



Distributionally robust optimization-based scheduling for a hydrogen-coupled integrated energy system considering carbon trading and demand response

Zhichun Yang^a, Lin Cheng^b, Huaidong Min^a, Yang Lei^a, Yanfeng Yang^{b,*}

^a Distribution Network Technology Center, Electric Power Research Institute of State Grid Hubei Co. Ltd, Wuhan 430077, PR China

^b Research Center for Energy Internet of Things, Wuxi Research Institute of Applied Technologies, Tsinghua University, Wuxi 214026, PR China

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Abstract

Addressing climate change and facilitating the large-scale integration of renewable energy sources (RESs) have driven the development of hydrogen-coupled integrated energy systems (HIES), which enhance energy sustainability through coordinated electricity, thermal, natural gas, and hydrogen utilization. This study proposes a two-stage distributionally robust optimization (DRO)-based scheduling method to improve the economic efficiency and reduce carbon emissions of HIES. The framework incorporates a ladder-type carbon trading mechanism to regulate emissions and implements a demand response (DR) program to adjust flexible multi-energy loads, thereby prioritizing RES consumption. Uncertainties from RES generation and load demand are addressed through an ambiguity set, enabling robust decision-making. The column-and-constraint generation (C&CG) algorithm efficiently solves the two-stage DRO model. Case studies demonstrate that the proposed method reduces operational costs by 3.56%, increases photovoltaic consumption rates by 5.44%, and significantly lowers carbon emissions compared to conventional approaches. Furthermore, the DRO framework achieves a superior balance between conservativeness and robustness over conventional stochastic and robust optimization methods, highlighting its potential to advance cost-effective, low-carbon energy systems while ensuring grid stability under uncertainty.

Keywords: Hydrogen-coupled integrated energy system (HIES); Low-carbon operation; Distributionally robust optimization (DRO); Carbon trading; Demand response (DR); Economy

0 Introduction

As global climate change intensifies, the need to advance energy transitions and reduce carbon emissions has become increasingly urgent [1]. An integrated energy system (IES) offers a viable solution by facilitating coordinated planning, operation, and management across various energy carriers to efficiently meet diverse energy needs [2]. In pursuit of low-carbon development, it is cru-

cial to promote clean energy technologies and enhance the integration of renewable energy sources (RESs) [3].

Transitioning to a cleaner, low-carbon, and efficient operational paradigm, IES must evolve from conventional modes characterized by high energy consumption, emissions, and pollution [4].

Hydrogen energy stands out due to its environmental benefits, high energy density, and scalability, making it a vital component for energy coupling, storage, and decarbonization efforts. Integrating hydrogen energy into conventional IES frameworks creates a hydrogen-coupled IES (HIES), which represents a significant step toward enhancing renewable energy utilization and improving energy supply flexibility, thus garnering significant aca-

* Corresponding author.

E-mail addresses: yangzhichun3600@163.com (Z. Yang), chenglin@mail.tsinghua.edu.cn (L. Cheng), minhuaidong@foxmail.com (H. Min), 304231569@qq.com (Y. Lei), 785080763@qq.com (Y. Yang).

demic interest. For example, research has led to the development of dynamic models for hydrogen energy storage systems (HESS), which cover hydrogen production, storage, and release, and are implemented within park-level HIES setups [5]. Advancements such as replacing conventional power-to-gas (P2G) units with hydrogen fuel cells (FCs), electrolyzers, and methane reactors have shown potential in reducing carbon emissions within HIES operations [6]. Additionally, the adoption of hybrid energy storage systems combining hydrogen and natural gas in the day-ahead dispatch of HIES has demonstrated improved economic and environmental outcomes by enabling the conversion of electricity into cleaner energy forms [7].

The implementation of a carbon-trading mechanism within the HIES operations can effectively enhance the consumption of RESs and reduce carbon emissions, thereby facilitating the scheduling of a low-carbon economic system. For example, the study referenced in [8] utilized free carbon allowance allocation to limit emissions from electricity purchases, gas turbines, and gas boilers. A reward-based ladder carbon-trading model, detailed in [9], was developed to control emissions during IES planning. The research in [10] established reasonable ladder carbon prices that surpass conventional models in reducing emissions. Additionally, a seasonal carbon-trading mechanism that employs reward and penalty factors has been proposed for a park-level IES [11], resulting in significant emission reductions. These mechanisms highlight the effectiveness of carbon trading in encouraging the adoption of cleaner energy and penalizing carbon-intensive practices, thus promoting a sustainable energy framework.

Furthermore, the energy consumption patterns of flexible loads, both in timing and intensity, can be optimized through demand response (DR) strategies to improve source-load coordination. This adjustment enhances the use of RESs and the low-carbon performance of the HIES. For example, flexible loads can be rescheduled to coincide with peaks in renewable energy production, or unnecessary loads can be reduced, thus diminishing reliance on fossil fuels and increasing renewable energy usage. A DR model that integrates multiple energy load reductions, transfers, and conversions was proposed in [12] to increase wind power consumption. Models focusing on flexible electrical and thermal loads were developed in [13] and applied to IES load regulation to lower carbon emissions. A sophisticated DR model that considers various heat disturbance factors was introduced in [14] to evaluate the response capability and potential of demand-side resources for reducing emissions. Additionally, both day-ahead and intra-day DR programs were implemented for the low-carbon scheduling of an IES in [15] to balance the load peak-valley differences. In summary, DR empowers user-side flexible loads to actively engage in system scheduling,

thereby augmenting operational flexibility and environmental advantages.

HIES operations face numerous inherent uncertainties, particularly the variability of RESs and multi-energy loads, which introduce additional costs and increase the likelihood of constraint violations. Stochastic programming (SP) and robust optimization (RO) are two predominant methodologies used to manage these uncertainties. The SP method has been effectively applied in various scenarios: for instance, a SP-based optimal operation method was introduced in [16] to address uncertainties from RESs, power loads, and electricity prices. Additionally, SP was employed in [17] to manage uncertainties and unscheduled islanded operations within an IES. Conversely, the RO method focuses on minimizing risks under worst-case scenarios. An RO-based optimization model for DR management was proposed, considering the unpredictability of wind power [18]. A scheduling model that incorporated P2G units was developed using RO in [19], enhancing the utilization of RESs and reducing overall system costs. However, the SP method often depends on the probability density function (PDF) to generate potential scenarios, which can be challenging to determine accurately and may require significant computational resources. On the other hand, the RO approach, by focusing on uncertainty intervals and the worst-case scenario, can yield overly conservative results that compromise economic efficiency. To address these issues, distributionally robust optimization (DRO) offers a promising alternative. DRO accounts for the worst-case probability distribution of uncertainties within a specified ambiguity set, thus reducing reliance on extensive data sets and alleviating computational demands. The DRO-based optimization schemes are generally less conservative than those based on RO, effectively balancing economic efficiency and robustness. For example, a DRO model introduced in [20], aimed to reduce the uncertainty of renewable generation, significantly lowering operating costs and enhancing system performance. A predictive control scheme using DRO was proposed in [21] to manage the variability and uncertainty of RES output. Additionally, a practical approach to managing source-load uncertainties in HIES was developed in [22]. Given the advantages of DRO in addressing uncertainties, the development of a DRO-based low-carbon economic dispatch method tailored for HIES presents a critical and urgent research challenge.

In this study, we propose a DRO-based scheduling method for the HIES that incorporates both carbon trading and DR. The primary contributions of this study are summarized as follows:

- (1) A two-stage DRO-based low-carbon economic scheduling model was developed to address uncertainties in RESs and loads. An ambiguity set was

constructed to accurately represent these uncertainties, and a column and constraint generation (C&CG) algorithm was designed to solve the model, achieving a balance between economic efficiency and robustness.

