



Optimization for Transformer District Operation Considering Carbon Emission and Differentiated Demand Response

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With the promotion of the “dual carbon” goal, a large number of distributed photovoltaic power are connected to the distribution network. Since the current operation optimization of the low-voltage transformer district is based on single objectives such as the economy and power reliability, the model is relatively simple and difficult to adapt to the large-scale access of photovoltaics. Therefore, this article comprehensively considers carbon emissions, different load characteristics, and differentiated demand response of the district. An optimization method for low-voltage transformer district operation under the dual-carbon background is proposed. First, the typical structure of a low-voltage transformer district is introduced. Second, the load types and characteristics of the low-voltage transformer district are analyzed, and differentiated demand response models are established for different types of loads. Finally, taking the minimum economic cost and carbon emission as the objective, the low-voltage transformer district operation optimization model considering carbon emission and differentiated demand response is established by considering the voltage overrun of the photovoltaic access point, substation capacity constraint, and carbon emission constraint. The simulation results show that the model can effectively reduce the economic cost and carbon emissions of the low-voltage transformer district, achieve more than 95% reasonable utilization rate of new energy in the low-voltage transformer district, improve the lateral time distribution of load in the low-voltage transformer district, and provide an effective means for low-carbon scheduling of distribution networks.

Keywords: low-voltage transformer district, photovoltaic access, load characteristics, differentiated demand response, carbon emission, optimal scheduling

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1 INTRODUCTION

In recent years, with the increasingly prominent global environmental pollution problems and energy crisis, General Secretary Xi Jinping proposed the strategic goal of “carbon peaking and carbon neutrality” at the United Nations General Assembly, demanding to reduce the carbon emission level of the distribution network transformer district (Wei et al., 2021). The new energy power generation represented by photovoltaics has developed rapidly. However, with the increase of photovoltaic penetration rate, the coordination of the source and load in the low-voltage transformer district has become more difficult (Zhao et al., 2019). Demand-side response can be used to absorb new energy

and improve the interaction between the source and load in the district (Huang D. et al., 2022). Therefore, carbon emissions and demand-side response characteristics should be fully considered in the optimal scheduling of the low-voltage transformer district.

At present, the optimal scheduling of the transformer district mainly focuses on distributed power generation. Ma et al., 2021 proposed a robust optimization planning model for a transformer district considering the uncertainty of photovoltaic intensity and considering the ability of the distribution network transformer district to accept distributed photovoltaics and obtained the best access point and optimal installation capacity of photovoltaics. Al-Ismail, 2020 started from the impact of distributed power generation on the transformer district and analyzed three aspects: distribution network reconfiguration technology, distributed power generation location and capacity optimization, and filter selection and location optimization, and summed up the strategy for optimal operation in the transformer district. Chen et al., 2020 proposed a layered control method for source-load-storage control in the transformer district to achieve optimal autonomy of the distribution network based on the multi-time scale complementary characteristics of controllable distributed power generation, energy storage systems, and loads. Cong et al., 2022 aimed at the volatility and intermittent problems brought by the increase in the installed capacity of photovoltaic power generation to the distribution network and proposed a fault recovery self-healing reconfiguration control optimization strategy for the distribution network based on an improved group search algorithm, which improved the efficiency of the distribution network. Zhang X. et al., 2021 analyzed the calculation method of flexibility provided by each component in the distribution network, established a two-layer optimal scheduling model for the distribution network with distributed photovoltaics considering flexibility, and introduced intuitive fuzzy programming to obtain the comprehensive optimal scheduling scheme. The above literature shows that in the optimal scheduling of the transformer district, taking into account the high proportion of the new energy consumption rate and low-carbon emissions at the same time is of great significance to the flexible resource planning of the transformer district, which is helpful to achieve energy saving and emission reduction in the transformer district.

Demand response is an important means to stabilize the output of distributed power generation and improve the consumption rate of new energy. The influence of demand response should be fully considered in the optimal scheduling of the low-voltage transformer district (Shafie-khah et al., 2019). Some scholars have carried out research on the demand response characteristics of low-voltage transformer districts. Shi et al., 2020 constructed a user DR model based on the elasticity coefficient matrix of real-time electricity prices, analyzed the charging load demand of electric vehicles at the same time, and established a robust optimal dispatch model for an active distribution network. Khalid et al., 2018 proposed an active distribution network that considers demand response; the double-layer collaborative configuration model stimulates the charging and discharging of electric vehicles to reduce the peak-to-valley difference of the load and adapt to the various planning requirements of

electric vehicle charging stations. Jin et al., 2020 applied the evaluation of the operation status of the distribution network transformer district based on a fuzzy comprehensive evaluation of the incentive demand-side response and realized the comprehensive optimization of the voltage and load of the distribution network transformer district while reducing the peak load. Zhu et al., 2022 considered the user participation in demand response and established an optimal scheduling model of active distribution based on price and incentive demand response; the model has given full play to the flexibility of demand response. Qiu et al., 2021 used triangular fuzzy numbers to describe the uncertainty of demand response and established a distribution system with the goal of minimum users on the load side and maximum wind power consumption. The network master-slave game economic model achieves the game equilibrium by optimizing the real-time electricity price strategy and demand response strategy. However, the existing related studies have not considered the timeliness of demand response and the impact of different loads, which will make the response resources not fully utilized, making it difficult to achieve the expected effect of district scheduling. At the same time, these studies have not considered the difference in response elasticity coefficient and real-time electricity price among different users, without classification of load types, and the amount of electricity change and price change in the considered price-based demand response is linear, which does not conform to the actual situation and cannot reflect the actual demand response features.

To sum up, in order to deal with the current adverse effects of the county's photovoltaics on the optimal dispatch reliability and economic low-carbon operation of the low-voltage transformer district and make full use of demand response resources to increase the consumption of renewable energy and smooth the load curve at the same time, this article comprehensively considers carbon emissions and differentiated demand response. First, the basic structure of the low-voltage transformer district is introduced. Second, the load types and characteristics of the low-voltage transformer district are analyzed, and a differentiated demand response model is established for different types of loads. Under the conditions of photovoltaic access point voltage exceeding the limit and carbon emission constraints, an optimization model of low-voltage transformer district operation was established considering carbon emissions and differentiated demand response. Finally, the effectiveness of the optimal scheduling model was verified through simulation solutions.

