewable energy sources across the distribution network. References [5-6] establish a multi-objective optimization model for coordinated control of EVs and distributed generation, maximizing equivalent load rate while minimizing node voltage violations, loss rates, grid service costs, and owner charging costs through dynamic adjustment of EV charging/discharging power. This model effectively matches load and distributed generation power fluctuations while reducing the impact of distributed generation intermittency on the grid. References [7-10] investigate collaborative optimization of wind power, photovoltaic generation, and EV loads, proposing corresponding optimization models and methods. Reference [11] establishes path selection and traffic satisfaction evaluation models while studying the temporal characteristics and complementarity of distributed generation.

In summary, the integration of distributed generation and electric vehicles into distribution networks affects node voltage and network losses [12-16]. Improving voltage stability and reducing network losses after DG and EV integration represents a current research challenge.

Building upon the aforementioned studies and considering the stochastic nature of distributed generation output, this paper obtains grid parameters at specific moments through probabilistic power flow calculations [17]. To balance the impacts of distributed generation integration, the system includes energy storage devices and reactive power compensation equipment. Coordinated operation of DS, EV, reactive compensation devices, and distributed generation reactive output [18] is employed to maintain node voltage stability and reduce network losses. This paper establishes a reactive power optimization model using DS, EV, reactive compensation devices, and distributed generation reactive output as control variables.

2.1 Stochastic Probability Model for Distributed Wind Turbine Output

Wind speed at a node can be described by a Weibull distribution [5], with its distribution function expressed as:

$$f(v) = \frac{v}{v_0} \exp\left(-\frac{v}{v_0}\right)$$

where v is wind speed; v_0, k, and c are the location, shape, and scale parameters of the Weibull distribution curve, respectively.

Considering the probabilistic characteristics of wind speed v, the probability density function of wind turbine output power is obtained as:

$$f(P_W) = f(v)dv \cdot f(v)dv \exp\left(\frac{P_W}{k_2}\right) \cdot f(v)dv \cdot \frac{P_W}{k_2}$$

$$P_W = 0 \quad 0 \leq P_W \leq P_e$$

$$P_W = P_e$$

where P_e is the rated power of the wind turbine; v_{ci} is the cut-in wind speed; v_{co} is the cut-out wind speed; and v_r is the rated wind speed.

2.2 Stochastic Probability Model for Photovoltaic Generation System Output

Solar irradiance over a period can be approximated as following a Beta distribution, and the probability density function of solar cell output power also follows a Beta distribution [5]:

$$f(P_{PV}) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \left(\frac{P_{PV}}{P_{max}}\right)^{\alpha-1} \left(1-\frac{P_{PV}}{P_{max}}\right)^{\beta-1}$$

where P_{PV} is the active power output of the solar generation system; P_{max} is the maximum active power output of the solar panel array; and α, β are the Beta distribution shape parameters.

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3 EV and Energy Storage Device Models

3.1 Electric Vehicle Characteristics

3.1.1 EV State of Charge The state of charge (SOC) of electric vehicles is closely related to user driving mileage. According to reference [19], the relationship between EV driving mileage and battery SOC is:

$$SOC_{EVi,h} = SOC_{EVi,q} - \frac{L}{M}$$

where $SOC_{EVi,q}$ and $SOC_{EVi,h}$ are the SOC before and after EV usage; L is the actual driving distance per trip; and M is the maximum driving range on a full charge.

Based on reference [19], the maximum charging/discharging power of the i-th EV ($i < N_{EV}$) during a time period is:

$$P_{EVi}^{c,\max} = \min\left(\frac{SOC_{EV,\max} - SOC_{EVi,0}}{T_c}, P_{EVi,N}^{c}\right)$$

$$P_{EVi}^{dc,\max} = \min\left(\frac{SOC_{EVi,0} - SOC_{EV,\min}}{T_{dc}}, P_{EVi,N}^{dc}\right)$$

where $SOC_{EVi,0}$ is the initial SOC; $P_{EVi,N}^{c}$ and $P_{EVi,N}^{dc}$ are the rated charging and discharging powers; and T_c, T_{dc} are charging and discharging times.

