Robust Optimal Dispatch of Park-Level Integrated Energy Systems Towards Carbon Neutrality: A Synergistic Strategy Based on Stepped Carbon Trading and Integrated Demand Response

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***Abstract*—A two-stage robust optimal dispatch model is proposed for park-level integrated energy systems with high wind and photovoltaic penetration. The model integrates stepped carbon trading, integrated demand response, battery energy storage, and thermal energy storage to improve low-carbon and economic operation under renewable energy uncertainty. A budgeted polyhedral uncertainty set is used to characterize wind and photovoltaic output deviations, and the resulting min – max – min optimization problem is decomposed into a mixed-integer linear master problem and subproblem using the column-and-constraint generation algorithm. A numerical case study based on representative winter profiles of an industrial park in northern China is conducted to evaluate the proposed strategy. Compared with the baseline deterministic dispatch case, the proposed method reduces carbon emissions by 15.4% and total operating cost by 12.3% under the specified parameter settings and uncertainty budget. The results indicate that the coordination of stepped carbon trading, demand-side flexibility, and robust dispatch can enhance the economic performance, carbon reduction capability, and renewable energy accommodation of park-level integrated energy systems. The study provides a case-based modeling framework for low-carbon robust dispatch, while further validation with long-period operational data is still required.**

Keywords—Carbon neutrality, Integrated energy system, Robust optimization, Stepped carbon trading, Integrated demand response

I. INTRODUCTION

The low-carbon transition of the energy sector has become one of the major issues in the research and engineering because of the growing complexity of the issue of global climate change. Park-scale energy systems (IESs), which integrate electricity, heat, gas, renewable energy production and energy storage, are a viable solution to enhance the efficiency of energy use and minimize carbon emissions. Recent works on low-carbon IES scheduling revealed that carbon trading schemes and source-load side sources may play an essential role in system dispatch choices and emission reduction outcomes [1].

The best possible combination of multi-energy systems and carbon reduction strategies have gained more significance as a part of carbon neutrality. A multi-energy system could achieve multi-energy complementarity and cascaded energy usage by synchronizing energy conversion devices, storage devices, and flexible loads rather than conventional independent energy supply systems. The given integration is especially useful in industrial parks because there is a possibility that electrical and heat power consumption will be interrelated and coexist [2].

Nevertheless, the growing market share of wind power and photovoltaics introduces significant uncertainty into the energy dispatch process in parks. The fluctuation of renewable generation can cause larger reserve needs, reduce the use of renewable power, and even make the operation costs inconsistent. Multi-energy complementary system long term planning has been studied as a solution to show that uncertainty, capacity configuration and low carbon limits need to be taken into consideration simultaneously when designing energy systems to achieve carbon neutrality [3]. It is thus essential to come up with a dispatch model that would allow coordinating economic operations, minimizing carbon emissions, incorporating renewable energies, and being able to resist unforeseeable wind and PV production.

The present paper will build upon the earlier background to come up with a two-stage robust optimal dispatch model of a park-level integrated energy system to be implemented in low-carbon operating conditions. The research is based on the joint simulation of the stepped carbon trading, demand-side flexibility, energy storage operation and wind/solar uncertainty. In particular, the first step is the modeling of a park-level IES with wind power, photovoltaic generation, CHP units, gas boilers, battery storage and thermal storage. Next, stepped carbon trading cost function and a combination of demand response models are added to the dispatch model. Lastly, the two-stage optimization algorithm is solved by the C&CG algorithm and the efficiency of the suggested strategy is measured using comparative numerical experiments. In the paper some contributions have been made, such as a reproducible modeling model and case-based assessment of a relationship between carbon price parameters, demand response depth, and robustness level.

The remaining sections of the paper are presented in the order below: In Section 2, the author discusses other sources of information concerning low-carbon IES dispatch, demand-side flexibility, uncertainty management, and robust optimization algorithms; In Section 3, the author describes the system architecture, carbon trading mechanism, demand

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response model, and the two-stage robust optimization formulation; In Section 4, the author gives the case data and parameters; In Section 5, the author shows the outcomes of the simulations and comparative analysis; In Section 6, the author presents the main results and limitations; and lastly, in Section 7, the author ends the paper by summarizing the opportunities of future research.

II. LITERATURE REVIEW AND RELATED WORK

A. Low-Carbon Optimal Dispatch of Integrated Energy Systems

Optimal dispatch of integrated energy systems with minimal carbon emissions has been a popular trend in recent years. The study of the regional IES has shown that the combined application of renewable energy, energy storage and inter-station energy exchange would enhance energy consumption efficiency and the effectiveness of emission reduction. Integrated energy system optimization model of regional integration with renewable energy, energy storage and energy sharing model were proposed by Jia et al., and it was highlighted that the scheduling of multiple energy resources should be coordinated [4].

Along with operational scheduling, system design is also very important in the application of low-carbon IES operations. As Wang et al. pointed out, the perfect design of an integrated energy system should incorporate the economic performance as well as the system autonomy and carbon emissions; thus, it is possible to state that carbon limits may play a large role in determining the equipment configuration and energy dispatch plans [5]. These sources offer a good reference point on the topic of low-carbon IES simulations, but they are mostly developed through a deterministic approach to planning or operating conditions.