2 BASIC STRUCTURE OF THE LOW-VOLTAGE TRANSFORMER DISTRICT

The low-voltage transformer district refers to the 10kV/0.4kV power supply area provided by several distribution transformers. The typical low-voltage transformer district structure constructed in this article is shown in **Figure 1**.

This low-voltage transformer district is divided into the transformer layer, the branch layer, the casing layer, and the user layer from top to bottom, which can play the function of

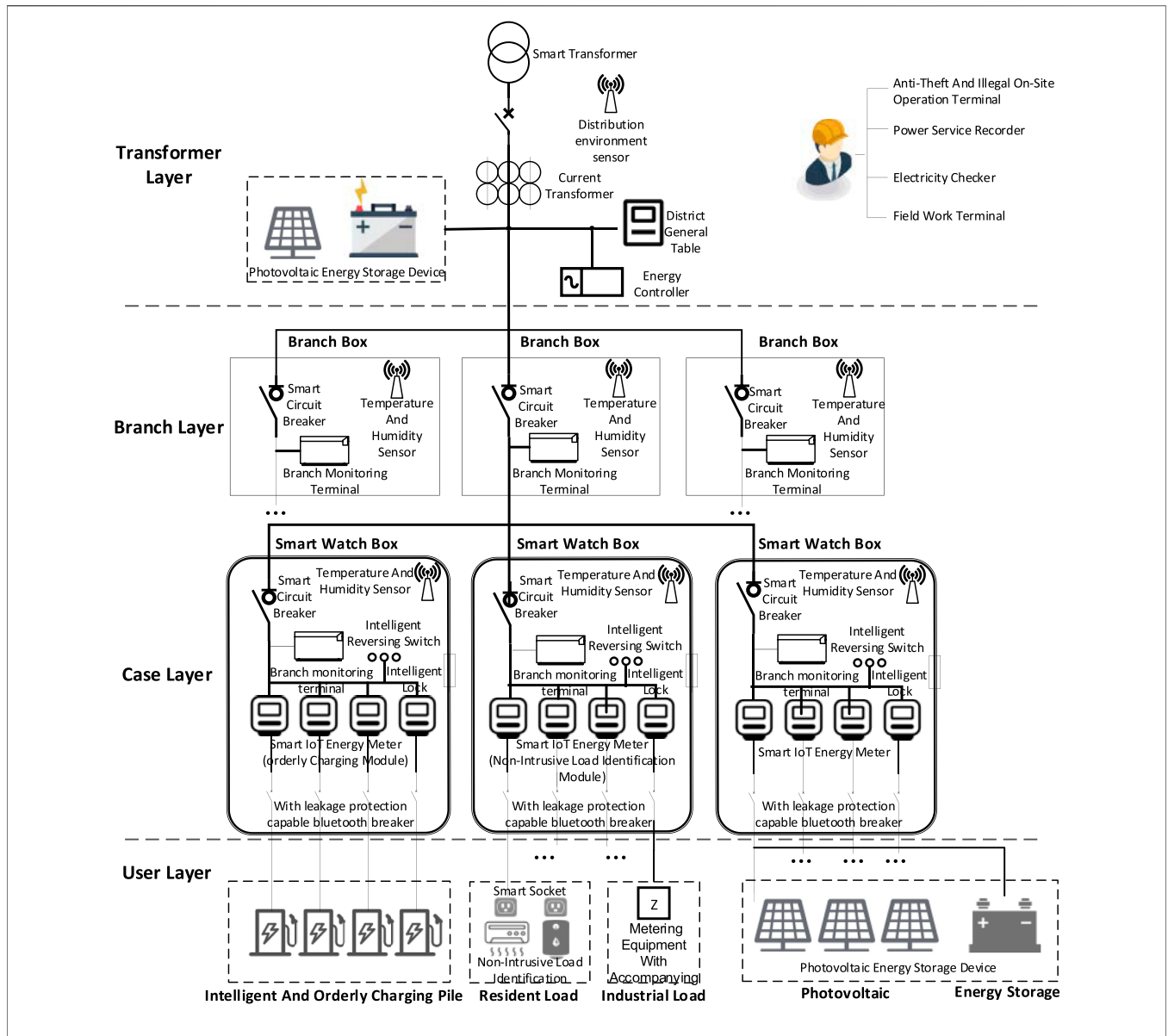


FIGURE 1 | Structure of the typical low-voltage transformer district.

“connecting the previous and the next” in the construction of the energy Internet. The transformer layer is composed of energy controllers, photovoltaic energy storage devices, and smart transformers. The branch layer includes branch monitoring terminals, environmental sensors, and single-phase intelligent miniature circuit breakers. The casing layer mainly includes smart IoT energy meters, intelligent reversing switches, and smart locks. The user layer includes residential load, industrial load, charging pile load, photovoltaics, and energy storage devices. The district can be used for online automated operations, distributed photovoltaic monitoring, reasonable analysis of the operating status of the platform, extraction of the differentiated behavior characteristics of users in the district, orderly charging of electric vehicles, and response to residential industrial energy consumption and take into account the

distributed photovoltaic consumption and carbon emissions in the district, which can effectively promote the district. It is an important guarantee for further attracting investment and construction of low-voltage transformer districts in the future.

3 DIFFERENTIATED DEMAND RESPONSE MODEL

The demand-side response mechanism is mainly divided into price-based demand response and incentive-based demand response (Chen et al., 2019). In order to more accurately describe the characteristics of demand response behavior in low-voltage transformer districts, this article considers the classification of loads and adopts differentiated price-based

demand response. There are certain differences in the electricity consumption behavior, real-time electricity price, and elastic coefficient of different loads.

3.1 Load Characteristics of the Low-Voltage Transformer District

This article divides the electricity load of low-voltage transformer districts into three types according to the electricity consumption characteristics of them. They are residential electricity load, industrial electricity load, and electric vehicle charging pile electricity load.

The typical low-voltage transformer district electricity consumption category is mainly residential electricity load. This kind of load is not restricted by grid dispatching. The user's consumption behavior greatly affects the load fluctuation of the low-voltage transformer district. With the popularization of air conditioners, lighting, and other equipment, the impact of climate change and time factors on residential electricity load has become more significant (Meng et al., 2019).

Industrial electricity load is linked to economic factors. The economic situation of the district where the low-voltage transformer district is located directly affects the power consumption level of the industrial load, thereby affecting the growth or decline trend of the load in the entire low-voltage transformer district. In the electricity market, the electricity price is variable. The stepped electricity price and the time-of-use electricity price also show a complex relationship with the industrial load in a low-voltage transformer district (Chau et al., 2018).

