
Research article

Optimal scheduling of a power-hydrogen-methanol multi-energy coupling system considering cross-regional methanol transportation

Borui Zhang, Yuming Yang, Xueru Liu and Sida Lv*

Northeast Electric Power University, 169 Changchun Road, Chuanying District, Jilin City, Jilin Province, 132012, China

* **Correspondence:** Email: 2202400358@neepu.edu.cn; Tel: +86-19843774214.

Abstract: The power-hydrogen-methanol multi-energy coupling system enables flexible conversion of electricity, hydrogen, and liquid chemical energy, providing an effective pathway for renewable energy accommodation and low-carbon operation. However, spatial mismatch between renewable-energy-rich regions and load centers, together with wind and photovoltaic fluctuations, brings challenges to cross-regional energy coordination, flexible regulation, and economic operation. To address these issues, this paper proposed an optimal scheduling method for a power-hydrogen-methanol multi-energy coupling system considering cross-regional methanol transportation. First, a coupled operation framework was established for the sending-end and receiving-end regions, where transmission tie-lines and methanol transportation jointly form dual cross-regional energy transfer pathways. Second, a methanol storage and transportation model considering transportation delay was developed. By integrating electrolytic hydrogen production, methanol synthesis, methanol reforming, and methanol fuel cell power generation, the coordinated operation of the methanol production-storage-transportation-utilization chain and the power-hydrogen system is realized. Furthermore, a unified multi-timescale scheduling model was constructed to coordinate hourly power balance with daily methanol storage and transportation characteristics. On this basis, a reward-penalty differentiated stepped carbon trading scheme and a data-driven robust optimization (DDRO) approach are incorporated. Wind and photovoltaic uncertainty sets were built using historical forecasting errors, and the resulting two-stage robust scheduling model was solved by the column-and-constraint generation (C&CG) algorithm. Case studies on the IEEE 39-bus system showed that the proposed method achieves an annual operating cost of ¥381.275 billion, carbon emissions of 672,500 kt, and a worst-case load shedding rate of only 0.05%. These results confirm that the proposed approach can promote interregional renewable energy utilization, improve the hydrogen

supply structure in the receiving-end region, and coordinate system economy, low-carbon performance, and supply reliability under renewable generation uncertainty.

Keywords: power-hydrogen-methanol coupling system; cross-regional methanol transportation; multi-timescale scheduling; ladder-type carbon trading; data-driven robust optimization; renewable energy accommodation

1. Introduction

1.1. Research background

Driven by global carbon neutrality strategies, renewable energy from wind and photovoltaic power is rapidly transforming from a supplementary energy source into a dominant power supply, becoming a major driver of incremental electricity demand growth [1]. However, the extensive deployment of wind and solar power is conducive to promoting the low-carbon transformation of the energy system, but it also introduces challenges related to intermittency and spatial-temporal mismatch; its inherent intermittency, volatility, and reverse peak-regulation characteristics increase the regulation burden of power systems. To overcome the bottleneck of renewable energy accommodation, Power-to-X technologies have gradually become an important pathway for converting surplus renewable electricity across different energy forms. Recent studies have shown that renewable electricity and green hydrogen can serve as the core inputs of Power-to-X pathways, enabling the production of e-fuels, e-chemicals, and other energy carriers, thereby expanding the utilization scope of renewable energy [2]. Among them, water electrolysis provides a fundamental route for converting electricity into hydrogen. Nevertheless, hydrogen still faces challenges in storage and transportation, such as high costs, limited energy density, and stringent infrastructure requirements, which restrict its large-scale cross-regional application. By comparison, methanol can be stored conveniently under normal environmental conditions, relies on a well-developed logistics and transportation network, and possesses stable properties as a liquid energy carrier. Therefore, it can serve as both a renewable-energy-derived product and a hydrogen carrier for cross-regional energy transfer [3]. However, in wind- and photovoltaic-driven power-hydrogen-methanol multi-energy coupling processes, several issues remain insufficiently addressed, including the inadequate consideration of renewable generation fluctuations, the limited diversity of cross-regional energy transmission pathways, and the insufficient characterization of timescale differences among multiple energy carriers.

Introducing cross-regional methanol transportation into power-hydrogen-methanol multi-energy coupling systems provides an effective approach to alleviating the above issues. In the sending-end region, excess wind and solar generation can be converted into hydrogen through electrolysis. The obtained hydrogen can then react with captured carbon dioxide to produce methanol, enabling variable renewable power to be transformed into a liquid chemical fuel suitable for storage and long-distance transport. In the receiving-end region, methanol can be converted back into hydrogen and electricity by means of methanol-to-hydrogen reforming and methanol fuel-cell-based power generation [4]. Compared with relying solely on electricity transmission, the joint mode of direct power delivery and interregional methanol transport can provide additional channels for renewable energy utilization across regions and enhance the flexibility of multi-energy supply on the demand side. Meanwhile,

electricity transmission and power balance are characterized by strong immediacy, whereas methanol production, storage, and cross-regional transportation exhibit obvious time-delay and slow-dynamic characteristics. The differences among energy carriers in response speed, storage and transportation cycles, and regulation modes may lead to insufficient coordination among power regulation, hydrogen supply, and cross-regional methanol utilization [5]. Furthermore, fluctuations in wind and photovoltaic output and carbon emission constraints jointly affect the energy conversion pathways and equipment output scheduling in both the sending-end and receiving-end regions, further increasing the difficulty of coordinating renewable energy accommodation, low-carbon operation, and supply reliability in power-hydrogen-methanol multi-energy coupling systems [6]. Accordingly, establishing a multi-energy coordinated scheduling framework for electricity, hydrogen, and methanol is essential for realizing cross-regional energy balance and collaborative operation. Such a framework can also evaluate how temporal and spatial disparities in renewable resources between sending-end and receiving-end areas affect system economy and low-carbon performance.

1.2. Literature review

To address the mismatch between energy supply in renewable-energy-rich regions and energy demand in load-center regions, Power-to-X and renewable methanol technologies provide new solutions for the cross-energy-form conversion and cross-regional utilization of surplus renewable energy. Reference [7] investigated the cost characteristics of renewable methanol in terms of production and delivery and suggested that methanol shows economic feasibility as an energy carrier for long-distance transport. Reference [8] established an integrated Power-to-X production framework that couples renewable hydrogen generation with methanol production and confirmed the coordination among hydrogen generation, carbon dioxide utilization, and methanol conversion. Reference [9] evaluated the Power-to-Methanol pathway from both techno-economic and environmental perspectives, showing that the conversion of renewable power and captured carbon dioxide into methanol has considerable potential for low-carbon applications. Reference [10] presented a Power-to-X-to-Power configuration based on green methanol, where renewable electricity is first converted into methanol and then recovered through reforming and electricity generation processes. Reference [11] developed a mixed-integer linear programming (MILP) optimization model for low-carbon hydrogen supply chains, in which renewable and grid electricity, hydrogen production, compression, storage, and transportation to end users were jointly considered. These studies indicate that methanol, as a liquid hydrogen carrier and a medium for renewable energy conversion, has certain advantages in storage and transportation. However, existing studies mainly focus on methanol production, techno-economic assessment, or single-site Power-to-X integration processes. Few studies have incorporated cross-regional methanol transportation into a unified model together with power balance, hydrogen supply, and methanol reutilization processes in both sending-end and receiving-end regions. As a result, the role of the full methanol production-storage-transportation-utilization chain in cross-regional multi-energy coordinated scheduling has not been fully reflected.

With the increasing integration of various energy conversion devices and storage units in integrated energy systems (IES), multi-timescale scheduling has gradually become an important approach for improving system operational flexibility. Reference [12] presented a multi-timescale energy management framework for microgrid operation under uncertainties on both the generation and load sides, where day-ahead planning is coordinated with intra-day regulation to improve operational

flexibility. Reference [13] established a multi-temporal optimization approach for IES, taking into account the influence of source-load fluctuations on dispatch decisions so as to enhance economic performance and operating stability. Reference [14] developed a distributed scheduling framework across multiple time resolutions for urban IES equipped with carbon capture power plants, with the objective of balancing renewable energy utilization and coordinated multi-energy supply and demand. Reference [15] proposed a multi-stage scheduling framework combining stochastic and robust optimization for hydrogen-based multi-energy microgrids, thereby strengthening the reliability of hydrogen energy system operation under renewable power fluctuations. These studies have demonstrated the effectiveness of multi-timescale scheduling in coping with renewable energy fluctuations and enhancing the flexibility of IES from different perspectives. Nevertheless, most existing studies concentrate on energy carriers including electricity, heat, natural gas, and hydrogen, and generally coordinate these carriers within a unified scheduling horizon or employ rolling optimization between day-ahead and intra-day stages. The daily delay characteristics of methanol transportation have not been sufficiently considered. For cross-regional systems with abundant renewable energy at the sending end and concentrated power and hydrogen loads at the receiving end, electricity transmission must satisfy hourly power balance requirements, whereas methanol transportation and storage exhibit slow-dynamic characteristics. Existing models are therefore limited in simultaneously characterizing their differences in both timescale and physical transmission mode.

For renewable energy uncertainty and low-carbon dispatch, DDRO approaches together with carbon trading schemes have been extensively introduced to enhance the economic efficiency, uncertainty resistance, and carbon reduction capability of energy systems. Reference [16] developed a data-oriented distributionally robust dispatch approach for community IES. In this method, renewable generation uncertainty was described using historical operating data, and the model was solved through the C&CG algorithm. Reference [17] proposed a data-driven stochastic-robust dispatch model for IES clusters under various uncertain factors, such as renewable power output, load variation, and electricity price fluctuation, aiming to improve system adaptability in uncertain operating environments. Reference [18] incorporated wind and solar power uncertainties, a two-stage Power-to-Gas process, and a stepped carbon trading scheme into IES dispatch, and demonstrated the effects of hydrogen utilization and carbon pricing mechanisms on low-carbon economic operation. Reference [19] developed a regional IES dispatch model oriented toward low-carbon economy under uncertain demand response and introduced a reward-penalty carbon trading scheme formulated with stepped carbon prices. Reference [20] further introduced bilateral supply-demand interaction together with a reward-penalty stepped carbon trading scheme and examined how the carbon trading mechanism guides system dispatch decisions. These studies provide useful references for renewable energy uncertainty modeling and low-carbon economic scheduling. Nevertheless, in most available studies, the modeling of renewable energy uncertainty and the introduction of carbon trading schemes are usually handled as two separate components. Their interactive impacts on cross-regional coordinated dispatch of power-hydrogen-methanol systems have not been fully investigated. In addition, existing studies mainly focus on electricity-gas-heat or electricity-hydrogen systems, and have not sufficiently considered the impacts of cross-regional methanol transportation on renewable energy accommodation, hydrogen supply costs at the receiving end, and low-carbon scheduling results. Consequently, existing methods still face difficulties in simultaneously balancing economic benefits, carbon reduction performance, and energy supply security under the fluctuation of renewable power output.

1.3. Research gap

Although previous studies have provided valuable insights into methanol-related Power-to-X systems, multi-timescale scheduling, uncertainty-aware dispatch, and low-carbon operation, several limitations still remain, as summarized in Table 1.

Table 1. Structured comparison between this study and representative previous publications.

Reference	System boundary	Transport	Uncertainty and carbon treatment	Constraints	System carriers	Temporal features
[7]	Green MeOH supply	MeOH transport	Techno-economic assessment	Supply chain	E/H ₂ /MeOH	Long-term scale
[11]	H ₂ supply chain	H ₂ transport;	Low-carbon optimization	Logistics	E/H ₂	Planning scale
[12]	Microgrid	×	Supply/load uncertainty	Microgrid	Multi-energy	Multi-timescale
[15]	H ₂ -based microgrid	×	Stochastic-robust optimization	Microgrid	E/H ₂	Multi-stage scheduling
[16]	Community IES	×	Data-driven distributionally robust optimization	IES	Multi-energy	Scheduling scale
[18]	IES with Power-to-Gas	×	Wind/photovoltaic uncertainty and ladder carbon trading	IES	Multi-energy	Scheduling scale
[19]	Regional IES	×	Demand-response uncertainty and reward-penalty carbon trading	Regional IES	Multi-energy	Scheduling scale
This study	Sending-receiving system	Tie-line and MeOH delay	Data-driven two-stage robust optimization + reward-penalty stepped carbon trading	Regional balance + tie-line + equipment	E/H ₂ /MeOH/CO ₂	Hourly/daily coupling

(1) Existing studies on methanol mainly focus on methanol production, techno-economic assessment, or single-site integration processes. Although hydrogen or methanol transportation has been discussed in some supply-chain studies, few works establish a unified cross-regional scheduling framework that simultaneously models the sending-end and receiving-end regions and coordinates the complete methanol production-storage-transportation-reutilization chain together with electricity and hydrogen operation.

(2) Existing multi-timescale scheduling studies have demonstrated the value of coordinating decision-making across different time resolutions. However, most of them mainly focus on electricity, heat, gas, and hydrogen systems, and usually adopt common scheduling horizons or

day-ahead/intra-day coordination schemes. The carrier-specific temporal characteristics between electricity transmission and methanol transportation are still insufficiently represented. In particular, hourly power balance and tie-line transfer requirements are rarely coordinated with day-level methanol storage, transportation, and delayed arrival processes in a unified cross-regional framework.

(3) Robust/stochastic optimization, stepped carbon trading, and C&CG-based solution methods have all been reported in previous IES studies. However, their combined role in cross-regional power-hydrogen-methanol coordinated scheduling remains insufficiently investigated. In particular, limited attention has been paid to how renewable generation uncertainty and differentiated carbon-emission incentives jointly affect the coordination of dual cross-regional transfer pathways, namely electricity transmission and methanol transportation, as well as the trade-off among economic performance, carbon reduction, and supply reliability.

1.4. Contribution

To address the above research gaps, this paper develops a unified cross-regional scheduling framework for a power-hydrogen-methanol multi-energy coupling system considering methanol transportation. The main contributions of this study are summarized as follows:

(1) A cross-regional power-hydrogen-methanol coordinated operation framework is established for the sending-end and receiving-end regions. In this framework, transmission tie-lines and methanol transportation form two complementary interregional energy-transfer pathways. By integrating electrolytic hydrogen production, methanol synthesis, methanol storage, methanol transportation, methanol reforming, and methanol fuel cell generation, the complete methanol production-storage-transportation-reutilization chain is explicitly embedded into the coordinated operation of electricity and hydrogen systems.

(2) A carrier-specific multi-timescale scheduling model is developed to coordinate the fast dynamics of the power system with the slow dynamics of methanol storage and transportation. Specifically, hourly electricity balance and tie-line transfer are coordinated with day-level methanol production, storage, transportation, and delayed arrival within a unified optimization framework. This modeling strategy explicitly reflects the temporal and physical differences among multiple energy carriers and improves the supply-demand matching capability between the sending-end and receiving-end regions.

(3) Based on the above cross-regional and multi-timescale framework, renewable generation uncertainty and low-carbon dispatch requirements are jointly incorporated. Historical forecast errors are used to construct a data-driven two-stage robust optimization model, while a reward-penalty differentiated stepped carbon trading mechanism is introduced to guide low-carbon operation. The resulting model is solved by the C&CG method, enabling the coordinated evaluation of operating economy, carbon-emission performance, and supply reliability under renewable uncertainty.

2. Cross-regional power-hydrogen-methanol system modeling

Considering the spatial mismatch between electricity and hydrogen energy resources and demand in China, an operation mechanism and overall framework for a power-hydrogen-methanol multi-energy coupling system can be established with cross-regional methanol transportation as the core. By fully exploiting the advantages of methanol in flexible conversion between electricity and hydrogen, as well as its suitability for large-scale storage and transportation, diversified pathways for

interregional multi-form energy transmission can be expanded. Through the coordinated operation of the interregional methanol logistics system, cross-regional complementarity of hydrogen energy can be realized, the coordinated supply capability of the multi-energy system can be enhanced, and high-penetration renewable energy accommodation over a wider spatial range and longer time horizon can be promoted.

2.1. Cross-regional methanol coupling mechanism

Taking a sending-end region and a receiving-end region as representative cases, this section describes the interregional coordinated operation framework of the electricity-hydrogen-methanol integrated system, as illustrated in Figure 1. In Figure 1, the sending end represents a renewable-energy-rich region, while the receiving end represents a region with concentrated electricity and hydrogen loads.

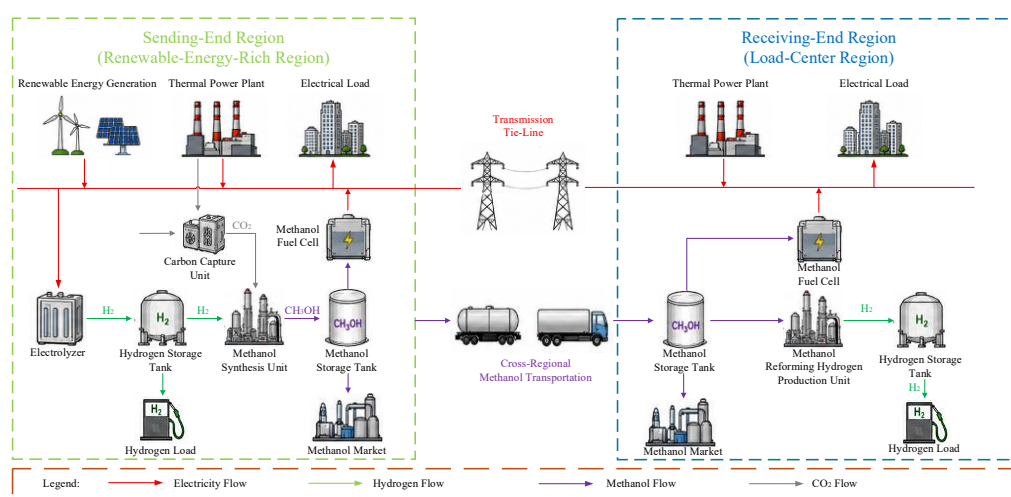


Figure 1. Configuration of the power-hydrogen-methanol system.

