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Optimization Scheduling of Power Systems Incorporating Carbon Trading and Demand Response

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Abstract. Coal-fired power plants are major carbon emitters, making CCS a crucial transitional technology for emission reduction. Among the three approaches—pre-combustion, oxy-fuel combustion, and post-combustion—capturing CO_2 after combustion is considered the most feasible option for current power plants, primarily because of its straightforward process and relatively low modification expenses. CCS enables the continued use of fossil fuels while supporting the shift to low-carbon energy. In this study, an optimized scheduling framework for power systems is developed, incorporating both carbon trading mechanisms and demand response programs, aiming to achieve both low-carbon operation and energy efficiency. By integrating carbon capture technologies, green certificate mechanisms, and dynamic carbon emission factors, an integrated framework for calculating carbon emission costs is established. Various types of demand response, including, Shiftable Load , Curtailable Load , and Replaceable Load , are modeled to reflect user-side flexibility. A carbon flow tracking mechanism is developed to support dynamic carbon accounting. Case studies demonstrate that integrating price-driven and substitution-oriented demand response helps to significantly flatten the system load profile, reduces system operating costs, and lowers carbon emissions, thereby improving the flexibility and economic performance of integrated energy systems. This study provides theoretical insights and practical references for advancing sustainable low-carbon energy systems.

Keywords: Carbon Emission, Energy storage, Energy systems, Green Certificates

1. Introduction

Currently, the power generation sector contributes to close to 40% of global carbon emissions, making it a leading force in emission reduction efforts. Among the available options, post-combustion carbon capture is widely recognized as a practical approach to mitigating CO_2 emissions from coal-based power generation. The core function of carbon capture and storage (CCS) [1] technology is to capture carbon dioxide (CO_2) from emissions of power plants or other industrial facilities using various techniques, preventing it from entering the atmosphere and thus alleviating the impacts of the greenhouse effect and global climate change. The mechanism can be broken down into the following main steps, which include three technical paths: pre-combustion capture, oxy-fuel combustion, and post-combustion capture.

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To address the dual goals of carbon reduction and efficiency in operations, this study suggests an optimal dispatch strategy. By modeling CL, SL, and RL loads and integrating carbon capture technologies and green certificate mechanisms, a comprehensive carbon cost model is established.

The method combines mixed-integer programming with carbon flow tracking to simulate system operations under varying demand-side scenarios. Case studies assess how coordinated demand response and energy storage contribute to cost reduction and emission management. This research provides a practical framework for low-carbon energy system optimization. By embedding carbon pricing into dispatch decisions and enhancing demand-side flexibility, it offers both theoretical and applied value for sustainable energy development.

2. Green Certificates – Carbon Market Trading and Demand Response Optimization Dispatch

2.1. Green certificates – carbon market trading

To validate the strategy of "Green Certificates–Carbon Market Trading and Demand Response Optimization Dispatch" [2], this study compares the changes in carbon emissions from park-level demand response before and after the intervention. Therefore, the demand response types for each park only consider transferable loads.

The implementation of the carbon trading mechanism can effectively promote carbon emissions reduction.

2.2. Carbon emission cost model

2.2.1. Demand response

When the same electricity price signal acts on different types of loads, the sensitivity of loads is significantly different. In the price-led demand response, the load can be divided into reducible load (CL) [3] and transferable load (SL) [4], and the modeling methods of the two will be described respectively in the following.Characteristic Analysis and Modeling of Cutdown Load (CL)

(1) Whether the load can be reduced (CL) reduces the electricity load depends on comparing the changes of electricity price before and after the demand response: by analyzing the differences of electricity price changes, the decision whether to reduce the load is finally made.The price-demand elasticity is described by a matrix, where the element E(t, j) indicates the load elasticity at time t with respect to the electricity price at time j.

(2) SL Characteristics Analysis and Modeling

A shiftable load represents an electrical load whose operational time can be flexibly adjusted in response to electricity price signals for demand response purposes. By using time-of-use pricing signals, users can shift peak loads to off-peak periods.