Flexibility in demand-side is also a very significant characteristic of integrated energy systems. Flexibility in demand of the integrated heat and electricity system has been simulated and it was found by Shao et al. that flexible load modeling can serve to enhance the interaction between thermal and electrical energy networks [6]. It offers a conceptual basis to the act of incorporating demand response into park-level IES dispatch particularly when there are flexible electrical and thermal loads.

Energy storage has also proven to increase the flexibility of distributed energy systems functionalities. Liu, et al. introduced a two-step optimization approach to the operation of a distributed energy system that used various forms of energy storage in a near-zero-energy community, and multi-energy storage was realized, which helped in the integration of renewable energy and the flexibility of the system [7]. The coordinated operation of battery storage and thermal storage is also required in the park-level IESs to balance the renewable fluctuations and satisfy the multi-energy demand.

The IES optimization models have also included carbon capture and power-to-gas technology. Modeling and optimization of combined heat and power systems with power-to-gas and carbon capture as part of an integrated energy system were investigated by Ma et al. and they concluded that carbon conversion and utilization technologies could minimize emissions but have the potential to become more intricate and costly to operate [8]. Stepped carbon trading is a market approach and it does not need to add new carbon capture equipment in contrast to some other hardware-based decarbonisation methods.

B. Uncertainty Handling Methods

Managing uncertainty was recognized as one of the most important problems in the optimization of energy systems. Zhao and Guan suggest a joint stochastic and robust formulation of the unit commitment problem to demonstrate that stochastic and robust optimization could be applied to the problem of uncertain generation and load renewable resources [9]. Stochastic optimization relies on the assumption of probabilistic distribution or generation of scenarios whereas robust optimization considers the viable and dependable decision-making in view of worst-case occurrence of uncertainty.

The powerful optimization approach has been popular in dispatching power and energy systems due to the fact that it does not involve precise probability distributions. As a solution to the security-constrained unit commitment problem, Bertsimas et al. proposed an adaptive robust optimization framework, which demonstrates that two-stage robust decision-making can be successfully applied to day-ahead decisions and real-time adjustments in case of uncertainty [10]. It is associated with park-level IES dispatch as it relates to both daily schedule and intra-day regulation that should be taken into account concurrently.

Distributedly robust optimization has been suggested as a replacement of stochastic and robust optimization. Wei et al. investigated distributionally robust simultaneous optimization of energy and reserve dispatching and revealed that ambiguity sets may be employed to represent uncertain probability distributions and remove excessive conservatism [11]. Nevertheless, distributionally robust techniques typically need enough historical data and a well-designed ambiguity set. On the contrary, budgeted polyhedral uncertainty sets are simpler to define and comprehend in practice when they are used to solve the engineering problems.

C. Demand Response and Energy Management in Integrated Energy Systems

There has also been an investigation into distributed energy systems optimization in terms of energy expenditure and exergy effectiveness. A study of a distributed energy system by Di Somma et al. was optimised with respect to both energy costs and exergy efficiency and it is shown that the multi-objective operational variables do have a strong effect on the system dispatch results [12]. The need to align economic and efficiency-oriented objectives in distributed energy management is demonstrated.

The idea of robust optimization has similarly been extended to combined cooling, heating, and power microgrids to enhance the efficiency of energy management under uncertain circumstances. Luo et al. developed an optimization model of CCHP microgrid energy management using the principle of robustness and they found that robust scheduling can also be applied to increase the reliability of the system in the case when renewable output and load demand vary [13]. This reference will be helpful in case you require information about the implementation of robust optimization in park-level IESs depending on electricity-heat-gas coupling.

The paper uses the integrated demand response model which relies on two types of flexible resources, namely, price-based electricity load variation and thermal loads that may be shifted. It is important to note that the current model is not specifically a depiction of electro-thermal exchange device that has a physical form, like electric boilers, or heat pumps. The mechanism will, however, be simulated at the load adjustment stage instead of being modeled as an advanced end-use conversion mechanism.

D. Research Gaps and Contributions

Nevertheless, these indicated studies have contributed significantly to the formulation of the low-carbon IES dispatch, demand-side flexibility and uncertainty optimization but there are still gaps in the research that ought to be brought to light. To start with, many of the available low-carbon dispatch models consider carbon costs or carbon limit but do not examine the relationship between stepped carbon trade and demand side flexibility sufficiently. Secondly, demand response strategies can be perceived as a limiting strategy instead of a responsive tool that can be applied to communicate with carbon pricing and storage. Thirdly, despite the fact that the connections between the strength, carbon trading variables and the depth of demand response have been commonly used, they require more quantitative study.

In order to solve the two-stage robust optimization problem successfully, the column-and-constraint generation algorithm was proposed by Zeng and Zhao, which means that the original problem needs to be broken down into a master problem and a subproblem and the worst case is added in the form of iterative steps to convergence [14]. It provides a good algorithmic basis to the solution of the two-stage robust dispatch model discussed in this work.

