

Optimal Dispatch of Electric Vehicles Considering Carbon Trading and Wind-Photovoltaic Uncertainty

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Abstract

The increasing integration of renewable energy and electric vehicles (EVs) introduces significant uncertainty to power system operations. This paper proposes a coordinated optimization model incorporating Conditional Value at Risk (CVaR) to quantify wind and solar output uncertainty under a carbon trading mechanism. The model maximizes both operator revenue and user benefits, accounting for carbon costs and environmental gains. Simulation results demonstrate the strategy reduces load fluctuations, lowers emissions, and enables efficient supply-demand coordination.

Keywords

Electric Vehicles (EV), Wind and Photovoltaic Power Generation, Conditional Value at Risk (CVaR).

1. Introduction

The global energy transition has led to a rapid increase in renewable energy and EV adoption [1,2]. However, the intermittency of wind and solar power, coupled with uncoordinated EV charging, poses risks to power system stability [3,4]. Vehicle-to-grid (V2G) technology offers a promising solution to mitigate these fluctuations. Meanwhile, carbon trading mechanisms provide economic incentives for renewable integration [5].

Existing studies have addressed EV scheduling or renewable uncertainty separately. For instance, Lu et al. developed a multi-objective EV charging model to reduce grid impact and user costs, highlighting the influence of user behavior on scheduling effectiveness [6]. Bin et al. proposed a model-free energy management strategy for microgrids under uncertainty [7]. However, systematic integration of these factors with carbon trading remains underexplored. This paper introduces CVaR to quantify wind-solar output risk and incorporates carbon trading into a unified optimization framework, pursuing dual objectives of operator revenue maximization and user benefit maximization.

2. System Operational Framework

A bilevel interaction framework is proposed. The operator first computes CVaR based on wind and solar output distributions to assess uncertainty and formulates an initial dispatch plan. EV users then optimize their charging/discharging behaviors to maximize individual benefits and report aggregated load. Finally, the operator adjusts thermal power dispatch and balances supply and demand to maximize profit, considering carbon trading costs and revenues. This iterative process improves system performance.

3. User-Side Optimization Model

EV users aim to maximize their benefits from charging and discharging while meeting travel needs. The user benefit function is expressed as:

$$U_u = a_{ch} \cdot P_{i,t}^{ch} - a_{dis} \cdot P_{i,t}^{dis} - br_t (P_{i,t}^{ch} - P_{i,t}^{dis}) \quad (1)$$

where $P_{i,t}^{ch}$ and $P_{i,t}^{dis}$ are the charging and discharging power of user i at time t , respectively; r_t is the electricity price at time t ; a_{ch} and a_{dis} are the benefit coefficients for charging and discharging; and b is the price sensitivity coefficient.

User decisions must satisfy the following constraints:

$$0 \leq P_{i,t}^{ch} \leq P_{max}^{ch}, 0 \leq P_{i,t}^{dis} \leq P_{max}^{dis}.$$

4. Supply-Side Optimization Model

4.1. Quantification of Wind and Solar Power Uncertainty.

Wind power and photovoltaic output exhibit significant randomness and volatility. This paper employs Conditional Value at Risk (CVaR) to quantify the operational risk arising from this uncertainty. For renewable energy output P_{ren} , CVaR at a given confidence level a is defined as:

$$CVaR_a = E [P_{ren} | P_{ren} \leq VaR_a] \quad (2)$$

A lower CVaR indicates higher risk of output shortfall, prompting the operator to schedule additional reserve capacity.

4.2. Operator Profit Function.

The operator profit R_{op} includes electricity sales revenue minus generation and maintenance costs, plus net carbon trading income:

$$R_{op} = \sum_{t=1}^T r_t D_t - \sum_{t=1}^T (C_{gen,t} + C_{om,t}) + I_{car} \quad (3)$$

where D_t is the total load at time t (including both base load and EV charging load), $C_{gen,t}$ represents the power generation cost, $C_{om,t}$ represents the operation and maintenance cost, and I_{car} represents the net carbon trading income.