3.1.2 EV Charging/Discharging Characteristics Due to technical limitations, EV charging/discharging power cannot maintain constant operation. Assuming constant power during charging/discharging, the EV characteristics [19] are:

$$SOC_{EVi}^{c} = SOC_{EVi,0} + \Delta SOC_{EV} = SOC_{EVi,0} + \frac{P_{EVi}^{c} T_c}{E_{EV}}$$

$$SOC_{EVi}^{dc} = SOC_{EVi,0} - \Delta SOC_{EV} = SOC_{EVi,0} + \frac{P_{EVi}^{dc} T_{dc}}{E_{EV}}$$

where $SOC_{EVi,0}$, SOC_{EVi}^{c}, and SOC_{EVi}^{dc} are the initial, post-charging, and post-discharging SOCs; ΔSOC_{EV} is the SOC change; P_{EVi}^{c} and P_{EVi}^{dc} are charging and discharging powers; T_c and T_{dc} are charging and discharging times; and E_{EV} is the full battery capacity.

3.1.3 EV Charging/Discharging Power To ensure battery lifespan, $SOC_{EVi,0}$ must satisfy:

$$SOC_{EV,\min} \le SOC_{EVi,0} \le SOC_{EV,\max}$$

When $SOC_{EVi,0} < SOC_{EV,\min}$, the EV can only charge; when $SOC_{EVi,0} > SOC_{EV,\max}$, the EV can only discharge.

Assuming m EVs in the system, the number of EVs connected to the grid during a time period, N_{EV}, follows a normal distribution [20]:

$$E[N_{EV}] = m \cdot f(t)$$

where m is the total number of EVs; t is the time period; and $f(t)$ is the probability distribution function of EV charging.

The actual number of EVs charging in a single period can be represented by a Poisson distribution:

$$p(N_{EV}) = \frac{(\lambda_{EV})^{N_{EV}}}{N_{EV}!} \exp(-\lambda_{EV})$$

The maximum charging/discharging power during a period is:

$$P_{EV}^{c,\max} = \sum_{i=1}^{N_{EV}} P_{EVi}^{c,\max}$$

$$P_{EV}^{dc,\max} = \sum_{i=1}^{N_{EV}} P_{EVi}^{dc,\max}$$

3.2 Energy Storage Device Operating Characteristics

(1) Efficiency η: For a single storage device with capacity E_{DSi} (maximum stored energy) and current energy E_{DSi}^{in}, the output energy [21] is:

$$E_{DSi}^{\text{out}} = \eta_i E_{DSi}^{\text{in}}$$

Due to technical and manufacturing differences, η_i varies across devices [21].

(2) Maximum Charging/Discharging Power: Subject to safety and technical constraints, the maximum charging power $P_{DSi}^{c,\max}$ and discharging power $P_{DSi}^{dc,\max}$ must not exceed device limits [21].

(3) State of Charge SOC_{DSi}: SOC_{DSi} represents the current capacity as a fraction of maximum storage capacity:

$$SOC_{DSi} = \frac{E_{DSi}^{\text{in}}}{E_{DSi}}$$

Since overcharging or over-discharging affects lifespan, SOC_{DSi} must satisfy [22]:

$$SOC_{DSi,\min} \leq SOC_{DSi} \leq SOC_{DSi,\max}$$

Similar to efficiency, different devices have different SOC_{DSi} limits due to internal factors.

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4 Reactive Power Optimization Model

DG integration can cause local voltage rise. DS and EV, as two typical controllable loads, can reduce voltage fluctuations and significantly decrease network power losses by controlling active power input/output when distributed generation output changes uncertainly. This represents a reactive power optimization problem for renewable energy distribution networks—a multi-variable, multi-constraint complex planning problem that can be formulated as a multi-objective reactive power optimization model.