To sum up, the major contributions of this paper may be stated as: (1) The integrated stepped carbon trading, demand response, energy storage and renewable energy uncertainty structure to formulate a coordinated dispatch model is a two-stage robust optimization model; (2) To enhance the computational performance of the model, the C&CG algorithm is used to address the min-max-min robust optimization problem in the form of tractable master and subproblems; (3) There is a description of numerical case study involving deterministic dispatch, carbon aware dispatch, stepped carbon trading and robust dispatch strategy and results of sensitivity analysis on the impact of robustness budget and carbon price parameter are given.

III. Methodology and System Modeling

A. Park-Level Integrated Energy System Architecture

The park-level integrated energy system studied in this paper covers three energy carriers: electricity, heat, and gas. Its core physical architecture consists of four layers: energy supply layer, energy conversion layer, energy storage layer, and multi-energy load layer. As shown in Fig. 1, the energy flow relationships of the system are illustrated.

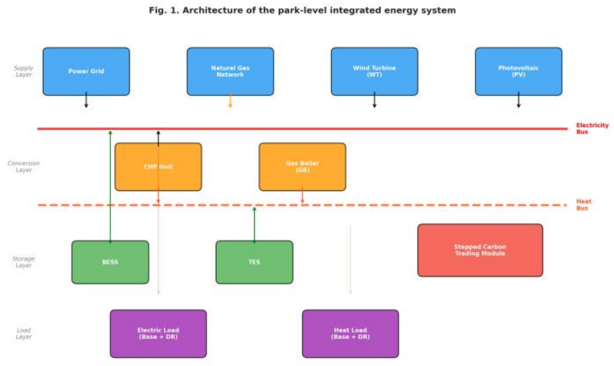

Fig. 1. Architecture of the park-level integrated energy system

The Energy Supply Layer includes the upstream power grid, natural gas network, and distributed wind turbines (WT) and photovoltaics (PV) within the park. The upstream power grid acts as the balance node of the system, providing power support when meeting internal supply-demand gaps; the natural gas network provides primary energy for CHP units and gas boilers. The main equipment of the Energy Conversion Layer includes combined heat and power (CHP) units and gas boilers (GB), which use natural gas as fuel to achieve efficient conversion into electrical and thermal energy. The Energy Storage Layer is configured with battery energy storage systems (BESS) and thermal energy storage (TES) tanks, used to smooth source-load fluctuations on the time scale and realize time-shift utilization of energy. The Multi-Energy Load Layer contains basic electrical loads, basic thermal loads, and flexible electrical and thermal loads participating in integrated demand response.

B. Stepped Carbon Trading Mechanism Model

The core of the carbon trading mechanism lies in allocating a certain carbon emission quota to the system. When actual emissions are lower than the quota, the surplus can be sold for profit; when higher, additional quotas must be purchased. This paper adopts a stepped carbon trading mechanism to strengthen the penalty for high-emission behaviors.

First, the system's free carbon emission quota E_{quota} is mainly generated by coal-fired power generation (converted through upstream grid power purchase) and natural gas consumption (CHP and gas boilers), calculated as follows:

$$quota = \lambda_e \sum_{t=1}^{T} P_{grid,t} \Delta t + \lambda_h \sum_{t=1}^{T} (Q_{CHP,t} + Q_{GB,t}) \Delta t \quad (1)$$

Where lambda_ and lambda_h are the carbon emission quota coefficients for unit electricity and heat (kg/kWh), respectively; $P_{grid,t}$ is the purchased power from the upstream grid at time period t (kW); $Q_{CHP,t}$ and $Q_{GB,t}$ are the heat production power of the CHP and gas boiler, respectively (kW); Delta t is the time step (h).

Secondly, the actual carbon emission of the system E_{actual} is:

$$E_{actual} = \mu_e \sum_{t=1}^{T} P_{grid,t} \Delta t + \mu_g \sum_{t=1}^{T} F_{gas,t} \quad (2)$$

where mu_e is the actual carbon emission intensity of upstream grid power purchase (kg/kWh); mu_g is the carbon emission intensity of natural gas combustion (kg/m³); $F_{gas,t}$ is the total gas consumption at time period t (m³/h).

The volume participating in carbon trading is

$$E_{trade} = E_{actual} - E_{quota} \quad (3)$$

The stepped carbon trading cost C_{carbon} is expressed as the following piecewise function, illustrated in Fig. 2.

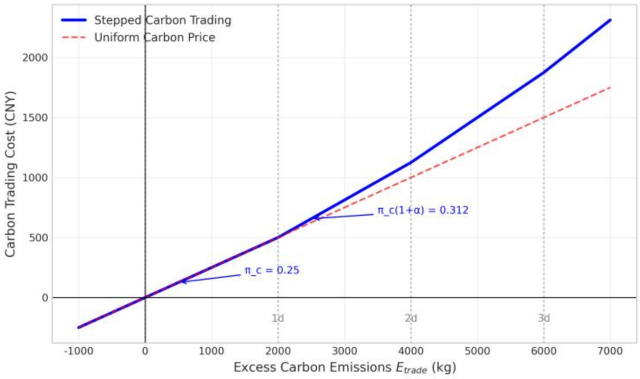

Fig. 2. Comparison of stepped vs. uniform carbon trading cost functions

$$C_{carbon} = \pi_c E_{trade}, 0 \le E_{trade} \le d\pi_c d + \pi_c(1+\alpha)(E_{trade} - d), d < E_{trade} \le 2d\pi_c d + \pi_c(1+\alpha)d + \pi_c(1+2\alpha)(E_{trade} - 2d), 2d < E_{trade} \le 3d \,\vdots\vdots \quad (4)$$

where $pi_c$is the base carbon price (CNY/kg); d is the step interval length (kg); $alpha$ is the step price growth rate. When $E_{trade} < 0$, the system can sell excess quotas at the base carbon price to gain revenue.