The load of electric vehicle charging piles is easily affected by many factors, including the parameters of the electric vehicle itself, the number of charging piles, and many other factors (Zhang Y. et al., 2021). The intraday charging and discharging characteristics of large-scale electric vehicle charging piles will increase the peak-to-valley difference of the load. When the electric vehicle charging piles are connected on a large scale during the peak load period, it is not conducive to the safe and economic operation of the low-voltage transformer district. Therefore, the maximum accessible load of the charging pile is limited by the distribution capacity of the low-voltage transformer district (Tan et al., 2021).

3.2 Differential Price-Based Demand Response

Price-based demand response guides users to actively adjust their electricity consumption habits according to their own electricity consumption through time-of-use electricity prices. In this article, the differential price-based demand response (DPDR) is used to construct a relationship model between the change of load demand and the change of electricity price according to the actual electricity consumption. Introducing power consumption satisfaction

can avoid user satisfaction drop due to excessive load response:

$$R_p = 1 - \frac{\sum_{t=1}^T |\Delta P_t|}{\sum_{t=1}^T P_t}$$

In the formula, R_p is satisfaction with electricity consumption. P_t and ΔP_t are the load amount and the load transfer amount before the demand response in the period of time, respectively. T is the scheduling period. Since different types of loads have different response characteristics of electricity consumption to electricity prices in the dispatch period, the corresponding elastic coefficients are also different. Considering the use of the differentiated electricity price elasticity coefficient matrix to build a demand response model as follows:

$$P_t^{PDR} = P_t + R_p \cdot \Delta P_t,$$

$$\epsilon_m = \frac{\Delta P_m / P_m}{\Delta D_m / D_m},$$

$$E_m = \begin{bmatrix} \epsilon_m^{1,1} & \epsilon_m^{1,2} & \dots & \epsilon_m^{1,t} \\ \epsilon_m^{2,1} & \epsilon_m^{2,2} & \dots & \epsilon_m^{2,t} \\ \vdots & \vdots & \ddots & \vdots \\ \epsilon_m^{t,1} & \epsilon_m^{t,2} & \dots & \epsilon_m^{t,t} \end{bmatrix},$$

$$\Delta P_{m,t} = [P_{m,1} \ \dots \ P_{m,t}] \cdot E_m \cdot \begin{bmatrix} \Delta D_{m,1} & \dots & \Delta D_{m,t} \\ \Delta D_{m,1} & \dots & D_{m,t} \end{bmatrix}^T,$$

In the formula, m represents the load type, where $m = 1, 2,$ and 3 represent the residential, industrial, and charging pile loads, respectively. P_t^{PDR} is the load amount after the demand response in period t . ϵ_m is the electricity price elasticity coefficient of the m class load. ΔP_m and ΔD_m are the amount of change in m class electricity P_m and electricity price D_m , respectively. E_m is the elastic coefficient matrix of electricity price of the m class load; the diagonal elements of the matrix are the self-elastic coefficients of each corresponding time period, and the off-diagonal elements are the cross elastic coefficients between the corresponding two time periods. $P_{m,t}$, $\Delta P_{m,t}$, $D_{m,t}$, and $\Delta D_{m,t}$ are respectively the load before the demand response, the load change amount, the electricity price, and the electricity price change amount of m class load- in period t .

The three types of loads in this transformer district mentioned in this article have different proportions in the entire station area, and different types of loads have different electricity price demand balance relationships in different time periods, and there are differences in response elasticity. At present, in the study of price-based demand response models, electricity price differentiation or elastic coefficient differentiation response models are mostly used (He et al., 2021), which are obviously insufficient. However, this article comprehensively considers the load power consumption characteristics of the station area and constructs a different type of load response elasticity according to the difference in response elasticity of different types of loads. A new price-type response mechanism is established based on the electricity price elasticity matrix response matrix that

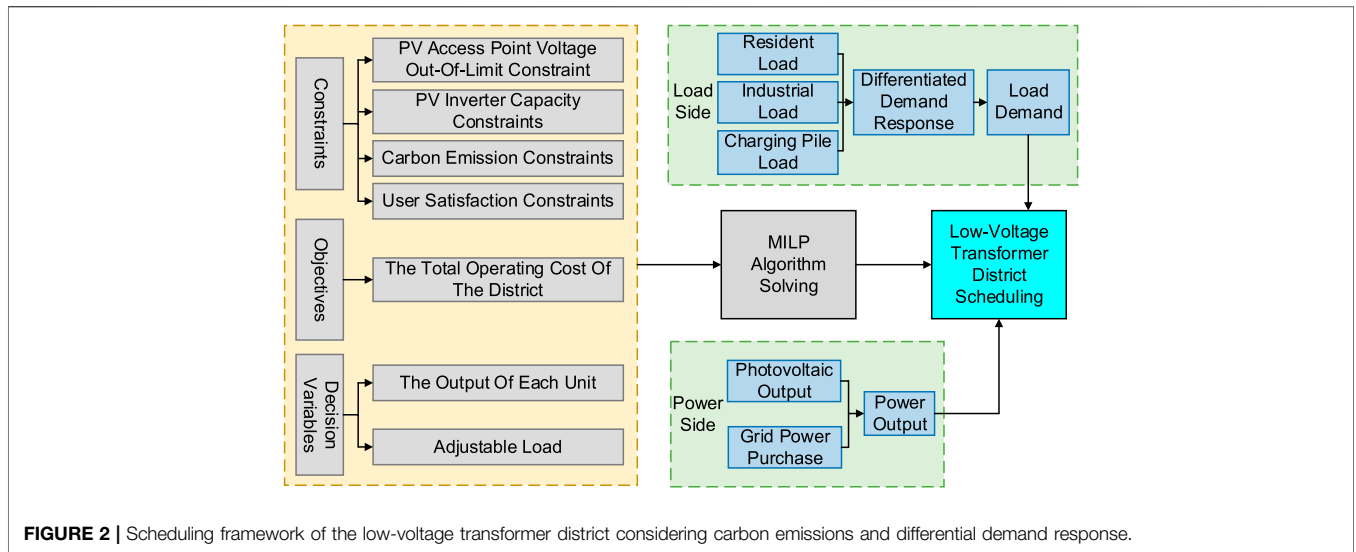


FIGURE 2 | Scheduling framework of the low-voltage transformer district considering carbon emissions and differential demand response.