In order to address the seasonal fluctuations of renewable generation and load requirements, the sending-end region establishes multi-energy conversion pathways through electrolyzers, hydrogen storage tanks, carbon dioxide hydrogenation-based methanol synthesis units, fuel cells, and other devices. These conversion and storage pathways support the temporal shifting of electricity within the region and help maintain multi-timescale consistency between power output, energy supply, and demand. Surplus renewable energy in the sending-end region can also be used for hydrogen production and further converted into methanol. The produced methanol is then transported to the receiving-end region through developed railway and highway transportation networks. This process not only helps ensure the multi-timescale power and energy balance of the receiving-end region but also satisfies the demand for methanol and hydrogen in its chemical industry.

The methanol received by the receiving-end region can be directly used for chemical production; it can also be converted into hydrogen through methanol reforming to meet various hydrogen demands. Through diversified energy conversion pathways, including electricity-to-hydrogen, methanol-to-hydrogen, and hydrogen-to-electricity conversion, the receiving-end region establishes a flexible energy utilization mechanism for the power-hydrogen coupling system. Meanwhile, the hydrogen energy system enables energy transfer across multiple timescales, further supporting the

power and energy balance of the receiving-end region. The system can flexibly satisfy electricity, hydrogen, and chemical feedstock demands, while strengthening energy coordination over multiple timescales in the sending-end and receiving-end regions. In this manner, the power-hydrogen coupled system can realize interregional collaborative operation through multi-energy interaction and complementary support, thereby improving the economic efficiency, carbon reduction effect, and operational security of interconnected regional energy systems.

2.2. Methanol storage-transportation and conversion model

2.2.1. Power-to-hydrogen equipment

Surplus electricity in the system can be converted into hydrogen through water electrolysis. The coupling between hydrogen output and electric power consumption can be expressed as follows [21]:

$$Q_t^H = \frac{P_t^{WE}}{h_1} \quad (1)$$

where Q_t^H denotes the hydrogen production amount in period t ; P_t^{WE} denotes the energy consumption of water electrolysis in period t ; and h_1 denotes the unit-mass energy consumption coefficient of the electrolyzer for hydrogen production.

2.2.2. Methanol synthesis equipment

(1) Methanol synthesis reaction:



According to the stoichiometric relationship in Eq (2), three moles of hydrogen are consumed to produce one mole of methanol. Therefore, η_{HM} is defined as a mass-yield coefficient rather than a dimensionless conversion efficiency. Considering the effective hydrogen conversion and methanol selectivity, the mass-yield coefficient can be expressed as:

$$\eta_{HM} = \frac{M_{\text{CH}_3\text{OH}}}{3M_{\text{H}_2}} X_{\text{H}_2} S_{\text{MeOH}} \quad (3)$$

where $M_{\text{CH}_3\text{OH}}$ and M_{H_2} denote the molar masses of methanol and hydrogen, respectively; X_{H_2} denotes the effective hydrogen conversion; and S_{MeOH} denotes the methanol selectivity. Under ideal stoichiometric conditions, the theoretical mass-yield coefficient is $32/(3 \times 2) = 5.33$ kg-MeOH/kg-H₂. In this study, an effective conversion-selectivity factor of 0.851 is adopted, resulting in $\eta_{HM} = 4.54$ kg-MeOH/kg-H₂.

Producing methanol from carbon dioxide and green hydrogen generated by renewable-electricity-based electrolysis offers a comparatively clean and sustainable production route. The methanol production amount $m_{\text{H}_2}^M$ is expressed as follows [22]:

$$m_{\text{H}_2,t}^M = \eta_{HM} m_{\text{H}_2,M,t} \quad (4)$$

where $m_{H_2}^M$ denotes the methanol production amount in period t ; $m_{H_2,M,t}$ denotes the hydrogen input to the methanol synthesis unit; and η_{HM} denotes the hydrogen-to-methanol mass-yield coefficient, with the unit of kg-MeOH/kg- H_2 .

The carbon dioxide hydrogenation-based methanol synthesis unit is subject to the safe operational constraint expressed in Eq (5).

$$0 \leq m_{H_2,M} \leq m_{H_2,M,\max} \quad (5)$$

where $m_{H_2,M,\max}$ represents the maximum allowable hydrogen input of the carbon dioxide hydrogenation-based methanol synthesis unit.

(2) Hydrogen production model via methanol reforming

Methanol steam reforming provides a convenient and efficient pathway for hydrogen production. The corresponding chemical reaction mechanism is given as follows:



According to the stoichiometric relationship of methanol steam reforming, one mole of methanol theoretically produces three moles of hydrogen. Therefore, η_{MH} is also defined as a mass-yield coefficient. In general, it can be expressed as:

$$\eta_{MH} = \frac{3M_{H_2}}{M_{CH_3OH}} X_{MeOH} S_{H_2} \quad (7)$$

where X_{MeOH} denotes the methanol conversion, and S_{H_2} denotes the effective hydrogen yield factor.

The energy conversion model for methanol steam reforming-based hydrogen generation is formulated as follows [23]:

$$m_{M,t}^{H_2} = \eta_{MH} m_{M,H_2,t} \quad (8)$$

where $m_{M,t}^{H_2}$ denotes the hydrogen production amount via methanol reforming; η_{MH} denotes the conversion efficiency of hydrogen production via methanol reforming; and $m_{M,H_2,t}$ denotes the methanol input.

The methanol feedstock input should satisfy the following constraint:

$$0 \leq m_{M,H_2} \leq m_{M,H_2,\max} \quad (9)$$

where $m_{M,H_2,\max}$ represents the maximum allowable methanol input of the methanol reforming hydrogen production unit.

2.2.3. Methanol fuel cell model

The direct methanol fuel cell (DMFC) enables the transformation of chemical energy into electrical energy. The energy conversion relationship and carbon emissions are expressed as follows [24]:

$$\begin{aligned} P_t^{\text{DMFC}} &= k_M Q_t^{\text{DMFC}} \\ Q_t^{\text{MCC}} &= m_C Q_t^{\text{DMFC}} \end{aligned} \quad (10)$$

where P_t^{DMFC} denotes the output power of the methanol fuel cell in period t ; k_M denotes the electricity generation per unit mass of methanol; Q_t^{DMFC} denotes the mass of methanol consumed by the methanol fuel cell in period t ; Q_t^{MCC} denotes the carbon emissions of the methanol fuel cell in period t ; and m_C denotes the carbon emission conversion coefficient per unit mass of methanol consumed by the methanol fuel cell.

The carbon-emission conversion coefficient m_C is derived from the complete oxidation stoichiometry of methanol. Since one mole of methanol ultimately corresponds to one mole of CO_2 ,

$$m_C = \frac{M_{\text{CO}_2}}{M_{\text{CH}_3\text{OH}}} \quad (11)$$

2.2.4. Carbon capture unit

In this study, the carbon capture device recovers carbon dioxide from the flue gas of thermal power plants, which is then used as a raw material for hydrogen-based methanol synthesis. The corresponding energy consumption P_t^{cc} is given by [25]:

$$P_t^{\text{cc}} = k_{\text{cc}} Q_t^{\text{cc}} \quad (12)$$

where k_{cc} denotes the energy consumption coefficient per unit mass of CO_2 captured by the carbon capture unit, and Q_t^{cc} denotes the amount of CO_2 captured by the carbon capture unit in period t .

$$Q_t^{\text{TP}} = \gamma_c \sum_{n=1}^{N_g} P_{n,t}^{\text{TP}} \Delta t \quad (13)$$

where Q_t^{TP} denotes the gross CO_2 emissions from thermal power generation in period t ; γ_c denotes the carbon-emission coefficient of thermal power generation; $P_{n,t}^{\text{TP}}$ denotes the output power of thermal unit n ; and Δt denotes the duration of the scheduling period.

$$0 \leq Q_t^{\text{CC}} \leq \rho_{\text{CC}} Q_t^{\text{TP}} \quad (14)$$

where Q_t^{CC} denotes the amount of CO_2 captured by the carbon capture unit, and ρ_{CC} denotes the maximum CO_2 capture rate.

To further characterize the operational coupling between the carbon capture unit and methanol synthesis, the captured CO_2 amount is explicitly linked to the CO_2 requirement of methanol production. According to the stoichiometric relationship of CO_2 hydrogenation for methanol synthesis, one mole of CO_2 is required for each mole of methanol produced. Therefore, the corresponding mass relationship can be expressed as:

$$m_{\text{CO}_2,t}^{\text{syn}} = \frac{44}{32} m_{M,t}^{\text{syn}} = 1.3775 m_{M,t}^{\text{syn}} \quad (15)$$

Since no independent CO₂ storage unit or external CO₂ supply is considered in the present system, the captured CO₂ is directly supplied to the methanol synthesis process. Accordingly,

$$m_{CO_2,t}^{syn} = \frac{44}{32} m_{M,t}^{syn} = 1.3775 m_{M,t}^{syn} \quad (16)$$

where $m_{CO_2,t}^{syn}$ denotes the CO₂ consumption of the methanol synthesis unit in period t ; $m_{M,t}^{syn}$ denotes the methanol production amount; and $m_{CO_2,t}^{cap}$ denotes the amount of CO₂ captured by the carbon capture unit.

2.2.5. Carbon-flow balance and net carbon emissions

To establish a closed carbon accounting boundary for the power-hydrogen-methanol conversion chain, the CO₂ flows among thermal power generation, carbon capture, methanol synthesis, methanol reforming, and DMFC operation are explicitly linked. In particular, the captured CO₂ used for methanol synthesis is treated as an intermediate carbon flow rather than permanent carbon removal, because the carbon incorporated into methanol can subsequently be released during methanol reforming or DMFC operation.

Similarly, according to the methanol steam reforming reaction, one mole of CO₂ is produced from one mole of converted methanol. The corresponding CO₂ emission is expressed as:

$$Q_t^{MR} = \frac{M_{CO_2}}{M_{CH_3OH}} \quad (17)$$

where Q_t^{MR} denotes the CO₂ released from methanol steam reforming.

Based on the above carbon-flow relationships, the net operational CO₂ emissions of the system are calculated as:

$$Q_t^{net} = Q_t^{TP} - Q_t^{CC} + Q_t^{MR} + Q_t^{DMFC} \quad (18)$$

where Q_t^{net} denotes the net operational CO₂ emissions of the system; Q_t^{TP} denotes gross thermal-plant emissions; Q_t^{CC} denotes captured CO₂; Q_t^{MR} denotes CO₂ released from methanol reforming; and Q_t^{DMFC} denotes CO₂ released from DMFC operation.

2.3. Reward-penalty carbon trading scheme

The actual CO₂ emissions participating in the carbon trading mechanism are defined as:

$$Q_t^c = Q_t^{net} \quad (19)$$

The system can generate economic benefits by transferring unused carbon quotas through the carbon market. Conversely, when the allocated carbon emission allowances are insufficient, additional allowances must be purchased, thereby incurring carbon trading costs [26]. In the conventional carbon trading scheme, the net cost associated with carbon allowance transactions can be described as follows:

$$C_t^c = \mu_c (Q_t^c - A_t^c) \quad (20)$$

$$A_t^c = \gamma_c (P_t^{\text{TP}} + P_t^{\text{DMFC}}) \quad (21)$$

where C_t^c represents the reward-penalty differentiated ladder-type carbon trading cost of the system in period t ; μ_c is the benchmark carbon trading price; Q_t^c denotes the actual net CO₂ emissions participating in carbon trading, which are obtained from the closed carbon-flow balance in Eq (18); A_t^c denotes the allocated carbon-emission allowance of the system; P_t^{TP} is the output power of thermal power plants in period t ; and γ_c is the benchmark value of carbon emission allowance allocated per unit output of power generation units [27].

To strengthen the system's incentive for participating in carbon allowance transactions and to refine the carbon pricing scheme, this study introduces a differentiated stepwise carbon trading mechanism with reward and penalty effects. The total carbon emission level is segmented into several ranges, and a higher trading price is imposed when emissions fall into a higher range. If the system's actual emissions are below the assigned carbon quota, a corresponding reward for emission reduction is granted. Moreover, the lengths of the reward and penalty intervals are differentiated, thereby improving the general applicability of the mechanism. The proposed differentiated stepwise carbon trading formulation with reward-penalty characteristics is given as follows:

$$C_t^c = \begin{cases} \mu_c(1+3s)(Q_t^c - A_t^c + 2N) - \mu_c(2+3s)N, & A_t^c - 3N \leq Q_t^c \leq A_t^c - 2N \\ \mu_c(1+2s)(Q_t^c - A_t^c + N) - \mu_c(1+s)N, & A_t^c - 2N < Q_t^c \leq A_t^c - N \\ \mu_c(1+s)(Q_t^c - A_t^c), & A_t^c - N < Q_t^c \leq A_t^c \\ \mu_c(Q_t^c - A_t^c), & A_t^c < Q_t^c \leq A_t^c + L \\ \mu_c(1+v)(Q_t^c - A_t^c - L) + \mu_c L, & A_t^c + L < Q_t^c \leq A_t^c + 2L \\ \mu_c(1+2v)(Q_t^c - A_t^c - 2L) + \mu_c(2+v)L, & A_t^c + 2L < Q_t^c \leq A_t^c + 3L \\ \mu_c(1+3v)(Q_t^c - A_t^c - 3L) + \mu_c(3+3v)L, & A_t^c + 3L < Q_t^c \leq A_t^c + 4L \end{cases} \quad (22)$$

where s and v represent the stepwise growth rates of the emission-reduction reward and carbon-emission penalty, respectively; and N and L represent the interval lengths of the emission-reduction reward and carbon-emission penalty, respectively.

Figure 2 illustrates the relationship between the carbon transaction price and the traded carbon amount. Positive intervals indicate that actual emissions exceed the allocated quota, requiring the system to purchase additional quotas and incur carbon penalty costs. Conversely, negative intervals indicate surplus quotas caused by lower actual emissions, which can be sold to obtain emission-reduction rewards.

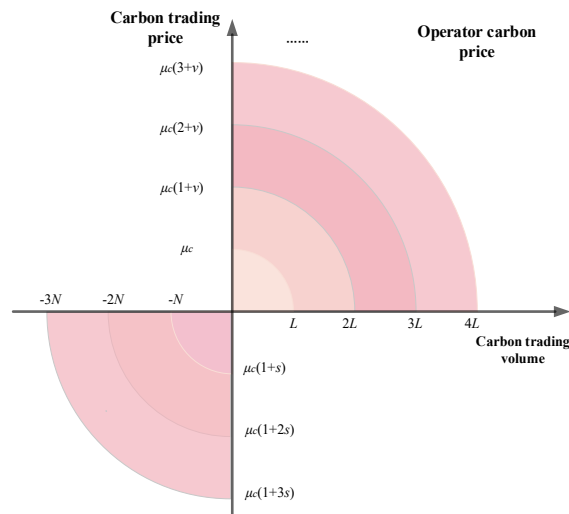


Figure 2. Carbon trading price-quantity relationship.

2.4. Cross-regional methanol storage-transportation model

To consistently characterize the methanol inventory evolution at the sending and receiving ends, the inventory balances of the two regions are formulated separately. The sending-end methanol inventory is supplied by local methanol synthesis and is consumed by cross-regional transportation and DMFC operation, whereas the receiving-end inventory is supplied by transported and purchased methanol and is consumed by market sales, methanol reforming, and DMFC operation. Accordingly, the methanol inventory balances are expressed as follows [28]:

$$Q_{j,d}^M = Q_{j,d-1}^M + m_{H_2,j,d}^M - T_{j \rightarrow r,d}^M - m_{j,DMFC,d}^M \quad (23)$$

$$Q_{r,d}^M = Q_{r,d-1}^M + T_{j \rightarrow r,d-\delta}^M + m_{b,r,d}^M - m_{r,MS,d}^M - m_{r,M_2E_2,d}^M - m_{r,DMFC,d}^M \quad (24)$$

$$0 \leq Q_{s,d}^M \leq Q_{s,\max}^M \quad (25)$$

$$0 \leq T_{s \rightarrow d}^M \leq Q_{s,d}^M \quad (26)$$

$$Q_{s,1}^M = Q_{s,T}^M \quad (27)$$

where $Q_{j,d}^M$ and $Q_{r,d}^M$ denote the methanol inventories of the sending-end and receiving-end regions on day d , respectively; $m_{H_2,j,d}^M$ denotes the daily methanol production at the sending end; $T_{j \rightarrow r,d}^M$ denotes the methanol dispatched from the sending end on day d ; $T_{j \rightarrow r,d-\delta}^M$ denotes the methanol dispatched on day $d-\delta$ and arriving at the receiving end on day d ; $m_{b,r,d}^M$ denotes the purchased methanol at the receiving end; $m_{r,MS,d}^M$ denotes the methanol sold to the external market; $m_{r,M,H_2,d}^M$ denotes the methanol consumed for hydrogen production via reforming; and $m_{j,DMFC,d}^M$ and $m_{r,DMFC,d}^M$ denote the daily

methanol consumption of the DMFCs at the sending and receiving ends, respectively. Considering regional supply-demand conditions and the economic utilization of system energy, methanol sales are only considered in the receiving-end region. $Q_{s,\max}^M$ is the upper limit of methanol storage capacity; δ is the transportation delay time related to the transportation distance; and $Q_{s,l}^M$ and $Q_{s,T}^M$ are the initial and terminal methanol inventories within the scheduling horizon, respectively.

