

Monthly-daily rolling operational optimization of electricity-heat-hydrogen integrated energy systems for supply-demand mismatch minimization

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ABSTRACT

With the increasing penetration of renewable energy, seasonal and short-term supply–demand mismatches have become critical challenges. Integrated energy systems with hybrid energy storage provide a promising pathway to address these mismatches. This paper proposes a monthly-daily rolling operational optimization framework for an electricity–heat–hydrogen integrated energy system, considering multi-energy balances and uncertainties. In the monthly aggregated optimization stage, K-medoids clustering is applied to multi-year data to obtain monthly total energy and establish monthly net hydrogen storage targets. In the intra-month rolling dispatch stage, a multi-scenario stochastic model predictive control method incorporating extreme events is developed, embedding monthly hydrogen targets into hourly rolling constraints to handle short-term uncertainties. Simulation results show that the framework enables coordinated operation of multi-energy devices across timescales and achieves an effective trade-off between economic efficiency and operational robustness, reducing annual operating costs by 2.71% and average daily costs under extreme conditions by 17.43%.

1. Introduction

High-penetration renewable energy integration is reshaping the operational paradigm of modern energy systems [1]. Although photovoltaic (PV) and other renewable sources significantly reduce carbon emissions, their inherent intermittency and temporal variability pose challenges to system stability, resulting in short-term supply–demand mismatches [2]. Moreover, PV generation is highly dependent on solar radiation, which leads to seasonal variations, while system loads also fluctuate seasonally due to factors such as temperature. This coupling of supply and demand characteristics results in severe seasonal supply–demand mismatches [3,4].

Hydrogen energy storage, as a seasonal storage option, has attracted wide attention. Gas leakage from hydrogen storage is typically negligible, allowing surplus renewable energy to be converted into hydrogen and stored over long periods. This stored hydrogen can then be converted back into electricity during energy-scarce seasons to address seasonal supply–demand mismatches [5,6]. Battery energy storage system (BESS), which serves as short-term storage, is also an effective solution for resolving daily supply–demand mismatches [7]. Therefore, integrating both seasonal hydrogen storage (SHS) and BESS into an

energy system offers a promising pathway to effectively manage mismatches across different timescales [8–10].

Recent research has developed foundational optimization models for SHS within integrated energy systems [11]. Early efforts focused on capacity configurations, such as a two-stage model for SHS sizing under economic and safety constraints [12], and a two-layer electric-hydrogen model coupling long-term capacity decisions with typical-day performance [13]. However, evaluating seasonal storage solely based on typical days oversimplifies intra-day stochasticity and neglects coordination with short-term storage such as BESS. To better capture system behaviors, techno-economic mixed-integer linear programming (MILP) frameworks were established to minimize costs while considering seasonal storage dynamics [14], alongside coordinated planning models explicitly optimizing short- and long-term storage capacities [15]. Furthermore, comprehensive multi-energy models have formulated the state transitions of green hydrogen [16] and defined dynamic charging/discharging sequences [17]. Although these models improve seasonal source-load balancing, they generally lack mechanisms to integrate seasonal state transitions with high-frequency operational fluctuations.

Beyond capacity sizing, recent literature has increasingly adopted

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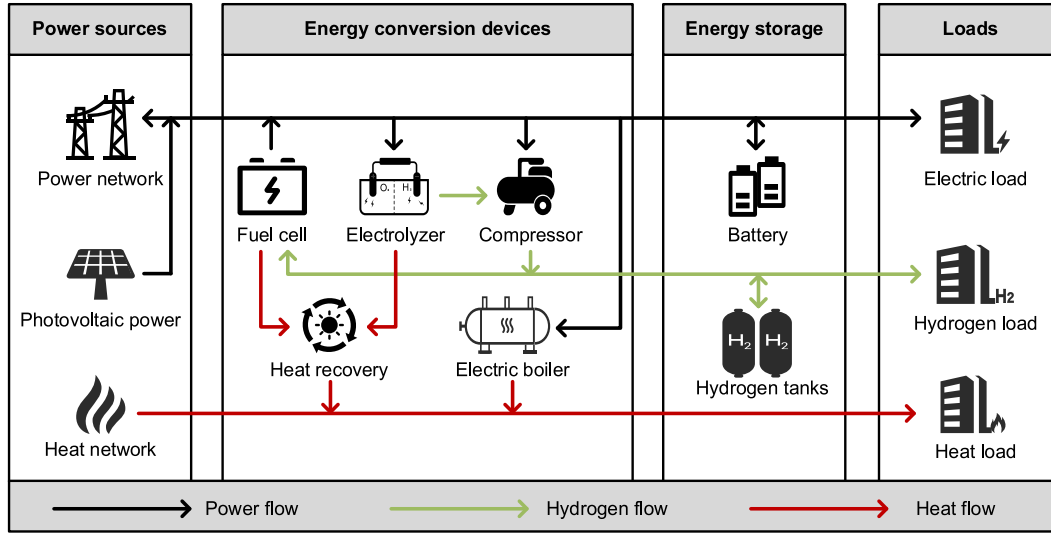


