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Multi-energy Coordinated Dispatch and Carbon-Constrained Optimization for Power Systems with High Renewable Penetration

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Abstract. The large scale integration of wind and photovoltaic generation is changing the dispatch logic of power systems. The random fluctuation of renewable output increases reserve demand, transmission flow pressure, and the risk of wind and solar curtailment. Carbon emission constraints also make traditional economic dispatch, which mainly minimizes thermal generation cost, less suitable for low carbon operation. For power systems with high renewable penetration, an electricity, heat, gas, and storage coordinated dispatch model with carbon constrained optimization is constructed. Thermal fuel cost, unit start up cost, renewable curtailment penalty, storage operation cost, and ladder type carbon cost are included in one objective function. Typical scenarios are generated from wind and solar forecast errors. Mixed integer linear programming is used to solve the day ahead dispatch scheme, and power flow verification is conducted to check line operating limits. The simulation results show that carbon constrained multi energy dispatch can reduce carbon emissions, lower reserve activation, and improve renewable accommodation while keeping operating cost under control. The method provides a reproducible technical path for low carbon dispatch modeling, flexible resource allocation, and coordinated multi energy operation in high renewable power systems.

Keywords: Multi-energy dispatch, carbon-constrained optimization, renewable energy, power systems, mixed-integer linear programming

1. Introduction

The large-scale integration of wind and photovoltaic generation is shifting power system operation from traditional economic dispatch toward the coordinated optimization of flexibility, security, and low-carbon performance. Renewable output is strongly affected by weather conditions, which may increase reserve demand, cause transmission-flow fluctuations, and lead to wind and solar curtailment. A dispatch mode centered on thermal units is therefore less capable of adapting to these operational changes [1]. At the same time, electricity, heat, gas, and storage resources can provide wider regulation space through coupled operation, but existing studies still lack a unified modeling logic that connects renewable fluctuation, carbon-emission limits, and multi-energy coordination [2]. For power systems with high renewable penetration, the research can follow the logic of multi-

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energy system modeling, carbon-constrained dispatch optimization, and multi-scenario simulation verification. The focus is placed on the coordination among operating cost, carbon emissions, and renewable accommodation.

2. Literature Review

2.1. Multi-energy dispatch mechanisms

Multi-energy dispatch emphasizes the joint operation of electricity, heat, natural gas, storage, and energy conversion devices. Its core idea is to improve overall system flexibility by using the differences among energy carriers in supply-demand timing, conversion efficiency, and regulation capability [3]. In integrated energy systems, CHP units, heat pumps, P2G devices, and storage can transfer part of the balancing pressure from the power system to heat, gas, and storage layers, thereby reducing the difficulty caused by unstable wind and solar output [4]. As renewable penetration increases, the value of multi-energy coordination is reflected not only in lower operating costs, but also in reduced reserve activation, higher renewable utilization, and lower dependence on high-emission units. Existing studies provide a useful basis for electricity-heat-gas joint optimization, while the interaction among device coupling, network security, and carbon constraints still needs more detailed modeling.

2.2. Renewable uncertainty modeling

Renewable uncertainty mainly comes from wind speed, solar irradiance, and load forecasting errors. These errors directly influence unit commitment, reserve capacity, storage charging and discharging schedules, and transmission-flow distribution [5]. Stochastic programming usually constructs multiple typical scenarios to describe wind and photovoltaic output variations, allowing day-ahead dispatch plans to consider different fluctuation risks in advance. However, excessive scenario numbers may increase model size and computational pressure [6]. Rolling optimization and model predictive control can continuously revise dispatch plans according to the latest forecasting results, shifting system operation from static scheduling to dynamic adjustment. Under multi-energy coupling, uncertainty modeling also needs to consider heat-load inertia, P2G conversion efficiency, storage state-of-charge limits, and carbon-emission constraints, so that dispatch optimization can be closer to actual operating conditions.

2.3. Carbon-constrained optimization

Carbon-constrained optimization usually changes traditional economic dispatch objectives through emission caps, carbon trading prices, or ladder-type carbon costs. In this way, the output of high-emission units is restricted by both operating cost and emission responsibility [7]. When carbon cost is introduced into the objective function, the marginal cost of thermal units increases, while the dispatch priority of low-carbon flexible resources such as renewables, storage, P2G, and CHP becomes higher [8]. Existing computational platforms and optimization tools can already support public test-system modeling, power-flow verification, and mixed-integer programming, providing an operational basis for low-carbon dispatch simulation [9]. However, under high renewable penetration, carbon constraints need to be considered together with multi-energy coupling, renewable uncertainty, and grid security constraints, so that the economic performance and engineering feasibility of low-carbon dispatch schemes can be evaluated more accurately.