In addition to the storage and delayed-arrival constraints, the available logistics capacity should also limit the daily methanol transportation amount. Therefore, the following transportation-capacity constraint is introduced:

$$0 \leq m_d^{M,tr} \leq \rho_d \bar{m}^{M,tr}, \quad d \in \mathcal{D} \quad (28)$$

where $m_d^{M,tr}$ denotes the methanol dispatched from the sending-end region on day d ; $\bar{m}^{M,tr}$ denotes the rated daily transportation capacity of the cross-regional methanol logistics channel; and ρ_d is the transportation availability coefficient, satisfying $0 < \rho_d \leq 1$. Under normal transportation conditions, $\rho_d = 1$. When adverse weather, traffic congestion, or temporary logistics restrictions occur, $\rho_d < 1$ can be adopted to represent the corresponding reduction in available transportation capacity.

To avoid restricting the transportation model to a strictly fixed travel time, the effective transportation delay is represented as:

$$\delta_d = \delta_0 + \Delta\delta_d \quad (29)$$

where δ_0 denotes the nominal transportation delay under normal operating conditions, which is set to 2 days in the case study, and $\Delta\delta_d$ denotes the additional delay caused by adverse transportation conditions, such as congestion or severe weather. Accordingly, the daily methanol arrival amount can be expressed as:

$$m_{\tau}^{M,arr} = \sum_{d \in \mathcal{D}} a_{d,\tau} m_d^{M,tr} \quad (30)$$

where $a_{d,\tau}$ is a predefined transportation-arrival parameter linking the dispatch day and the corresponding arrival day.

2.5. Regional multi-energy balance model

With coordinated electricity-methanol transportation, the sending-end region can supply both electricity and methanol to the receiving-end region, thereby improving renewable energy accommodation at the sending end and supporting diversified energy demands at the receiving end. Accordingly, taking into account the coupled energy exchanges between the sending-end and receiving-end regions, this study formulates a regional supply-demand equilibrium model for both areas.

2.5.1. Sending-end energy balance model

(1) Power and energy balance model for the sending-end region

1) Electrical energy balance model:

$$Q_{j,E,d} + Q_{j,h,d} + Q_{j,l,d} + Q_{j, \text{cap},d} + Q_{r,d} = Q_{R,d} + \sum_{n=1}^{N_{j,h}} Q_{H,d,n} \quad (31)$$

where $Q_{j,E,d}$ denotes the electricity demand of the sending-end region on day d ; $Q_{j,l,d}$ denotes the electricity transmitted from the sending-end region on day d ; $Q_{j,h,d}$ denotes the electricity consumption of the electrolyzer on day d ; $Q_{j, \text{cap},d}$ denotes the electricity consumption of the carbon capture unit on day d ; $Q_{r,d}$ denotes the total curtailed wind and photovoltaic energy on day d ; $Q_{R,d}$ denotes the total wind and photovoltaic power generation on day d ; $Q_{H,d,n}$ denotes the electricity generation of thermal unit n on day d ; and $N_{j,h}$ denotes the number of thermal units in the sending-end region.

2) Power balance model:

$$P_{j,E,t} + P_{j,h,t} + P_{j,l,t} + P_t^{cc} + P_{r,t} = P_{R,t} + \sum_{n=1}^{N_{j,h}} P_{H,t,n} + P_{t,j}^{\text{DMFC}} + P_{j,F,t} \quad (32)$$

where $P_{j,E,t}$ denotes the electrical load of the sending-end region in period t ; $P_{j,h,t}$ denotes the power consumption of the electrolyzer in the sending-end region in period t ; $P_{j,l,t}$ denotes the power transmitted from the sending-end region in period t ; P_t^{cc} denotes the power consumption of the carbon capture unit in period t ; $P_{r,t}$ denotes the total curtailed wind and photovoltaic power in period t ; $P_{R,t}$ denotes the total wind and photovoltaic power generation in period t ; $P_{H,t,n}$ denotes the power generation of thermal unit n in period t ; $P_{t,j}^{\text{DMFC}}$ denotes the power generation of the methanol fuel cell in the sending-end region in period t ; and $P_{j,F,t}$ denotes the load shedding power of the sending-end region in period t .

(2) Hydrogen supply-demand balance model for the sending-end region:

$$m_{j,E,d}^{H_2} + m_{j,\text{out},d}^{H_2} + m_{j,\text{buy},d}^{H_2} = m_{j,D,d}^{H_2} + m_{j,\text{in},d}^{H_2} + m_{H_2,M,d}^{H_2} \quad (33)$$

where $m_{j,E,d}^{H_2}$ denotes the hydrogen production of the electrolyzer in the sending-end region on day d ; $m_{j,\text{in},d}^{H_2}$ and $m_{j,\text{out},d}^{H_2}$ denote the hydrogen charging and discharging amounts of the hydrogen storage tank, respectively; $m_{j,\text{buy},d}^{H_2}$ denotes the purchased hydrogen amount; $m_{j,D,d}^{H_2}$ denotes the hydrogen load demand; and $m_{H_2,M,d}^{H_2}$ denotes the hydrogen consumed for methanol synthesis. The hydrogen produced by the electrolyzer can directly supply the hydrogen load, while the remaining hydrogen can be stored or used for methanol synthesis according to the system operating conditions.

2.5.2. Receiving-end energy balance model

(1) Power and energy balance model for the receiving-end region

1) Electrical energy balance model:

$$Q_{r,E,d} + Q_{r,h,d} = Q_{r,l,d} + \sum_{n=1}^{N_{r,h}} Q_{H,d,n} \quad (34)$$

where $Q_{r,E,d}$ denotes the electricity demand of the receiving-end region on day d ; $Q_{r,l,d}$ denotes the electricity received by the receiving-end region through transmission tie-lines on day d ; $Q_{r,h,d}$ denotes the electricity consumption of the electrolyzer in the receiving-end region on day d ; and $N_{r,h}$ denotes

the number of thermal units in the receiving-end region.

2) Power balance model:

$$P_{r,E,t} + P_{r,h,t} = P_{r,l,t} + \sum_{n=1}^{N_{r,h}} P_{H,t,n} + P_{t,r}^{\text{DMFC}} + P_{r,F,t} \quad (35)$$

where $P_{r,E,t}$ denotes the electrical load of the receiving-end region in period t ; $P_{r,h,t}$ denotes the power consumption of the electrolyzer in the receiving-end region in period t ; $P_{r,l,t}$ denotes the power received by the receiving-end region through transmission tie-lines in period t ; $P_{t,r}^{\text{DMFC}}$ denotes the power generation of the fuel cell in the receiving-end region in period t ; and $P_{r,F,t}$ denotes the load shedding power of the receiving-end region in period t .

(2) Receiving-end hydrogen supply-demand balance model:

$$m_{r,E,d}^{H_2} + m_{M,H_2,d}^{H_2} + m_{r,out,d}^{H_2} + m_{r,buy,d}^{H_2} = m_{r,D,d}^{H_2} + m_{r,in,d}^{H_2} \quad (36)$$

where $m_{r,E,d}^{H_2}$ denotes the hydrogen production of the electrolyzer in the receiving-end region on day d ; $m_{M,H_2,d}^{H_2}$ denotes the hydrogen production via methanol reforming; $m_{r,in,d}^{H_2}$ and $m_{r,out,d}^{H_2}$ denote the hydrogen charging and discharging amounts of the hydrogen storage tank, respectively; $m_{r,buy,d}^{H_2}$ denotes the purchased hydrogen amount; and $m_{r,D,d}^{H_2}$ denotes the hydrogen load demand. Electrolytic hydrogen and reforming-produced hydrogen can directly supply the hydrogen load, and surplus hydrogen can be charged into the hydrogen storage tank for subsequent use.

2.5.3. Sending-receiving energy coupling model

Energy exchange across the two regions is realized by means of interregional transmission tie-lines and methanol delivery channels. Accordingly, the electricity supply-demand coupling constraints and methanol transportation coupling constraints across different timescales should be satisfied.

(1) Electrical energy coupling constraints between the sending-end and receiving-end regions

Across different timescales, the transmitted power and electrical energy at the sending end should be consistent with the received power and electrical energy at the receiving end.

$$\begin{cases} Q_{j,l,d} = Q_{r,l,d} \\ P_{j,l,t} = P_{r,l,t} \end{cases} \quad (37)$$

(2) Methanol transport coupling constraints between the sending-end and receiving-end regions:

$$T_{r,d}^{M,arr} = T_{j \rightarrow r, d-\delta}^{M,dep}, \quad d = \delta + 1, \dots, D \quad (38)$$

where $T_{j \rightarrow r, d}^{M,dep}$ denotes the amount of methanol dispatched from the sending-end region on day d ; $T_{r,d}^{M,arr}$ denotes the amount of methanol arriving at the receiving-end region on day d ; δ denotes the methanol transportation delay in days; and D denotes the total number of days in the scheduling horizon.

Equation (38) describes the delayed methanol transportation relationship between the sending-end and receiving-end regions. Specifically, methanol dispatched from the sending-end region on day $d-\delta$ arrives at the receiving-end region on day d , or equivalently, methanol dispatched on day

d arrives at the receiving end on day $d + \delta$. For the first δ days of the scheduling horizon, the initial in-transit methanol quantity is assumed to be zero; therefore, no methanol dispatched before the scheduling horizon is considered to arrive during these periods. Methanol dispatched during the final δ days arrives after the current scheduling horizon and is therefore treated as terminal in-transit methanol and is not included in the receiving-end inventory or available for utilization within the current horizon.

3. Cross-regional electricity-methanol scheduling model

Based on the multi-energy collaborative operation mechanism and dispatch framework for the sending-end and receiving-end areas with coordinated electricity transmission and methanol transport, a unified dispatch model is developed for the cross-regional power-hydrogen-methanol coupled system. In this model, the supply-demand relationships among different energy carriers and the interregional transfer channels are jointly considered. The proposed model introduces both daily-level and hourly-level decision variables within the same optimization framework, and describes the interdependencies among thermal unit commitment, transmission tie-line power, methanol transportation, electrolytic hydrogen production, hydrogen storage, and methanol reutilization through cross-timescale coupling constraints, thereby coordinating real-time power balance with daily-level methanol storage and transportation. Moreover, to handle wind and solar generation fluctuations in the sending-end area, this study incorporates a DDRO approach. The original deterministic dispatch formulation is further transformed into a two-stage robust counterpart, which is then addressed through the C&CG method.

3.1. Multi-timescale scheduling model

3.1.1. Objective function

The objective function is given as follows:

$$\min C = C_{\text{HSC}} + C_K + C_O + C_L + C_Q + C_H + C_t^c + C_B + C_F \quad (39)$$

where C denotes the total cost of the scheduling model; C_{HSC} denotes the hydrogen supply cost; C_K denotes the startup and shutdown cost of thermal units; C_O denotes the operation and maintenance cost of hydrogen storage tanks; C_L denotes the cross-regional electricity transmission cost; C_Q denotes the renewable energy curtailment penalty cost; C_H denotes the generation cost of thermal units; C_t^c denotes the reward-penalty differentiated ladder-type carbon trading cost; and C_B and C_F denote the operation and maintenance cost of methanol fuel cells and the load shedding penalty cost, respectively.

$$C_{\text{HSC}} = \sum_{d=1}^D \sum_{s \in S} \left[\lambda_T D_d T_{s \rightarrow d}^M + \lambda_e E_{r,E,d} + \lambda_p m_{H_2,M,d} + \lambda_{MH} m_{M,H_2,d} + \lambda_H m_{s,\text{buy},d}^{H_2} + (\lambda_{b,d}^M + \lambda_E) m_{b,d}^M - \lambda_M m_{s,M,H_2,d} \right] \quad (40)$$

$$C_K = \sum_{d=1}^D \sum_{n=1}^{N_h} \left[U_{n,d} (1 - U_{n,d-1}) + U_{n,d-1} (1 - U_{n,d}) \right] S_n^d \quad (41)$$

$$C_O = \sum_{d=1}^D \sum_{s \in S} \lambda_g (m_{s,\text{in},d}^{\text{H}_2} + m_{s,\text{out},d}^{\text{H}_2}) \quad (42)$$

$$C_L = \sum_{d=1}^D \lambda_{\text{line}} E_{s,1,d} \quad (43)$$

$$C_Q = \sum_{d=1}^D \lambda_r E_{r,d} \quad (44)$$

$$C_H = \sum_{d=1}^D \sum_{n=1}^{N_h} f(E_{H,d,n}) \quad (45)$$

$$C_B = \sum_{d=1}^D \sum_{t=1}^{T_d} \sum_{s \in S} \lambda_B P_{s,t}^{\text{DMFC}} \quad (46)$$

$$C_F = \sum_{d=1}^D \sum_{t=1}^{T_d} \sum_{s \in S} \lambda_F P_{s,F,t} \quad (47)$$

where D denotes the scheduling horizon of the model, which is set to 365 days in this paper; λ_T denotes the unit transportation price of methanol; D_d denotes the transportation distance; λ_c denotes the transmission and distribution tariff; λ_p denotes the unit cost of methanol synthesis via carbon dioxide hydrogenation; λ_{MH} denotes the unit cost of hydrogen production via methanol reforming; $\lambda_{b,d}^M$ and λ_E denote the purchase price of methanol and the environmental penalty cost coefficient of purchased methanol, respectively; $\lambda_{b,d}^{\text{H}_2}$ denotes the purchase price of hydrogen; $m_{b,d}^M$ denotes the methanol purchase amount; λ_M denotes the methanol selling price; λ_H denotes the hydrogen selling price; λ_g denotes the unit operation and maintenance cost of the hydrogen storage tank; λ_{line} denotes the unit cost of electricity transmission; λ_r denotes the renewable energy curtailment penalty coefficient; N_h denotes the total number of thermal units in the sending-end and receiving-end regions; $f(E_{H,d,n})$ denotes the generation cost function of thermal unit n ; $U_{n,d}$ denotes the startup and shutdown state of thermal unit n on day d , where $U_{n,d} = 0$ indicates that the unit is off, and $U_{n,d} = 1$ indicates that the unit is on; S_n^d denotes the startup and shutdown cost of thermal unit n ; T_d denotes the lower-level scheduling horizon on day d , which is set to 24 h; λ_B denotes the unit operation and maintenance cost of methanol fuel cells; and λ_F denotes the unit load shedding penalty cost.

3.1.2. Daily-level operational constraints

In addition to Eqs (1)–(47), the power and hydrogen subsystems are further subject to thermal unit operational constraints, renewable energy curtailment constraints, transmission tie-line transfer constraints, electrolyzer operational constraints, and hydrogen storage tank constraints.

(1) Power subsystem

1) Thermal unit operational constraints:

$$U_{n,d} Q_{H,n,\min} \leq Q_{H,d,n} \leq U_{n,d} Q_{H,n,\max} \quad (48)$$

$$\begin{cases} (U_{n,d-1} - U_{n,d})(T_{n,d-1}^H - T_{n,\text{on}}^H) \geq 0 \\ (U_{n,d} - U_{n,d-1})(T_{n,d-1}^H - T_{n,\text{off}}^H) \geq 0 \end{cases} \quad (49)$$

$$\begin{cases} \sum_{n=1}^{N_{j,h}} U_{n,d} Q_{H,n,\max} \geq (1 + K_L) Q_{j,E,d} + K_W Q_{R,d} \\ \sum_{n=1}^{N_{r,h}} U_{n,d} Q_{H,n,\max} \geq (1 + K_L) Q_{r,E,d} \end{cases} \quad (50)$$

where $Q_{H,n,\max}$ and $Q_{H,n,\min}$ are the upper and lower limits of the daily electricity generation of thermal units, respectively; $T_{n,d-1}^H$ is the accumulated on/off duration of thermal unit n before day $d-1$; $T_{n,\text{on}}^H$ and $T_{n,\text{off}}^H$ are the minimum on-time and off-time durations, respectively; and K_L and K_W are the reserve coefficients associated with load demand and renewable energy generation, respectively. Eq (48) gives the daily generation constraint of thermal units; Eq (49) describes the unit commitment constraint, which is nonlinear and can be linearized; and Eq (50) gives the reserve constraint of thermal units.

2) Renewable energy curtailment constraints:

$$0 \leq Q_{r,d} \leq Q_{R,d} \quad (51)$$

3) Transmission tie-line transfer constraints:

$$Q_{l,\min} \leq Q_{s,l,d} \leq Q_{l,\max} \quad (52)$$

where $Q_{l,\max}$ and $Q_{l,\min}$ denote the upper and lower limits of the daily electricity transmission through regional transmission tie-lines, respectively.

(2) Hydrogen subsystem

1) Daily operational constraints of electrolyzers [29]

To guarantee the practicability and consistency of daily methanol delivery decisions and thermal unit commitment arrangements, the daily operating constraints of electrolyzers need to be incorporated. The electrolyzer operation model is formulated as follows:

$$m_{s,E,d}^{H_2} = \frac{\eta^{H_2} Q_{s,h,d}}{\text{LHV}_{H_2}} \quad (53)$$

$$0 \leq Q_{s,h,d} \leq Q_{s,h,\max} \quad (54)$$

where η^{H_2} denotes the operating efficiency of the electrolyzer; $Q_{s,h,d}$ denotes the daily electricity consumption of the electrolyzer in the sending-end or receiving-end region on day d ; LHV_{H_2} denotes the lower heating value of hydrogen, which is usually taken as 33.3 kWh/kg; and $Q_{s,h,\max}$ denotes the upper limit of the daily electricity consumption of the electrolyzer.