Fig. 1. Structure of the electricity-heat-hydrogen multi-energy flow system.

advanced mathematical frameworks to optimize long-term regulation and intertemporal state transitions of SHS. Capacity allocation models have integrated seasonal storage with external hydrogen trading to minimize annualized costs [18]. Extending into dynamic regulation, Markov decision processes have been utilized to optimize seasonal hydrogen inventory decisions under constrained distribution capacities [19], while robust stochastic planning models have been established to continuously track storage state-of-charge across annual horizons [20]. However, these intertemporal models primarily address seasonal energy shifting and often fail to capture daily operational fluctuations. This limitation reduces the effectiveness of multi-timescale coordination between long-term SHS and short-term BESS, preventing simultaneous optimization of hybrid storage units across coupled time scales [18–20]. Even as research structurally embeds green hydrogen storage to shift surplus renewables across seasons [21], or introduces stochastic multi-horizon expansion models for tactical weather and demand variations [22], the focus remains largely on single-timescale scheduling.

To bridge the inherent gap between seasonal and daily fluctuations, recent research has actively explored multi-timescale coordination for hybrid energy systems. At the planning level, models have synergistically configured multi-energy storages to handle long-term uncertainties [23], while optimal sizing frameworks have applied seasonal-trend decomposition techniques to coordinate multi-timescale operations [24]. However, such scenario-transformation models often rely on a single typical year or a limited set of representative days, failing to capture multi-year stochasticity and long-term climatic variations. At the operational level, hierarchical dispatch methods have divided control parameters into fast and slow timescales to balance long-term economics with real-time power balancing [25], coordinating day-ahead macroscopic scheduling with intra-day moving horizons [26]. Advanced strategies have aligned dynamic response times of diverse hydrogen components [27] and employed model predictive control (MPC) for short-term rolling feedback [28]. Moreover, current frameworks primarily optimize economic performance without fully ensuring reliable power supply under extreme weather or severe energy shortages [25, 26]. Therefore, there is still a need for a comprehensive modeling framework that simultaneously coordinates multi-timescale hybrid storage, incorporates multi-year uncertainties, and ensures robust operation under extreme conditions.

To address daily randomness and extreme events, mathematical frameworks like multi-stage robust optimization (MSRO) and distributionally robust optimization (DRO) have been explored. MSRO has been formulated to manage dynamic uncertainty sets for unit

commitment and hydrogen-based microgrid scheduling [29,30], and optimize the spatial-temporal scheduling of mobile energy storages [31], guaranteeing absolute system security under worst-case scenarios. However, the strict worst-case boundaries of the method inevitably lead to severe over-conservatism in long-term hydrogen inventories, reducing annual economic performance. Alternatively, DRO effectively balances operational risk and cost via data-driven ambiguity sets, demonstrating strong adaptability in joint energy and reserve dispatch, complex spatiotemporal coordination, and multi-stakeholder energy management [32–34]. While DRO handles distributional ambiguity efficiently, it struggles to capture high-frequency temporal correlations and fat-tail distributions in multi-year renewable data. Therefore, there is still a need for a comprehensive modeling framework that simultaneously coordinates multi-timescale hybrid storage, incorporates multi-year uncertainties, and ensures robust operation under extreme conditions.