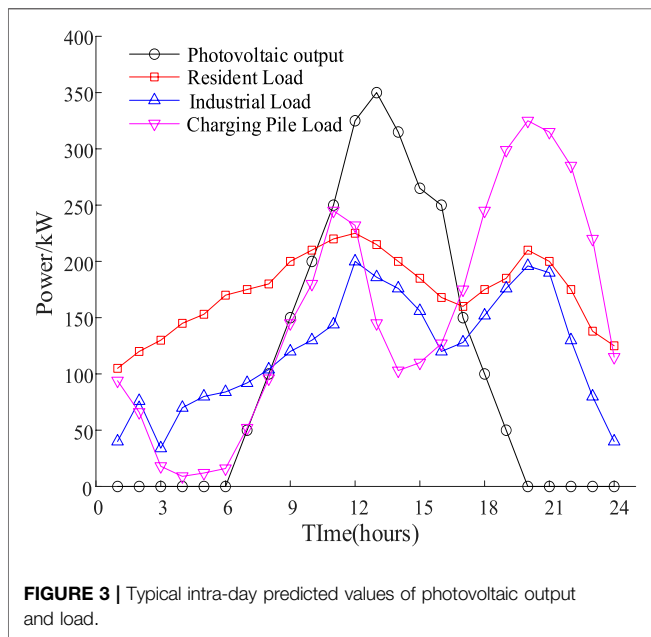


FIGURE 3 | Typical intra-day predicted values of photovoltaic output and load.

a low-voltage transformer district scheduling framework considering carbon emissions and DPDR can be constructed as shown in **Figure 2**. On the premise that the output of each unit in the low-voltage transformer district and the battery charge and discharge meet various constraints, different considerations are considered on the power side and the load side. The output of different types of power sources and the power consumption characteristics of different types of loads are aimed at the lowest total operating cost of the low-voltage transformer district, and the MILP algorithm is used to solve the problem to realize the optimal scheduling scheme of the low-voltage transformer district.

4.1 Objective Functions

In the optimal scheduling of the low-voltage transformer district, according to the forecasted values of photovoltaics and load power, taking into account the carbon emission and DPDR and aiming at the lowest total operation cost of the low-voltage transformer district, the objective function of the operation optimization of the low-voltage transformer district is established as follows:

$$\min F = \sum_{t=1}^T (F_{buy,t} + F_{w,t} + F_{CO_2,t} + F_{SL,t} - F_{sell,t}),$$

In the formula, F is the total operating cost of the low-voltage transformer district. T is the scheduling cycle for the day ahead. $F_{buy,t}$ is the power purchase cost. $F_{w,t}$ is the operation and maintenance cost. $F_{CO_2,t}$ is the carbon disposal cost. $F_{SL,t}$ is the satisfaction loss cost. $F_{sell,t}$ is the electricity sales revenue. The specific model of each scheduling cost is as follows:

4.1.1 Power Purchase Costs

$$F_{buy,t} = C_{buy,t} \cdot P_{buy,t} \cdot \Delta t,$$

takes into account the differences in classified loads and electricity consumption periods.

4 INTRADAY OPTIMAL DISPATCH MODEL OF THE LOW-VOLTAGE TRANSFORMER DISTRICT CONSIDERING CARBON EMISSIONS AND DPDR

This article divides the load side into three types to participate in differentiated price-based demand response when constructing the optimal dispatch framework of a low-voltage transformer district. The power side includes photovoltaic output and grid power purchase. In summary,

In the formula, $F_{buy,t}$ is the electricity purchase cost in the transformer district in period t . $C_{buy,t}$ is the unit power purchase cost in period t . $P_{buy,t}$ is the power purchased in period t . Δt is the duration of the scheduling period.

4.1.2 Operation and Maintenance Costs

$$F_{w,t} = \sum_{i=1}^{N_w} C_{w,i} \cdot P_{i,t} \cdot \Delta t$$

In the formula, $F_{w,t}$ is the operation and maintenance cost in period t . N_w is the number of units for which the operation and maintenance cost needs to be calculated. $C_{w,i}$ is each operation and maintenance cost of unit i . $P_{i,t}$ is the operating power of unit i in period t .

4.1.3 Carbon Disposal Costs

$$F_{CO_2,t} = C_{CO_2} \cdot Q_{CO_2,t} \cdot \Delta t$$

$$Q_{CO_2,t} = \sum_{x=1}^{N_{CO_2}} E_{CO_2,x} \cdot P_{x,t}$$

In the formula, $F_{CO_2,t}$ is the carbon disposal cost in period t . C_{CO_2} is the unit carbon disposal cost. $Q_{CO_2,t}$ is the total amount of carbon emissions in the transformer district in period t . N_{CO_2} is the number of units that need to calculate the carbon treatment cost. External power purchase, photovoltaic power generation, and battery charging and discharging all have carbon emissions. $E_{CO_2,x}$ is the carbon emission intensity of unit x , which refers to the carbon emission generated by the unit power growth. $P_{x,t}$ is the output power of unit x in period t .

4.1.4 Satisfaction Loss Costs

The user has the most suitable energy consumption in each period, which calls the users baseline load. When the user deviates from the baseline load, there is a satisfaction loss, which is quantified by the following function:

$$F_{SL,t} = \left(\frac{1}{2} \lambda_{j,m} \cdot P_{j,m,t}^2 - \theta_{j,m} \cdot P_{j,m,t} \right) \cdot \Delta t,$$

In the formula, $F_{SL,t}$ is the satisfaction loss cost in period t . $\lambda_{j,m}$ and $\theta_{j,m}$ are the constant coefficients of energy preference. $P_{j,m,t}$ is the actual load of the m class load in low-voltage transformer district j during period t .

4.1.5 Electricity Sales Revenues

$$F_{sell,t} = C_{sell,t} \cdot P_{sell,t} \cdot \Delta t$$

In the formula, $F_{sell,t}$ is the electricity sales revenue in period t . $C_{sell,t}$ is the benefit of electricity sales per unit in period t . $P_{sell,t}$ denotes the photovoltaic power sales in period t .

4.2 Constraints

4.2.1 Power Balance Constraint

$$P_{buy,t} + P_{PV,t} + P_{dis,t} = P_{cha,t} + P_{sell,t} + P_t^{PDR}$$

In the formula, $P_{PV,t}$ is the photovoltaic power generation in period t . $P_{cha,t}$ and $P_{dis,t}$ are the battery charging and discharging powers in period t , respectively.