2) Operational constraints of hydrogen storage tanks [30]

In the daily-level model, its daily storage characteristics are mainly considered. Its operation should satisfy constraints related to the temporal evolution of hydrogen storage and the safe hydrogen storage capacity, which are formulated as follows:

$$m_{s,g,d+1}^{H_2} = m_{s,g,d}^{H_2} + m_{s,\text{in},d}^{H_2} \eta_{g,\text{in}} - \frac{m_{s,\text{out},d}^{H_2}}{\eta_{g,\text{out}}} \quad (55)$$

$$0 \leq m_{s,g,d}^{H_2} \leq m_{s,g,\max}^{H_2} \quad (56)$$

$$0 \leq m_{s,\text{in},d}^{H_2} \leq m_{s,\text{in},\max}^{H_2} \quad (57)$$

$$0 \leq m_{s,\text{out},d}^{H_2} \leq m_{s,\text{out},\max}^{H_2} \quad (58)$$

$$m_{s,g,l}^{H_2} = m_{s,g,T}^{H_2} \quad (59)$$

where $m_{s,g,d}^{H_2}$ denotes the hydrogen storage amount of the hydrogen storage tank in the sending-end or receiving-end region on day d ; $\eta_{g,\text{in}}$ and $\eta_{g,\text{out}}$ denote the hydrogen charging and discharging efficiencies of the hydrogen storage tank, respectively; $m_{s,g,\max}^{H_2}$ denotes the capacity of the hydrogen storage tank; $m_{s,\text{in},\max}^{H_2}$ and $m_{s,\text{out},\max}^{H_2}$ denote the upper limits of the daily hydrogen charging and discharging amounts of the hydrogen storage tank, respectively; and $m_{s,g,l}^{H_2}$ and $m_{s,g,T}^{H_2}$ denote the initial and terminal hydrogen storage amounts of the hydrogen storage tank within the scheduling horizon, respectively.

3.1.3. Hourly-level operational constraints

The hourly-level constraints mainly involve thermal unit output, power balance, electrolyzer operation, fuel cell output, methanol synthesis, and methanol reforming in each hourly period.

(1) Power subsystem

Thermal unit ramping constraints [31]:

$$P_{n,\text{down}} \leq (P_{H,t,n} - P_{H,t-1,n})U_{n,t-1}U_{n,t} \leq P_{n,\text{up}} \quad (60)$$

where $P_{n,\text{up}}$ and $P_{n,\text{down}}$ denote the upper and lower ramping rate limits of thermal unit n , respectively.

(2) Hydrogen subsystem

1) Hourly-level operational constraints of electrolyzers [32]:

$$m_{s,E,t}^{H_2} = \frac{\eta^{H_2} Q_{s,h,t}}{\text{LHV}_{H_2}} \quad (61)$$

$$0 \leq Q_{s,h,t} \leq Q_{s,h,\max} \quad (62)$$

$$m_{s,E,d}^{H_2} = \sum_{t \in T_d} m_{s,E,t}^{H_2} \quad (63)$$

where $m_{s,E,t}^{H_2}$ denotes the electrolytic hydrogen production amount of the electrolyzer in the sending-end or receiving-end region in period t ; $Q_{s,h,t}$ denotes the electricity consumption of the electrolyzer in the sending-end or receiving-end region in period t ; and $Q_{s,h,\max}$ denotes the upper limit of the electricity consumption of the electrolyzer in period (t). Eq (63) indicates that the daily electrolytic hydrogen production amount of the electrolyzer on day d is equal to the sum of its hydrogen production amounts over all periods of day d .

2) Methanol fuel cell operational constraints [33]:

$$P_{\min}^{\text{DMFC}} \leq P_t^{\text{DMFC}} \leq P_{\max}^{\text{DMFC}} \quad (64)$$

where $P_{\min}^{\text{DMFC}}$ and $P_{\max}^{\text{DMFC}}$ denote the upper and lower power limits of the methanol fuel cell, respectively.

(3) Operational constraints of methanol production, storage, and transportation

1) Sending-end methanol synthesis operational constraints [34]:

$$m_{j,H_2,t}^M = \eta_{\text{HM}} m_{H_2,M,t} \quad (65)$$

$$0 \leq m_{H_2,M,t} \leq \min \left\{ m_{j,E,t}^{H_2}, m_{H_2,M,\max} \right\} \quad (66)$$

where $m_{j,H_2,t}^M$ denotes the methanol synthesis amount via carbon dioxide hydrogenation at the sending end in period t ; and $m_{H_2,M,t}$ denotes the hydrogen input of the sending-end methanol synthesis unit in period t . Eq (66) indicates that the hydrogen input of the sending-end methanol synthesis unit in period t should not exceed either its safety limit or the electrolytic hydrogen production amount of the sending-end electrolyzer in period t .

2) Hydrogen production constraints via receiving-end methanol reforming [35]

To avoid directly assigning the methanol purchased and received on a given day to the reforming unit, the receiving-end methanol utilization is determined through the inventory balance in Eq (24). The following constraints are introduced only to establish consistency between the daily-level and hourly-level methanol variables:

$$\begin{cases} m_{r,M,H_2,d} = \sum_{t \in T_d} m_{M,H_2,t} \\ m_{b,r,d}^M = \sum_{t \in T_d} m_{b,t}^M \\ m_{r,DMFC,d}^M = \sum_{t \in T_d} Q_{r,t}^{\text{DMFC}} \end{cases} \quad (67)$$

$$0 \leq m_{M,H_2,t} \leq m_{M,H_2,\max} \quad (68)$$

where $m_{M,H_2,t}$ denotes the hourly methanol consumption for hydrogen production via reforming at the receiving end; $m_{b,t}^M$ denotes the hourly purchased methanol amount; and $Q_{r,t}^{\text{DMFC}}$ denotes the hourly methanol consumption of the receiving-end DMFC. Eq (67) establishes the daily-hourly coupling relationships for methanol reforming, methanol purchases, and DMFC consumption, while Eq (68) limits the hourly methanol input of the reforming unit. The allocation of methanol among storage, market sales, reforming, and DMFC utilization is governed by the unified receiving-end inventory balance in Eq (24).

3) Daily-hourly coupling of methanol production and consumption:

$$m_{H_2,j,d}^M = \sum_{t \in T_d} m_{j,H_2,t}^M \quad (69)$$

$$m_{j,DMFC,d}^M = \sum_{t \in T_d} Q_{j,t}^{\text{DMFC}} \quad (70)$$

where $m_{j,H_2,t}^M$ denotes the hourly methanol production via carbon dioxide hydrogenation at the sending end, and $Q_{j,t}^{DMFC}$ denotes the hourly methanol consumption of the sending-end DMFC. Eqs (69) and (70) establish the daily-hourly consistency of methanol production and DMFC consumption, respectively. The daily sending-end methanol inventory is no longer independently recalculated in the hourly-level model; instead, it is uniquely determined by the inventory balance in Eq (23), thereby avoiding duplicated or inconsistent methanol balance constraints.

3.1.4. Cross-timescale coupling constraints

The daily-level variables and hourly-level variables are linked through the following coupling constraints to ensure the consistency of the model across multiple timescales. Multi-timescale scheduling is capable of coordinating the dynamic response features of electrolyzers, fuel cells, and hydrogen storage units across different operating horizons, and has been utilized to enhance the capability of power-hydrogen IES in accommodating renewable power variations [36].

The daily-level electricity variables are obtained by aggregating the corresponding hourly power variables over all hourly periods within day d . Specifically, the relationship between the daily electricity transmission quantity $Q_{j,l,d}$ and the hourly transmission power $P_{j,l,t}$ is expressed as:

(1) Coupling between daily electricity and hourly power:

$$Q_{H,d,n} = \sum_{t \in d} P_{H,t,n} \cdot \Delta t \quad (71)$$

$$Q_{j,l,d} = \sum_{t \in d} P_{j,l,t} \cdot \Delta t \quad (72)$$

$$Q_{j,h,d} = \sum_{t \in d} P_{j,h,t} \cdot \Delta t \quad (73)$$

$$Q_{r,h,d} = \sum_{t \in d} P_{r,h,t} \cdot \Delta t \quad (74)$$

(2) Daily-hourly coupling of hydrogen production:

$$m_{j,E,d}^{H_2} = \sum_{t \in d} m_{j,E,t}^{H_2} \quad (75)$$

$$m_{r,E,d}^{H_2} = \sum_{t \in d} m_{r,E,t}^{H_2} \quad (76)$$

(3) Daily-hourly coupling constraint between methanol transportation and methanol production:

$$T_{s \rightarrow, d}^M \leq Q_{s, d-1}^M + \sum_{t \in d} m_{H_2, t}^M \quad (77)$$

where $\mathcal{T}_d$ denotes the set of hourly periods belonging to day d , and Δt denotes the hourly scheduling interval, which is set to 1 h in this study. Therefore, the daily-level variables represent the accumulated energy corresponding to the hourly operating variables, ensuring consistency between the daily and hourly scheduling scales.

3.2. Two-stage robust scheduling model

Wind and photovoltaic generation in the sending-end region is characterized by significant randomness and fluctuation. The associated prediction deviations may disturb hourly power equilibrium, thus influencing the economic performance and secure operation of interregional energy delivery. Accordingly, the deterministic single-level optimization formulation developed in Section 3.1 is transformed into a two-stage robust framework to handle the uncertainty caused by renewable power generation [37].

3.2.1. Data-driven uncertainty sets

Prediction deviations associated with wind and solar generation constitute the primary uncertain factors in the system. To make the uncertainty sets consistent with the historical prediction accuracy of renewable energy stations, this section employs a data-oriented approach. Specifically, the uncertainty sets are formed using historical forecast error samples of wind and photovoltaic generation in the sending-end area. Existing studies have indicated that uncertainty sets derived from historical samples can reduce reliance on precise probability distributions and support a balanced consideration of economic performance and robustness [16]. Let the forecast values of wind and photovoltaic output in hour t be $\bar{P}_t^w$ and $\bar{P}_t^{pv}$, respectively. Their actual output can be expressed as the sum of the forecast value and the corresponding forecasting error:

$$\begin{aligned} P_t^w &= \bar{P}_t^w + \Delta P_t^w \\ P_t^{pv} &= \bar{P}_t^{pv} + \Delta P_t^{pv} \end{aligned} \quad (78)$$

where ΔP_t^w and ΔP_t^{pv} are forecasting error random variables following unknown distributions. To extract their fluctuation characteristics from historical data, the normalized forecasting deviation coefficients ξ_t^w and ξ_t^{pv} are defined as follows:

$$\begin{aligned} \xi_t^w &= \frac{\Delta P_t^w}{\bar{P}^w} \\ \xi_t^{pv} &= \frac{\Delta P_t^{pv}}{\bar{P}^{pv}} \end{aligned} \quad (79)$$

where $\bar{P}^w$ and $\bar{P}^{pv}$ denote the installed capacities of the wind farm and photovoltaic station, respectively, which are used to normalize forecasting errors with different magnitudes. By analyzing historical operation data, a historical sample set of deviation coefficients can be obtained.

To avoid overly conservative robust optimization results, a budget uncertainty set is introduced to limit the total deviation magnitude within the scheduling horizon. The boundary parameters of this uncertainty set can be determined through statistical analysis of historical samples. Specifically, let $\Delta \bar{P}_t^w$ and $\Delta \bar{P}_t^{pv}$ denote the wind and photovoltaic forecast-error bounds, respectively, obtained from the historical samples at the 95% confidence level. Based on these statistically derived deviation bounds, the uncertainty set U is formulated as follows:

$$U = \left\{ \begin{array}{l} P_t^W = \hat{P}_t^W + \Delta P_t^W \xi_t^W \\ P_t^{PV} = \hat{P}_t^{PV} + \Delta P_t^{PV} \xi_t^{PV} \\ |\xi_t^W| \leq 1, \quad |\xi_t^{PV}| \leq 1, \quad \forall t \in T \\ \sum_{t \in T} |\xi_t^W| \leq \Gamma_W \\ \sum_{t \in T} |\xi_t^{PV}| \leq \Gamma_{PV} \end{array} \right. \quad (80)$$

where $T = \{1, \dots, T\}$ denotes the set of hourly scheduling periods; ξ_t^W and ξ_t^{PV} are the normalized wind and photovoltaic deviation variables, respectively; and Γ_W and Γ_{PV} denote the corresponding uncertainty budgets. The absolute-value constraints limit the deviation magnitude in each period, while the summation constraints restrict the total number and magnitude of adverse deviations over the scheduling horizon [38].

To provide a unified measure of the overall robustness level and facilitate the subsequent sensitivity analysis, a normalized robustness coefficient $A \in [0, 1]$ is introduced. The wind and photovoltaic uncertainty budgets are proportionally adjusted according to:

$$\begin{aligned} \Gamma^W &= A \bar{\Gamma}^W \\ \Gamma^{PV} &= A \bar{\Gamma}^{PV} \end{aligned} \quad (81)$$

where $\bar{\Gamma}^W$ and $\bar{\Gamma}^{PV}$ denote the upper-bound robustness budgets for wind and photovoltaic uncertainty, respectively. Therefore, A is not an additional uncertainty-budget parameter, but a common normalized scaling coefficient used to simultaneously adjust the robustness levels of wind and photovoltaic generation. When $A = 0$, the uncertainty budgets are reduced to zero and the model approaches deterministic scheduling. As A increases toward 1, larger renewable-generation deviations are allowed to enter the uncertainty set, resulting in a more conservative scheduling strategy.

3.2.2. Two-stage robust optimization model

Under the unified scheduling framework, the decision variables are divided into two stages. The first-stage *Here-and-Now* decisions include the on/off status of thermal units and the daily methanol transportation amount, which must be determined before the realization of renewable-generation uncertainty. The second-stage *Wait-and-See* decisions include the adjustable operating and state variables after uncertainty is realized, such as thermal unit output, electrolyzer operation, fuel cell output, tie-line transmission power, hydrogen storage charging/discharging and storage level, methanol synthesis and reforming, methanol storage variables, renewable energy curtailment, and load shedding. Therefore, electrolyzer operation, storage variables, and tie-line power are treated as second-stage recourse variables rather than predetermined first-stage decisions.

The two-stage robust optimization model can be described in the following mathematical form:

$$\min_{x \in X} \left\{ c^T x + \max_{u \in U} \min_{y \in \Omega(x, u)} d^T y \right\} \quad (82)$$

where X denotes the feasible region of the first-stage decision variable x ; U denotes the uncertainty set defined above; and $\Omega(x, u)$ denotes the feasible region of the second-stage recourse variable y .

under the given first-stage decision x and uncertainty realization u , which is constructed from the corresponding operational and cross-timescale coupling constraints in Section 3.1. In the objective function, the first-stage cost mainly consists of the costs associated with thermal-unit commitment and the predetermined methanol transportation schedule, whereas the second-stage cost represents the scenario-dependent recourse operating cost, including thermal generation, hydrogen and methanol conversion, storage operation, tie-line transmission, renewable-energy curtailment, carbon trading, and load-shedding costs.

The adverse scenario is identified from the uncertainty set, and the dispatch strategy must remain feasible under this scenario through the adjustment of y , so that robust feasibility can be guaranteed.

3.3. C&CG-based solution method

Equation (82) presents a two-stage robust formulation with a three-level min-max-min structure, which makes direct solution computationally challenging. For this reason, this study employs the C&CG method. The C&CG method reformulates the original model into two coupled parts, namely the master problem and the subproblem. By solving the master problem and the subproblem in an alternating iterative manner, the solution gradually converges to the optimum of the initial formulation [37,39].

3.3.1. Two-stage robust optimization model

Given the current set of identified worst-case scenarios, the C&CG master problem determines the first-stage variable x and the corresponding second-stage variables for each scenario, thus providing a lower bound for the objective value of the original model. In iteration k , the master problem (MP) is formulated as follows:

$$\min_{x, \eta, y^{(l)}} c^T x + \eta \quad (83)$$

$$\text{s.t. } \eta \geq d^T y^{(l)}, \quad l = 1, 2, \dots, k \quad (84)$$

$$x \in X \quad (85)$$

$$y^{(l)} \in \Omega(x, u^{(l)*}), \quad l = 1, 2, \dots, k \quad (86)$$

where $u^{(l)}$ denotes the worst-case scenario identified and returned by the subproblem in iteration l ; $y^{(l)}$ denotes the second-stage decision variable corresponding to scenario $u^{(l)}$; and η is an auxiliary variable representing the upper bound of the second-stage cost under all identified scenarios. Constraint (86) indicates that, for each identified worst-case scenario, there must exist a feasible second-stage adjustment scheme $y^{(l)}$.

3.3.2. Subproblem

The subproblem is used to identify the worst-case renewable generation scenario under the

first-stage scheduling decisions obtained from the master problem. It can be expressed as the following max-min optimization problem:

$$Q(x^*) = \max_{u \in U} \min_{y, z} d^T y \quad (87)$$

$$Ay + Gz \geq b - Bx^* - Cu, \quad y \geq 0, \quad z \in Z \quad (88)$$

where x^* denotes the first-stage solution obtained from the master problem; y denotes the continuous second-stage recourse variables; and z denotes the binary variables introduced for the piecewise carbon-trading formulation. Since the thermal-unit commitment status is included in x^* , it is fixed when solving the subproblem and, therefore, does not participate in the subsequent strong-duality transformation. The logical relationships associated with unit startup and shutdown are linearized in advance using auxiliary binary variables and corresponding linear constraints.

For the reward-penalty differentiated stepped carbon-trading cost in Eq (22), the carbon-trading quantity is defined as $q_t = Q_t^c - A_t^c$. Let $\mathcal{R}$ denote the set of carbon-trading intervals and let $z_{t,r}$ be a binary variable indicating whether interval r is active. The piecewise function can be uniformly expressed as $C_t^c = a_r q_t + b_r$ within interval r , and the corresponding mixed-integer linear constraints are formulated as follows:

$$\begin{cases} \sum_{r \in \mathcal{R}} z_{t,r} = 1, \\ \underline{q}_r - M(1 - z_{t,r}) \leq q_t \leq \bar{q}_r + M(1 - z_{t,r}), \\ -M(1 - z_{t,r}) \leq C_t^{rc} - (a_r q_t + b_r) \leq M(1 - z_{t,r}) \end{cases} \quad (89)$$

where a_r , b_r , $\underline{q}_r$, and $\bar{q}_r$ denote the slope, intercept, lower bound, and upper bound of interval r , respectively, and M is a sufficiently large positive constant. Therefore, the differentiated stepped carbon-trading function is converted into an equivalent MILP formulation.