C. Integrated Demand Response Model

The integrated demand response considered in this paper includes price-based electrical load shifting (Time-of-Use response) and substitution-based electro-thermal interchange.

Price-based Shiftable Electrical Load: Users adjust their electricity consumption periods according to time-of-use price signals, shifting part of the electrical load from high-price periods to low-price periods. Let $DeltaP_{shift,t}$ be the load shift amount at time period t (positive for shifting in, negative for shifting out), which must satisfy the total conservation constraint over the dispatch cycle:

$$sum_{t=1}^{T} \Delta P_{shift,t} = 0 \quad (5)$$

$$DeltaP_{shift,t}| \le \beta_e \cdot P_{load,t}^{base} \quad (6)$$

where $beta_e$is the maximum shiftable proportion (taken as 15% in this paper); $P_{load,t}^{base}$ is the base electrical load.

Curtailable Thermal Load: Under the premise of satisfying basic heating requirements, a limited proportion of thermal load can be curtailed during peak periods. Let ΔQ_cut,t denote the thermal load curtailment at time period t. The curtailment is constrained by the maximum allowable response ratio β_h, and the post-response thermal load is expressed as

$$Q_load, t^DR = Q_load, t^base - \Delta Q_cut, t. \quad (7)$$

In this paper, β_h is set to 10% to avoid overestimating the flexibility of industrial thermal demand. This simplified treatment reflects short-term operational flexibility but does not represent detailed user comfort dynamics or production-process constraints.

$$le\Delta Q_{cut,t} \le \beta_h \cdot Q_{load,t}^{base} \quad (8)$$

where$beta_h$is the maximum curtailment proportion (taken as 10% in this paper). The actual electrical load

$P_{load,t}^{DR} = P_{load,t}^{base} + \Delta P_{shift,t}$\$andthermalload\$$Q_{load,t}^{DR} = Q_{load,t}^{base} - \Delta Q_{cut,t}$ (9)

after demand response will directly participate in the system's power balance constraints.

D. Two-Stage Robust Optimal Dispatch Model

To cope with the uncertainty of wind and solar output, this paper constructs a two-stage robust optimization model. The first stage is day-ahead pre-dispatch, where decision variables include equipment start-stop states and basic output plans; the second stage is intra-day adjustment, which, based on the first-stage decisions, seeks the optimal regulation strategy under the worst-case wind and solar output scenarios.

Objective Function:

$$min_{x \in X} \quad C_{base}(x) + \max_{u \in U} \min_{y \in Y(x,u)} \quad C_{adjust}(y) \quad (10)$$

where x represents the first-stage decision variables (e.g., CHP start-stop status, day-ahead output plans, initial storage dispatch schemes); $C_{base}(x)$ is the day-ahead basic operating cost (including energy purchase and maintenance costs); u is the uncertainty variable (actual wind and solar output); U is the uncertainty set; y represents the second-stage adjustment variables (e.g., unit output adjustments, storage charge/discharge power corrections, wind/solar curtailment);

$$C_{adjust}(y) \quad (11)$$

is the sum of intra-day adjustment costs and carbon trading costs.

Uncertainty Set U is described using a Box-Budget Uncertainty Set:

$$U = \quad \tilde{P}w/s,t\colon \tilde{P}w/s,t \in [\hat{P}w/s,t - \Delta Pw/s,t, \hat{P}w/s,t + \Delta Pw/s,t],\ \sum_{t=1}^{T} \frac{|\tilde{P}w/s,t - \hat{P}w/s,t|}{\Delta P_{w/s,t}} \le \Gamma \quad (12)$$

where hatPw/s, tis the predicted wind/solar output;

DeltaPw/s, t is the maximum prediction error (taken as 20% of the predicted value); Gamma is the robustness conservatism parameter (budget parameter), with a value range of [0, T], controlling the system's conservatism against uncertainty.

Main Constraints include:

1) Electrical Power Balance Constraint:

$$P_{grid,t} + P_{CHP,t}^{e} + \tilde{P}WT, t + \tilde{P}PV, t + P_{BESS,t}^{dis} - P_{BESS,t}^{ch} = P_{load,t}^{DR} + P_{cur,t} \quad (13)$$

2) Thermal Power Balance Constraint:

$$Q_{CHP,t} + Q_{GB,t} + Q_{TES,t}^{dis} - Q_{TES,t}^{ch} = Q_{load,t}^{DR} \quad (14)$$

3) Equipment Operation Constraints: Ramp rate limits and upper/lower bound constraints for CHP and gas boilers.

4) Energy Storage Constraints: Mutually exclusive charge/discharge state constraints, State of Charge (SOC) upper/lower bound constraints, and equal initial and final capacity constraints over the dispatch cycle.