An integrated energy system equipped with carbon capture, utilization, and storage (CCUS) technologies must operate under a set of constraints, including capacity limits, non-negativity conditions, state-dependent constraints, and ramping limitations of generation units.

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$$\begin{cases} P^{chp} \leq P_t^{chp} \leq P^{-chp} \\ P^{gb} \leq P_t^{gb} \leq P^{-gb} \\ 0 \leq P_t^{eb,t} \leq P^{-eb,e} \\ P^{p2g,e} \leq P_t^{p2g,e} \leq P^{-p2g,e}\ ,\ t \in \tau \\ P^{cc,e} \leq P_t^{cc,e} \leq P^{-cc,e} \\ 0 \leq E_t^{cs} \leq E^{-cs} \end{cases} \tag{1}$$

$$\begin{cases} 0 \leq P_t^{buy,e}, P_t^{wt,cur}, P_t^{pv,cur} \\ 0 \leq V_t^{buy,g}\ ,\ t \in \tau \\ 0 \leq E_t^{cc}, E_t^{cs}, E_t^{out} \end{cases} \tag{2}$$

$$G_{CHP,i,t} = \frac{1}{Q_{LHV}} \bullet \frac{P_{GT,i,t}}{\eta_{GT,i}} \bullet \Delta t \tag{3}$$

$$P_{GT,i,min} \leqslant P_{GT,i,t} \leqslant P_{GT,i,max}$$

Where $G_{CHP,i,t}$ represents the natural gas consumption of the i-th gas turbine at time t. Q_{LHV} refers to the lower heating value of the fuel, which indicates the effective thermal energy released per unit of fuel. $P_{GT,i,t}$ denotes the power output of the i-th gas turbine at time t, while $\eta_{GT,i}$ signifies the electrical efficiency of the gas turbine; and Δt is the time step.

$$H_{EB,i,t} = \eta_{EB,i} \bullet P_{EB,i,t} \tag{4}$$

$$P_{EB,i,min} \leqslant P_{EB,i,t} \leqslant P_{EB,i,max}$$

Where $H_{EB,i,t}$ denotes the thermal output of the i electric boiler at time t; $\eta_{EB,i}$ donates the energy conversion efficiency of the electric boiler; and $P_{EB,i,t}$ is the electricity consumption of the electric boiler at time t.

$$P_{PV,i,t} + P_{GT,i,t} + P_{ES,i,t}^{cha} - P_{ES,i,t}^{dis} + P_{buy,i,t} = P_{i,t}^{tr} + P_{EB,i,} \tag{5}$$

$$H_{GT,i,t} + H_{ORC,i,t} + H_{EB,i,t} + H_{HS,i,t}^{cha} - H_{HS,i,t}^{dis} = H_{i,t}^{tr}$$

Where $P_{PV,i,t}$ denotes the photovoltaic power generation (zero carbon emissions); $P_{GT,i,t}$ represents the gas turbine's power generation (associated with carbon emissions); $P_{ES,i,t}^{cha}$ and $P_{ES,i,t}^{dis}$ represent the power used for charging and discharging in the energy storage system, respectively (i.e., power absorbed and released by the storage unit); $P_{buy,i,t}$ is the power bought from the grid (carbon emissions depend on the grid mix); $P_{i,t}^{tr}$ represents the power transmission or export; $P_{EB,i,t}$ is the electricity usage of the electric boiler (indirect carbon emissions); $H_{GT,i,t}$ denotes the gas turbine's thermal generation (co-generated with electricity and accompanied by carbon emissions); $H_{ORC,i,t}$ is the thermal output of the Organic Rankine Cycle (potentially from waste heat recovery, zero carbon emissions); $H_{EB,i,t}$ denotes the thermal output of the electric boiler (indirect carbon emissions); $H_{HS,i,t}^{cha}$ and $H_{HS,i,t}^{dis}$ represent the power used for charging and discharging heat of the thermal energy storage system, respectively; and $H_{i,t}^{tr}$ indicates the total thermal transmission or demand.