It should be noted that, because z contains binary variables, the complete second-stage recourse problem is an MILP, and strong duality cannot be directly applied to the entire problem. Therefore, an inner iterative procedure is embedded in the subproblem. For a given carbon-trading interval pattern $z^{(l)}$, the discrete variables are fixed, and the remaining second-stage problem becomes an LP:

$$\begin{cases} \min_y d^T y \\ y \geq b - Bx^* - Cu - Gz^{(l)} \\ y \geq 0 \end{cases} \quad (90)$$

According to strong duality, Eq (90) can be transformed into its dual problem:

$$\begin{cases} \max_{\lambda} \quad \lambda^T (b - Bx^* - Cu - Gz^{(l)}) \\ A^T \lambda \leq d \\ \lambda \geq 0 \end{cases} \quad (91)$$

where λ denotes the dual variable corresponding to constraint (90).

Let Z^k denote the set of carbon-trading interval patterns generated in the current inner iteration.

By introducing the auxiliary variable θ , the worst-case scenario search can be formulated as:

$$\begin{aligned}
 & \max_{u, \theta, \lambda^{(\ell)}} \theta \\
 & \theta \leq \lambda^{(\ell)T} (b - Bx^* - Cu - Gz^{(\ell)}), \quad \forall z^{(\ell)} \in \mathcal{Z}^k \\
 & A^T \lambda^{(\ell)} \leq d, \quad \lambda^{(\ell)} \geq 0 \\
 & u \in U.
 \end{aligned} \tag{92}$$

The above formulation contains bilinear terms between the uncertainty variables and dual variables. According to the polyhedral structure of the uncertainty set U , auxiliary variables and the big- M method are further introduced to linearize these bilinear terms. Consequently, the worst-case scenario search problem is converted into an MILP and can be solved using commercial optimization solvers.

After obtaining the adverse scenario u^* , the original second-stage recourse MILP is solved under x^* and u^* to determine the corresponding optimal carbon-trading interval pattern z^* . If z^* has not been included in $\mathcal{Z}^k$, it is added to the pattern set and the inner iteration is repeated. Otherwise, the inner iteration terminates, and the obtained worst-case scenario and objective value are returned to the outer C&CG procedure. In this way, strong duality is applied only to the continuous recourse problem under a fixed discrete carbon-trading pattern, while the discrete and piecewise features of the original model are retained through the MILP formulation.

To explicitly linearize the bilinear terms between the dual variables and the uncertainty-selection variables, an auxiliary variable $w_{i,t}$ is introduced to represent $w_{i,t} = \lambda_i z_t$. Assuming $0 \leq \lambda_i \leq M$, the bilinear relationship can be equivalently reformulated as Eq (93). Therefore, all bilinear terms in the dualized subproblem are replaced by linear constraints, and the resulting worst-case scenario search problem becomes an MILP.

$$\begin{cases} 0 \leq w_{i,t} \leq M \\ z_t w_{i,t} \leq \lambda_i \\ w_{i,t} \geq \lambda_i - M(1 - z_t) \\ z_t \in \{0, 1\} \end{cases} \tag{93}$$

3.3.3. C&CG iteration and convergence

The proposed solution procedure consists of an outer C&CG iteration and an inner iteration for handling the discrete carbon-trading interval variables. In each outer iteration, the master problem determines the first-stage scheduling decisions and provides a lower bound of the original robust optimization problem. Based on the obtained first-stage solution, the subproblem identifies the corresponding worst-case renewable-generation scenario. Within the subproblem, the carbon-trading interval pattern is iteratively updated, while strong duality is applied to the continuous recourse problem under each fixed interval pattern. After the inner iteration converges, the resulting worst-case scenario is added to the master problem. The above procedure is repeated until the gap between the upper and lower bounds satisfies the preset convergence tolerance. Figure 3 illustrates the complete implementation process of the proposed solution method.

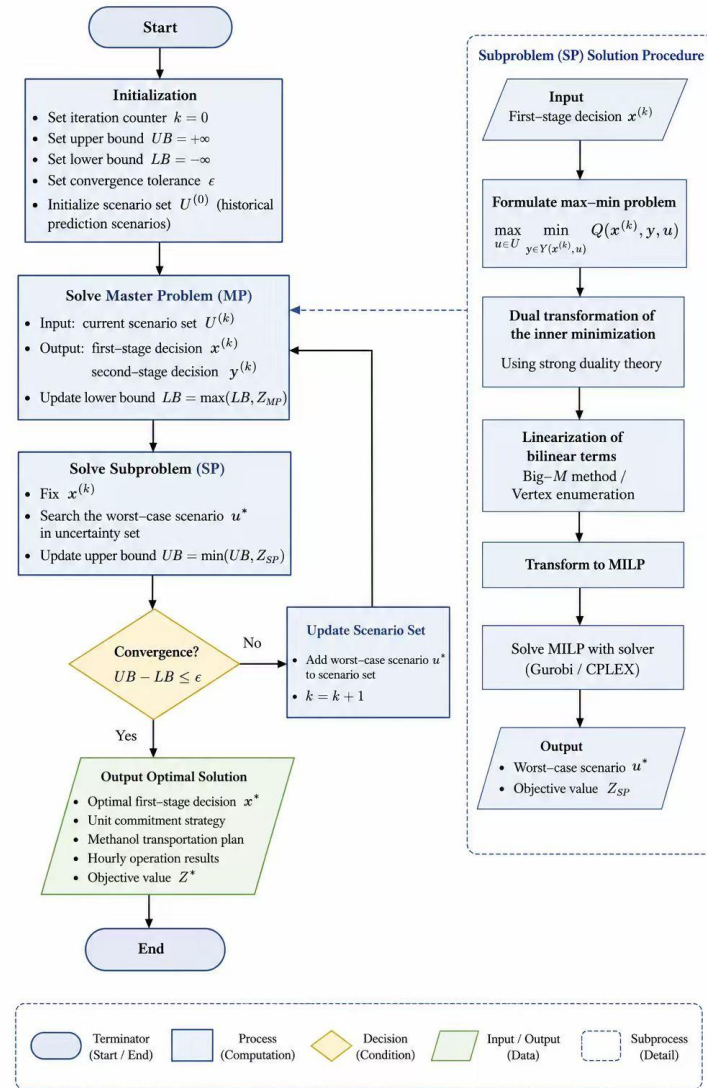


Figure 3. Flowchart of the proposed algorithm.

4. Case study

4.1. Test system and parameter settings

Figure 4 presents the IEEE 39-bus test system used for the simulation study, where the whole system is separated into a sending-end region and a receiving-end region. Specifically, buses 1–20 constitute the sending-end region, while buses 21–39 constitute the receiving-end region, as illustrated in Figure 4. The key parameter settings of different system components are provided in Table A1. The sending-end region mainly undertakes renewable energy development and energy export functions, and is equipped with thermal units, wind power, photovoltaic power, electrolyzers, hydrogen storage tanks, methanol synthesis units, methanol storage tanks, and methanol fuel cells. The receiving-end region mainly undertakes electricity and hydrogen load supply functions, and is equipped with thermal units, electrolyzers, hydrogen storage tanks, methanol reforming hydrogen production units, methanol storage tanks, and methanol fuel cells. Interregional energy exchange between the sending-end and receiving-end areas is implemented through transmission tie-lines and methanol delivery networks.

The standard IEEE 39-bus system is used in this study primarily as a network-topology reference and regional-partitioning framework rather than as a detailed nodal power-flow model or a direct representation of the original system at its nominal capacity level. To construct a synthetic cross-regional system consistent with the regional-scale energy and methanol transportation problem considered in this study, the original bus numbering and connectivity are retained for system partitioning and visualization, while the generation and load capacities are modified to represent aggregated regional energy scales. Specifically, buses 1–20 are configured as the renewable-energy-rich sending-end region and buses 21–39 as the load-center receiving-end region. The total thermal generation, wind and photovoltaic capacities, and peak loads are set according to the regional-scale assumptions listed in Table A1.

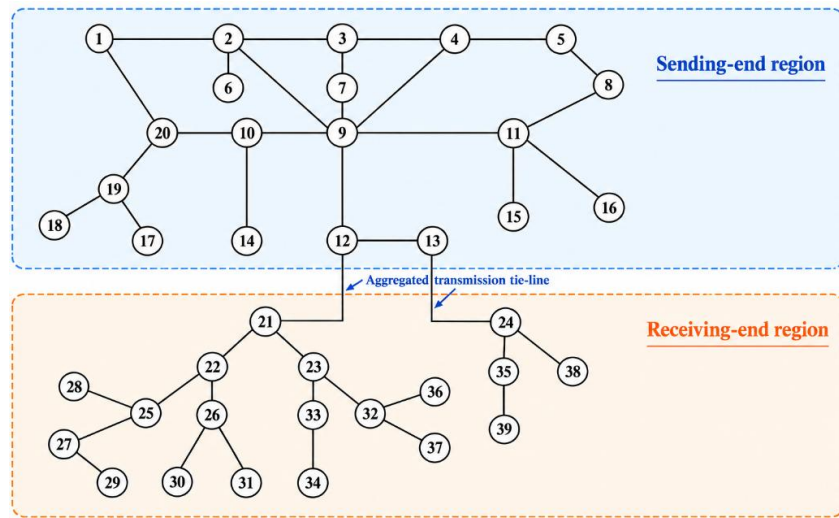


Figure 4. IEEE 39-bus system diagram.

The historical renewable-generation data used in the case study was obtained from anonymized operating records of a regional power system in Northeast China. Considering the large-scale system boundary adopted in this study, the wind and photovoltaic data represent aggregated outputs of multiple wind farms and photovoltaic stations in the renewable-energy-rich sending-end region rather than measurements from a single plant or city. A complete annual dataset from January to December 2023 was adopted, with an hourly temporal resolution, resulting in 8760 samples for wind power and photovoltaic generation. The hourly resolution is consistent with the scheduling interval adopted in the proposed model. The corresponding day-ahead renewable-generation forecasts were used to calculate the forecast errors by comparing the forecasted and measured outputs at each hourly interval. Before constructing the uncertainty sets, missing and abnormal records were screened, values outside the physically feasible ranges determined by the installed capacities were removed, and the forecast errors were normalized by the corresponding installed capacities. The processed historical forecast-error samples were subsequently used to determine the wind and photovoltaic uncertainty bounds at the 95% confidence level. The empirical coverage probabilities of the constructed 95% uncertainty intervals were further evaluated using independent validation samples. The coverage rates were 95.31% for wind power and 94.86% for photovoltaic power, which are close to the nominal 95% confidence level, confirming the statistical reasonableness of the adopted uncertainty bounds. A representative daily profile of the electric load, wind-power output, and photovoltaic output is shown in Figure 5.

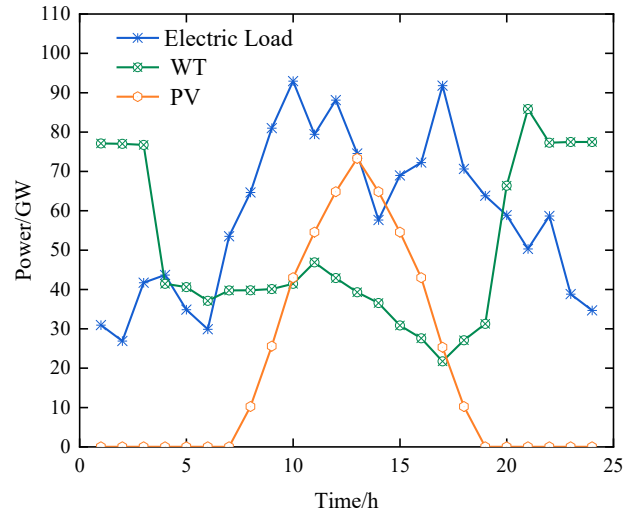


Figure 5. Forecast curves of load demand and wind and PV output.

The key economic parameters used in the case study are summarized in Tables A1 and A2. The methanol transportation distance of 2150 km is selected to represent a typical long-distance interregional transportation scenario between the sending-end and receiving-end regions. The hydrogen and methanol purchase prices, methanol transportation cost, benchmark carbon trading price, and load-shedding penalty coefficient are selected based on representative market levels, engineering practice, and parameter settings commonly adopted in related studies. Their specific values, units, and corresponding references or selection basis are provided in Table A2.

4.2. Simulation result analysis

To evaluate the performance of the proposed coordinated dispatch strategy for the cross-regional power-hydrogen-methanol coupled energy system, six comparison cases are established.

Table 2. Detailed case settings.

Case	Tie-line	Methanol transportation	Hydrogen tube-trailer transportation	Reward-penalty carbon trading	DDRO
Case1	×	√	×	×	×
Case2	√	×	×	×	×
Case3	√	×	√	×	×
Case4	√	√	×	×	×
Case5	√	√	×	√	×
Case6	√	√	×	√	√

In Case 1, transmission tie-lines are disabled, and only methanol transportation is adopted for cross-regional energy transfer. In Case 2, methanol transportation is disabled, and cross-regional electricity transmission is realized only through transmission tie-lines. In Case 3, hydrogen tube trailers are introduced as a supplementary cross-regional hydrogen transportation pathway. In Case 4, both transmission tie-lines and methanol transportation are enabled to realize coordinated

electricity-methanol transportation. On this basis, Case 5 further introduces the reward-penalty differentiated stepped carbon trading mechanism, while Case 6 additionally incorporates DDRO to handle wind and photovoltaic generation uncertainties. The detailed case settings are listed in Table 2.

4.2.1. Cost and renewable energy accommodation

To verify the impacts of different cross-regional energy transportation modes, carbon trading mechanisms, and renewable energy uncertainty treatments on system operating economy, low-carbon performance, and energy supply reliability, the system costs and key operational indicators under the six operating cases are compared and analyzed. The corresponding results are presented in Table 3.

Table 3. System operation results under six cases.

Parameter	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Annual total system operating cost (¥100 million)	4182.20	4287.04	4254.89	3800.02	3806.84	3812.75
Coal consumption cost of thermal units (¥100 million)	2518.38	2450.69	2456.91	2457.58	2453.10	2464.40
Startup and shutdown cost (¥100 million)	3.76	2.73	2.73	2.73	2.73	2.73
Transportation cost (¥100 million)	4.76	0	193.01	4.75	4.78	4.75
Hydrogen purchase cost (¥100 million)	673.59	947.06	814.62	401.90	399.35	395.92
Hydrogen supply chain cost (¥100 million)	1251.02	1531.92	1520.18	1060.18	1056.60	1052.17
Carbon emissions (kt)	685,083	673,376	675,065	675,166	673,120	672,500
Transportation amount (kt)	589	0	129	584	586	584
Electricity transmission amount (GW·h)	0	52,990	49,560	50,743	50,820	50,700
Renewable energy curtailment amount (GW·h)	40,985	10,366	7541	7102	7040	7220
Renewable energy curtailment rate (%)	13.63	3.45	2.51	2.36	2.34	2.40
Load shedding rate (%)	1.85	0.62	0.58	0.28	0.26	0.05

According to Table 3, Case 4 provides the most favorable economic result, with an annual total operating cost of ¥380.002 billion. Case 2 has the highest total cost, reaching ¥428.704 billion, while the total costs of Cases 1 and 3 fall between these two. Compared with Case 4, Case 5 further introduces the reward-penalty differentiated stepped carbon trading mechanism. As a result, the annual operating cost increases slightly from ¥380.002 billion to ¥380.684 billion, while carbon emissions decrease from 675,166 to 673,120 kt, and the renewable energy curtailment rate decreases from 2.36% to 2.34%. Case 6 further incorporates DDRO on the basis of Case 5. The annual operating cost increases moderately to ¥381.275 billion, while carbon emissions further decrease to 672,500 kt, and the load shedding rate decreases markedly from 0.26% to 0.05%. These results indicate that the comparison between Cases 4 and 5 mainly reflects the low-carbon regulation effect of the differentiated carbon trading mechanism, whereas the comparison between Cases 5 and 6 demonstrates the reliability improvement brought by DDRO under renewable generation uncertainty.

This is because Case 1 relies only on methanol transportation for cross-regional energy transfer and lacks the hourly-level transfer capability of transmission tie-lines for surplus renewable energy. As a result, the renewable energy curtailment amount and curtailment rate reach 40,985 GW·h and 13.63%, respectively, leading to a relatively high system operating cost. In Case 2, although the curtailment rate is reduced to 3.45% through transmission tie-lines, the absence of a cross-regional methanol transportation channel makes it difficult for the receiving-end region to obtain chemical energy converted from renewable energy at the sending end. Consequently, the hydrogen purchase cost and hydrogen supply chain cost increase to ¥94.706 billion and ¥153.192 billion, respectively, resulting in the highest total cost. After gaseous hydrogen transportation is introduced in Case 3, the curtailment rate further decreases to 2.51%. However, the long-distance transportation cost of gaseous hydrogen reaches ¥19.301 billion, which limits the improvement in economic performance.