E. Model Solution Strategy

The aforementioned two-stage robust optimization model is a typical "Min-Max-Min" three-level optimization problem, which is extremely complex to solve directly. This paper employs the Column-and-Constraint Generation (C&CG) algorithm to decompose it into an outer Master Problem (MP) and an inner Subproblem (SP) for iterative solution .

Master Problem (MP): Under a finite set of identified worst-case scenarios $u^{(1)}, u^{(2)}, ..., u^{(k)}$ solve for the optimal first-stage decision x^* and provide a Lower Bound (LB) for the original problem.

Subproblem (SP): Given the first-stage decision x from the master problem, find the worst-case scenario u that maximizes the second-stage adjustment cost. Using strong duality theory, the inner "Max-Min" bi-level problem is transformed into a single-level "Maximization" Mixed-Integer Linear Programming (MILP) problem to obtain the Upper Bound (UB).

The algorithm continuously iterates between the master problem and the subproblem, adding the newly discovered worst-case scenario u^* as constraints to the master problem until the difference between the upper and lower bounds meets the convergence condition

$$UB - LB \leq \epsilon \qquad (15)$$

The overall algorithm flowchart is shown in Fig. 3.

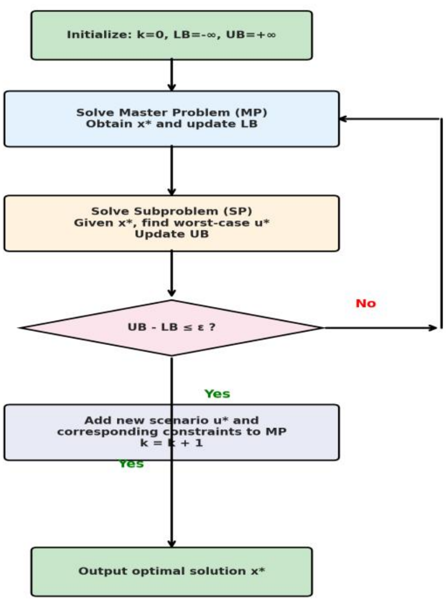

Fig. 3. Flowchart of the C&CG algorithm

IV. Data and Experimental Settings

A. Experimental Scenarios and Data Sources

To verify the effectiveness and scientific validity of the proposed model, operational data from a typical industrial park in northern China during the winter heating period (January) was selected for simulation analysis. The dispatch cycle is set to T=24 hours with a time step of 1 hour. The installed capacities of wind power (WT) and photovoltaics (PV) in the system are set to 1500 kW and 1000 kW, respectively. The day-ahead prediction curves for base electrical and thermal loads, as well as wind and solar output, are generated based on historical operational data from January 2023. The descriptive statistical characteristics of key variables are shown in Table I.

Due to data confidentiality, the original metering records of the industrial park are not disclosed in this paper. To improve reproducibility, the simulation dataset is represented by typical 24-hour winter profiles and descriptive statistics of wind power, PV output, electrical load, and thermal load. The results should therefore be interpreted as case-based numerical evidence rather than direct field experimental validation. Future work will further validate the model using longer-period operational datasets and real-time dispatch records.

TABLE I. Descriptive statistics of key variables

Variable	Mean (kW)	Std. Dev. (kW)	Max (kW)	Min (kW)	Median (kW)
Wind Power Forecast	845.2	312.4	1420.5	120.3	892.7
PV Power Forecast	310.5	385.6	980.2	0.0	145.8
Base Electrical Load	1250.8	245.7	1850.0	850.5	1195.3
Base Thermal Load	1680.3	350.2	2300.0	1100.0	1725.6

In the data preprocessing stage, a small number of abnormal extreme values caused by sensor failures in the original collected sequence (exceeding physical capacity limits, totaling 7 periods, accounting for about 1.2%) were eliminated and filled using linear interpolation. Additionally, zero-value data for PV output during nighttime periods (19:00-06:00) are physical true values and were retained. The prediction-error ranges of wind and PV output are set according to the assumed maximum deviation of 20% from the day-ahead forecast. The uncertainty set is therefore constructed as a budgeted polyhedral set for robust optimization. Since only aggregated descriptive statistics are reported, the statistical distribution of prediction errors is not used as a core assumption of the model.

B. Parameter Settings

The main equipment parameters and economic parameters of the system are shown in Table II.

TABLE II. SYSTEM PARAMETER SETTINGS

Category	Parameter Name	Value	Unit
Electricity Price	Valley period (23:00-07:00)	0.35	CNY/kWh
Electricity Price	Flat period (07:00-10:00, 15:00-18:00)	0.65	CNY/kWh
Electricity Price	Peak period (10:00-15:00, 18:00-23:00)	1.05	CNY/kWh
Gas Price	Natural gas price	3.20	CNY/m³
CHP	Electrical / Thermal efficiency	0.35 / 0.45	-
CHP	Output upper / lower limits	1200 / 200	kW
Gas Boiler	Thermal efficiency	0.90	-
BESS	Capacity / Max charge/discharge power	2000 / 500	kWh / kW
TES	Capacity / Max charge/discharge power	3000 / 800	kWh / kW
Carbon Trading	Base carbon price pi_c	0.25	CNY/kg
Carbon Trading	Step interval length d	2000	kg
Carbon Trading	Price growth rate alpha	0.25	-
Carbon Emission	Grid purchase emission intensity mu_e	0.85	kg/kWh
Carbon Emission	Natural gas emission intensity mu_g	1.96	kg/m³
Robust Params	Conservatism parameter Gamma	6	-
Robust Params	Max prediction error deviation DeltaP	20%	-

The simulation platform uses MATLAB R2023b, with Gurobi 10.0 as the optimization solver. The running environment is an Intel Core i7-12700H processor with 32GB RAM.