To this end, this paper proposes a monthly-daily rolling operational optimization framework for an electricity-heat-hydrogen integrated energy system (EHHIES) with SHS. The framework decomposes the dispatch problem into a monthly aggregated optimization stage and an intra-month rolling dispatch stage. By considering multi-timescale supply-demand mismatches, the proposed approach captures both seasonal uncertainties through multi-year historical data and short-term uncertainties including low-probability extreme events, linking monthly hydrogen targets to daily rolling dispatch to ensure coordinated and robust operation across time scales. The main contributions are summarized as follows.

- (1) A monthly-daily rolling operational optimization framework is developed for the EHHIES, integrating SHS and BESS to address seasonal and short-term supply-demand mismatches, thereby enhancing coordination of hybrid storage across multiple timescales.
- (2) In the monthly aggregated optimization stage, monthly total energy is obtained from multi-year historical data via clustering, and monthly net hydrogen storage targets are derived to capture monthly uncertainties.
- (3) Based on the monthly hydrogen targets, a multi-scenario stochastic MPC (MSMPC) with rolling dispatch is formulated, incorporating extreme events and achieving an improved trade-off between economic performance and robustness.

The remainder of this paper is organized as follows. Section 2

describes the EHHIES framework and the modeling of controllable units and multi-energy supply-demand balances. Section 3 presents the proposed framework, comprising the monthly aggregated optimization and the intra-month rolling dispatch models. Section 4 validates the proposed method, and the conclusions are summarized in Section 5.

2. Mathematical modeling

2.1. System description

This paper focuses on an EHHIES that couples electricity, heat and hydrogen flows, as shown in Fig. 1. Electricity is supplied by the power network and PV generation, while a battery is employed to regulate the daily power balance between supply and demand. Hydrogen is produced by an electrolyzer (EL), compressed and stored in tanks to meet hydrogen demand, which also serves as seasonal storage and can be reconverted to electricity by a fuel cell (FC). Waste heat from the EL and FC is recovered to serve the heat load, with an electric boiler (EB) providing additional heating when required. Coordinated operation of these components enables effective multi-energy supply-demand balance [35].

In the EHHIES, hydrogen storage serves as long-term storage, capable of regulating the supply-demand balance on a seasonal scale by storing energy from surplus to deficit periods, while BESS is primarily used for short-term regulation, maintaining daily power balance. The objective of this paper is to propose a monthly-daily rolling operational optimization framework by developing a monthly aggregated optimization model and an intra-month rolling dispatch model to effectively address seasonal and short-term supply-demand mismatches while considering extreme scenarios, thereby achieving an optimal trade-off between economic performance and operational robustness [36].

2.2. Modeling of controllable units

2.2.1. Electrolyzer unit

The energy conversion of the EL is described by Eqs. (1) and (2), while Eq. (3) constrains its input power.

$$H^{EL}(t) = \eta^{EL} P^{EL}(t) / LHV_{H_2} \quad (1)$$

$$Q^{EL}(t) = (1 - \eta^{EL}) P^{EL}(t) \quad (2)$$

$$P_{\min}^{EL} \leq P^{EL}(t) \leq P_{\max}^{EL} \quad (3)$$

where t is the time slot index; H^{EL} , Q^{EL} and P^{EL} represent the hydrogen and heat production, and electricity consumption of the EL, respectively; LHV_{H_2} is the lower heating value of hydrogen; η^{EL} is the efficiency of the EL; $P_{\max}^{EL}$ and $P_{\min}^{EL}$ denote maximum and minimum input electric power of the EL, respectively.

2.2.2. Compressor unit

The compressor (CMP) power consumption mainly depends on the compression ratio and the inlet hydrogen flow rate, and it is modeled as Eq. (4) [37].

$$P^{CMP}(t) = \frac{1}{\eta^{CMP}} \Pi^{CMP} H^{EL}(t) \quad (4)$$

where P^{CMP} denotes the power consumption of the CMP; η^{CMP} is the efficiency of the CMP; Π^{CMP} represents the specific compression work determined by the compression ratio.