The power generation cost $C_{gen,t}$ is a function of the output of each unit. This paper adopts a quadratic function form:

$$C_{gen,t} = aP_{w,t}^2 + bP_{s,t}^2 + cP_{t,t}^2 \quad (4)$$

where $P_{w,t}$, $P_{s,t}$ and $P_{t,t}$ are the power outputs of wind, solar, and thermal power at time t , respectively, and a , b and c are the corresponding cost coefficients.

Carbon revenue I_{car} depends on the difference between actual emissions and allocated quotas:

$$I_{car} = x_{re} \max(0, E_q - E_a) - x_{pe} \max(0, E_a - E_q) \quad (5)$$

Actual carbon emissions primarily originate from thermal power units: $E_a = e \cdot \sum_t P_{t,t} \Delta t$, where e is the carbon emission factor for thermal power.

(1) Power balance constraint: $P_{w,t} + P_{s,t} + P_{t,t} + \sum_i P_{i,t}^{dis} = D_{base,t} + \sum_i P_{i,t}^{ch}$.

(2) Unit output constraints: $P_{w, min} \leq P_{w, t} \leq P_{w, max}$; similar constraints apply to photovoltaic and thermal power.

(3) Spinning reserve constraint: Considering the uncertainty of wind and solar power, sufficient reserve capacity must be reserved.

5. Simulation Results

As shown in Fig. 1, compared with the thermal-power-only scenario, the integration of wind and solar power reduces carbon emissions by approximately 10.1%. This indicates that the integration of renewable energy effectively reduces system carbon emissions.

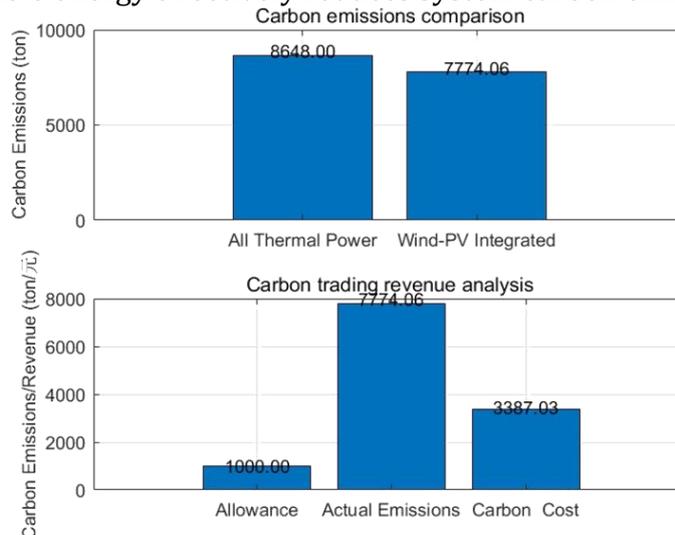


Fig. 1 Carbon emissions and trading revenue analysis

As illustrated in Fig. 2, lower fuel costs and carbon trading incentives lead to an 84% increase in operator revenue, significantly enhancing operational economics.

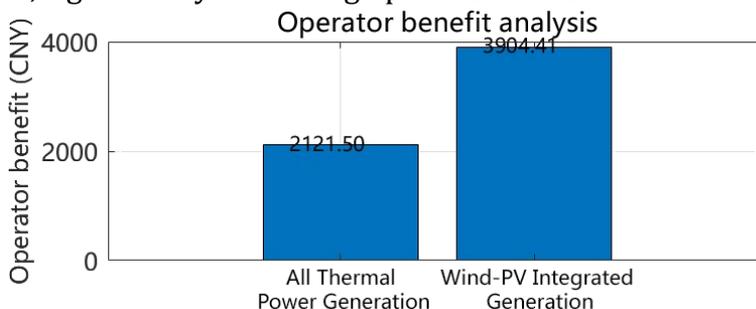


Fig. 2 Operator benefit analysis

6. Conclusion

A collaborative optimization model for power systems with EVs and wind-solar generation under carbon trading is developed. CVaR quantifies renewable uncertainty, enabling risk-aware dispatch. The bilevel framework coordinates supply and demand, achieving emission reductions and revenue gains. The proposed strategy effectively supports low-carbon transition and system stability.

Acknowledgements

The work is supported by National Natural Science Foundation of China (NSFC) (No. 71871144) and the Innovation Fund Project for Undergraduate Student in Shanghai (No. SH2025080).

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