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2.3. Power system optimization dispatch

Power system optimization dispatch ensures that electricity demand is met while considering system safety and reliability. It involves planning the generation output, power transmission methods, and load distribution to optimize economic benefits, environmental performance, or other objectives such as reducing carbon emissions.

Currently, the practical applications of power system optimization dispatch involve three aspects: day-ahead scheduling, real-time scheduling, and reserve scheduling. Researchers can formulate power generation plans one day in advance based on load forecasts and generation resources; dynamically adjust generation output to maintain system balance based on system operation status and real-time load changes; and configure reserve capacity to deal with unexpected events, such as generator failures or load fluctuations.

The Demand Response (DR) model: The Demand Response model [5] represents the adjustment of energy usage patterns influenced by electricity prices or incentive mechanisms, allowing users to interact with the grid to enhance the load curve and enhance system operation efficiency. DR can be classified into price-based demand response and substitute-based demand response.

Free Carbon Emission Quota Model: A well-established carbon trading system requires the determination of carbon emission quotas. There are two widely used ways of carbon quota allocation, namely, free allocation and paid allocation. According to the current development of China, this paper chooses the baseline-oriented free allocation method to allocate carbon emission quotas for the system. In the integrated energy heating system (IEHS) [6] with demand response (DR), the carbon emission sources are GT (gas turbine) and GB (gas boiler): GT has the capacity of cogeneration of electricity and heat, while GB only undertakes the task of thermal production.Carbon emission quotas are allocated based on the total equivalent thermal output.At time t, the carbon emission quota for the system Ep,t, is given by:

$$E_{p,t}=\kappa(P^{h}_{GT,t}+\varphi P^{e}_{GT,t}+P^{h}_{GB,t}) \tag{6}$$

where κ represents the regional carbon emission allocation per unit of electricity. In this study, we use the weighted average of the operating margin (OM) and build margin (BM) emission factors for the system area, which is 0.57 t/(MW·h); $P^{e}_{GT,t}$ and $P^{h}_{GT,t}$ are the electricity and heat power generation from GT at time t, respectively; φ is the conversion coefficient for electricity, and $P^{h}_{GB,t}$ is the heat power output from GB at time t.

Carbon Emission Cost Model: The actual carbon emission amount [7] of the system at time t, Eac,t is the sum of the emissions from GT and GB. Based on the emission factor method, it is hypothesized that the actual carbon emissions of the units are relative to their output. Thus, the actual carbon emission amount Eac,t at time t is given by:

$$E_{ac,t}=k_{GT}\left(P^{h}_{GT,t}+\varphi P^{e}_{GT,t}\right)+k_{GB}P^{h}_{GB,t} \tag{7}$$

where k_{GT} and k_{GT} are the carbon emission coefficients of GT and GB, respectively, with values of 0.6101 t/(MW·h) in this study.

This study develops a carbon trading strategy to incentivize the system to actively participate in the carbon trading market. This strategy allows users to independently trade carbon emission quotas: when actual emissions fall below the allocated quota, users can sell the remaining quota at market prices to gain profit; in contrast, if emissions surpass the quota, users must purchase the

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corresponding excess emission quotas from the market. Consequently, the carbon trading cost at time t, $C_{Ca,t}$ is given by:

$$C_{Ca,t} = k_{Ca}(E_{ac,t} - E_{p,t}) \tag{8}$$

In the equation, market price of carbon emission quotas k_{Ca}

It eventually reaches the consumer terminals on the consumer side (load nodes). Since carbon emission flow exists along the power flow, power flow calculations are fundamental to carbon flow calculations. However, carbon flow calculations focus more on analyzing the mechanisms of carbon production, transfer, and consumption within the system. To clearly describe carbon emission flow, it is necessary to establish and calculate matrices that will lay the foundation for dynamic carbon emission factors.