2.2.3. Fuel cell unit

The energy conversion of the FC can be expressed by Eqs. (5) and (6), and the electric power output is constrained by Eq. (7).

$$P^{FC}(t) = \eta^{FC} H^{FC}(t) LHV_{H_2} \quad (5)$$

$$Q^{FC}(t) = (1 - \eta^{FC}) H^{FC}(t) LHV_{H_2} \quad (6)$$

$$0 \leq P^{FC}(t) \leq P_{\max}^{FC} \quad (7)$$

where P^{FC} , Q^{FC} and H^{FC} are electricity and heat production, and hydrogen consumption of FC, respectively; η^{FC} is the efficiency of the FC; and $P_{\max}^{FC}$ is the maximum electricity generated by the FC.

2.2.4. Electric boiler unit

The EB converts electricity into heat to meet part of the heat demand, and its energy conversion relationship and heat output bounds are given in Eq. (8) and Eq. (9), respectively.

$$Q^{EB}(t) = \eta^{EB} P^{EB}(t) \quad (8)$$

$$0 \leq Q^{EB}(t) \leq Q_{\max}^{EB} \quad (9)$$

where Q^{EB} and P^{EB} denote heat production and electricity consumption of the EB; η^{EB} is the efficiency of the EB; and $Q_{\max}^{EB}$ represents maximum heat generated by the EB.

2.2.5. Heat recovery unit

The heat generated by the EL and the FC can be recovered by the heat recovery unit. The recovery model is given in Eqs. (10)–(12), and the recovered heat is constrained by Eq. (13).

$$Q^{REC}(t) = Q^{EL,REC}(t) + Q^{FC,REC}(t) \quad (10)$$

$$Q^{EL,REC}(t) = \eta^{REC} Q^{EL}(t) \quad (11)$$

$$Q^{FC,REC}(t) = \eta^{REC} Q^{FC}(t) \quad (12)$$

$$0 \leq Q^{REC}(t) \leq Q_{\max}^{REC} \quad (13)$$

where Q^{REC} denotes the total recovered heat; $Q^{EL,REC}$ and $Q^{FC,REC}$ denote the recovered heat from the EL and the FC, respectively; η^{REC} is the efficiency of the heat recovery unit; $Q_{\max}^{REC}$ represents the maximum recoverable heat.

2.2.6. Battery energy storage system unit

The state of charge (SOC) of the BESS at each time slot is described by Eq. (14) and constrained by Eq. (15). To prevent simultaneous charging and discharging, two binary variables $I^{P, ch}$ and $I^{P, dch}$ are introduced in Eq. (16). The charging and discharging power limits are given in Eqs. (17) and (18), respectively [38].

$$SOC(t) = (1 - \eta^{loss}) SOC(t-1) + \frac{(\eta^{ch} P^{ch}(t) - P^{dch}(t) / \eta^{dch})}{CAP^{Bat}} \Delta t \quad (14)$$

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max} \quad (15)$$

$$I^{P, ch}(t) + I^{P, dch}(t) \leq 1 \quad (16)$$

$$0 \leq P^{ch}(t) \leq I^{P, ch}(t) P_{\max}^{ch} \quad (17)$$

$$0 \leq P^{dch}(t) \leq I^{P, dch}(t) P_{\max}^{dch} \quad (18)$$

where P^{ch} and P^{dch} represent the charging and discharging power of the BESS, respectively; η^{loss} is the self-discharge coefficient of the BESS; η^{ch} and η^{dch} are the charging and discharging efficiencies; CAP^{Bat} denotes the energy capacity of the battery; $SOC_{\min}$ and $SOC_{\max}$ are the lower and upper bounds of SOC; $P_{\max}^{ch}$ and $P_{\max}^{dch}$ represent the maximum charging and discharging power, respectively.