- (2) Models for hydrogen-blended combined heat and power (H2-CHP) and HESS were developed to coordinate the production, storage, and consumption of hydrogen within the HIES.
- (3) A ladder-type carbon-trading mechanism was implemented to regulate carbon emissions within the HIES, alongside a DR program designed to maximize the potential of flexible loads and enhance the consumption of RESs.

The structure of this paper is organized as follows: Section 1 introduces the construction of the HIES models. Section 2 discusses the implementation of the ladder-type carbon-trading mechanism and the DR program. Section 3 details the proposed two-stage DRO model and its solution methods. Case studies are presented in Section 4. Finally, Section 5 offers a summary of the conclusions.

1 Modeling of the HIES

1.1 Structure of the HIES

Fig. 1 depicts the architecture of a typical HIES, which integrates various forms of energy including electricity, thermal energy, hydrogen, and natural gas. The HESS components, consisting of an electrolytic cell (EL), hydrogen tank (HT), and FC, facilitate the generation, storage, and utilization of hydrogen energy. A H2-CHP unit enhances the efficiency of hydrogen use and reduces carbon emissions. The HIES also includes a photovoltaic unit (PV), electric boiler (EB), electricity storage (ES), and thermal storage (TS), all of which are integrated into the DR programs. The system is designed to interact with upper networks for the transaction of electricity and natural gas, enhancing its operational flexibility and environmental sustainability.

The unified energy-bus-based model was employed to represent the multi-energy coupling and conversion among various energy carriers within the HIES [23]. This model facilitates the efficient management of energy flows, partic-

ularly when the PV unit produces excess electricity or when electricity prices are low. Under such conditions, surplus electricity can be converted into hydrogen or stored in the ES and TS. Conversely, when the output from the PV unit diminishes or electricity prices rise, the stored hydrogen can be reconverted into electricity. Additionally, the integration of ladder-type carbon trading and DR mechanisms incentivizes low-carbon and economically efficient operations within the HIES.

1.2 Equipment modeling

1) H2-CHP model

Unlike conventional CHP systems, the H2-CHP model utilizes a blend of natural gas and hydrogen as fuels [24]. This integration captures waste heat through a heat exchanger, subsequently used for thermal energy supply. The energy efficiency of the H2-CHP system exceeds that of conventional CHP setups, resulting in significantly reduced carbon emissions. The H2-CHP model is formulated as follows:

$$\psi^t = (P_H^t/L_H)/(P_H^t/L_H + P_G^t/L_G) \quad (1)$$

$$0 \leq \psi^t \leq \psi^{\max}, \quad (2)$$

$$P_{\text{CHP_in}}^t = L_{\text{mix}}^t (P_H^t/L_H + P_G^t/L_G), \quad (3)$$

$$L_{\text{mix}}^t = \psi^t L_H + (1 - \psi^t) L_G, \quad (4)$$

$$T_{\text{CHP}}^t = \eta_{\text{CHP_h}} P_{\text{CHP_in}}^t, \quad (5)$$

$$P_{\text{CHP}}^t = \eta_{\text{CHP_e}} P_{\text{CHP_in}}^t, \quad (6)$$

$$0 \leq P_{\text{CHP}}^t \leq U_{\text{on}}^t P_{\text{CHP}}^{\max} \quad (7)$$

where ψ^t is the mixing volume ratio of hydrogen at time t , $\psi^{\max}$ is the maximum mixing volume ratio, and P_H^t and P_G^t are the hydrogen and natural gas input powers, respectively. L_H and L_G denote the lower heating values of hydrogen and natural gas, L_{mix}^t is the lower heating value of the mixed gas, P_{CHP}^t and T_{CHP}^t are the electric and thermal powers generated by H2-CHP at time t , respectively, $\eta_{\text{CHP_e}}$ and $\eta_{\text{CHP_h}}$ are the electricity and thermal energy conversion efficiencies of the H2-CHP unit, $P_{\text{CHP}}^{\max}$ is the maximum electric power generated by the H2-CHP unit, and U_{on}^t represents the start-up status of the H2-CHP unit.

2) HESS model

In the HESS, surplus electricity from the PV unit and the upper grid is converted into hydrogen through the electrolysis of water in the EL. The hydrogen produced is stored in the HT. As the demand for electricity increases, the stored hydrogen is released and converted back into electricity via the FC [25]. The HESS provides a flexible and low-carbon approach to hydrogen supply. The HESS model is expressed as follows:

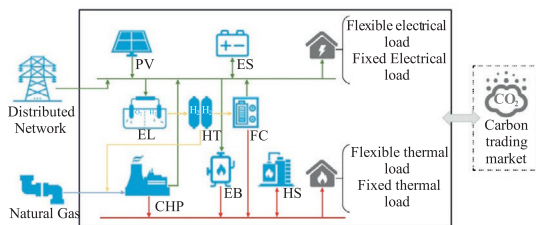


Fig. 1. Structure of the HIES.

$$0 \leq P'_{EL} \leq P'_{EL}{}^{\max} \quad (8)$$

$$0 \leq P'_{FC} \leq P'_{FC}{}^{\max} \quad (9)$$

$$T'_{FC} = \eta_{FC,h} P'_{FC}, \quad (10)$$

$$S_{HT} = \min_{HT}^0 \sum_{t'=1}^t P'_{EL} / C_{P2H} \Delta t - \sum_{t'=1}^t P'_{FC} \Delta t / \eta_{FC} C_{H2P} - \sum_{t'=1}^t P'_{HT} \Delta t / C_{H2P} \leq S_{HT}^{\max} \quad (11)$$

$$S_{HT}^0 = S_{HT}^{N_T}, \quad (12)$$

where P'_{EL} and P'_{FC} denote the electric power outputs of the EL and FC at time t , respectively, $P'_{EL}{}^{\max}$ and $P'_{FC}{}^{\max}$ are the upper operational limits for the EL and FC, respectively, T'_{FC} represents the thermal power output from the FC at time t , $\eta_{FC,h}$ represents the ratio of thermal energy to electric power output of the FC, S_{HT}^0 represents the initial hydrogen storage in the HT (kg), Δt denotes the time interval for scheduling, $S_{HT}^{\min}$ and $S_{HT}^{\max}$ represent the minimum and maximum permissible levels of hydrogen stored in the HT, η_{EL} and η_{FC} represent the efficiencies of EL and FC, respectively, C_{P2H} is the power-to-hydrogen ratio (kWh/kg), C_{H2P} denotes the hydrogen-to-power ratio (kg/kWh), and N_T represents the number of time intervals during the operational period.

3) PV model

The PV unit is a renewable-energy-based generator that converts solar energy into electricity. The power consumption of the PV unit does not exceed the forecasted maximum output power. The surplus output power of the PV unit should be curtailed to maintain equilibrium between the electricity supply and demand.

$$0 \leq P'_{PV} \leq \tilde{P}_{PV}^t, \quad (13)$$

$$P'_{PV} + P'_{PV,cur} = \tilde{P}_{PV}^t, \quad (14)$$

where P'_{PV} denotes the consumption power of the PV unit at time t , $P'_{PV,cur}$ denotes the curtailment power of the PV unit at time t , and $\tilde{P}_{PV}^t$ represents the forecasted maximum output power of the PV unit at time t .