4.2.2 Constraint on the Receiving Capacity of the Low-Voltage Transformer District

The penetration capacity of distributed photovoltaics affects the operation state of the transformer district. If the penetration rate of photovoltaics is too high, it will have adverse effects on the district, such as power quality degradation (Ma et al., 2021). Therefore, when the distributed photovoltaics are connected to the low-voltage transformer district, it is necessary to consider the receiving capacity of the distributed photovoltaics in the pressing area. The total capacity of the distributed photovoltaics in the access point should not exceed the receiving capacity of the transformer district for photovoltaics. The constraint formula of the admission capacity of the low-voltage transformer district as follows:

$$\sum_{t=1}^T P_{PV,t} \leq P_{PV,max}$$

In the formula, $P_{PV,max}$ is the maximum receiving capacity of the low-voltage transformer district for photovoltaics.

4.2.3 Access Point Voltage Violation Constraint

There is a certain error in the forecast value of photovoltaic output, and with the increase of photovoltaic penetration rate, the voltage of the access point has a greater possibility of exceeding the limit (Huang M. et al., 2022). To reduce the probability of voltage overlimit, we set constraints as follows:

$$V_{min} \leq \varphi_{buy} \cdot P_{buy,t} + \varphi_{PV} \cdot P_{PV,t} \leq V_{max}$$

In the formula, V_{min} and V_{max} are the upper and lower limits of the voltage, respectively; 0.4 and 5.4 are taken in this article. φ_{buy} and φ_{PV} are the power-voltage sensitivity coefficients corresponding to the purchasing power and photovoltaic power, respectively.

4.2.4 PV Inverter Capacity Constraint

During photovoltaic power generation, the photovoltaic inverter provides a certain amount of power to the grid, while maintaining a part of the adjustable ability, and can absorb or emit part of the power to adjust the voltage of the photovoltaic access point (Elkayam and Kuperman, 2019). The total output in the PV inverter must meet the capacity constraints:

$$\sqrt{P_{PV,t}^2 + P_{sell,t}^2} \leq P_{INV}$$

In the formula, P_{INV} is the rated capacity of the photovoltaic inverter.

4.2.5 Battery Charge and Discharge Constraints

$$\begin{cases} 0 \leq P_{dis,t} \leq P_{dis,max} \\ 0 \leq P_{cha,t} \leq P_{cha,max} \\ P_{dis,max} = (SOC_{t-1} - SOC_{min}) \cdot C_{ESS} \cdot \gamma_{dis} \\ P_{cha,max} = (SOC_{max} - SOC_{t-1}) \cdot C_{ESS} / \gamma_{cha} \\ \begin{cases} SOC_{min} \leq SOC_t \leq SOC_{max} \\ SOC_0 = SOC_T \end{cases} \end{cases}$$

In the formula, $P_{cha,max}$ and $P_{dis,max}$ are the maximum charge and discharge powers of the battery, respectively. SOC_t is the state of charge of the battery in period t . SOC_0 and SOC_T represent the state of charge in period 0 and T , respectively. SOC_{max} and SOC_{min} are the maximum and minimum states of charge of the battery, respectively. C_{ESS} is the rated capacity of the battery. γ_{cha} and γ_{dis} are the charge and discharge rates of the battery, respectively.

4.2.6 Carbon Emission Constraints

$$\sum_{t=1}^T Q_{CO2,t} \leq Q_{CO2,max}$$

In the formula, $Q_{CO2,t}$ is the carbon emission of the low-voltage transformer district in period t . $Q_{CO2,max}$ is the maximum allowable carbon emission of the low-voltage transformer district.

4.2.7 Grid Interactive Power Constraints

$$\begin{cases} P_{buy,min} \leq P_{buy,t} \leq P_{buy,max} \\ P_{sell,min} \leq P_{sell,t} \leq P_{sell,max} \end{cases}$$

In the formula, $P_{buy,max}$ and $P_{buy,min}$ are the maximum and minimum values of the purchased power, respectively. $P_{sell,min}$ and $P_{sell,max}$ are the maximum and minimum values of the sold power, respectively.

4.2.8 User Satisfaction Constraint

$$R_p \leq R_{p,min}$$

In the formula, $R_{p,min}$ is the minimum electricity consumption satisfaction.

4.3 Solving the Algorithm

The low-voltage transformer district operation optimization model established in this article, considering carbon emissions and differentiated demand response includes variables such as power purchase and photovoltaics as well as the charging and discharging states of the battery. It is a nonlinear programming problem. Therefore, the mixed integer linear programming (MILP) method is used to convert into a linear model for solving. The method

searches the nodes in the solution space tree, discards the nodes that cannot generate feasible solutions, and searches the child nodes of the live nodes until the optimal solution is found (Zhu et al., 2017). The MILP model established is simulated and solved by calling the Yalmip toolbox and Gurobi solver in Matlab.

5 SIMULATION ANALYSIS

In order to verify the correctness of the optimization model of the low-voltage transformer district proposed in this article, a typical low-voltage transformer district demonstration project in a city is taken as an example scenario. The type of users in the transformer district is analyzed according to the information such as the low-voltage transformer district geographic information, the number of users, and the capacity of the power system. The users in the low-voltage transformer district are divided into residential users, industrial users, and charging pile users. The load of this low-voltage transformer district has a trend of upward translation, showing a certain load characteristic.

5.1 Basic Data

The summary of the calculation example is as follows: the total capacity of the photovoltaic power generation system in the low-voltage transformer district is 2800 kW. The rated capacity of the photovoltaic inverter is 250 kW. The total capacity of the battery is 300 kW. The charge and discharge rates are both 30%. The maximum and minimum charge states are 0.8 and 0.2, respectively. The initial energy storage is 30 kW. The parameters of each element in the calculation example are shown in **Table 1**. The calculation example takes 24 h before the day as the scheduling period and 1 h as the length of the scheduling period, and the power is constant during the scheduling period. The power consumption on the load side is divided into three periods: peak periods, usual periods, and valley periods. The peak periods are the 10:00–15:00 period and the 18:00–21:00 period; the usual periods are the 7:00–10:00 period, the 15:00–18:00 period, and the 21:00–23:00 period; the valley periods are the 0:00–7:00 period and the 23:00–24:00 period. The time-of-use electricity prices for residential, industrial, and charging pile loads are shown in **Table 2**. The elastic coefficients of the three types of loads are shown in **Table 3**. The photovoltaic electricity sales prices are 0.68, 0.4, and 0.11 yuan/(kW · h) during the peak-to-valley period. The maximum allowable carbon emission in the low-voltage transformer district is 1500 kg.