4.1 Objective Function

This paper uses active power loss and voltage deviation as objective functions. The multi-objective function is:

$$F = \min[\lambda_1 f_{\text{loss}} + \lambda_2 f_{\Delta V}]$$

where:

$$f_{\text{loss}} = \min \sum_{i \in N_L, j \in B_i} G_{ij}(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij})$$

$$f_{\Delta V} = \min \sum_{i=1}^{N} \frac{|V_i - V_{Bi}|}{V_{i,\max} - V_{i,\min}}$$

f_{loss} and $f_{\Delta V}$ represent network loss and voltage deviation; N_L is the total number of buses; V_i, V_j are voltage magnitudes at nodes i and j; G_{ij} is the mutual conductance; θ_{ij} is the phase angle difference; N is the total number of system nodes; B_i is the set of neighboring nodes; $V_{i,\max}$, $V_{i,\min}$, and V_{Bi} are the upper limit, lower limit, and base voltage values, respectively; and λ_1, λ_2 are weighting coefficients with $\lambda_1 + \lambda_2 = 1$, $0 \leq \lambda_1 \leq 1$, $0 \leq \lambda_2 \leq 1$.

4.2 Constraint Conditions

(1) Power Flow Balance Equations: With uncertain distributed generation output and uncertain DS/EV charging/discharging power under different control requirements, power flow equations must be satisfied:

$$\Delta P_i = P_i - V_i \sum_{j \in B_i} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij})$$

$$\Delta Q_i = Q_i - V_i \sum_{j \in B_i} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij})$$

where P_i, Q_i are the active and reactive power injections at node i.

(2) Control Variable Inequality Constraints: The reactive power optimization problem involves control variables including DG reactive power output, reactive compensation device output, DS charging/discharging power, and EV charging/discharging power. These must satisfy:

$$Q_{DG,i,\min} \leq Q_{DG,i} \leq Q_{DG,i,\max}$$

$$Q_{C,i,\min} \leq Q_{C,i} \leq Q_{C,i,\max}$$

$$P^{c}_{DS,i,\min} \leq P^{c}_{DS,i} \leq P^{c}_{DS,i,\max}$$

$$P^{dc}_{DS,i,\min} \leq P^{dc}_{DS,i} \leq P^{dc}_{DS,i,\max}$$

$$P^{c}_{EV,i,\min} \leq P^{c}_{EV,i} \leq P^{c}_{EV,i,\max}$$

$$P^{dc}_{EV,i,\min} \leq P^{dc}_{EV,i} \leq P^{dc}_{EV,i,\max}$$

where subscripts "min" and "max" denote lower and upper bounds.

(3) State Variable Constraints: State variables (node voltages) must remain within allowable limits:

$$V_{i,\min} \leq V_i \leq V_{i,\max}$$

5 Genetic Algorithm

The genetic algorithm [23] is an adaptive global optimization probabilistic search algorithm that simulates natural genetic and evolutionary processes. Variables are encoded as chromosomes that can undergo genetic variation. The objective function corresponding to a set of variable values is transformed into an individual' s fitness function. Starting from random initial values, superior individuals are selected through survival of the fittest. These individuals undergo genetic operations including reproduction, crossover, and mutation to produce the next generation. This process repeats until an optimal solution is found or the maximum generation limit is reached [24].

When applied to power system optimization [25], the power flow solution is constrained by multiple conditions. The objective function evaluates solution quality—low-quality solutions are discarded while high-quality solutions pass their characteristics to subsequent iterations, eventually converging to an optimal solution.

5.1 Encoding

Due to its suitability for mixed-integer optimization, the genetic algorithm conveniently encodes reactive power optimization problems. Each chromosome represents an optimization scheme.

This paper employs integer encoding, using parallel compensation capacitors, EVs, storage devices, and distributed generation reactive power outputs as control variables, all represented as integers. The control variable chromosome is:

$$X = [Q_C \ Q_{DS} \ Q_{EV} \ Q_G] = [Q_{C1} \cdots Q_{Ci} \ Q_{DS1} \cdots Q_{DSi} \ Q_{EV1} \cdots Q_{EVi} \ Q_{G1} \cdots Q_{Gi}]$$

where Q_C, Q_{DS}, Q_{EV}, Q_G represent reactive power outputs of capacitors, storage devices, EVs, and distributed generation, respectively.