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3. Experimental Methods

3.1. Test system and data processing

The IEEE RTS-GMLC system is selected as the base test system. Its buses, transmission lines, conventional generators, load profiles, wind power series, and photovoltaic series are retained. The dispatch horizon is set to 24 h, and the time resolution is set to 1 h. To represent operating pressure under high renewable penetration, three wind and solar penetration scenarios are configured at 40%, 60%, and 80%, with the 80% case used as the main test scenario. A 300 MWh battery storage system, CHP units, P2G devices, and heat-load profiles are added to the original grid structure. This forms an electricity-heat-gas-storage coupled system. The collected data include nodal load, renewable forecasts, generator capacity, ramping limits, line capacity, fuel price, carbon-emission factor, storage efficiency, and P2G conversion efficiency. Missing values are filled by linear interpolation. Abnormal renewable output is capped by installed capacity. Load, renewable generation, and heat demand are then unified at the hourly scale. Typical renewable scenarios are generated from wind and solar forecast errors, which provide input data for the later carbon-constrained dispatch model.

3.2. Carbon-constrained dispatch model

The carbon-constrained dispatch model minimizes the total operating cost of the system. The objective function includes thermal fuel cost, start-up cost, renewable curtailment penalty, storage operation cost, and carbon-emission cost [10]. This objective directly reflects the trade-off among economic operation, renewable accommodation, and low-carbon dispatch, as shown in Eq. (1).

$$\min F=\sum_{t\in T}\left[\begin{array}{c}\sum_{i\in G}\left(a_iP_{i,t}+b_iu_{i,t}+c_i^{su}v_{i,t}\right)+c^{cur}\left(P_{w,t}^{cur}+P_{pv,t}^{cur}\right)+\\ c^{ess}\left(P_t^{ch}+P_t^{dis}\right)+C_t^{co2}\end{array}\right] \quad (1)$$

Here, $P_{i,t}$ denotes generator output, $u_{i,t}$ denotes unit commitment status, $v_{i,t}$ denotes the start-up variable, and $P_{w,t}^{cur}$ and $P_{pv,t}^{cur}$ denote curtailed wind and photovoltaic power. The carbon-emission component combines a total emission cap with ladder-type carbon cost. High-emission output is therefore affected by both the emission limit and the carbon price, as shown in Eq. (2).

$$E^{tot}=\sum_{t\in T}\left(\sum_{i\in G}\epsilon_iP_{i,t}\Delta t+\epsilon_gG_t^{chp}\right),\ E^{tot}\le E^{cap},\ C^{co2}=\sum_{m\in M}\lambda_mz_m \quad (2)$$

Here, E^{tot} denotes total system carbon emissions, E^{cap} denotes the carbon-emission cap, ϵ_i and ϵ_g denote emission factors of thermal units and gas-fired devices, and λ_m and z_m denote the segmented carbon price and the corresponding emission segment.

3.3. Carbon-constrained dispatch model

The solution process follows scenario generation, day-ahead optimization, real-time correction, and power-flow verification. First, 100 renewable output scenarios are generated from wind and

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photovoltaic forecast errors. K-means clustering is then used to reduce them to 10 typical scenarios, which lowers the computational scale of the mixed-integer linear programming model. In the day-ahead stage, the model determines thermal unit commitment, conventional generator output, storage charging and discharging schedules, CHP heat-power output, and P2G electricity-to-gas power [11]. In the real-time stage, a rolling-horizon method is used. Wind and solar forecasts are updated every 1 h, and the outputs of storage, P2G devices, and adjustable generators are corrected. The model is built in Python with Pyomo. Gurobi is used to solve the MILP problem. The optimality gap is set to 0.5%, and the time limit for each solution is 600 s. The optimized results are then imported into MATPOWER or PyPSA for DC power-flow verification. If line flow exceeds its capacity limit, the line-security constraint is fed back into the optimization model for re-solving.

4. Results

4.1. Dispatch performance

Under the 24 h simulation scenario with 80% renewable penetration, a carbon price of 40 USD/tCO_2, and 300 MWh storage capacity, the results of the four dispatch schemes are shown in Table 1. The baseline economic dispatch has an operating cost of USD 1.236 million, but its carbon emissions reach 21,860 tCO_2. Its renewable curtailment rate is 8.7%, which indicates that pure cost minimization keeps a relatively high output level from high-emission units. After carbon constraints are added, carbon emissions decrease to 19,420 tCO_2, while operating cost increases to USD 1.314 million. This shows that carbon cost can suppress thermal generation, but it provides limited ability to absorb renewable fluctuation. Multi-energy coordinated dispatch reduces renewable curtailment to 5.9% and reserve activation to 1,080 MWh. This suggests that storage, CHP, and P2G provide cross-energy regulation capacity. Carbon-constrained multi-energy dispatch further reduces carbon emissions to 18,160 tCO_2 and curtailment to 4.8%, while the operating cost is controlled at USD 1.289 million. This result reflects a balanced performance among economy, low-carbon operation, and renewable accommodation.