2.2.7. Hydrogen storage unit

The dynamics of the SHS are expressed in Eq. (19), with the storage

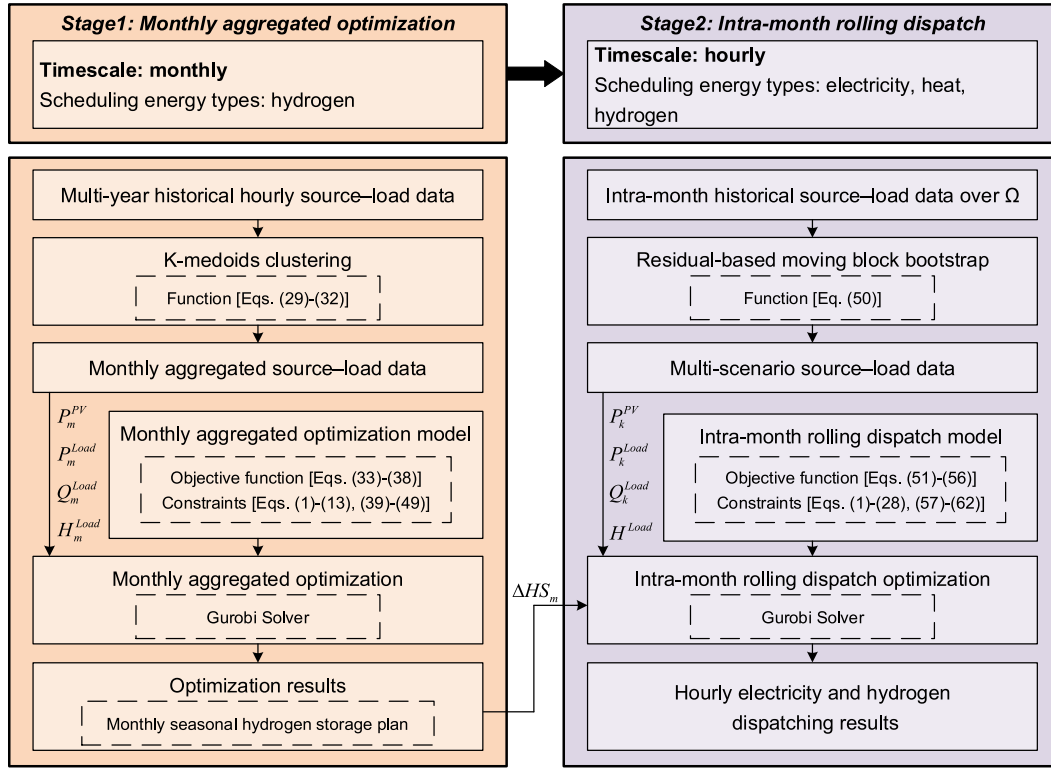


Fig. 2. Framework of the proposed multi-timescale energy optimization.

capacity constrained by Eq. (20). As described in Eq. (21), two binary variables $I^{H, ch}$ and $I^{H, dch}$ ensure that the hydrogen storage tank cannot charge and discharge simultaneously. The charging and discharging rate limits are given in Eqs. (22) and (23), respectively [39].

$$HS(t) = HS(t-1) + H^{ch}(t) - H^{dch}(t) \quad (19)$$

$$HS_{\min} \leq HS(t) \leq HS_{\max} \quad (20)$$

$$I^{H, ch}(t) + I^{H, dch}(t) \leq 1 \quad (21)$$

$$0 \leq H^{ch}(t) \leq I^{H, ch}(t) H_{\max}^{ch} \quad (22)$$

$$0 \leq H^{dch}(t) \leq I^{H, dch}(t) H_{\max}^{dch} \quad (23)$$

where HS denotes the stored hydrogen level in the hydrogen storage tank at time slot t ; H^{ch} and H^{dch} represent the hydrogen charging and discharging rates, respectively; $HS_{\min}$ and $HS_{\max}$ are the minimum and maximum storage capacities; $H_{\max}^{ch}$ and $H_{\max}^{dch}$ denote the maximum allowable charging and discharging rates, respectively.