In order to verify the effectiveness of the operation optimization model of the low-voltage transformer district proposed in this article, three types of load scenarios in two modes are designed for comparative analysis. Mode 1 is the most basic optimization mode, and carbon emissions and demand response are not considered in the dispatch model. Mode 2 is a comprehensive optimization model on the basis of considering DPDR, and carbon emission factors are further considered. Three types of load scenarios are resident load, industrial load, and charging pile load.

TABLE 1 | Operation parameters of each unit in the low-voltage transformer district.

Transformer district unit	Lower power limit/kW	Upper power limit/kW	Operation and maintenance cost in each period/yuan/(KW-h)	Carbon intensity/Kg/(kW-h)
Photovoltaic	0	350	0.0235	0.015
Electricity Purchase	0	400	-	0.79
Electricity Sales	0	100	-	-
ESS Power Storage	0	300	0.012	0.15
ESS Power Discharge	0	300	0.1	0.15

TABLE 2 | Time-of-use electricity price of three types of load.

Load type	Peak electricity price/Yuan/(KW-h)	Usual electricity price/yuan/(KW-h)	Valley electricity price/yuan/(KW-h)
Resident Load	0.86	0.52	0.13
Industrial Load	0.94	0.6	0.51
Charging Pile Load	1.5	0.8	0.5

TABLE 3 | Differential elastic coefficients of three types of load.

Load type	Self-elastic coefficient	Mutual-elastic coefficient
Resident Load	-0.2	0.03
Industrial Load	-0.05	0.33
Charging Pile Load	-0.12	0.02