4) EB model

EB model describes how thermal energy is generated by consuming electricity. The model can be stated as follows:

$$0 \leq P'_{EB} \leq P'_{EB}{}^{\max}, \quad (15)$$

$$T'_{EB} = \eta_{EB} P'_{EB}, \quad (16)$$

where P'_{EB} represents the electric power consumed by the EB at time t , $P'_{EB}{}^{\max}$ is the maximum electric power consumed by the EB, T'_{EB} indicates the thermal power generated by the EB at time t , and η_{EB} is the efficiency of the EB.

5) ES/TS model

The ES and TS systems are modeled using a generalized energy storage approach, reflecting their similar operational mechanisms [19]. For instance, taking the ES as an example, the model is outlined as follows:

$$0 \leq P'_{ES,Ch} \leq (1 - u'_{ES}) P'_{ES}{}^{\max}, \quad (17)$$

$$0 \leq P'_{ES,Dis} \leq u'_{ES} P'_{ES}{}^{\max}, \quad (18)$$

$$S_{ES} = \min_{ES}^0 \sum_{t'=1}^t P'_{ES,Ch} \Delta t - \sum_{t'=1}^t P'_{ES,Dis} \Delta t / \eta_{ES,dis} \leq S_{ES}^{\max} \quad (19)$$

$$S_{ES}^0 = S_{ES}^{N_T}, \quad (20)$$

where $P'_{ES,Ch}$ and $P'_{ES,Dis}$ denote the charging and discharging powers of the ES at time t , respectively, u'_{ES} is the binary variable indicating the discharge status of the ES, $P'_{ES}{}^{\max}$ represents the maximum power for both charging and discharging of the ES, $\eta_{ES,Ch}$ and $\eta_{ES,Dis}$ represent the charging and discharging efficiencies, S_{ES}^0 is the initial state, and $S_{ES}^{\min}$ and $S_{ES}^{\max}$ are the lower and upper limits of the stored energy, respectively.

6) Electric/Thermal energy balance model

The balance of electric and thermal power is crucial, governed by constraints listed below:

$$P'_{Grid} + P'_{CHP} + P'_{PV} + P'_{ES,Dis} + P'_{FC} - P'_{ES,Ch} - P'_{EB} - P'_{EL} = P'_L, \quad (21)$$

$$T'_{CHP} + T'_{EB} + T'_{FC} + T'_{ES,Dis} - T'_{ES,Ch} = T'_L, \quad (22)$$

where P'_{Grid} represents the electric power bought from the upper electricity network, and P'_L and T'_L denotes the electrical and thermal loads, respectively.

2 Carbon trading and demand response models

2.1 Ladder-type carbon trading mechanism

The carbon trading mechanism is designed to control carbon emissions through the establishment of legal emission allowances, facilitating market-based trading of these permits. Regulatory authorities distribute initial carbon allowances to emitters, allowing them to plan their operations and emissions accordingly. Participants can trade surplus allowances in the carbon market if their actual emissions fall below the allocated amounts. Conversely, if emissions exceed their allowances, they must purchase additional permits.

This study incorporates a ladder-type carbon trading mechanism that consists of three main components: a carbon emissions allowance model, an actual carbon

emissions model, and the ladder-type carbon trading model itself.

1) Carbon emission allowance model

Carbon emissions in the HIES primarily originate from two sources: electricity procured from the upper grid and natural gas utilized by the H2-CHP system. Some countries such as China have adopted a free allowance allocation method [26]. The model is expressed as follows:

$$\begin{cases} E_{\text{IES}} = E_{\text{Grid}} + E_{\text{Nat}} \\ E_{\text{Grid}} = \alpha_{\text{Grid}} \sum_{t=1}^{N_T} P'_{\text{Grid}} \\ E_{\text{Nat}} = \alpha_{\text{Nat}} \sum_{t=1}^{N_T} (P'_{\text{CHP}} + T'_{\text{CHP}}) \end{cases}, \quad (23)$$

where E_{IES} , E_{Grid} , and E_{Nat} represent carbon emission allowances for the IES, purchased electricity, and natural gas consumption, respectively, α_{Grid} and α_{Nat} are the carbon allowance coefficients for electricity obtained from the upper grid and natural gas consumption, respectively.

2) Actual carbon emission model

The carbon emissions model for electricity procurement from the upper grid and natural gas combustion can be expressed as:

$$\begin{cases} E_{\text{IES},a} = E_{\text{Grid},a} + E_{\text{Nat},a} \\ E_{\text{Grid},a} = \gamma_{\text{Grid}} \sum_{t=1}^{N_T} P'_{\text{Grid}} \\ E_{\text{Nat}} = \gamma_{\text{Nat}} \sum_{t=1}^{N_T} P'_G \end{cases}, \quad (24)$$

where γ_{Grid} and γ_{gas} denote the carbon emission factors for grid electricity and natural gas, respectively, and $E_{\text{IES},a}$, $E_{\text{Grid},a}$, and $E_{\text{Nat},a}$ represent the actual carbon emissions for the IES, purchased electricity, and natural gas consumption, respectively.

3) Ladder-type carbon-trading model

The amount of carbon traded in the market is determined by comparing the carbon emission allowances with the actual emissions of the IES:

$$E_{\text{IES},t} = E_{\text{IES},a} - E_{\text{IES}}, \quad (25)$$

where $E_{\text{IES},t}$ is the carbon emission trading amount of the HIES.

In contrast to the conventional carbon-trading pricing mechanism, this study employs a ladder-type pricing mechanism, which imposes incremental restrictions on carbon emissions. This pricing mechanism divides the purchasing process into several intervals, with the purchase price increasing as the required amount of carbon emission allowances grows. The cost associated with the ladder-type carbon trading is formulated as:

$$C_{\text{CO}_2} = \begin{cases} \lambda E_{\text{IES},t} & 0 \leq E_{\text{IES},t} \leq l \\ \lambda(1+a)(E_{\text{IES},t} - l) + \lambda l & l \leq E_{\text{IES},t} \leq 2l \\ \lambda(1+2a)(E_{\text{IES},t} - 2l) + \lambda(2+a)l & 2l \leq E_{\text{IES},t} \leq 3l \\ \lambda(1+3a)(E_{\text{IES},t} - 3l) + \lambda(3+3a)l & 3l \leq E_{\text{IES},t} \leq 4l \\ \lambda(1+4a)(E_{\text{IES},t} - 4l) + \lambda(4+6a)l & 4l \leq E_{\text{IES},t} \end{cases}, \quad (26)$$

where C_{CO} represents the cost of ladder-type carbon trading, λ represents the base price of carbon trading, l denotes the interval length of carbon emissions, and a is the price growth rate.

2.2 Demand response model

DR is a strategy that encourages consumers to adjust their electrical or thermal demands in response to fluctuating energy prices or incentives. In this study, the HIES has implemented DR to shift or curtail loads, thereby optimizing the operational scheme to reduce operational costs and carbon emissions. For example, some loads can be shifted to periods when the output of the PV unit is high, and some non-essential loads can be curtailed. This approach not only enhances renewable energy consumption but also minimizes waste.