2.3. Modeling of multi-energy supply-demand balance

The energy balance of the EHHIES is established for the electricity, heat, and hydrogen subsystems to enforce supply-demand equilibrium at each time step. The corresponding balance constraints are expressed in Eqs. (24)–(26), with the electricity and heat purchase limits defined in Eqs. (27) and (28).

$$P^{Grid}(t) + P^{PV}(t) + P^{FC}(t) + P^{dch}(t) = P^{EL}(t) + P^{CMP}(t) + P^{EB}(t) + P^{ch}(t) + P^{Sell}(t) + P^{Load}(t) + P^{Curt}(t) \quad (24)$$

$$Q^{Grid}(t) + Q^{EB}(t) + Q^{EL, REC}(t) + Q^{FC, REC}(t) = Q^{Load}(t) + Q^{Curt}(t) \quad (25)$$

$$H^{EL}(t) + H^{dch}(t) = H^{FC}(t) + H^{ch}(t) + H^{Load}(t) + H^{Curt}(t) \quad (26)$$

$$0 \leq P^{Grid}(t) \leq P_{\max}^{Grid} \quad (27)$$

$$0 \leq Q^{Grid}(t) \leq Q_{\max}^{Grid} \quad (28)$$

where P^{Grid} and Q^{Grid} are the electricity and heat purchased from the

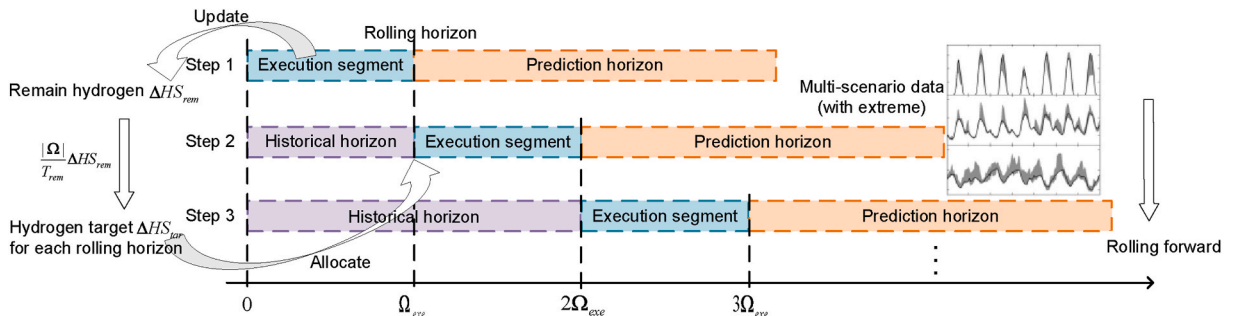


Fig. 3. Framework of the intra-month rolling dispatch.

utility grid and the heat network, respectively; P^{PV} is the PV power output; P^{Load} , Q^{Load} , H^{Load} are the electrical, heating, and hydrogen demands of the load, respectively; P^{Sell} denotes the electricity sold to the utility grid; P^{Curt} , Q^{Curt} , H^{Curt} denote the PV, heat, and hydrogen curtailment, respectively; P_{max}^{Grid} and Q_{max}^{Grid} represent the maximum allowable electricity and heat purchase powers, respectively.

3. Optimization framework

Fig. 2 illustrates the proposed monthly-daily rolling operational optimization framework for the EHHIES. Since system operation inherently exhibits multi-timescale characteristics, the BESS is mainly used to maintain daily balance, whereas hydrogen storage, as a seasonal storage, enables cross-day and cross-season energy shifting [40]. Accordingly, the dispatch problem is formulated as a monthly-daily model, consisting of monthly aggregated optimization and intra-month rolling dispatch. By leveraging monthly hydrogen storage targets to guide intra-month rolling dispatch, the framework enables temporally coordinated operation and avoids myopic hydrogen charging/discharging decisions, i.e., temporal myopia, in hybrid storage management [41,42]. To decouple uncertainties across time scales, the monthly stage captures inter-annual variability for planning purposes, while the intra-month stage focuses on short-term operational stochasticity within the rolling horizon. The two stages are linked by the monthly hydrogen target, which is progressively tracked during intra-month optimization. The detailed procedures are described below.