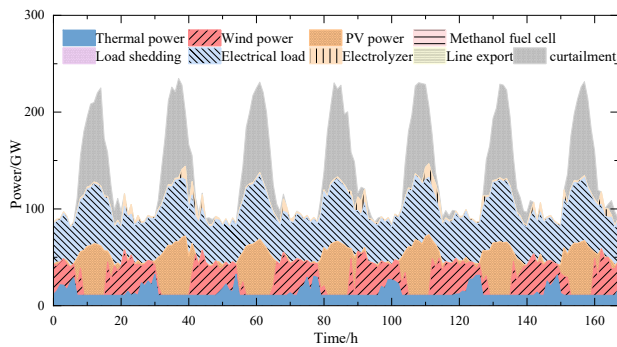
Case 4 adopts both transmission tie-lines and cross-regional methanol transportation. The electricity transmission amount and methanol transportation amount reach 50,743 GW·h and 584 kt, respectively, while the hydrogen purchase cost and hydrogen supply chain cost decrease to ¥40.190 billion and ¥106.018 billion, respectively. This indicates that direct electricity transmission and cross-regional methanol storage and transportation can complement each other, undertaking hourly-level electricity transfer and cross-timescale chemical energy transfer, respectively, thereby reducing the overall system operating cost. Compared with Case 4, Case 5 further introduces the differentiated reward-penalty stepped carbon trading mechanism. The thermal power fuel cost decreases from ¥245.758 billion to ¥245.310 billion, while the carbon emissions decrease by 2,046 kt, showing that the differentiated carbon price signal can restrain high-carbon energy use and improve low-carbon operation with only a small increase in the total cost.

Case 6 further introduces DDRO on the basis of Case 5. To cope with adverse wind and photovoltaic output deviations, the system reserves additional regulation margins, resulting in a slight increase in the thermal power fuel cost and renewable energy curtailment rate. Specifically, the curtailment rate increases from 2.34% to 2.40%, while the total operating cost increases from ¥380.684 billion to ¥381.275 billion. However, the hydrogen purchase cost and hydrogen supply chain cost further decrease to ¥39.592 billion and ¥105.217 billion, respectively, and the load shedding rate decreases markedly from 0.26% to 0.05%. Therefore, the comparison between Cases 4 and 5 reflects the low-carbon regulation effect of the stepped carbon trading mechanism, while the comparison between Cases 5 and 6 further demonstrates that the proposed DDRO method can significantly improve energy supply reliability under renewable energy uncertainty at the expense of only a limited increase in operating cost.

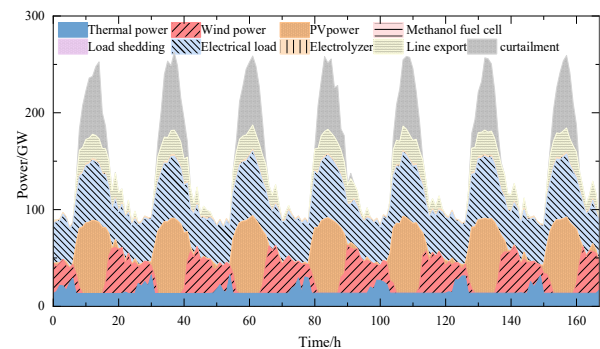
To verify the impacts of different cross-regional energy transportation modes and the low-carbon robust optimization mechanism on system power balance, a comparative experiment on typical-week power scheduling is conducted in this paper. The results are shown in Figure 6.

As shown in Figure 6(a), in Case 1, the system relies only on methanol transportation for cross-regional energy transfer, and the tie-line export power is zero. Obvious renewable energy curtailment occurs during periods of high wind and photovoltaic output. This is because methanol transportation is a slow-dynamic energy transfer pathway and cannot directly participate in hourly power balancing, while the electrolyzer capacity is also limited. Therefore, relying solely on methanol transportation cannot fully accommodate short-term renewable energy fluctuations. As shown in Figure 6(b), after the transmission tie-line is enabled in Case 2, surplus renewable electricity can be directly exported during high-output periods, and renewable energy curtailment is significantly

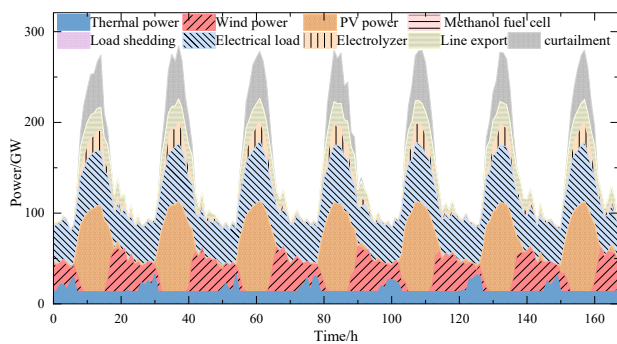
reduced compared with Case 1. This is because the tie-line provides fast hourly-scale power transfer capability. However, its regulation capability is still limited by the transmission capacity, and some curtailment remains during renewable energy peaks. As shown in Figure 6(c), Case 3 further introduces hydrogen tube-trailer transportation. Compared with Case 2, the operating range of the electrolyzer is expanded, and renewable energy curtailment is further reduced. This is because hydrogen transportation provides an additional pathway for utilizing electrolytic hydrogen produced from surplus renewable electricity. However, the improvement remains limited by the relatively high cost and limited efficiency of long-distance gaseous hydrogen transportation.



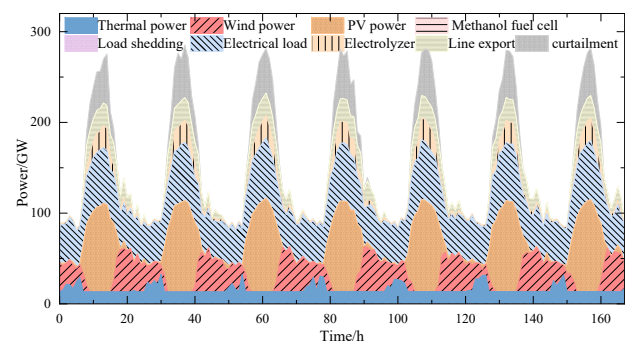
(a) Power supply-demand balance of Case 1.



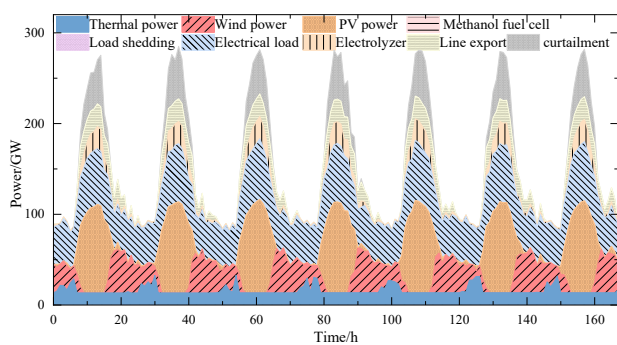
(b) Power supply-demand balance of Case 2.



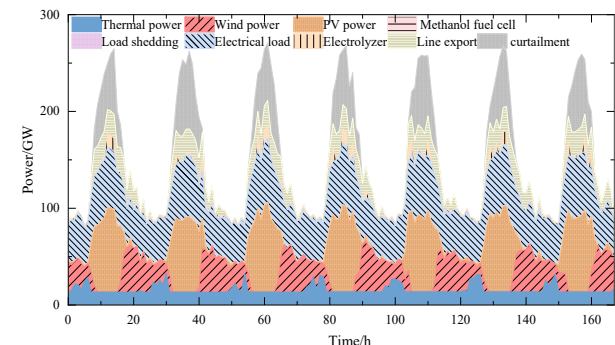
(c) Power supply-demand balance of Case 3.



(d) Power supply-demand balance of Case 4.



(e) Power supply-demand balance of Case 5.



(f) Power supply-demand balance of Case 6.

Figure 6. Power supply-demand balance under different cases.

As shown in Figure 6(d), Case 4 introduces cross-regional methanol transportation together with tie-line electricity transmission. The electrolyzer is more fully utilized during renewable energy peak

periods, while the curtailment level is further reduced. This is because the tie-line undertakes fast hourly electricity transfer, whereas methanol converts surplus renewable electricity into storable chemical energy for cross-timescale transportation. Therefore, the two pathways form a complementary coordination mechanism for renewable energy accommodation. As shown in Figure 6(e), after the reward-penalty differentiated stepped carbon trading mechanism is introduced in Case 5, the overall power-balance structure remains similar to that of Case 4, while thermal generation is slightly reduced and renewable energy utilization is further improved. This is because the differentiated carbon-price signal increases the economic penalty for high-carbon generation and encourages greater utilization of low-carbon energy. As shown in Figure 6(f), Case 6 further incorporates DDRO. Compared with Case 5, the system maintains additional regulation margins to cope with adverse wind and photovoltaic deviations, resulting in a slight increase in renewable energy curtailment while maintaining a more reliable power balance. This indicates that the proposed DDRO method improves the system's adaptability to renewable generation uncertainty at the expense of a limited robustness cost.

4.2.2. Methanol storage and transportation

To verify the energy transfer capability of the cross-regional methanol storage and transportation channel under seasonal renewable energy fluctuations, the monthly variations in system energy storage and transportation amounts are analyzed under Case 5. The results are shown in Figure 7.

As shown in Figure 7, renewable energy generation remains at a relatively high level from March to May, decreases significantly in June, rebounds to some extent from July to August, and then generally declines after September. Corresponding to the variation in renewable energy output, methanol storage and methanol transportation exhibit obvious staged variation characteristics. Methanol storage remains at a high level from March to May, indicating that the system can use surplus electricity for hydrogen production and further synthesize methanol when renewable energy output is abundant, thereby realizing the conversion and storage of electricity into chemical energy. Methanol transportation increases significantly from September to October, indicating that the system can centrally transport the methanol accumulated in earlier periods to the receiving-end region according to the energy demand at the receiving end and the inventory level at the sending end.

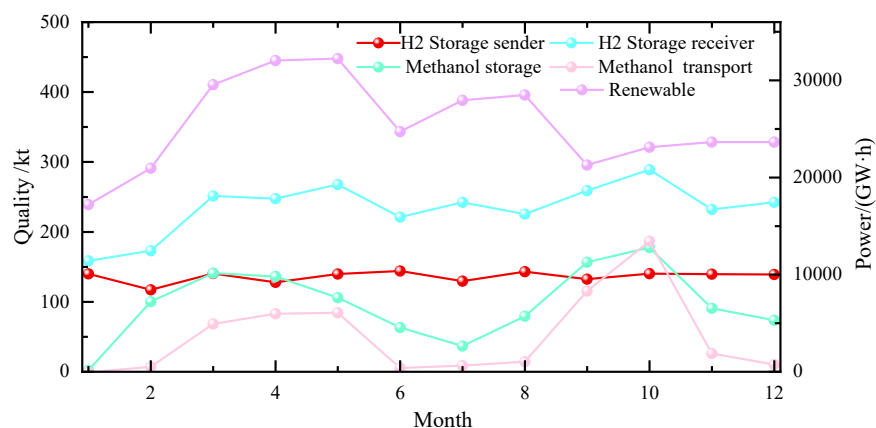


Figure 7. System energy storage and transportation amounts in Case 5.

Meanwhile, the hydrogen storage amount at the receiving end is generally higher than that at the sending end, indicating that the receiving-end region can use cross-regionally imported methanol for

energy supplementation and maintain a relatively high hydrogen supply level. This is because methanol has strong storage and transportation characteristics, which can compensate for the limitation of transmission tie-lines in long-period energy transfer. As a result, surplus renewable energy is no longer limited to local immediate accommodation but can be utilized across different timescales and regions in the form of methanol. This indicates that the proposed approach can fully coordinate the processes of methanol synthesis, storage, delivery, and utilization. It also facilitates interregional renewable energy consumption and strengthens the multi-timescale complementary energy support between the sending-end and receiving-end areas.

4.2.3. Analysis of hydrogen supply cost

To analyze the hydrogen supply-demand balance characteristics of the receiving-end region under different cross-regional hydrogen supply modes, a comparative experiment between Case 3 and Case 5 is conducted in this paper. The corresponding results are presented in Figure 8.

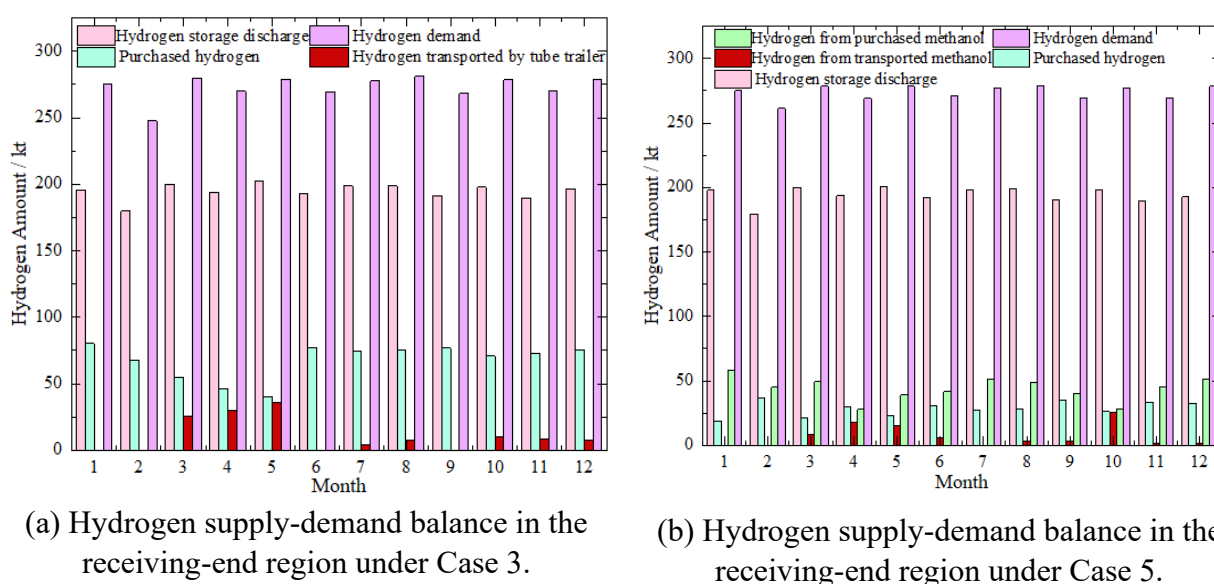


Figure 8. Hydrogen supply-demand balance characteristics of the receiving-end region under different hydrogen supply modes.

As shown in Figure 8(a), in Case 3, the hydrogen demand of the receiving-end region remains generally stable in each month. Hydrogen released from the storage tank remains the main source of hydrogen supply throughout the scheduling period, whereas externally purchased hydrogen acts as a supplementary supply option. Hydrogen supplied by tube trailer transportation only provides supplementary support in certain months, and its supply scale is relatively limited. This is because, when only hydrogen tube trailers are introduced, cross-regional hydrogen transportation is still constrained by high transportation cost, low volumetric energy density, and limited efficiency for long-distance transportation. As a result, the system still relies heavily on local hydrogen storage release and external hydrogen purchases to satisfy load demand. This indicates that, although hydrogen tube trailers can enhance the hydrogen supply capability of the receiving-end region to a certain extent, their support for large-scale cross-regional hydrogen transfer remains limited.

As shown in Figure 8(b), in Case 5, the hydrogen demand of the receiving-end region also remains stable, and hydrogen discharged from the storage tank still plays a dominant role. However, the hydrogen supply structure becomes more diversified than that in Case 3. In addition to hydrogen discharged from the storage tank and purchased hydrogen, hydrogen production from transported methanol and hydrogen production from purchased methanol both participate in hydrogen supply in the receiving-end region, while the scale of purchased hydrogen decreases compared with Case 3. This is mainly attributed to methanol's favorable characteristics, including ease of storage and delivery, relatively high volumetric energy density, and well-developed interregional transport conditions. Surplus renewable energy at the sending end can first be converted into methanol and then reformed into hydrogen at the receiving end to supplement hydrogen supply, thereby reducing dependence on direct hydrogen purchases and long-distance transportation of gaseous hydrogen. This demonstrates that the cross-regional methanol transportation mode adopted in this paper can effectively expand the hydrogen supply channels of the receiving-end region, improve cross-regional hydrogen allocation capability, and enhance the flexibility of hydrogen supply-demand balancing in the system.

In addition, to further compare the composition characteristics of hydrogen supply costs in the receiving-end region under different hydrogen supply modes, Figure 9 presents the distribution of hydrogen supply cost components in the receiving-end region for Cases 3 and 5.

As illustrated in Figure 9, in Case 3, hydrogen supplied by tube trailers contributes the largest share of the total hydrogen supply cost, accounting for 53%. In comparison, electrolytic hydrogen production contributes 39%, while externally purchased hydrogen represents only 8%. In Case 5, the proportion of hydrogen production cost via water electrolysis increases to 55%, the proportion of purchased hydrogen cost is 38%, and the proportions of hydrogen supply costs via purchased methanol and transported methanol are only 6% and 1%, respectively. This is because cross-regional hydrogen supply via hydrogen tube trailers can provide an additional hydrogen source, but its transportation cost is relatively high, resulting in a large cost burden in Case 3. In contrast, in Case 5, methanol participates in cross-regional energy transfer as a hydrogen carrier, and the cost proportion of hydrogen supply via transported methanol is significantly lower, indicating that the methanol pathway has better economic performance in cross-regional hydrogen transportation.

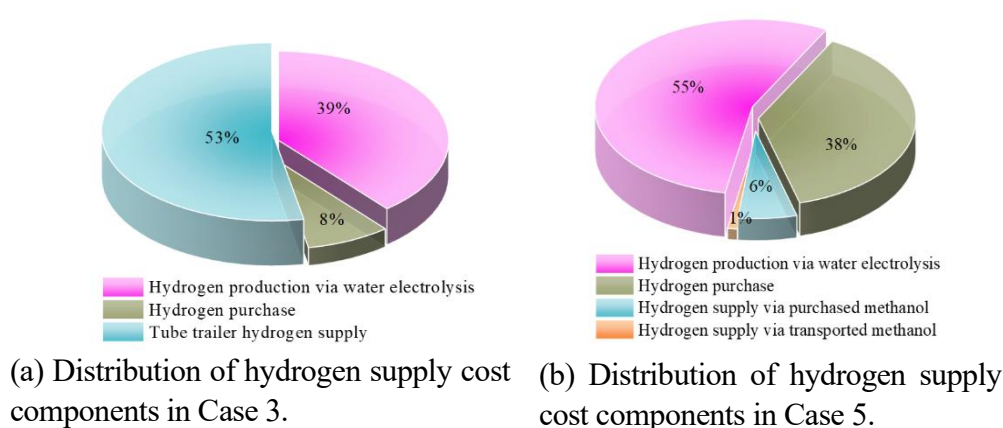


Figure 9. Proportions of hydrogen supply costs in the receiving-end region under different hydrogen supply modes.