Loads are categorized as fixed or flexible based on their characteristics. Flexible loads, which can participate in DR, are further divided into curtailable and shiftable categories. The DR model for electrical loads is described by (27)–(30). Eqs. (27)–(28) establish that the curtailed and shiftable loads at time t cannot exceed the predefined maximum limits for curtailable and shiftable loads, respectively. Eq. (29) controls the timing shifts of shiftable loads across different time intervals without reducing the total load volume. Eq. (30) calculates the load post-DR adjustments. A similar DR model applies to thermal loads, as described by (31)–(34).

$$0 \leq P'_{\text{cur}} \leq P_{\text{cur}}^{\text{max}}, \quad (27)$$

$$0 \leq P'_{\text{shift}} \leq P_{\text{shift}}^{\text{max}}, \quad (28)$$

$$\sum_{t=1}^{N_T} P'_{\text{shift}} = 0, \quad (29)$$

$$P'_{\text{L,DR}} = P'_L - P'_{\text{shift}} - P'_{\text{cur}}, \quad (30)$$

$$0 \leq T'_{\text{cur}} \leq T_{\text{cur}}^{\text{max}}, \quad (31)$$

$$0 \leq T'_{\text{shift}} \leq T_{\text{shift}}^{\text{max}}, \quad (32)$$

$$\sum_{t=1}^{N_T} T'_{\text{shift}} = 0, \quad (33)$$

$$T'_{\text{L,DR}} = T'_L - T'_{\text{shift}} - T'_{\text{cur}}, \quad (34)$$

where P'_{cur} and P'_{shift} are the curtailed and shifted power of the flexible electrical load at time t , respectively, $P_{\text{cur}}^{\text{max}}$ and $P_{\text{shift}}^{\text{max}}$ denote the maximum allowed power for curtailable and shiftable electrical loads, respectively, P'_L and $P'_{\text{L,DR}}$ represent the electrical load power before and after DR, T'_{cur} and T'_{shift} represent the curtailed and shifted power of the thermal load at time t , respectively, $T_{\text{cur}}^{\text{max}}$ and $T_{\text{shift}}^{\text{max}}$

are the maximum allowed power for curtailable and shiftable thermal loads, respectively, T_L^t and $T_{L,DR}^t$ are the thermal load power before and after DR.

To motivate customers to participate in DR, the program combines financial incentives with variable pricing. Both curtailable and shiftable loads can respond to electricity price fluctuations and receive corresponding incentives, as shown in (35)–(36). The incentive for curtailable loads is typically higher than that for shiftable loads.

$$C_{DR,E} = \sum_{t=1}^{N_T} (c_{\text{shift},e} P_{\text{shift}}^t + c_{\text{cur},e} P_{\text{cur}}^t), \quad (35)$$

$$C_{DR,H} = \sum_{t=1}^{N_T} (c_{\text{shift},h} T_{\text{shift}}^t + c_{\text{cur},h} T_{\text{cut}}^t), \quad (36)$$

where $C_{DR,E}$ and $C_{DR,H}$ represent the total incentives paid by the HIES for flexible electrical and thermal loads, respectively, $c_{\text{shift},e}$ and $c_{\text{cur},e}$ represent the unit incentive costs for shiftable and curtailable electrical loads, respectively, and $c_{\text{shift},h}$ and $c_{\text{cur},h}$ represent the unit incentive costs for shiftable and curtailable thermal loads, respectively.

3 Distributionally robust optimization-based scheduling model for HIES

3.1 Uncertainty model

To model the uncertainties in PV output and load variations, we employed an ambiguity set based on historical data. This set was constructed by clustering the M actual collected samples into K representative scenarios. These scenarios reflect the potential probability distributions of the PV output along with the electrical and thermal loads. Using comprehensive norm constraints, the corresponding probability distribution ambiguity set was then formulated.

A composite norm probability confidence interval was adopted to accurately depict the uncertainty of these probability distributions across different scenarios. This interval combines the 1-norm and ∞ -norm, as expressed by (37). The first condition ensures that the total deviation between the actual and nominal probabilities across all scenarios does not exceed θ_1 . The second condition limits the maximum deviation for any individual scenario using the ∞ -norm.

$$\begin{cases} \Pr\left\{\sum_{k=1}^K |p_k - p_k^0| \leq \theta_1\right\} \geq 1 - 2Ke^{-2M\theta_1/K} \\ \Pr\left\{\max_{1 \leq k \leq K} |p_k - p_k^0| \leq \theta_\infty\right\} \geq 1 - 2Ke^{-2M\theta_\infty} \end{cases}, \quad (37)$$

where $\Pr\{\cdot\}$ represents the probability operator, p_k is the actual probability of scenario k , p_k^0 is the nominal probability of scenario k after clustering, and θ_1 and θ_∞ are the probability deviation limits under the 1-norm and ∞ -norm constraints, respectively.

To set the uncertainty limits for these probability deviations within the ambiguity set, the confidence intervals on the right-hand side were set to θ_1 and θ_∞ :

$$\begin{cases} \theta_1 = \frac{K}{2M} \ln \frac{2K}{1-\alpha_1} \\ \theta_\infty = \frac{1}{2M} \ln \frac{2K}{1-\alpha_\infty} \end{cases}, \quad (38)$$

where α_1 and α_∞ represent the confidence level parameters for the 1-norm and ∞ -norm constraints, respectively. These parameters can be adjusted based on the preferences of the decision-makers.

Then, the ambiguity set is represented as:

$$\Omega = \left\{ p_k \left| \begin{array}{l} p_k \geq 0, k = 1, \dots, K \\ \sum_{k=1}^K p_k = 1 \\ \sum_{k=1}^K |p_k - p_k^0| \leq \theta_1 \\ \max_{1 \leq k \leq K} |p_k - p_k^0| \leq \theta_\infty \end{array} \right. \right\}. \quad (39)$$

The ambiguity set was globally consistent and robust against extreme deviations in individual scenarios, providing a more reliable and balanced representation of uncertainty.

3.2 Two-stage distributionally robust model

A two-stage DRO-based scheduling model for the HIES was developed to address the uncertainties in PV output and multi-energy loads using the ambiguity set. This model operates within a min-max-min framework to minimize total costs under the worst-case probability distribution.

The first stage, termed the day-ahead stage, features a 'min' structure where decision variables include the start-up/shut-down status of the H2-CHP unit, charging/discharging statuses of the ES and TS, and electricity procurement from the day-ahead market. The functions and response times of different equipment and operation mechanisms are crucial at this stage.

The second stage, or intra-day stage, focuses on minimizing the expected cost, assuming the worst-case probability distribution. The decision variables for this stage include electricity procurement from the intra-day market, adjustments in equipment outputs, implementation of DR, and the curtailment of PV output.

The objective function aims to minimize the total operational cost, encompassing energy purchases, maintenance, carbon trading, DR, and penalties for renewable energy curtailment. Eq. (40) provides the overall framework for calculating the total operational cost. The day-ahead operation cost is detailed in (41), which includes the startup costs of the H2-CHP unit and the day-ahead electricity purchase costs. The intra-day cost for scenario k is expressed in (42). (43)–(47) the costs associated with intra-day electricity purchases, natural gas purchases, maintenance, DR incentives, and penalties for PV curtailment.