Suppose there are N nodes in the system, including K generators and M load nodes, with the network topology known. Assuming no system line loss, the system's power flow distribution can be obtained using DC power flow analysis.

Dynamic Carbon Emission Factor Model: Principles of constructing dynamic carbon emission factors [8] are as follows: 1. Completeness: The dynamic carbon emission factor should include CO_2 emissions from all stages. 2. Transparency: Users should be able to clearly and intuitively perceive the process of establishing the dynamic carbon emission factor curve. 3. Fairness: The same carbon emission factor curve should be applied at the same spatial scale, such as provincial or municipal administrative units. 4. Perceptibility: Users are required to be aware of the forecast data of future dynamic carbon emission factors, on the other hand, users need to be supported to adjust their own electricity consumption according to this data.

Dynamic carbon emission coefficient is based on carbon flow tracking model. By measuring the capacity and carbon load of each node in a given time, the dynamic carbon emission coefficient can be obtained. The emission factor at each time point will vary, allowing more accurate carbon emission measurement over time.

3. Case study analysis

3.1. Analyzing the operational effectiveness of demand response under the carbon trading mechanism

The implementation of demand response reduces electricity loads at peak times and elevates them at off-peak times, thereby enabling the system to adopt more cost-efficient power procurement strategies. When the carbon trading mechanism comes into effect, the value of demand response is not only to reduce unnecessary power consumption by adjusting the load period (from peak to trough), but also to promote the alternative allocation of power and thermal energy on the user side, so as to realize the smooth operation of the load curve. The system can compare the electricity and gas procurement costs at different times and the output of gas turbines (GT) and gas boilers (GB), thereby selecting an operational strategy that minimizes carbon emissions while optimizing economics. Compared with the original load, which has a clear peak-valley [9] distribution, CL-type loads reduce some electricity demand during peak periods (09:00–12:00, 19:00–22:00); SL-type loads shift some of the peak period loads (09:00–12:00, 19:00–22:00) to off-peak periods (00:00–08:00), thereby reducing the load during peak periods and increasing it during off-peak periods, smoothing the load curve. RL-type loads replace part of the electricity load with thermal load during peak periods (09:00–12:00, 19:00–22:00), and convert some thermal load to electricity during off-

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peak periods (12:00–19:00, 22:00–09:00). In contrast, the thermal energy storage system (HS) stores heat during peak hours, and then releases heat during low hours. Through this mode of peak shifting operation, the adjustment flexibility of the system has been effectively improved.

3.2. Sensitivity analysis of demand response

The proportion of different types of demand response loads significantly impacts the optimization effect of the system's DR strategy. Building upon the research in section 3.1, this section further analyzes how price-based and substitute-based demand response affect system costs under different load distribution conditions(as shown in Figure1-2). By keeping the substitute load proportion constant, the proportions of CL and SL loads are varied between 10% and 40% to investigate the effect of price-based demand response on system operating costs. The results show that as the proportions of CL and SL increase, the total operating costs decrease, indicating a negative correlation between system cost and price-based demand response load. While the electric and thermal load balance are shown in figure 3 and figure 4.

This is because, under a constant total load, increasing the proportions of CL and SL reduces system energy procurement costs by shifting loads during peak periods and increasing loads during off-peak periods, thereby decreasing the total operating cost. When the proportions of CL and SL are fixed at 20%, increasing the RL proportion [10] from 10% to 60% leads to an increase in total system operating costs, indicating a positive correlation between substitute-based demand response load and system cost, requiring optimization of its allocation to minimize costs.