This demonstrates that the coordinated mechanism of cross-regional methanol transportation and receiving-end hydrogen production adopted in this paper can not only improve the hydrogen supply

structure of the receiving-end region but also optimize the cost composition of hydrogen supply, showing better economic performance and application potential than the hydrogen tube trailer mode.

4.2.4. Carbon trading mechanism comparison

To independently evaluate how the differentiated stepped carbon trading scheme with reward-penalty incentives affects low-carbon dispatch, Cases 4 and 5 are compared to reveal system operation under different carbon pricing mechanisms. The two cases share the same cross-regional electricity-methanol transportation configuration and deterministic renewable-generation setting, and differ only in the carbon trading mechanism. The corresponding results are presented in Figure 10.

Figure 10 shows that the carbon trading volume is positive during the nighttime and some evening periods, while it becomes negative from 8:00 to 16:00, with the most significant emission-reduction benefit occurring around 12:00–13:00. Meanwhile, compared with the linear carbon trading mechanism in Case 4, the reward-penalty differentiated stepped carbon trading mechanism introduced in Case 5 results in higher carbon costs when emissions exceed the allocated quota and greater emission-reduction benefits when emissions remain below the quota. This is because the stepped carbon pricing mechanism increases the penalty for excess emissions and strengthens the reward for emission reduction according to the deviation between actual emissions and the allocated carbon quota. These results indicate that the reward-penalty differentiated stepped carbon trading mechanism can strengthen carbon cost constraints, thereby encouraging the system to reduce high-emission thermal generation and improve the utilization of low-carbon energy.

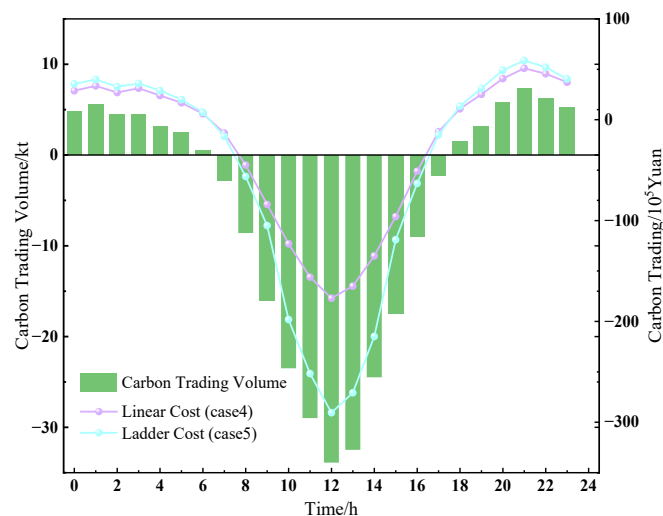


Figure 10. System operation results under different carbon trading mechanisms.

4.2.5. Data-driven robust optimization verification

To further examine how the DDRO approach characterizes renewable generation uncertainty, photovoltaic and wind power uncertainty sets are developed using historical forecast-error data, and the corresponding worst-case scenarios are selected for analysis. The results are presented in Figure 11.

As shown in Figure 11(a), the forecasted photovoltaic output exhibits a clear single-peak characteristic during the daytime, reaching its peak during 11:00–13:00, while the output is zero during

nighttime. The worst-case photovoltaic scenario lies within the fluctuation interval as a whole and is lower than the forecasted value during the daytime high-output periods, with particularly obvious deviations near the photovoltaic peak. This is because photovoltaic output is concentrated during the daytime, and high-output periods have a greater impact on system power balance and renewable energy accommodation. If the actual photovoltaic generation falls below its predicted level, the system must maintain supply-demand equilibrium by regulating thermal unit generation, hydrogen storage operation, electrolyzer consumption, and tie-line transmission power. Therefore, these periods are more likely to become adverse scenarios in robust optimization. This demonstrates that the data-driven uncertainty set constructed in this paper can effectively reflect the impact of photovoltaic forecasting errors on system operation, thereby avoiding the problem of over-reliance on forecasted photovoltaic output in deterministic scheduling.

Figure 11(b) indicates that the predicted wind generation is relatively abundant during nighttime and evening hours, whereas it decreases around noon, showing obvious fluctuation and an inverse peak-shaving feature. The worst-case wind scenario remains within the fluctuation range and is below the predicted output in most time periods. This suggests that the robust dispatch model tends to regard wind power shortage as the critical risk condition for system operation. This phenomenon is mainly caused by the randomness and uncertainty inherent in wind generation. If wind generation is lower than expected, the system has to increase conventional unit output or modify the operating states of multi-energy conversion equipment. These adjustments may raise operating costs and weaken the system's low-carbon operating performance. This indicates that the DDRO approach used in this study can describe the influence of wind generation variability on dispatch decisions without requiring precise probability distributions, thereby enhancing system feasibility and robustness under renewable energy uncertainty.

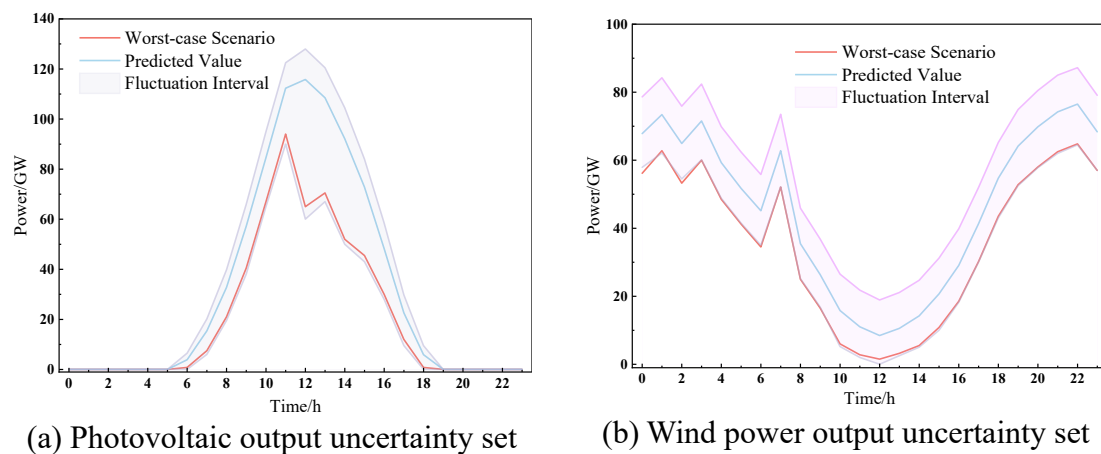


Figure 11. Schematic diagram of uncertainty sets for wind and photovoltaic output.

Taken together, Figures 11(a),(b) show that the worst-case scenarios of both photovoltaic and wind power do not exceed their corresponding fluctuation intervals, indicating that the constructed uncertainty sets can provide reasonable boundary constraints for renewable energy output fluctuations. Meanwhile, the worst-case scenarios do not take the extreme lower bound in all periods, indicating that the DDRO method can control the degree of conservativeness through uncertainty budgets and avoid the over-conservativeness of traditional robust optimization. This verifies that the proposed approach can maintain operational security under renewable generation uncertainty while jointly

considering economic efficiency and low-carbon performance.

To further evaluate the influence of the overall robustness level on system economy and supply reliability, a sensitivity analysis is conducted by varying the normalized robustness coefficient A from 0 to 1. According to the relationships defined in Section 3.2.1, the wind and photovoltaic uncertainty budgets, Γ^W and Γ^{PV} , are simultaneously scaled with A . The annual operating cost and worst-case load shedding rate are selected to characterize the economic cost and supply-security benefit associated with different robustness levels. The corresponding results are presented in Figure 12.

Figure 12 shows the impact of the normalized robustness coefficient A on system operation. As A increases from 0 to 1, the annual operating cost rises gradually, while the worst-case load shedding rate decreases markedly. When $A = 0$, the uncertainty budgets are reduced to zero, and the model approaches the deterministic scheduling strategy of Case 5. With increasing A , larger wind and photovoltaic forecast deviations are considered, requiring additional thermal generation, hydrogen storage, and multi-energy conversion reserves. Therefore, higher robustness improves supply reliability at the expense of a moderate increase in operating cost. The results also indicate that the operational differences between Cases 5 and 6 are mainly attributed to the introduction of DDRO rather than the carbon trading mechanism.

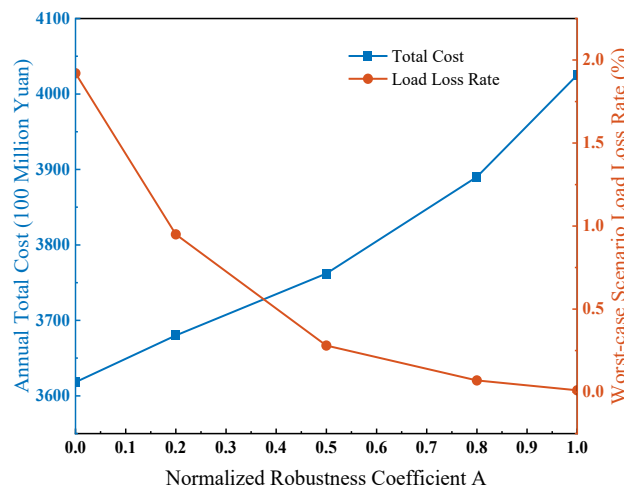


Figure 12. System operation results under different normalized robustness levels.

To further verify the scheduling performance of the proposed DDRO method under renewable energy output uncertainty, stochastic optimization (SO), conventional robust optimization (RO), and DDRO are selected for comparison. The photovoltaic and wind power outputs under the three methods are shown in Figure 13. The fluctuation interval is obtained from historical forecast-error samples and is used to characterize the possible variation range of renewable energy output.

As shown in Figure 13(a), photovoltaic output exhibits a distinct daytime single-peak pattern, with zero output at night and relatively high output around 11:00–13:00. The SO result shows relatively large fluctuations, with noticeable deviations from the reference power during several periods and occasional values outside the empirical fluctuation interval, indicating relatively weak constraints on extreme forecast deviations. In contrast, the conventional RO method exhibits more pronounced conservatism. During periods of high photovoltaic output, its optimized results are generally lower than both the reference power and the DDRO results, with a particularly obvious reduction around

noon. By comparison, DDRO can better preserve the original variation trend of photovoltaic output. Its results are mainly distributed within the fluctuation range derived from historical data and remain relatively close to the reference power, indicating that the proposed method can account for adverse photovoltaic output scenarios while avoiding the excessive reduction of available renewable power caused by conventional RO.

As shown in Figure 13(b), wind power output differs from photovoltaic output in that it exhibits noticeable fluctuations throughout the day, with relatively high output during nighttime and evening hours and lower output around noon. The SO result shows large fluctuations during several periods and relatively obvious deviations from the reference power. The conventional RO result is lower than both the DDRO result and the reference power during most periods, and its conservative characteristics become more evident when renewable energy output is relatively low. In comparison, the DDRO result follows the variation trend of the reference wind power more closely, adjusts to adverse output scenarios within the uncertainty range, and, at the same time, avoids excessive curtailment of renewable energy output.

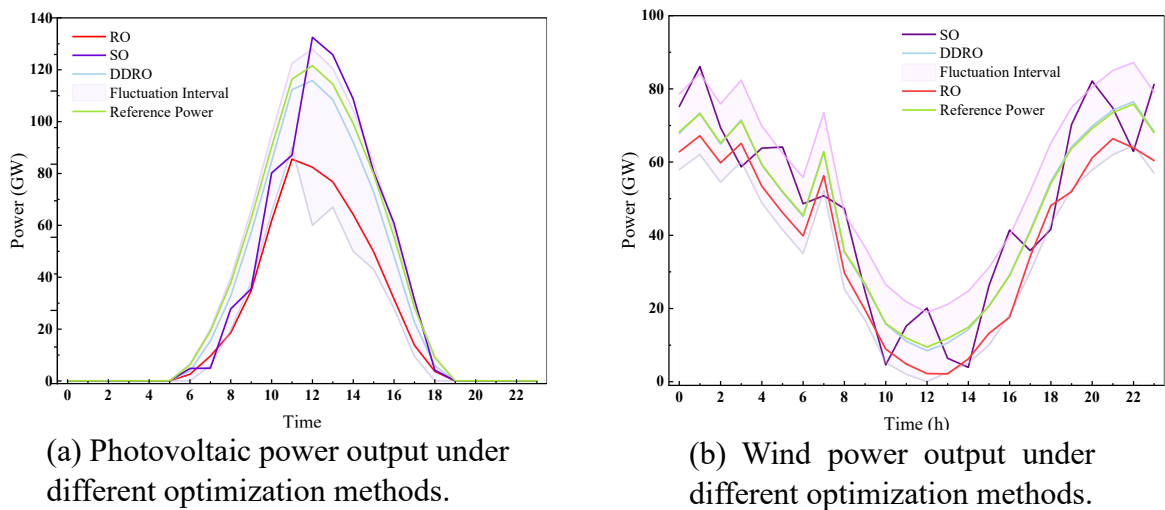


Figure 13. Comparison of renewable energy output under different optimization methods.

4.2.6. Sensitivity analysis

To further investigate the influence of the carbon trading price on the economic and low-carbon operation of the system, a sensitivity analysis is conducted by varying the benchmark carbon trading price μ_c from 210 to 490 ¥/t while keeping the other parameters unchanged. The corresponding results are presented in Table 4.

As shown in Table 4, with the increase in the carbon trading price, the annual operating cost gradually increases from ¥380.62 billion to ¥382.29 billion, while carbon emissions decrease from 676,300 to 669,650 kt, and the renewable energy curtailment rate decreases from 2.52% to 2.31%. Meanwhile, the load shedding rate remains within a relatively narrow range of 0.04%–0.06%. This is because a higher carbon trading price strengthens the economic penalty for high-emission thermal generation and encourages the system to increase the utilization of renewable energy through transmission tie-lines and power-hydrogen-methanol conversion pathways. However, the corresponding adjustment of thermal-unit output and multi-energy conversion equipment also

introduces additional operating costs. Therefore, the results indicate that increasing the carbon trading price can enhance the low-carbon regulation capability and renewable-energy utilization of the system at the expense of a moderate increase in operating cost, while exerting only a limited influence on supply reliability.

Table 4. Sensitivity analysis of carbon trading price.

μ_c	Annual cost/¥billion	Carbon emissions/kt	Curtailment rate %	Load shedding rate %
210	380.62	676300	2.52	0.06
280	380.91	674150	2.46	0.05
350	381.28	672500	2.40	0.05
420	381.73	670950	2.35	0.05
490	382.29	669650	2.31	0.04

To further evaluate the influence of cross-regional transportation conditions on the economic performance of the proposed system, the methanol transportation distance is varied from 1500 to 3000 km, corresponding to approximately 70%–140% of the baseline value of 2150 km, while the other parameters remain unchanged. The corresponding results are shown in Table 5.

Table 5. Sensitivity analysis of methanol transportation distance.

Transportation distance (km)	Annual operating cost (¥billion)	Methanol transportation amount (kt)	Hydrogen purchase cost (¥ billion)	Renewable energy curtailment rate (%)
1500	380.46	623	38.72	2.31
1800	380.83	606	39.08	2.34
2150	381.75	584	39.59	2.40
2500	381.89	553	40.31	2.47
3000	382.76	509	41.43	2.58

As shown in Table 5, with the increase in methanol transportation distance, the annual operating cost gradually increases, while the methanol transportation amount decreases. Meanwhile, the hydrogen purchase cost and renewable energy curtailment rate show a slight upward trend. This is because a longer transportation distance increases the cost of cross-regional methanol delivery and weakens its economic advantage, causing the system to rely more on local energy supply and purchased hydrogen. However, methanol transportation remains involved in the optimal scheduling strategy throughout the tested range, indicating that the coordinated electricity-methanol transportation mode maintains its effectiveness under moderate variations in transportation distance.

5. Discussion

Although the proposed scheduling framework is verified on the modified IEEE 39-bus test system, the quantitative results obtained in this study are dependent on the assumed system configuration, renewable-energy capacity, load level, transportation distance, methanol-related parameters, and carbon trading settings. Therefore, the reported economic, low-carbon, and reliability improvements

should be interpreted as case-specific results under the adopted synthetic test system rather than as general quantitative evidence for practical large-scale cross-regional methanol deployment. Synthetic power-system models are useful for reproducible methodological evaluation, but their ability to reproduce real operating characteristics depends on the realism of the adopted network parameters and time-series data [40]. The optimization model itself adopts a regional aggregated representation of the power system. The sending-end and receiving-end regions are each represented by regional power-balance constraints, while cross-regional electricity exchange is modeled through an aggregated transmission tie-line variable subject to its transfer-capacity limits. Therefore, detailed nodal power flows, individual branch thermal limits, bus-voltage constraints, and N-1 security constraints within each region are not explicitly considered in the present scheduling model. The IEEE 39-bus structure is mainly used to construct and illustrate the synthetic two-region system rather than to perform nodal AC/DC optimal power-flow calculations. This abstraction enables the present study to focus on the coordinated scheduling of electricity, hydrogen, and methanol across multiple timescales. It should be noted that the present study quantitatively compares methanol transportation with compressed gaseous hydrogen transportation by tube trailers, while other potential long-distance hydrogen carriers, such as liquid hydrogen and ammonia, are not explicitly modeled. These pathways involve carrier-specific processes and infrastructure requirements, including hydrogen liquefaction and cryogenic storage for liquid hydrogen, as well as ammonia synthesis and cracking for ammonia. Therefore, the current results should be interpreted as demonstrating the relative advantage of methanol over the tube-trailer hydrogen transportation pathway under the adopted system configuration, rather than establishing a general superiority over all alternative hydrogen carriers [41].