$$C = \min \left\{ C_{DA} + \max_{p_k \in \Omega} \sum_{k=1}^K \sum_{ID} p_k \min\{\cdot\} \right\}, \quad (40)$$

$$C_{DA} = \sum_{t=1}^{N_T} \left(c_{on} U_{on}^t + c_{Grid,DA}^t P_{Grid,DA}^{k,t} \right), \quad (41)$$

$$C_{ID}^k = C_{Grid,ID}^k + C_{gas}^k + C_{main}^k + C_{CO_2}^k + C_{DR}^k + C_{pvcur}^k, \quad (42)$$

$$C_{Grid,ID}^k = \sum_{t=1}^{N_T} c_{Grid,ID}^t P_{Grid,ID}^{k,t}, \quad (43)$$

$$C_{gas}^k = \sum_{t=1}^{N_T} c_{gas}^t P_{gas}^{k,t}, \quad (44)$$

$$C_{main}^k = \sum_{t=1}^{N_T} \left\{ \begin{aligned} & c_{CHP} P_{CHP}^{k,t} + c_{EB} P_{EB}^{k,t} + c_{ES} (P_{ES_ch}^{k,t} + P_{ES_dis}^{k,t}) \\ & + c_{HESS} (P_{EL}^{k,t} + P_{FC}^{k,t} + P_H^{k,t}) + c_{PV} P_{PV}^{k,t} \\ & + c_{TS} (T_{TS_ch}^{k,t} + T_{TS_dis}^{k,t}) \end{aligned} \right\}, \quad (45)$$

$$C_{DR} = C_{DR,E} + C_{DR,T}, \quad (46)$$

$$C_{pvcur}^k = \sum_{t=1}^{N_T} c_{pvcur} P_{PV,cur}^{k,t}, \quad (47)$$

where C_{DA} represents the day-ahead system operation cost, C_{ID}^k denotes the intra-day operation cost under scenario k , c_{on} is the unit start-up cost, $c_{Grid,DA}^t$ and $c_{Grid,ID}^t$ are the day-ahead and intra-day electricity prices at time t , respectively. c_{CHP} , c_{EB} , c_{ES} , c_{HESS} , c_{PV} , and c_{TS} denote the unit maintenance costs for the H2-CHP, EB, ES, HESS, PV, and TS, respectively. c_{pvcur} denotes the unit penalty cost for the PV curtailment.

The constraints include equipment operation constraints such as the H2-CHP unit, HESS, PV unit, EB, ES, and TS, as shown in (1)–(22), the carbon-trading constraints of (23)–(25), and the DR constraints of (27)–(34). Electricity transaction and power balance constraints.

The electricity transaction constraints are expressed as follows:

$$0 \leq P_{Grid,DA}^t \leq P_{Grid}^{max}, \quad (48)$$

$$0 \leq P_{Grid,ID}^{k,t} \leq P_{Grid}^{max}, \quad (49)$$

where P_{Grid}^{max} represents the maximum electricity purchase power.

The power balance constraints of electricity and thermal energy are defined as follows:

$$P_{Grid,DA}^t + P_{Grid,ID}^t + P_{CHP}^{k,t} + P_{PV}^{k,t} + P_{ES_dis}^{k,t} + P_{FC}^{k,t} - P_{ES_ch}^{k,t} - P_{EL}^{k,t} - P_{EB}^{k,t} = P_{L,DR}^{k,t}, \quad (50)$$

$$T_{CHP}^{k,t} + T_{EB}^{k,t} + T_{TS_dis}^{k,t} + T_{FC}^{k,t} - T_{TS_ch}^{k,t} = T_{L,DR}^{k,t}, \quad (51)$$

where $T_{TS_ch}^{k,t}$ and $T_{TS_dis}^{k,t}$ represent the charging and discharging powers of the TS at time t under scenario k .

3.3 Solution methodology

The proposed two-stage DRO-based scheduling model for HIES is expressed in a compact form as:

$$\min_x \mathbf{b}^T \mathbf{x} + \max_{p_k \in \Omega} \sum_{k=1}^K p_k \min_{y_k} \mathbf{c}^T \mathbf{y}_k, \quad (52)$$

$$s.t. \begin{cases} Ax + By_k \geq d \\ Dy_k \geq e \\ Ky_k = 0 \\ Ly_k = \mathbf{u}_k \end{cases},$$

where $\mathbf{x}$ represents the first-stage decision variables, $\mathbf{y}_k$ is the set of second-stage decision variables under scenario k , $\mathbf{u}_k$ denotes the random variables under the scenario k , $\mathbf{b}$ and $\mathbf{c}$ are cost coefficient vectors, and $\mathbf{A}$, $\mathbf{B}$, $\mathbf{D}$, $\mathbf{K}$, $\mathbf{I}$, $\mathbf{d}$, $\mathbf{e}$ represent parameter matrixes.

Due to the min-max-min structure of the optimization model, achieving a direct resolution presents significant challenges. To manage this complexity, the C&CG algorithm is employed. This algorithm decomposes the initial problem into a master problem and a subproblem, enabling the optimal solution to be obtained through iterative resolution.

The master problem is formulated as in (53), which aims to determine the optimal solution that satisfies the first-stage constraints and accounts for the worst-case uncertainty values. η represents the cost associated with the second stage in the context of the worst-case uncertainty. As the number of iterations increases, additional variables and constraints are incorporated into the master problem.

$$\min_x \mathbf{b}^T \mathbf{x} + \eta \quad (53)$$

$$s.t. \begin{cases} \eta \geq \sum_{k=1}^K p_k^{n,*} \min_{y_k^n} \mathbf{c}^T \mathbf{y}_k^n \\ Ax + By_k^n \geq d \\ Dy_k^n \geq e \\ Ky_k^n = 0 \\ Ly_k^n = \mathbf{u}_k \end{cases}, \forall n \leq l$$

where l represents the current iteration number, $\mathbf{y}_k^n$ is the optimal solution derived from the subproblem of the n -th iteration, and $p_k^{n,*}$ denotes the worst-case probability of scenario k of the n -th iteration, where $n \leq l$.

The subproblem is expressed as (54), which identifies the worst-case realization of the probability distribution for each scenario k within the defined ambiguity set Ω .

$$\max_{p_k \in \Omega} \sum_{k=1}^K p_k \min_{y_k} \mathbf{c}^T \mathbf{y}_k, \quad (54)$$

$$s.t. \begin{cases} Ax + By_k \geq d \\ Dy_k \geq e \\ Ky_k = 0 \\ Ly_k = \mathbf{u}_k \end{cases}.$$

The discrete scene probability value p_k in the subproblem and second-stage variable $\mathbf{y}_k$ are independent of each other; therefore, the subproblem calculations can be performed using parallel processing methods.

The solution process for the two-stage DRO-based scheduling model using the C&CG algorithm is illustrated in Fig. 2, and can be outlines as:

Step1: Initialize the probability distribution; establish the upper and lower bounds, $\mathbf{UB} = +\infty$, $\mathbf{LB} = -\infty$, iteration counter $l = 1$, and set the initial worst-case probability distribution $\mathbf{p}^{0,*}$.

Step2: Solve the master problem with the worst-case probability distribution to obtain $\mathbf{x}^{l,*}$, and update $\mathbf{LB}$.

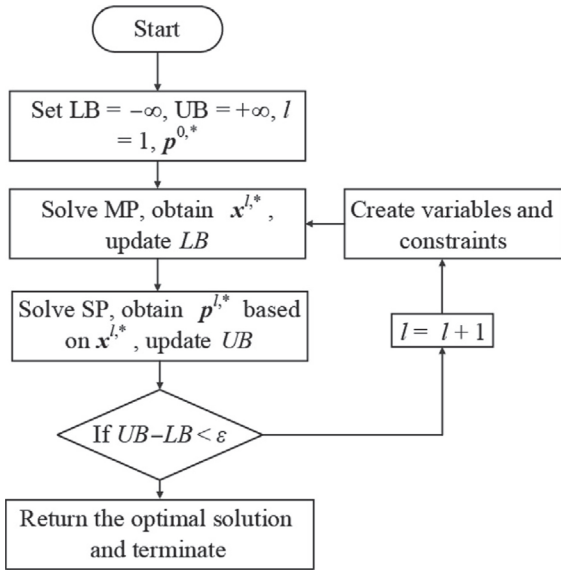


Fig. 2. Solution process for the two-stage DRO model.

Step3: Solve the subproblem based on $x^{l,*}$, determine the worst-case probability distribution $p^{l,*}$ within the ambiguity set Ω , and update UB .