- (1) Monthly aggregated optimization stage: to capture comprehensive monthly uncertainties, multi-year historical hourly PV and load data are first clustered into several typical days per month. By clustering multi-year data for each month, inter-annual variability of monthly source and load patterns is captured, providing a representative planning basis and avoiding bias from a single-year dataset. This aggregation preserves the seasonal energy patterns while reducing computational complexity, ensuring that system characteristics are maintained [43]. The energy for each time period of the typical days is summed to obtain the daily energy, which is then aggregated based on weights to calculate the monthly total energy. The monthly aggregated optimization model is constructed using the monthly total energy as the timescale, and minimizes the annual operating cost subject to energy balance and device operational constraints, producing the monthly net hydrogen storage targets. These targets serve as reference points for subsequent intra-month dispatch and provide an effective allocation for multi-timescale coordination.
- (2) Intra-month rolling dispatch stage: an hourly MSMPC is employed for intra-month rolling dispatch, as shown in Fig. 3. In this stage, uncertainty is considered only at the short-term scale within the prediction horizon via residual-based scenario generation, comprising a baseline forecast and several extreme scenarios. If the monthly target is evenly allocated to each day, the daily scheduling loses flexibility, as the hydrogen tank is forced to follow a fixed daily target rather than adapt to varying load characteristics. Such rigid enforcement severely restricts the system's robust operating region under uncertainties [44]. To address this, a dynamic target allocation mechanism is applied to maintain flexibility and mitigate rolling errors caused by mismatches between monthly targets and short-term stochastic fluctuations. A portion of the remaining monthly hydrogen target is allocated to the current prediction horizon as a rolling constraint. After executing the first step, the actual hydrogen storage level is measured, and the remaining monthly target is updated for subsequent steps. This helps the system gradually meet the monthly target while still allowing flexible operation under daily fluctuations and extreme events. The monthly

hydrogen target is based on typical load characteristics, and the rolling updates reduce deviations between actual and target storage, collectively supporting the convergence of the MSMPC algorithm.

3.1. Monthly aggregated optimization model

3.1.1. K-medoids clustering

To comprehensively represent monthly uncertainties, multi-year historical hourly data are utilized, which can effectively capture the typical characteristics for each month while mitigating the influence of anomalous data from any individual year. For each month $m \in \mathcal{M}$, the historical PV and load data are arranged into daily sample vectors and clustered via K-medoids. This process extracts the seasonal energy patterns to form a set of representative typical days $\mathcal{K}_m$ and the corresponding weights $\omega_{m,k}$. The number of clusters for each month is determined by silhouette analysis. For each month, K-medoids clustering is performed under different candidate values of K, and the silhouette coefficient is used to evaluate the clustering quality. A suitable K is then selected to ensure the representativeness of typical days while maintaining a compact monthly aggregation model [45,46]. The daily energy of PV and electric load for each typical day is computed by Eqs. (29) and (30), and the monthly total energy is then obtained by the weighted summation in Eqs. (31) and (32).

$$E_{m,k}^{PV} = \sum_{t=1}^{24} P_{m,k}^{PV}(t) \Delta t \quad (29)$$

$$E_{m,k}^{Load} = \sum_{t=1}^{24} P_{m,k}^{Load}(t) \Delta t \quad (30)$$

$$E_m^{PV} = D_m \sum_{k \in \mathcal{K}_m} \omega_{m,k} E_{m,k}^{PV} \quad (31)$$

$$E_m^{Load} = D_m \sum_{k \in \mathcal{K}_m} \omega_{m,k} E_{m,k}^{Load} \quad (32)$$

where m denotes the month index and $\mathcal{M}$ is the set of months; D_m is the number of days in month m ; $P_{m,k}^{PV}$ and $P_{m,k}^{Load}$ denote the PV power and electric load of typical day k in month m , respectively; $E_{m,k}^{PV}$ and $E_{m,k}^{Load}$ represent the corresponding daily energies; E_m^{PV} and E_m^{Load} are the monthly aggregated PV and electric load energy; the weight $\omega_{m,k}$ represents the occurrence ratio of typical day k in month m , satisfying $\sum_{k \in \mathcal{K}_m} \omega_{m,k} = 1$. The monthly total energy of heat and hydrogen are computed in the same manner as in Eqs. (29)–(32).