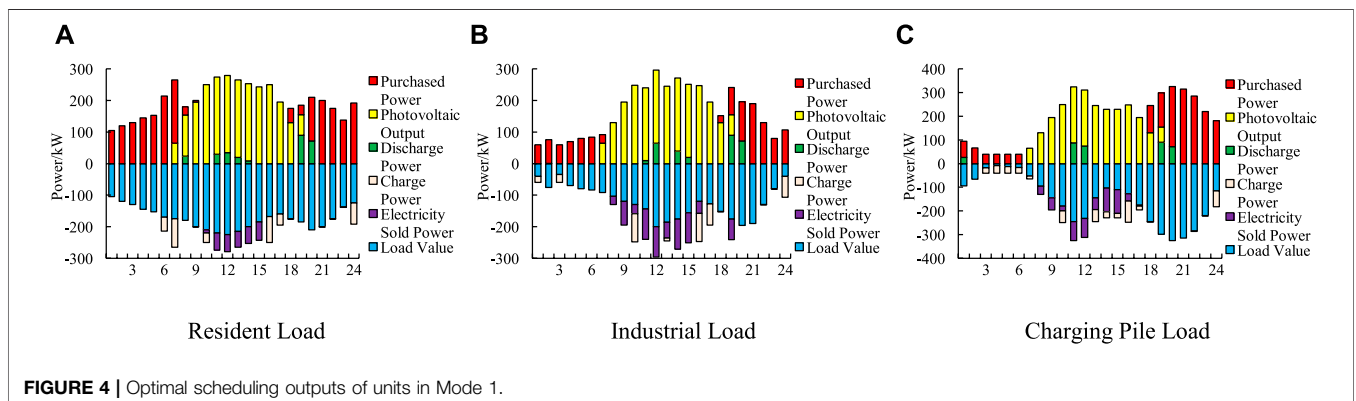
5.2 Simulation Results

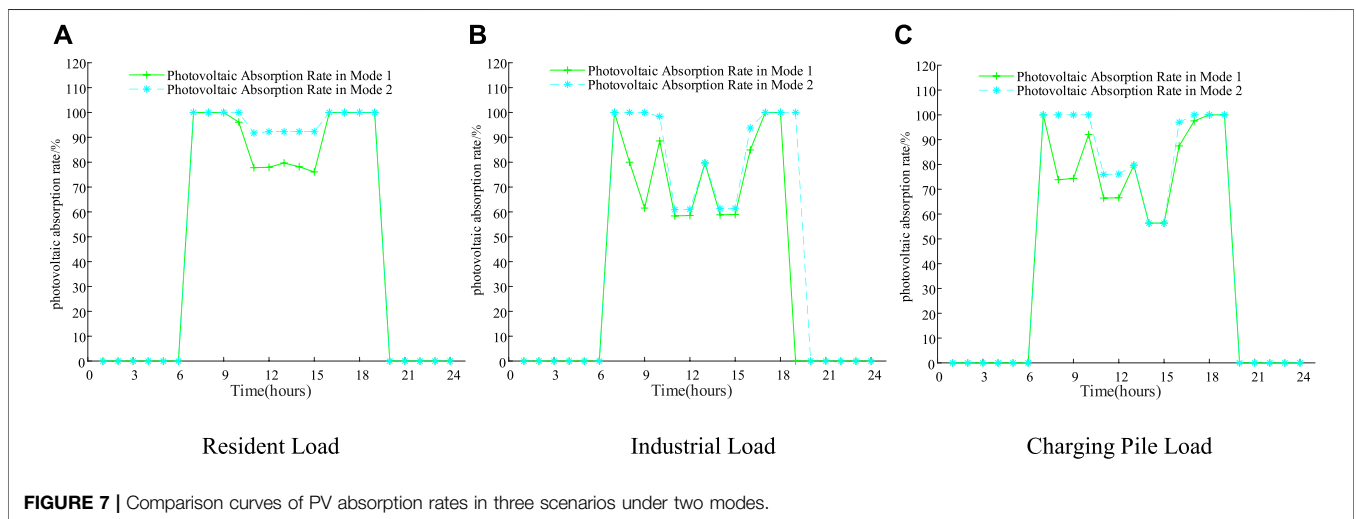
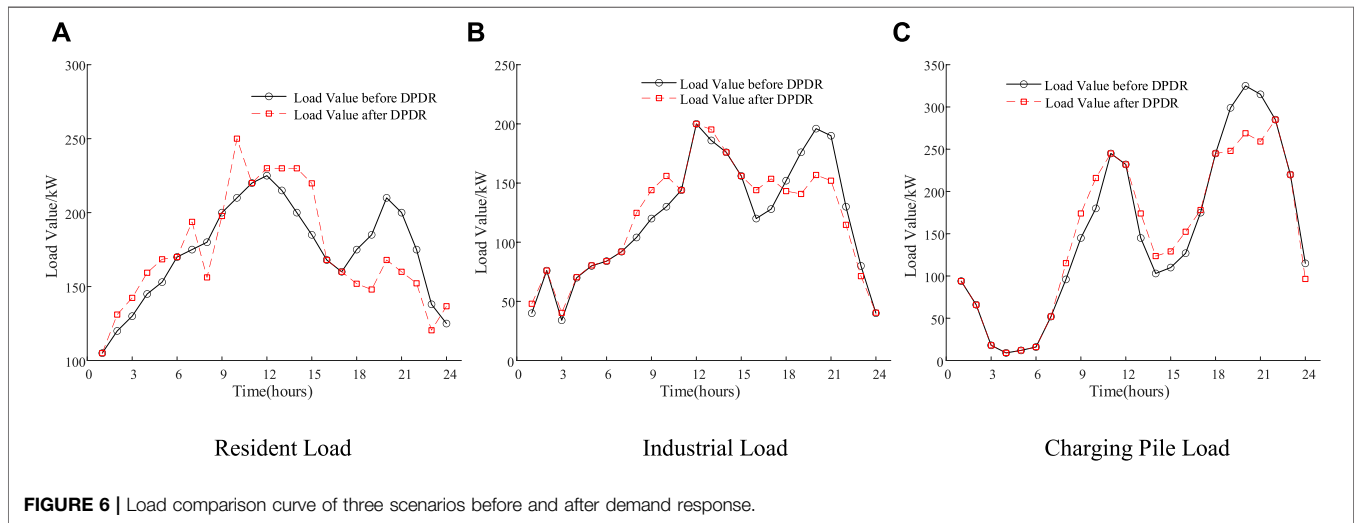
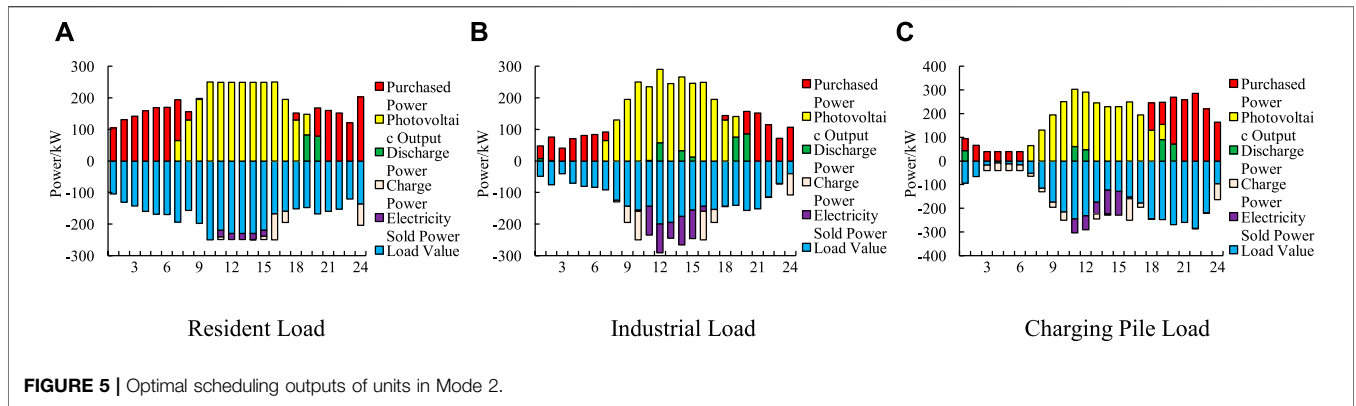
Figures 4, 5 shows the scheduling results, including the load demand, conventional output, and battery charge and discharge conditions of the three types of load scenarios in different modes.

From Figure 4 and Figure 5, it can be concluded that Mode 1 does not consider DPDR and carbon emissions, and the load of the three types of loads in each period remains unchanged. When the load is in the valley period, the photovoltaic output not only meets the load demand but also charges the battery. When charging to the maximum state of charge, the solar panel may be abandoned in the transformer district. When the load is in the usual period, the state of charge of the battery remains constant, and the load demand is jointly supplied by photovoltaics and

power grid purchases. When the load is in the peak period, the photovoltaic output is low. In addition to battery discharge, a large amount of power needs to be purchased from the external power grid to meet the load demand. This model has a relatively high power purchase, a low photovoltaic consumption rate, and a high photovoltaic rejection rate. This operation mode is not conducive to the safe and stable operation of the transformer district and will also increase the economic cost of the transformer district. Mode 2 considers DPDR and carbon emissions. DPDR reduces the load during peak hours and increases the load during valley hours in response to the electricity price. The photovoltaic power generation increases; also, the photovoltaic consumption rate increases, and the economic cost of the transformer district is reduced. In summary, considering demand response and carbon emissions in the optimal scheduling of low-voltage transformer districts can improve the photovoltaic absorption rate and the utilization rate of demand response resources in the transformer district and improve the matching degree of source-load measurements.

The load comparison curve before and after considering the DPDR is shown in Figure 6, including the load values of the three