Step 4: If the condition $UB - LB \leq \varepsilon$ is met, return the optimal solution and terminate the process. Alternatively, define new variables y_k^l , incorporate the relevant constraints into the master problem, update $l = l + 1$, and return to Step 2.

4 Case study

4.1 Parameters and setting

The HIES depicted in Fig. 1 served as the simulation object for this case study. Equipment parameters are detailed in Table A1 in Appendix [27,28]. This study adopted the time-of-use electricity pricing model, as shown in Fig. 3, where intra-day market electricity prices are 1.3

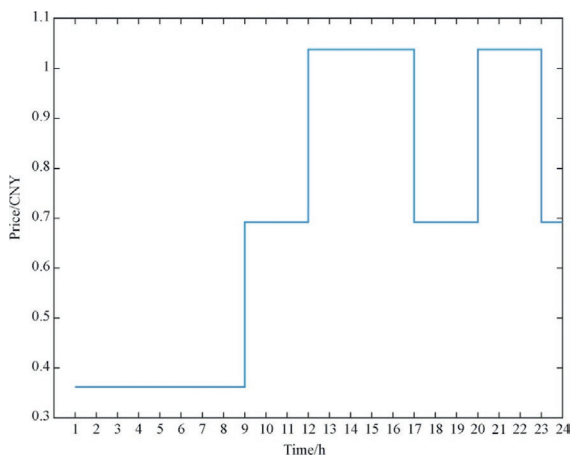


Fig. 3. Day-ahead time-of-use electricity prices.

times those of the day-ahead market. The price of the natural gas was set at 0.35 CNY/kWh. The base price λ for carbon trading was set at 200 CNY/kg, with a price growth rate a of 0.25 and an interval length l of 2000 kg. $c_{\text{shift,e}}$ and $c_{\text{shift,h}}$ were set at 0.3 CNY/kW, and $c_{\text{cur,e}}$ and $c_{\text{cur,h}}$ were set at 0.4 CNY/kW. Table A2 in the Appendix provides parameters for carbon emissions. The base values for the electrical and thermal loads were set at 500 and 600 kW, respectively, while the maximum hydrogen mixing volume ratio in the H2-CHP unit ψ^{max} was capped at 10 %.

To address the uncertainties in PV output, electrical loads, and thermal loads, the Monte Carlo sampling method was utilized to generate 200 scenarios based on beta and normal distributions. The K -means clustering method was then applied to identify representative scenarios. The sum of squared errors (SSE) served as the metric to evaluate the clustering performance. As illustrated in Fig. 4, the optimal number of clusters was determined to be four. This number represents the “elbow point,” striking an effective balance between computational efficiency and accuracy.

Fig. 5 displays four typical winter days, where the shaded areas indicate the prediction intervals for the uncertainties.

4.2 Results and analysis

To evaluate the effectiveness of the proposed scheduling method for a HIES that incorporates DR, HESS, and carbon-trading mechanisms, three different schemes were compared:

Scheme 1: Focuses on scheduling for a HIES, incorporating both HESS and a carbon-trading mechanism.

Scheme 2: Pertains to a conventional IES that utilizes CHP systems but excludes both H2-CHP and HESS.

Scheme 3: Involves scheduling for a HIES but without considering the carbon-trading mechanism.

Results of the proposed method

Post-DR adjustments, as depicted in Fig. 6, the profiles for electrical and thermal loads were realigned to better

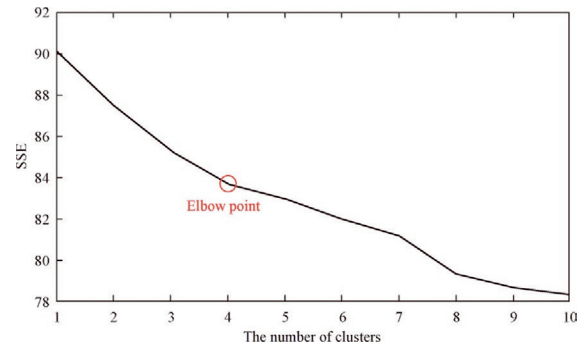
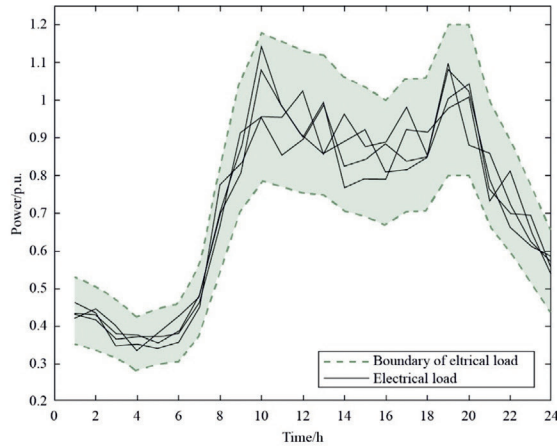
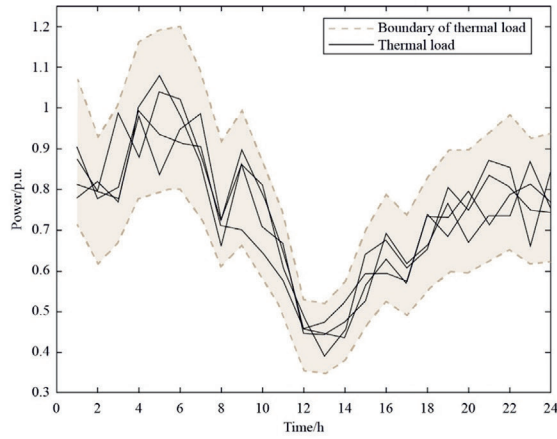


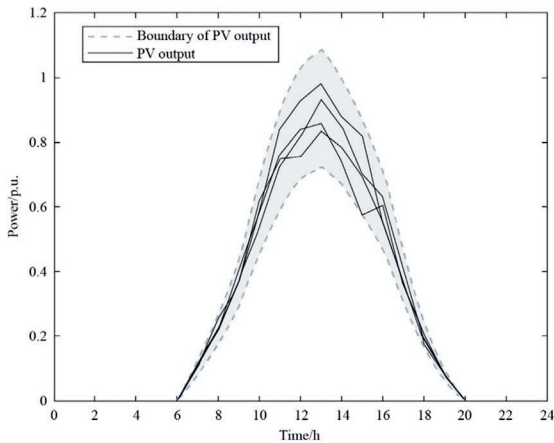
Fig. 4. SSE of different clustering numbers.



(a) Electrical load.



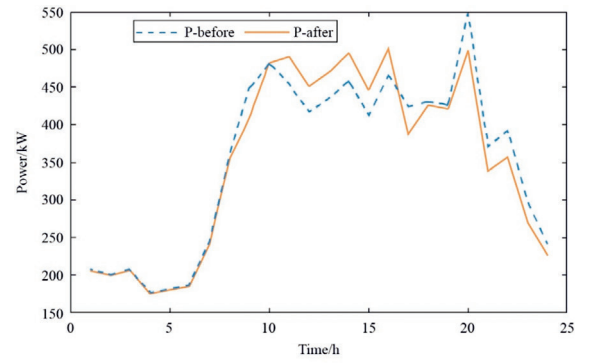
(b) Thermal load.