Table 1. Twenty-four-hour simulation results under different dispatch schemes

Dispatch scheme	Operating cost / USD million	Carbon emissions / tCO_2	Renewable curtailment rate / %	Reserve activation / MWh
Baseline economic dispatch	1.236	21860	8.7	1460
Carbon-only dispatch	1.314	19420	7.9	1325
Multi-energy coordinated dispatch	1.268	20470	5.9	1080
Carbon-constrained multi-energy dispatch	1.289	18160	4.8	965

4.2. Sensitivity and robustness

The sensitivity analysis further examines the joint effect of carbon price and storage capacity on renewable curtailment, as shown in Figure 1. The horizontal axis represents carbon price. The

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vertical axis represents battery storage capacity. The filled contour surface and contour lines represent the renewable curtailment rate. This type of contour plot can show the interactive effect of two dispatch parameters on curtailment. It is suitable for analyzing the relationship between carbon constraints and flexible resource allocation. When storage capacity is 100 MWh and the carbon price is 0 USD/tCO_2, the curtailment rate is 9.6%. When storage capacity increases to 500 MWh and the carbon price rises to 80 USD/tCO_2, the curtailment rate decreases to 3.5%. The decline is more obvious when storage capacity increases from 100 MWh to 300 MWh, which shows that storage expansion can directly absorb wind and solar fluctuations. After storage capacity increases from 400 MWh to 500 MWh, the improvement becomes smaller. This indicates diminishing marginal returns. A higher carbon price compresses the output space of high-emission units. The system then tends to dispatch renewables, storage, and P2G resources, which improves the robustness of low-carbon dispatch.

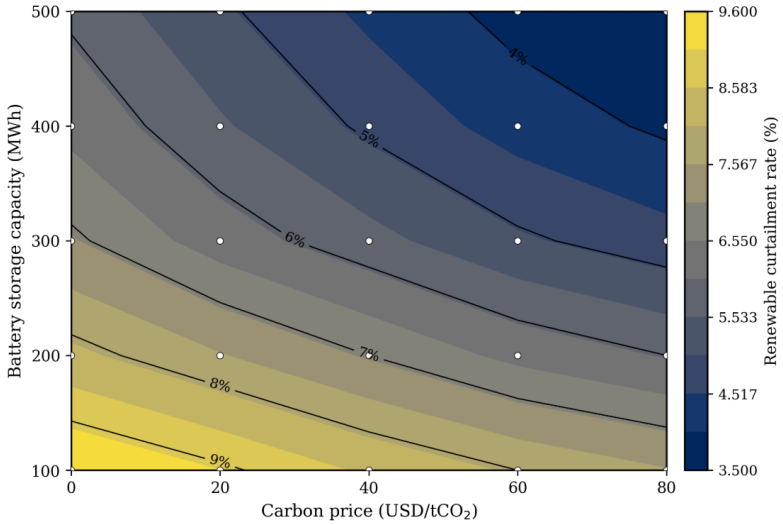

Figure 1. Contour-based sensitivity analysis of renewable curtailment under carbon price and storage capacity

5. Discussion

The experimental results show that carbon constraints reduce the output of thermal units and lead to a clear decrease in system carbon emissions. However, operating cost also increases, while the improvement in renewable curtailment remains limited. This indicates that carbon cost mainly changes the dispatch priority of high-emission resources. Multi-energy coordinated dispatch has a more direct effect on curtailment reduction and reserve activation. Storage, CHP, and P2G can absorb wind and solar fluctuation through cross-energy regulation. When carbon constraints are combined with multi-energy coordination, renewable generation is accommodated first, flexible devices support system balancing, and high-emission units are restricted. The system therefore forms a more reasonable dispatch relationship among cost, emissions, and operational stability.

6. Conclusion

An electricity, heat, gas, and storage coordinated dispatch framework with carbon-constrained optimization is established for power systems with high renewable penetration. The model minimizes total system operating cost and considers renewable uncertainty, carbon-emission caps,

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ladder-type carbon cost, storage operation, multi-energy conversion, and transmission-flow constraints. A public test system is used for simulation verification. The results show that the framework can reduce carbon emissions and wind-solar curtailment, lower reserve activation, and maintain a relatively reasonable operating cost. Future work can further introduce AC power flow, demand response, and real-time market mechanisms to improve engineering applicability.

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