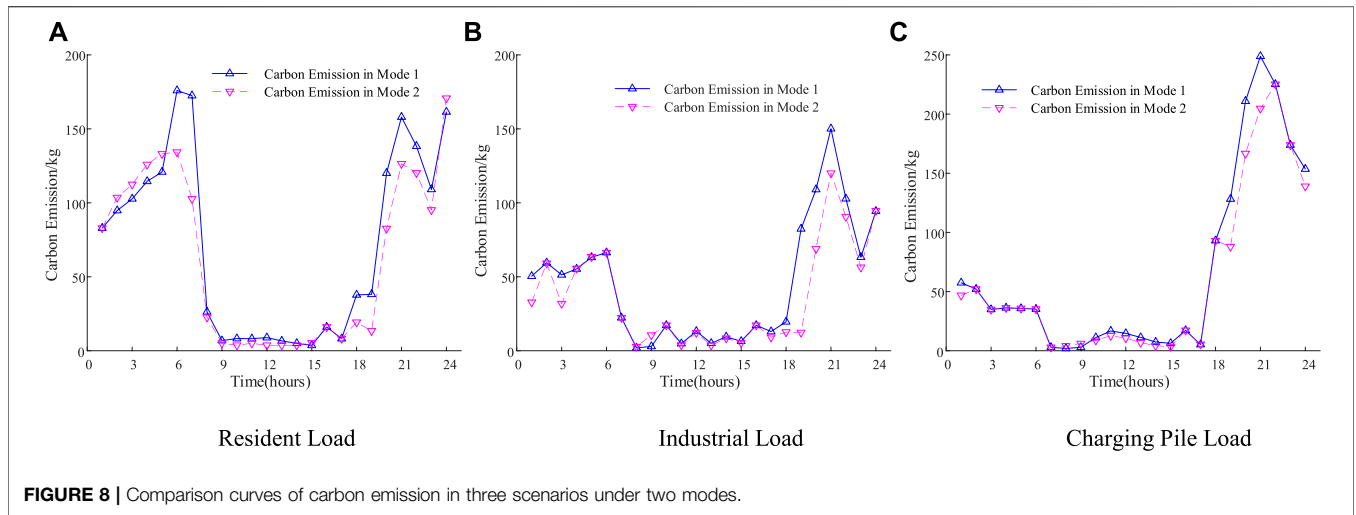


FIGURE 8 | Comparison curves of carbon emission in three scenarios under two modes.

types load scenarios of users in each time period under the two models.

As can be seen from **Figure 6**, compared with Mode 1 and Mode 2, the three types of loads in Mode 2 use the elastic change of electricity price to guide the load to transfer laterally in time during the dispatch cycle under the action of DPDR and perform peak shaving and valley filling to reduce the load. DPDR smooths the load curve, reduces the cost of demand response, and provides a guarantee for the stable operation of the low-voltage transformer district.

Figure 7 shows the comparison curves of photovoltaic consumption in three types of load scenarios under the two modes.

It can be seen from **Figure 7** that the photovoltaic absorption rate of the three types of loads in Mode 1 are only 88.8, 72.8, and 77.7%, the rate is low, and the photovoltaic rejection rate is high. The photovoltaic absorption rate of the three types of loads in Mode 2 compared with that of Mode 1 has improved, reaching 96.1, 82.5, and 84.9%, meeting the requirement of a photovoltaic

consumption rate of 80% or more in the low-voltage transformer district. Photovoltaic energy is fully utilized.

Figure 8 shows the comparison curve of carbon emissions before and after comprehensively considering carbon emissions and differentiated demand response, including the carbon emissions of three types of load scenarios in each period under two modes.

It can be seen from **Figure 8** that in Mode 1, the overall carbon emission level of the low-voltage transformer district is relatively high during the dispatch period because the carbon emission factor is not considered. Mode 2 considers carbon emissions in the optimization objective while taking into account carbon constraints. Since the carbon emission of new energy sources such as photovoltaic power generation is very small, the charging and discharging of the battery itself will not produce a lot of carbon emissions, and the carbon emission intensity of external power purchases in the transformer district is relatively high, so it is preferred to use new energy for power generation. The battery will store the excess energy in part of the

TABLE 4 | Optimal scheduling costs in three scenarios under two modes.

Scenarios	Operation costs/yuan	Mode 1	Mode 2
Resident Load	Electricity Purchase Cost	683.13	540.11
	Operation And Maintenance Cost	71.31	66.64
	Satisfaction Loss Cost	69.77	61.34
	Carbon Disposal Cost	434.74	378.00
	Electricity Sales Revenue	186.99	66.42
	Total Operating Cost Of Transformer District	1071.96	979.67
Industrial Load	Electricity Purchase Cost	802.91	596.58
	Operation And Maintenance Cost	70.76	70.15
	Satisfaction Loss Cost	33.91	28.76
	Carbon Disposal Cost	272.44	221.19
	Electricity Sales Revenue	563.21	419.15
	Total Operating Cost Of Transformer District	616.81	497.53
Charging Pile Load	Electricity Purchase Cost	1802.64	1540.67
	Operation And Maintenance Cost	73.38	72.08
	Satisfaction Loss Cost	52.90	46.51
	Carbon Disposal Cost	398.93	356.36
	Electricity Sales Revenue	464.37	369.19
	Total Operating Cost Of Transformer District	1863.48	1646.39

period for use in the photovoltaic valley period. If the photovoltaic and the battery cannot meet the load demand, the electricity will be purchased from the outside. From the optimization results, it can be seen that in the optimization model of the three scenarios, the photovoltaic power generation increased by 1.0, 0.5, and 0.6%, the power purchase decreased by 11.7, 20.8, and 11.0%, and the carbon emissions decreased by 13.1, 18.8, and 10.7%. It is proved that considering carbon emission targets and constraints in the optimal scheduling of a low-voltage transformer district can reduce the total carbon emissions of the district.

From **Table 4**, it can be concluded that due to the good economy of DPDR, it has a significant impact on the operation cost of the transformer district, in addition. The dispatch model takes carbon emissions as the optimization target, which reduces the carbon treatment cost of the transformer district and further reduces the total operating cost of the transformer district. Compared with Mode 1, Mode 2 reduces the total operating costs of the three user types by 8.6, 19.3, and 11.6%, respectively. The scheduling results show that considering carbon emissions and differentiated demand response in the optimal scheduling of the low-voltage transformer district can reduce the total operating cost and carbon emissions of the transformer district, which proves the correctness of the scheduling model.

6 CONCLUSION

In order to deal with the carbon emission and source-load coordination problems of the low-voltage transformer district under the dual-carbon background, this article takes into account the differences in time-of-use electricity prices and the elasticity of different types of loads and builds a differentiated price-based demand response model. On this basis, considering the carbon emission factor, a low-voltage transformer district optimization model is established with the goal of the lowest total operation cost of the station area, and the MILP method is used to solve the algorithm optimization. The simulation results show that

- 1) This article proposes a low-voltage transformer district operation optimization method that considers demand response differences and carbon emissions so that demand response resources can be fully utilized, and the output fluctuations of the district are reduced. The optimization method also reduces errors due to PV uncertainty and improves the reliability of the optimal scheduling of the district.
- 2) The MILP method proposed in this article can efficiently solve the above model, can significantly improve the optimization convergence speed, and has good adaptability to the dynamic environment.
- 3) The research in this article has important significance for improving the coordination of the source, load, and storage in the low-voltage transformer district. However, this article only considers the differential price demand response and does not consider the incentive demand response. The reliability of optimal dispatch is relatively low. More research is needed in this area in the future.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

DJ designed an optimal scheduling method; YZ carried out experiments; HG and JL analyzed experimental results. YD and GL wrote the manuscript.

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The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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