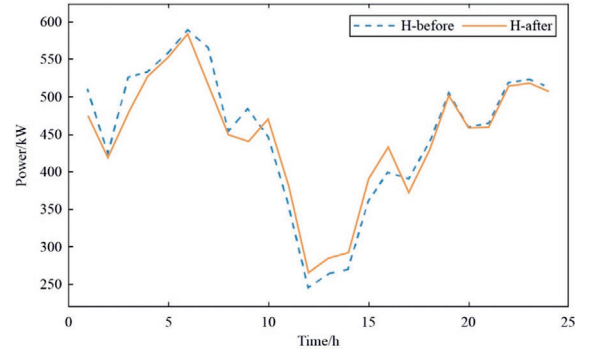
(c) PV output

Fig. 5. Curves of PV output and loads.

match the availability of PV output and the fluctuations in electricity prices. During periods of high PV output (10:00–16:00), a significant portion of the electrical and thermal loads are shifted, thereby enhancing the consump-



(a) DR results of electrical load



(b) DR result of thermal load

Fig. 6. Results of DR.

tion of PV-generated electricity and reducing dependence on natural gas, which in turn lowers carbon emissions. In periods of elevated electricity prices (19:00–24:00), the H2-CHP predominantly supplies electricity and thermal energy, and some non-essential loads are curtailed to decrease natural gas consumption, operational costs, and carbon emissions.

The day-ahead scheduling was initially optimized by accounting for the uncertainties in RES and loads. In the intra-day stage, as these uncertainties gradually became apparent, the intra-day scheduling was refined to accommodate real-time conditions [16]. The proposed scheduling method has proven effective in maintaining a balance between energy supply and demand, as evidenced in Fig. 7. The operational conditions of the HESS and H2-CHP systems are detailed in Fig. 8, demonstrating the system's overall functionality and efficiency.

During periods of low electricity prices (1:00–8:00), day-ahead market strategies prioritize purchasing electricity from the upper grid to minimize operational costs. Thermal loads during these hours are predominantly supplied by the EB, which converts electricity into thermal energy. To address load volatility, additional electricity is procured in the intra-day market, especially during high-load periods. From 10:00 to 16:00, when PV output peaks, the entire electrical load is directly powered by the PV unit. Simultaneously, the EB supplies all thermal loads by converting electricity generated by the PV into thermal energy.

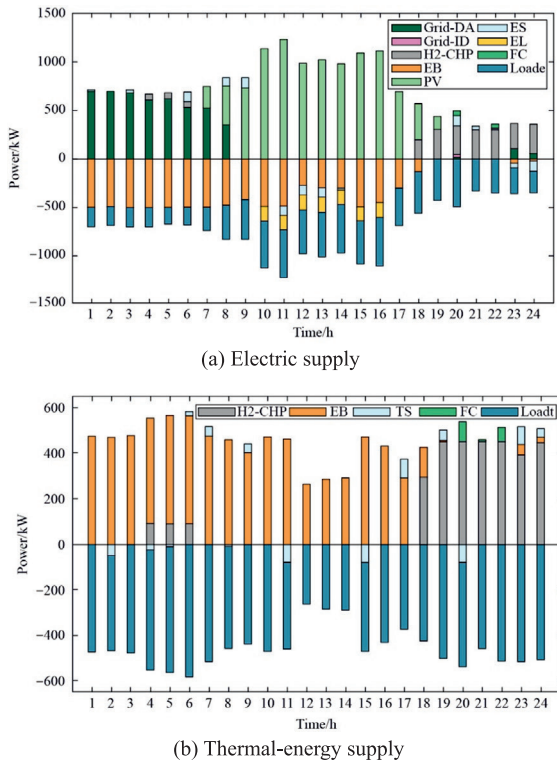


Fig. 7. Results of energy supply in Scheme 1.

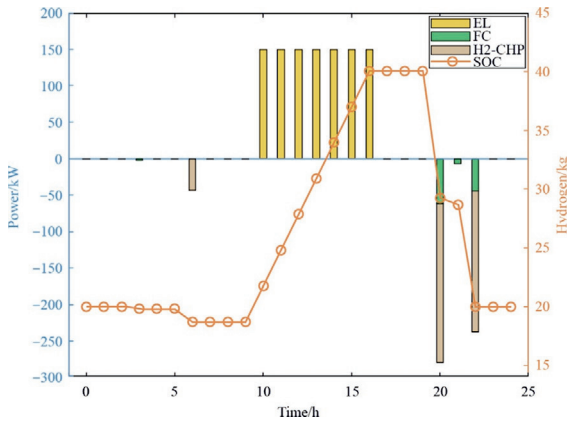


Fig. 8. Operational conditions of hydrogen energy.

Surplus photovoltaic output is either stored in the energy storage system or converted into hydrogen via electrolysis, enhancing renewable energy utilization and reducing carbon emissions. During peak electricity price periods (20:00–24:00), the H2-CHP system primarily generates both electricity and thermal energy to further reduce operational costs. From 20:00 to 22:00, stored hydrogen is converted back into electricity and thermal energy by the FC and H2-CHP, facilitating renewable energy transfer and enhancing system flexibility.

Overall, the integration of hydrogen technology, renewable energy, and energy storage significantly lowers the operational costs of the HIES and reduces carbon emissions.

4.3 Comparison of schemes

The scheduling costs and carbon emissions of the three schemes are detailed in Tables 1 and 2, respectively. The optimization results highlight the benefits of incorporating hydrogen energy via the HESS and H2-CHP. Scheme 1 is notably more cost-effective, reducing total operational costs (C_{total}) by 3.56 % compared to Scheme 2. The HESS and H2-CHP systems in Scheme 1 efficiently utilize surplus PV generation, thereby improving the RES consumption rate and avoiding any PV curtailment, as evidenced in Scheme 1. In contrast, Scheme 2 incurs a PV curtailment cost of 86 CNY, indicating lower energy utilization efficiency. Additionally, by blending hydrogen with natural gas in the H2-CHP unit, Scheme 1 not only diminishes natural gas consumption but also substantially cuts carbon emissions. As a result, both gas purchase and carbon trading costs in Scheme 1 are lower than those in Scheme 2.

The integration of the HESS and H2-CHP in Scheme 1 significantly enhances both the operational economy and environmental sustainability. This scheme effectively increases the utilization of renewable energy and reduces reliance on fossil fuels.

Comparing Schemes 2 and 3 highlights the beneficial impact of the carbon-trading mechanism. Notably, Scheme 1 achieves a reduction in carbon emissions of 26 kg per day compared to Scheme 3. The ladder-type carbon-trading mechanism actively incentivizes the reduction in usage of high-carbon emission equipment and promotes the adoption of cleaner, renewable energy sources along with hydrogen technologies.

4.4 Effectiveness of DRO model

To evaluate the effectiveness of the proposed DRO-based method against SP and RO methods in managing the uncertainties of RESs and multi-energy loads during HIES scheduling, the Monte Carlo sampling method was employed to generate 200 uncertain scenarios. The performance outcomes of these scenarios are summarized in Table 3.

The DRO method exhibited the lowest average total cost, comparable to that of the SP method, yet proved economically superior to the RO method. This advantage

Table 1
Costs of Schemes 1–3.

Scheme	C_{total}	C_{grid}	C_{gas}	C_{DR}	C_{pvcur}	C_{CO2}
Scheme 1	7,439	2,175	3,114	125	0	981
Scheme 2	7,714	2,138	3,294	179	86	1,007
Scheme 3	7,494	2,008	3,133	118	0	990

Table 2
Carbon emissions of Schemes 1–3.

Scheme	Carbon emissions (kg)
Scheme 1	4,273
Scheme 2	4,357
Scheme 3	4,299

Table 3
Comparison of DRO, SP and RO.