Future work will further validate the proposed framework using actual regional power-network, renewable-generation, energy-demand, methanol-logistics, and market data. On this basis, practical factors such as region-specific transmission constraints, transportation conditions, and market-price differences will be incorporated to evaluate the applicability of cross-regional methanol-based energy transfer under real operating environments [40]. Detailed nodal power-flow and network-security constraints will be incorporated in future work for validation on practical regional power systems. Future work will extend the present framework by incorporating liquid hydrogen and ammonia transportation pathways into a unified cross-regional optimization model. Their carrier-specific conversion efficiencies, storage characteristics, transportation costs, energy consumption, and reconversion requirements will be explicitly considered, so that the economic and operational performance of different hydrogen carriers can be evaluated under consistent system boundaries and operating conditions.

6. Conclusions

To mitigate the temporal and spatial mismatch of electricity and hydrogen supply-demand relationships between renewable-resource-rich areas and load centers, this study develops an optimal dispatch approach for a cross-regional power-hydrogen-methanol coupled energy system with methanol transportation. By establishing two interregional transfer channels, namely electricity transmission and methanol delivery, and integrating a differentiated stepwise carbon trading scheme with reward-penalty effects and DDRO, multi-timescale coordinated scheduling between the sending-end and receiving-end regions is achieved. Simulation studies on the IEEE 39-bus system demonstrate that the proposed approach is effective in promoting renewable energy utilization, lowering hydrogen supply

cost, enhancing low-carbon operation, and improving energy supply reliability.

(1) A power-hydrogen-methanol multi-energy coupling operation mechanism based on cross-regional methanol transportation is constructed, and a methanol storage and transportation model considering transportation delay is established. In this way, the whole-chain coordination of methanol production, storage, transport, and utilization is achieved, together with the collaborative operation of the power-hydrogen system. When only methanol transportation is adopted, the renewable energy curtailment rate reaches 13.63% due to the absence of hourly-level transfer capability provided by transmission tie-lines for surplus renewable energy. After both transmission tie-lines and cross-regional methanol transportation are introduced, the total system cost decreases to ¥380.002 billion, and the renewable energy curtailment rate decreases to 2.36%. This indicates that direct electricity transmission and cross-regional methanol storage and transportation can complement each other by undertaking real-time electricity transfer and cross-timescale hydrogen energy transfer, respectively, thereby improving cross-regional renewable energy accommodation and reducing the overall system operating cost.

(2) An optimal scheduling model adapted to the differentiated timescale characteristics of electricity, hydrogen, and methanol is developed, in which hourly-level power balance and daily-level methanol storage and transportation processes are coordinated. This improves the multi-energy supply-demand matching capability between the sending-end and receiving-end regions. The case results show that methanol storage and transportation amounts can be dynamically adjusted according to monthly variations in renewable energy output. When renewable energy output is abundant, surplus electricity is converted into methanol for storage; when the receiving-end demand increases, methanol transportation and reforming-based hydrogen production are used to supplement hydrogen supply. Relative to the hydrogen tube trailer scheme, interregional methanol delivery substantially lowers the expense of long-distance hydrogen energy transfer. The hydrogen supply cost associated with transported methanol accounts for only 1%, confirming the economic and regulation benefits of methanol as a hydrogen carrier for interregional storage and delivery.

(3) A differentiated stepwise carbon trading scheme with reward-penalty incentives is combined with DDRO to further enhance system operation under carbon reduction requirements and renewable generation uncertainty. The simulation results indicate that, compared with the case using only dual electricity-methanol transportation, the proposed method only slightly increases the total cost from ¥380.002 billion to ¥381.275 billion, while reducing carbon emissions from 675,166 to 672,500 kt and decreasing the load shedding rate from 0.28% to 0.05%. In addition, the robustness budget sensitivity results reveal that a higher robustness budget leads to a gradual rise in annual system cost, while the worst-case load curtailment rate declines significantly. This means that the proposed DDRO strategy can flexibly coordinate economic efficiency and energy supply dependability. Therefore, the proposed approach is verified to be effective in enhancing low-carbon operation, robustness, and supply security of the system under renewable power uncertainty.

Conflict of interest

The authors declare that we have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions

Borui Zhang: Conceptualization (equal); Data curation (equal); Formal analysis (equal); Yuming Yang: Funding acquisition (equal); Xueru Liu: Investigation (equal). Sida Lv: Methodology (equal); Software (equal); Writing-original draft (equal).

Data availability atatement

The data that support the findings of this study are available from the Corresponding Author, [Sida Lv], upon reasonable request.

References

1. Jiang H, Yao L, Qin J, et al. (2025) Globally interconnected solar-wind system addresses future electricity demands. *Nat Commun* 16: 4523. <https://doi.org/10.1038/s41467-025-59879-9>
2. Oyewo AS, Lopez G, ElSayed M, et al. (2024) Power-to-X economy: Green e-hydrogen, e-fuels, e-chemicals, and e-materials opportunities in Africa. *Energy Rep* 12: 2026–2048. <https://doi.org/10.1016/j.egy.2024.08.011>
3. Cui J, Aziz M (2023) Techno-economic analysis of hydrogen transportation infrastructure using ammonia and methanol. *Int J Hydrogen Energy* 48: 15737–15747. <https://doi.org/10.1016/j.ijhydene.2023.01.096>
4. Sánchez A, Blanco EC, Martín M (2024) Comparative assessment of methanol and ammonia: Green fuels vs. hydrogen carriers in fuel cell power generation. *Appl Energy* 374: 124009. <https://doi.org/10.1016/j.apenergy.2024.124009>
5. Fasihi M, Breyer C (2024) Global production potential of green methanol based on variable renewable electricity. *Energy Environ Sci* 17: 3503–3522. <https://doi.org/10.1039/D3EE02951D>
6. Fulham GJ, Mendoza-Moreno PV, Marek EJ (2024) Managing intermittency of renewable power in sustainable production of methanol, coupled with direct air capture. *Energy Environ Sci* 17: 4594–4621. <https://doi.org/10.1039/D4EE00933A>
7. Galimova T, Fasihi M, Bogdanov D, et al. (2025) Analysis of green e-methanol supply costs: Domestic production in Europe versus imports via pipeline and sea shipping. *Renew Energy* 241: 122336. <https://doi.org/10.1016/j.renene.2024.122336>
8. Alamia A, Partoon B, Rattigan E, et al. (2024) Optimizing hydrogen and e-methanol production through Power-to-X integration in biogas plants. *Energy Convers Manag* 322: 119175. <https://doi.org/10.1016/j.enconman.2024.119175>
9. Pakdel A, Eslamloueyan R (2024) Techno-economic and sustainability assessment of the power to MeOH processes: The present and future perspective. *Heliyon* 10: e39860. <https://doi.org/10.1016/j.heliyon.2024.e39860>
10. Duan Z, Xu P, Xu C, et al. (2025) An integrated Power-to-X-to-Power system in green methanol carrier with gas turbine combined cycle and carbon capture: Energy-exergy-cost-carbon intensities. *Energy Convers Manag* 342: 120141. <https://doi.org/10.1016/j.enconman.2025.120141>
11. Dautel JL, Thakur J, Elberry AM (2024) Enabling industrial decarbonization: A MILP optimization model for low-carbon hydrogen supply chains. *Int J Hydrogen Energy* 77: 863–891. <https://doi.org/10.1016/j.ijhydene.2024.06.050>

12. Cheng Z, Jia D, Li Z, et al. (2022) Multi-time scale energy management of microgrid considering the uncertainties in both supply and demand. *Energy Rep* 8: 10372–10384. <https://doi.org/10.1016/j.egy.2022.08.179>
13. Wang M, Zhang B, Su B, et al. (2024) An multi-timescale optimization strategy for integrated energy system considering source-load uncertainties. *Energy Rep* 12: 5083–5095. <https://doi.org/10.1016/j.egy.2024.10.040>
14. Liu H, Lu R, Dou Z, et al. (2024) A distributed multi-timescale dispatch strategy for a city-integrated energy system with carbon capture power plants. *Energies* 17: 1395. <https://doi.org/10.3390/en17061395>
15. Zhou Y, Zhai Q, Xu Z, et al. (2024) Multi-stage adaptive stochastic-robust scheduling method with affine decision policies for hydrogen-based multi-energy microgrid. *IEEE Trans Smart Grid* 15: 2738–2750. <https://doi.org/10.1109/TSG.2023.3340727>
16. Li Y, Han M, Shahidehpour M, et al. (2023) Data-driven distributionally robust scheduling of community integrated energy systems with uncertain renewable generations considering integrated demand response. *Appl Energy* 335: 120749. <https://doi.org/10.1016/j.apenergy.2023.120749>
17. Xu X, Shao Z, Chen F, et al. (2025) Stochastic robust optimization scheduling for integrated energy system cluster based on data-driven method. *Appl Energy* 400: 126512. <https://doi.org/10.1016/j.apenergy.2025.126512>
18. Gao J, Meng Q, Liu J, et al. (2024) Thermoelectric optimization of integrated energy system considering wind-photovoltaic uncertainty, two-stage power-to-gas and ladder-type carbon trading. *Renew Energy* 221: 119806. <https://doi.org/10.1016/j.renene.2023.119806>
19. Yan N, Li X, Wu Z, et al. (2024) Low-carbon economic scheduling with demand-side response uncertainty in regional integrated energy system. *Int J Electr Power Energy Syst* 156: 109691. <https://doi.org/10.1016/j.ijepes.2023.109691>
20. Yi T, Ren W (2024) Low carbon economy scheduling of integrated energy system considering the mutual response of supply and demand. *Sustain Energy Grids Netw* 38: 101279. <https://doi.org/10.1016/j.segan.2024.101279>
21. Ni Q, Xu C, Cai Z, et al. (2025) Optimal dispatch of integrated energy system with CCUS-P2G coupling and hydrogen-doped gas equipment based on ladder-type carbon trading mechanism. *Energy* 336: 138397. <https://doi.org/10.1016/j.energy.2025.138397>
22. Yousaf M, Mahmood A, Elkamel A, et al. (2022) Techno-economic analysis of integrated hydrogen and methanol production process by CO₂ hydrogenation. *Int J Greenh Gas Control* 115: 103615. <https://doi.org/10.1016/j.ijggc.2022.103615>
23. Mohammed Abbas AH, Cheralathan KK, Porpatham E, et al. (2024) Hydrogen generation using methanol steam reforming-catalysts, reactors, and thermo-chemical recuperation. *Renew Sustain Energy Rev* 191: 114147. <https://doi.org/10.1016/j.rser.2023.114147>
24. Wang Y, Lu Z, Li Y, et al. (2024) Performance analysis and multi-optimization of direct methanol fuel cell based on a novel numerical model considering mass transfer. *Int J Hydrogen Energy* 62: 362–374. <https://doi.org/10.1016/j.ijhydene.2024.03.015>
25. Wu Q, Li C (2023) Modeling and operation optimization of hydrogen-based integrated energy system with refined power-to-gas and carbon-capture-storage technologies under carbon trading. *Energy* 270: 126832. <https://doi.org/10.1016/j.energy.2023.126832>
26. Wang L, Dong W, Wang S, et al. (2025) Optimizing flexibility and low-carbon emissions in integrated energy systems: A two-stage robust optimization model incorporating hydrogen and carbon trading. *Energy Rep* 13: 1620–1631. <https://doi.org/10.1016/j.egy.2025.01.035>

27. Sun ZY, Wang YJ, Li D (2023) Carbon allowance allocation rules under emission intensity regulation: Grandfathering versus benchmarking. *Manag Decis Econ* 44: 3185–3198. <https://doi.org/10.1002/mde.3870>
28. Mucci S, Mitsos A, Bongartz D (2023) Cost-optimal Power-to-Methanol: Flexible operation or intermediate storage? *J Energy Storage* 72: 108614. <https://doi.org/10.1016/j.est.2023.108614>
29. Chang P, Li C, Zhu Q, et al. (2024) Optimal scheduling of electricity and hydrogen integrated energy system considering multiple uncertainties. *iScience* 27: 109654. <https://doi.org/10.1016/j.isci.2024.109654>
30. Yan L, Zhang X, Ullah Z, et al. (2025) Optimal scheduling of hydrogen storage in integrated energy system including multi-source and load uncertainties. *Alex Eng J* 114: 266–278. <https://doi.org/10.1016/j.aej.2024.11.061>
31. Jiang J, Zhu Y, Wang Y, et al. (2025) Unit commitment with bidirectional ramping constraints of flexibility retrofit thermal power unit. *Int J Electr Power Energy Syst* 168: 110709. <https://doi.org/10.1016/j.ijepes.2025.110709>
32. Zhao Y, Chen C, Teng M, et al. (2024) Refined modeling and approximated aggregation method for alkaline water electrolyzers in power system optimal scheduling. *Int J Hydrogen Energy* 52: 200–212. <https://doi.org/10.1016/j.ijhydene.2023.11.204>
33. Wang Y, Ma Z, Zhu Y, et al. (2024) 4E performance analysis and multi-optimization of a novel system integrating direct methanol fuel cell and ORC. *Fuel* 371: 132091. <https://doi.org/10.1016/j.fuel.2024.132091>
34. Sollai S, Porcu A, Tola V, et al. (2023) Renewable methanol production from green hydrogen and captured CO₂: A techno-economic assessment. *J CO₂ Util* 68: 102345. <https://doi.org/10.1016/j.jcou.2022.102345>
35. Song D, Lee J, Kim YH, et al. (2025) Integrated process modeling and optimization on methanol reforming-fuel cell systems via genetic algorithm with techno-economic analysis. *Energy* 335: 137856. <https://doi.org/10.1016/j.energy.2025.137856>
36. Han L, Wang S, Cheng Y, et al. (2024) Multi-timescale scheduling of an integrated electric-hydrogen energy system with multiple types of electrolysis cells operating in concert with fuel cells. *Energy* 307: 132707. <https://doi.org/10.1016/j.energy.2024.132707>
37. Yang M, Liu Y (2024) A two-stage robust configuration optimization framework for integrated energy system considering multiple uncertainties. *Sustain Cities Soc* 101: 105120. <https://doi.org/10.1016/j.scs.2023.105120>
38. Li F, Wang D, Guo H, et al. (2024) Distributionally robust optimization for integrated energy system accounting for refinement utilization of hydrogen and ladder-type carbon trading mechanism. *Appl Energy* 367: 123391. <https://doi.org/10.1016/j.apenergy.2024.123391>
39. Zong X, Yuan Y (2023) Two-stage robust optimization of regional integrated energy systems considering uncertainties of distributed energy stations. *Front Energy Res* 11: 1135056. <https://doi.org/10.3389/fenrg.2023.1135056>
40. Chatzos M, Tanneau M, Van Hentenryck P (2022) Data-driven time series reconstruction for modern power systems research. *Electr Power Syst Res* 212: 108589. <https://doi.org/10.1016/j.epsr.2022.108589>
41. Arrigoni A, D'Agostini T, Dolci F, et al. (2025) Techno-economic and life-cycle assessment comparisons of hydrogen delivery options. *Front Energy* 19: 1129–1142. <https://doi.org/10.1007/s11708-025-1041-1>

Appendix

Table A1. System operation parameters.

Sending-end region parameter	Value	Receiving-end region parameter	Value
Installed capacity of thermal units	191 GW	Installed capacity of thermal units	89.8 GW
Installed capacity of wind power	96 GW	Peak electrical load	79.03 GW
Installed capacity of photovoltaic power	150 GW	Peak hydrogen load	10473.7 t
Renewable energy penetration rate	56%	Methanol fuel cell capacity	50 MW
Peak electrical load	102.45 GW	Transmission tie-line capacity	26 GW
Peak hydrogen load	2704.7 t		
Electrolyzer capacity	24.51 GW		
Hydrogen storage tank capacity	400 t		

Table A2. Operation parameters of key system equipment.

Parameter	Value	Parameter	Value
η_{HM} (kg _{MeOH} /kg _{H₂})	4.54	η_{MH} (kg _{H₂} /kg _{MeOH})	0.19
η^{H_2}	0.75	k_{M} (MW/t)	1.047
m_{C}	1.375	K_{L}	0.02
K_{W}	0.05	λ_{E} (¥/kg)	0.36
λ_{line} (¥/MW·h)	161.25	λ_{r} (¥/MW·h)	677.25
λ_{F} (¥/MW·h)	14620	D_{d} (km)	2150
δ (d)	2	λ_{T} (¥/t·km)	0.43
$\lambda_{\text{b,d}}^{\text{M}}$ (¥/t)	2700	$\lambda_{\text{sd}}^{\text{w}}$ (¥/kg)	107.5
λ_{g} (¥/kg)	0.5	λ_{p} (¥/kg)	0.36
λ_{MH} (¥/kg)	0.06	$m_{\text{M,H2,max}}$ (t/h)	324
$m_{\text{H2,M,max}}$ (t/h)	270	μ_{c} (¥/t)	350
k_{cc} (MW/t)	0.23	γ_{c} (t/MW·h)	0.827
s (%)	20	V (%)	25
N (t)	40	L (t)	20



AIMS Press

© 2026 the Author(s), licensee AIMS Press. This is an open access article distributed under the terms of the Creative Commons Attribution License (<https://creativecommons.org/licenses/by/4.0>)