Initial values are:

$$X_i = (X_{\max} - X_{\min}) \frac{d}{2^k - 1} + X_{\min}$$

where d is a random number and k is the string length for each parameter [26].

5.2 Fitness Function

The fitness function is fundamental to genetic algorithm performance. A reasonable fitness function significantly improves algorithm effectiveness. The fitness transformation formula is:

$$\mathrm{Fit}(F) = \frac{1}{F}$$

where F is the objective function value [26].

5.3 Solution Steps

The genetic algorithm-based reactive power optimization procedure is:

1. Input network data, equality constraints, and inequality constraints.
2. Encode variables and generate the initial chromosome population.
3. Calculate fitness function values for each chromosome.
4. Apply reproduction, crossover, and mutation to produce a new generation.
5. Decode post-operation chromosomes and calculate their fitness values.
6. If the generation count exceeds the maximum limit, terminate; otherwise, return to step 4.

7. Verify constraints including state variable equations/inequalities and control variable ranges. If violated, return to step 4.
8. Extract optimization results. When converged, the best-fit chromosome represents the optimal solution [27].

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6 Case Study and Analysis

This paper uses the modified IEEE 33-node distribution system shown in [Figure 1: see original paper] [28]. The IEEE 33-node system is a pure radial network with 33 nodes and 32 branches. The base voltage is 12.66 kV, base capacity 10,000 kV·A, load node voltage range [0.95, 1.05], active load 5,084.26 kW, and reactive load 3,347.32 kvar [29].

Assume node 31 has parallel capacitors (0.15 × 4,000 kvar); node 3 connects a doubly-fed induction generator rated at 850 kW; node 26 connects a photovoltaic system rated at 500 kW; battery maximum continuous discharge power is 80 kW with rated capacity 200 kW·h; single EV maximum continuous charging/discharging power is 3 kW; and nodes 3 and 26 have 500 and 400 EVs, respectively.

Algorithm parameters: population size $M = 40$, maximum generations $T = 100$, crossover probability $p_c = 0.8$, mutation probability $p_m = 0.1$ [30]. With integer encoding, chromosome length equals the number of control variables (7).

After genetic algorithm optimization, active power loss is 86 kW, representing a 39% reduction from the pre-optimization value of 141 kW. Node voltage deviations from reference voltage decrease significantly, as shown in [Figure 2: see original paper]. In the figure, Scheme 1 shows voltage fluctuation without DG; Scheme 2 shows voltage fluctuation with DG but without optimization; Scheme 3 shows voltage fluctuation with DG and optimization.

Pre-optimization minimum node voltage is 0.978; post-optimization minimum is 0.9906. Results demonstrate significantly reduced voltage fluctuations and enhanced voltage stability. Optimal control variable values after optimization are shown in the table.

[TABLE] Optimal Values of Control Variables After Optimization

Control Variable	Value
Reactive compensation (kvar)	600
Storage discharge (Node 3) (kW)	80
Storage discharge (Node 26) (kW)	80
EV discharge (Node 3) (kW)	1500
EV discharge (Node 26) (kW)	1200
DG reactive output (Node 3) (kvar)	425
DG reactive output (Node 26) (kvar)	250

7 Conclusion

The coordinated operation of distributed generation, distributed storage, and electric vehicle charging/discharging represents a current research hotspot. Large-scale integration of these elements significantly impacts traditional distribution network capacity, voltage quality, operational economy, and reliability. EV battery systems and energy storage devices, as controllable loads, can mitigate voltage fluctuations caused by distributed generation and help maintain voltage stability.

This paper considers the uncertainty of distributed generation output, using network loss and voltage stability indices as objective functions. A reactive power optimization model for distribution networks is constructed with coordinated operation of DG, DS, EV charging stations, and reactive compensation devices, using their reactive power outputs as control variables. The genetic algorithm effectively solves the optimization problem, with simulation results validating the proposed method' s effectiveness.

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