Method	Average total cost (CNY)	Maximum total cost (CNY)
DRO	6,946	7,699
SP	6,951	7,743
RO	7,032	7,635

arises because the DRO method avoids overly conservative decisions by using an ambiguity set that accounts for the worst-case distribution within a reasonable limit. In contrast, the RO method must prepare for worst-case scenarios without such flexibility.

The maximum total cost observed under the DRO method is lower than that of the SP method, but slightly higher than that of the RO method, indicating that DRO effectively balances cost efficiency with risk reduction. While the SP method's robustness is lower, leading to higher risks in unfavorable scenarios, the RO method, although highly robust, often compromises economic performance due to its conservative nature.

Therefore, the DRO method demonstrates superior performance in managing uncertainties, providing an optimal trade-off between economy and risk.

To evaluate the impact of three optimization methods (DRO, RO, and SP) on the day-ahead scheduling scheme, the electricity procurement during off-peak and peak price periods was analyzed, as depicted in Fig. 9. During the off-peak period from 0:00 to 9:00, all methods increased electricity purchases to minimize overall operational costs. Among these, the SP method secured the highest quantity of electricity, capitalizing on lower prices to reduce costs. In contrast, the RO method resulted in the least electricity

procurement, maintaining a conservative approach to handling load fluctuations. The DRO method, while purchasing less electricity than the SP method, struck a balance between robustness and cost efficiency, reflecting its moderate approach. During the high-electricity price period from 19:00 to 24:00, all methods significantly reduced electricity purchases to avoid elevated costs. However, the RO method maintained relatively higher purchasing levels compared to others, aimed at managing potential worst-case scenarios with high load demand. The SP method, on the other hand, minimized its electricity purchases, effectively reducing operational costs. The purchasing activity of the DRO method was intermediate between the SP and RO methods, demonstrating a balanced trade-off between robustness and economic efficiency.

5 Conclusion

This paper introduced a DRO-based scheduling method for the HIES that incorporated DR and a carbon-trading mechanism. Through case studies, the following conclusions were drawn:

- (1) The integration of the HESS and H2-CHP within the HIES significantly enhanced the multi-energy coupling and conversion processes. This integration improved the utilization of cleaner RESs and hydrogen energy, increasing the PV consumption rate by 5.44 % and reducing the total operational costs by 3.56 %.
- (2) The implementation of a ladder-type carbon-trading mechanism alongside the DR program promoted a lower-carbon operational mode within the system, which led to a reduction in carbon emissions by 26 kg per day.
- (3) The DRO-based scheduling method demonstrated a superior balance between operational economy and robustness against uncertainties in RESs and load fluctuations, compared to SP and RO methods.

Hydrogen energy, widely utilized across various sectors including transportation and industry, was shown to hold significant potential for diverse applications. Future studies will explore the scalability of hydrogen within the HIES framework, focusing on developments such as hydrogen fuel stations and hydrogen fuel cell vehicles, to further enhance the efficiency and utilization of hydrogen energy.

CRediT authorship contribution statement

Zhichun Yang: Writing – original draft, Formal analysis. **Lin Cheng:** Writing – review & editing, Validation. **Huaidong Min:** Resources, Methodology, Investigation. **Yang Lei:** Writing – review & editing, Methodology. **Yanfeng Yang:** Project administration, Investigation.

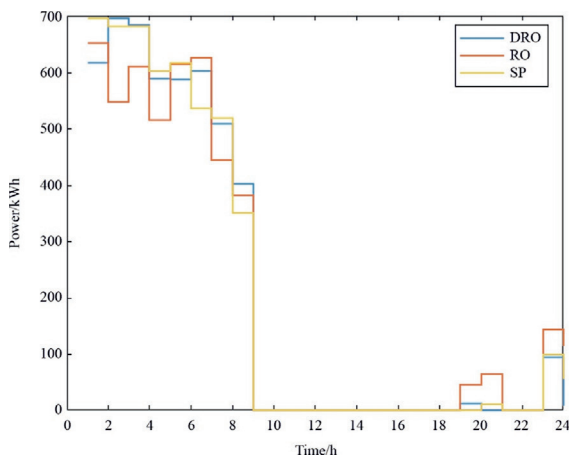


Fig. 9. Day-ahead electricity purchase patterns.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zhichun Yang, Huaidong Min, Yang Lei are currently employed by Electric Power Research Institute of State Grid Hubei Co., Ltd.

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Appendix A

Table A1
Arrangement of channels.

Parameter	Value	Parameter	Value
P_{CHP}^{max}	300 kW	P_{ES}^{max}	400 kW
η_{CHP_e}	0.3	$S_{ES}^{min}/S_{ES}^{max}$	40/360 kWh
η_{CHP_h}	0.45	$\eta_{ES_ch}/\eta_{ES_ch}$	1/1
c_{on}	30 CNY	P_{TS}^{max}	200 kW
P_{EL}^{max}	150	$S_{TS}^{min}/S_{TS}^{max}$	1/1
P_{FC}^{max}	200	c_{CHP}	0.05 CNY/kW
η_{FC_h}	0.7	c_{EB}	0.04 CNY/kW
$S_{HT}^{min}/S_{HT}^{max}$	14/126 kg	c_{ES}	0.026 CNY/kW
C_{P2H}	0.0254 kg/kWh	c_{HESS}	0.05 CNY/kW
C_{H2P}	39.4 kWh/kg	c_{PV}	0.039 CNY/kW
η_{EL}	0.8	c_{TS}	0.013 CNY/kW
η_{FC}	0.3	c_{pvcu}	0.2 CNY/kW
P_{PV}^{max}	1800 kW	c_{TS}	0.013 CNY/kW
P_{Grid}^{max}	10000 kW		

Table A2
Carbon emission parameters.

Parameter	Value
α_{Grid}	0.2 kg/kWh
α_{Nat}	0.385 kg/kWh
γ_{grid}	0.798 kg/kWh
γ_{Nat}	0.5647 kg/kWh

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Zhichun Yang received his bachelor, master's, and Ph.D. degree from Wuhan University in Wuhan, China, in 2013. He is working in Electric Power Research Institute, State Grid Hubei Electric Power Company in Wuhan China. His research interests include grid-connected protection for active distribution networks, cluster control of distributed power sources, coordinated interaction and active support for microgrids, and the characteristics and networking technologies of smart distribution grids.



Lin Cheng received the bachelor and master's degree in electrical engineering from Tianjin University, Tianjin, China, in 1996 and received a Ph.D. degree from Tsinghua University in Beijing, China, in 2001. He is currently a tenured professor with the Department of Electrical Engineering, Tsinghua University. His research interests include operational reliability evaluation and application of power systems, operation optimization of distribution systems considering flexible load-side resources, and perception and control of uncertainty in wide-area measurement systems.



HuaiDong Min received the master's degree from Huazhong University of Science and Technology in Wuhan, China, in 2021. He is working in the Electric Power Research Institute, State Grid Hubei Electric Power Company. His research interests include distributed power sources, microgrids, distribution network automation, and the characteristics of active distribution networks.



Yang Lei received the master's degree from Wuhan University in Wuhan, China, in 2013. He is working in Electric Power Research Institute, State Grid Hubei Electric Power Company in Wuhan, China. His research interests include distribution automation, distribution Internet of Things, relay protection, and automation-related work.



Yanfeng Yang received the bachelor's degree from South China Normal University in Guangzhou, China, in 2009 and received master's degree from Daegu University in Daegu, South Korea, in 2012. She is working in Wuxi Research Institute of Applied Technologies, Tsinghua University. Her research interests include comprehensive energy management, power system operation and optimization, flexible interconnection technology for distribution networks.

(Editor Yu Zhang)