To ensure that the optimization results can be interpreted consistently, the following assumptions are adopted in the numerical case: the initial and final SOC values of BESS and TES are set equal; the SOC range is limited to 10%–90%; charging and discharging are mutually exclusive in each time period; renewable curtailment is allowed with a penalty cost; and all dispatch variables are optimized over a 24-hour horizon with hourly resolution. Parameters not listed in Table II are kept identical across all comparison cases so that the effects of carbon trading, demand response, and robust optimization can be isolated.

V. Results and Analysis

To evaluate the effects of different modeling components, four comparison cases are designed. The comparison focuses on the incremental impacts of carbon trading, demand response, stepped carbon pricing, and robust optimization under the same load, renewable generation, equipment, and price assumptions.

TABLE III. COMPARISON SCENARIOS FOR DIFFERENT DISPATCH STRATEGIES

Scenario	Carbon Trading Mechanism	Demand Response	Optimization Method
Case 1	None	None	Deterministic Dispatch
Case 2	Uniform Carbon Price	Yes	Deterministic Dispatch
Case 3	Stepped Carbon Trading	Yes	Deterministic Dispatch
Case 4 (Proposed)	Stepped Carbon Trading	Yes	Two-Stage Robust Optimization

A. Analysis of Base Dispatch Results for a Typical Day

Taking the proposed model (Case 4) as an example, Fig. 4 shows the electrical power balance dispatch results of the system under the worst-case scenario with robust conservatism Gamma = 6.

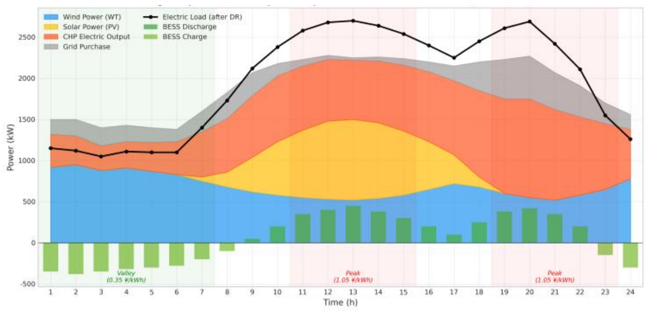

Fig. 4. Optimal electrical power dispatch under worst-case scenario (Case 4, Γ=6)

The objective data analysis indicates that in terms of electrical power balance, during the valley price period of 01:00-06:00 when wind power output is high (averaging about 920 kW), the system tends to purchase cheap electrical energy from the upstream grid (averaging about 180 kW).

Simultaneously, the battery energy storage system (BESS) charges at a power of about 350 kW, preparing for discharge during subsequent peak periods. During the peak price period of 10:00-15:00, PV output reaches its zenith (maximum about 980 kW). The system prioritizes the accommodation of wind and solar resources, and the shortfall is supplemented by CHP unit output (maintained at about 800 kW). At this time, BESS discharges at a power of about 450 kW to reduce expensive grid power purchases. Notably, during the evening load peak period of 18:00-22:00, both wind and solar outputs drop significantly, and the system mainly relies on the CHP unit (full output 1200 kW) and BESS discharge (about 480 kW) to meet electricity demand.

Regarding thermal power balance (Fig. 5), thermal load demand is large at night (averaging about 2150 kW from 01:00-06:00), and the gas boiler (GB) and CHP unit jointly undertake the heating task. Due to the introduction of the stepped carbon trading mechanism, the CHP unit (whose carbon emission intensity is lower than pure coal-fired power purchase) maintains a relatively high output baseline during daytime periods. It not only meets the thermal load but its generated electricity also effectively replaces some high-carbon grid purchased electricity. Thermal energy storage (TES) stores heat at a power of about 600 kW during periods of excess heat production (e.g., 10:00-14:00) and releases heat at a power of about 750 kW during evening thermal load peaks (18:00-22:00), playing a significant "peak-shaving and valley-filling" role.

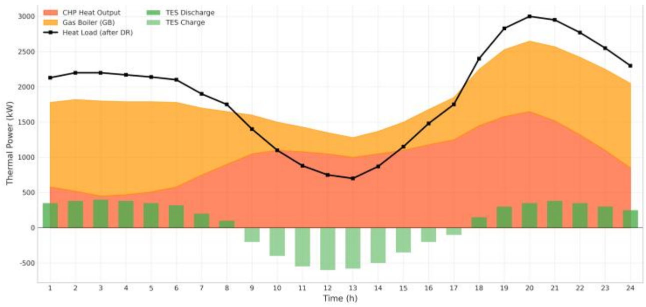

Fig. 5. Optimal thermal power dispatch under worst-case scenario (Case 4, Γ=6)

The State of Charge (SOC) profiles for both storage systems are depicted in Fig. 6, demonstrating their operational cycles strictly within the safety limits of 10% to 90%.