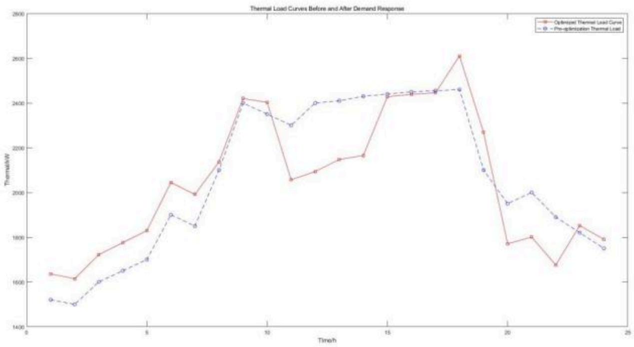

Figure 1. Thermal load curves before and after demand response

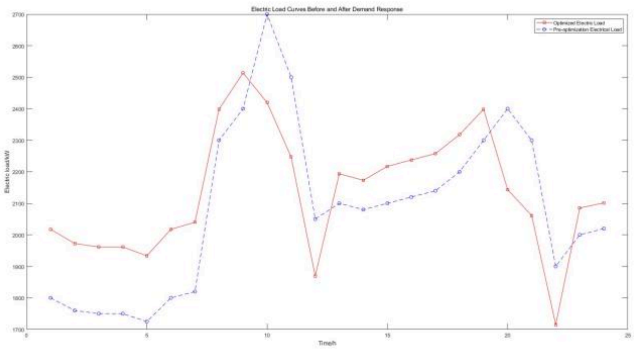

Figure 2. Electric load curves before and after demand response

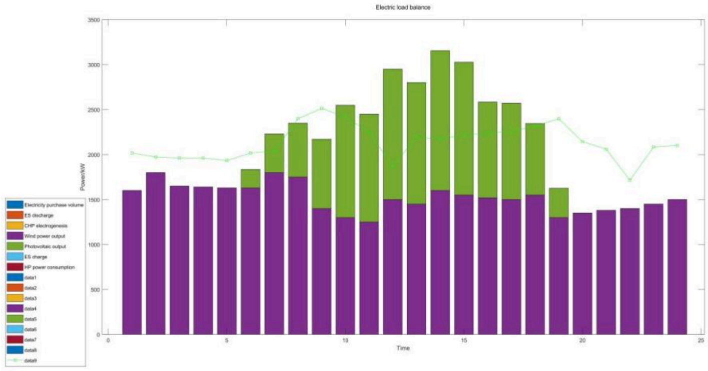

Figure 3. Electric load balance

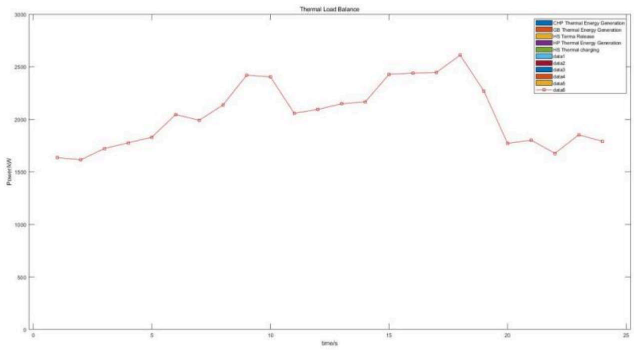

Figure 4. Thermal load balance

4. Conclusion

This study findings indicate that within a carbon trading framework, demand response can effectively guide user behavior, thereby achieving peak reduction and valley filling while lowering operational costs. Increasing the proportions of CL and SL loads leads to lower system costs, whereas excessive RL loads may raise expenditures, highlighting the need for balanced load distribution. The carbon trading strategy incentivizes users to minimize emissions by trading surplus or deficit carbon quotas, enhancing both environmental and economic performance. Additionally, energy storage systems further strengthen operational flexibility by shifting energy use across different price periods. The presentation of dynamic carbon emission factors improves the accuracy and fairness of carbon accounting over time and space. Overall, this research confirms the feasibility and effectiveness of coordinated optimization between carbon trading and demand response, offering valuable insights for the green and efficient operation of integrated energy systems.

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