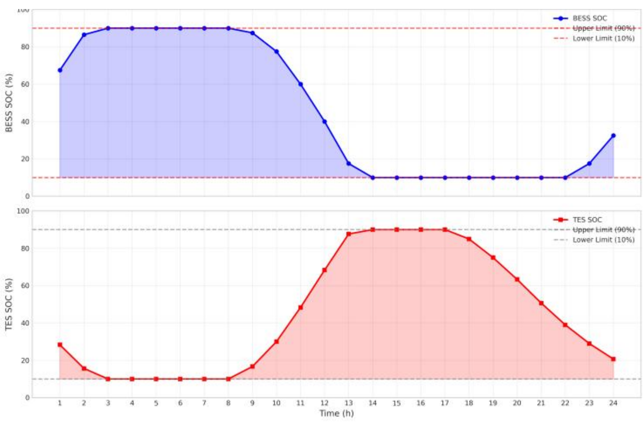

Fig. 6. State of charge profiles for BESS and TES

B. Comparative Analysis of Different Dispatch Strategies

Fig. 7 and Table III summarize the key economic and environmental performance indicators under the four comparison scenarios.

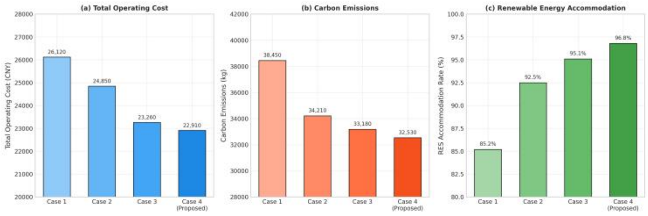

Fig. 7. Comparison of key performance indicators across different scheduling strategies

TABLE IV. COMPARISON OF DISPATCH RESULTS UNDER DIFFERENT SCENARIOS

Scenario	Energy Purchase Cost (CNY)	Carbon Trading Cost (CNY)	O&M Cost (CNY)	Total Operating Cost (CNY)	Carbon Emissions (kg)	RES Accomm. Rate
Case 1	24,560	0	1,560	26,120	38,450	85.2%
Case 2	21,840	1,520	1,490	24,850	34,210	92.5%
Case 3	20,680	1,150	1,430	23,260	33,180	95.1%
Case 4	20,350	980	1,580	22,910	32,530	96.8%

From Table IV and Fig. 7, the following significant patterns and trends can be observed:

Carbon Emission Control Effect: Compared with Case 1, the carbon emissions of Case 2, Case 3, and Case 4 decrease by 11.0%, 13.7%, and 15.4%, respectively. This trend suggests that introducing carbon cost into the dispatch objective can guide the system toward lower-carbon operating schedules. The stepped carbon trading mechanism in Case 3 further strengthens the marginal cost of excess emissions compared with the uniform carbon price in Case 2. In Case 4, robust optimization changes the day-ahead schedule to reserve more flexibility for renewable uncertainty, which also contributes to emission reduction under the selected scenario. However, the magnitude of emission reduction depends on the assumed carbon price, load flexibility, renewable profiles, and uncertainty budget.

Economic Performance: Case 4 obtains the lowest total operating cost among the four cases in this numerical setting. Although robust optimization may increase reserve-related costs, the coordinated use of demand response and storage shifts part of the energy demand away from high-price periods and reduces renewable curtailment. Therefore, the cost reduction observed in Case 4 should be interpreted as the result of the specific parameter combination used in this study, rather than as a universal conclusion for all park-level IESs.

Renewable Energy Accommodation: The renewable energy accommodation rate increases from 85.2% in Case 1 to 96.8% in Case 4. This improvement is mainly related to the additional operational flexibility provided by battery storage, thermal storage, and demand response. Under the robust framework, part of the storage capacity is reserved to cope with wind and PV deviations, which helps maintain power balance when renewable output fluctuates. Nevertheless, the accommodation rate is sensitive to storage capacity, load flexibility limits, and the assumed curtailment penalty.

C. Robustness and Uncertainty Level Analysis

To further explore the impact of uncertainty parameters on system operation, a sensitivity analysis was conducted on the robust conservatism parameter Gamma. The value of Gamma was gradually increased from 0 (representing a completely deterministic scenario, i.e., no prediction errors considered) to 24 (representing the most extreme scenario where maximum prediction errors occur in all periods throughout the day). The analysis results are shown in Fig. 8.

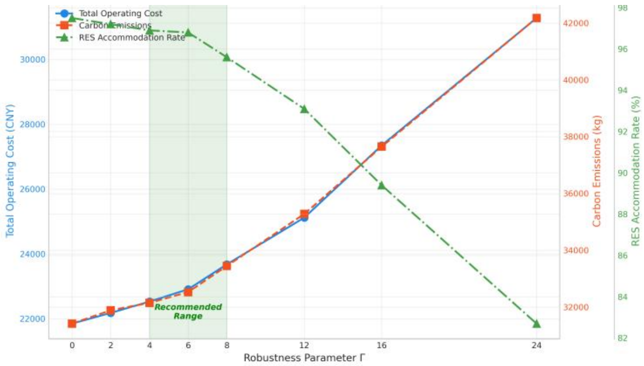

Fig. 8. Sensitivity analysis of robustness parameter Γ on system performance

The analysis results show that as Gamma increases, the system's total operating cost exhibits a nonlinear stepped upward trend. When Gamma increases within the [0, 6] interval, the cost rise is relatively gentle (an increase of about 4.8%); however, when Gamma > 8, the cost increase significantly magnifies (cost grows by 32.1% as Gamma increases from 8 to 24). This is because under mild uncertainty, the system can mainly rely on demand response and energy storage to complete power balance regulation; whereas under high uncertainty, the system is forced to frequently start backup gas units or increase high-priced grid power purchases to ensure safety, leading to sharp surges in both cost and carbon emissions.

In terms of solution time, the C&CG algorithm converges within 1 minute when Gamma ≤ 8, meeting the timeliness requirements of day-ahead dispatch. When Gamma increases to 24, the solution time extends to about 3 minutes, which remains within an acceptable range. The sensitivity analysis indicates that in practical engineering applications, setting Gamma between 4 and 8 can strike an optimal balance between system reliability and economy.

VI. Discussion

The present paper has seen a thorough analysis of the findings of the dispatch as well as the combined approach of stepped carbon trading-integrated demand response-robust optimization with more focus on compare and attribute it.

A. Horizontal Comparison

These findings of this paper support the claim that the stepped carbon trading mechanism is more sensitive to the marginal carbon emission cost of the system compared to the existing literature, which assumes the presence of one type of carbon tax mechanism [1]. As system emissions become close to the step values, the marginal carbon price that increases in steps makes the model cut down on buying high-emission electricity and increase the usage of the storage and flexible load sources. The reason behind this regulation is that dispatch is optimized with such carbon price structure, not because of some other physical carbon reduction equipment.

B. Vertical Correlation

The sensitivity analysis also suggests that the carbon price parameters may influence the dispatch of energy conversion units, and utilization of flexible demand-side resources. With the rise of the growth rate 0 of stepped carbon prices, the model will become susceptible to reducing the buy of high emission grids and buying more of available flexibility such as load shifting, thermal load reduction, and storage charging/discharge. The conclusion of this observation is that carbon prices may influence demand-side contribution to a low-carbon dispatch. Nevertheless, since the response ratios are fixed in the current structure, the changes observed are consequences of optimalization based on assumed flexibility boundaries instead of experimentally measured performance of users.

C. Difference Attribution

Nevertheless, the difference attribution analysis proves that in very unpropitious conditions (Gamma=24) the carbon footprint of the considered model is 42,180 kg, or 34.2 times larger than the carbon footprint of 31,420 kg registered in the case of deterministic methods. As it will be demonstrated by an in-depth examination of the explanations, in the daytime the power generation via wind and sun power decreases at a steady rate till the energy storage systems (BESS) are discharged at a high rate (discharge rates are approximately four per hour), and the system has no other choice than to resort to gas units or electricity purchases on the electricity grid, which responds fast but with much carbon dioxide emission. The situation demonstrates that deep decarbonization cannot be attained by day-ahead/intra-day dispatch and short-term storage of energy to deal with prolonged severe weather; it needs to be planned carefully together with long-duration storage technology of energy(e.g., hydrogen storage or compressed air energy storage).

Moreover, this model requires that the demand response participation rate is fixed, however in practice it depends on many factors such as the power of the incentive, weather conditions, working hours etc. and there is a degree of uncertainty in it. The demand uncertainty can also be removed by assuming the real emission reduction to be somewhat lower than the modeled emission.

VII. Conclusion

First, according to the figures, combined use of stepped carbon trading and demand response can enhance economic and low-carbon performance of the park-level IES at the chosen simulation scenarios. As compared to the baseline scenario, the suggested case is associated with a reduction of total operating costs by 12.3 percent and carbon dioxide emissions by 15.4 percent. These findings indicate that coordinated source load storage carbon dispatch may be useful, however, it needs to be confirmed based on its data of the long-term operation.

Another argument is that the step-wise carbon trading system offers a piecewise-increasing carbon-price signal, so it is possible to minimize the acquisition of power with large emission levels and maximize storage and load-side flexibility. In the hypothetical situation, the renewable energy accommodation rate is 96.8 percent which shows that demand response and storage could be used to assist in accommodating wind and PV generation in the modeled situation.

Three possible extensions of future research exist. Firstly, longer observations of various seasons ought to be taken into consideration to evaluate the effectiveness of the proposed strategy. Secondly, the demand response uncertainty should be modeled explicitly because it can be used to represent the real desire of the users to respond to a specific demand and the operational capacities of the system. Lastly, this model can also be expanded to include multi-park energy sharing and carbon quota coordination, where the distributed optimization algorithms might be necessary to preserve informational privacy and computational complexity.

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AUTHOR CONTRIBUTIONS

Guobo Huang: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing—original draft.

Shicai Wen: Supervision, Project administration, Validation, Resources, Writing—review and editing. All authors have read and approved the final manuscript.

COMPETING INTERESTS

The authors declare no competing interests.