3.1.2. Objective function

Based on the monthly aggregated inputs obtained from Eqs. (29)–(32), the monthly aggregated optimization model is formulated to minimize the annual operating cost C^{Year} . The objective function is given in Eqs. (33)–(38).

$$\min C^{Year} = \sum_{m \in \mathcal{M}} (C_m^{Buy} + C_m^{Run} + C_m^{Env} + C_m^{Pen} - C_m^{Sell}) \quad (33)$$

$$C_m^{Buy} = c^{E,Buy} P_m^{Grid} + c^{Q,Buy} Q_m^{Grid} \quad (34)$$

$$C_m^{Run} = c^{EL} P_m^{EL} + c^{CMP} P_m^{CMP} + c^{FC} P_m^{FC} + c^{EB} P_m^{EB} + c^{REC} Q_m^{REC} \quad (35)$$

$$C_m^{Env} = c^{Env} (\lambda^E P_m^{Grid} + \lambda^Q Q_m^{Grid}) \quad (36)$$

$$C_m^{Pen} = c^{E,Pen} P_m^{Curt} + c^{H,Pen} H_m^{Curt} \quad (37)$$

$$C_m^{Sell} = c^{E,Sell} P_m^{Sell} \quad (38)$$

where C_m^{Buy} , C_m^{Run} , C_m^{Env} , C_m^{Pen} and C_m^{Sell} denote the energy purchase cost, O&M cost, environmental cost, penalty cost and electricity sales revenue, respectively; $c^{E,Buy}$, $c^{Q,Buy}$ and $c^{E,Sell}$ are the electricity/heat purchase prices and electricity selling price; c^{EL} , c^{CMP} , c^{FC} , c^{EB} and c^{REC} are O&M cost coefficients; c^{Env} represents the environmental cost factor; λ^E and λ^Q are the electricity/heat emission factors; $c^{E,Pen}$ and $c^{H,Pen}$ are penalty coefficients. Other variables follow the definitions in Section 2, but are interpreted as monthly total energy in the model.

3.1.3. Constraints

The constraint set of the monthly aggregated optimization model is obtained by aggregating the unit models and balance equations in Section 2 to the monthly timescale. The BESS-related constraints are excluded, as the BESS is dedicated to daily balancing in the inter-month rolling dispatch. Since the monthly energy supply-demand balances can be expressed as Eqs. (39)–(41).

$$P_m^{Grid} + P_m^{PV} + P_m^{FC} = P_m^{EL} + P_m^{CMP} + P_m^{EB} + P_m^{Sell} + P_m^{Load} + P_m^{Curt} \quad (39)$$

$$Q_m^{Grid} + Q_m^{EB} + Q_m^{EL,REC} + Q_m^{FC,REC} = Q_m^{Load} + Q_m^{Curt} \quad (40)$$

$$H_m^{EL} + H_m^{dch} = H_m^{FC} + H_m^{ch} + H_m^{Load} + H_m^{Curt} \quad (41)$$

where P_m , Q_m and H_m denote the monthly total energy, i.e., the cumulative electricity/heat energies and hydrogen amount over month m , rather than the instantaneous power/flow rates.

To remain consistent with the hourly operating limits, the capacity constraints are aggregated to the monthly timescale by multiplying the rated limits by the number of hours T_m in month m , as given in Eqs. (42)–(45).

$$0 \leq P_m^i \leq P_{\max}^i T_m \quad i \in \{Grid, EL, FC\} \quad (42)$$

$$0 \leq Q_m^j \leq Q_{\max}^j T_m \quad j \in \{Grid, EB, REC\} \quad (43)$$

$$0 \leq H_m^{ch} \leq H_{\max}^{ch} T_m \quad (44)$$

$$0 \leq H_m^{dch} \leq H_{\max}^{dch} T_m \quad (45)$$

In addition, the hydrogen storage constraints in Eqs. (46)–(48) are enforced to describe the inter-month storage dynamics and to ensure cyclic operation over the annual horizon. The monthly net hydrogen storage target ΔHS_m is then defined in Eq. (49).

$$HS_m = HS_{m-1} + H_m^{ch} - H_m^{dch} \quad (46)$$

$$HS_0 = HS_{init} \quad (47)$$

$$HS_{|\mathcal{N}|} = HS_0 \quad (48)$$

$$\Delta HS_m = H_m^{ch} - H_m^{dch} \quad (49)$$

where HS_{init} is the initial hydrogen storage value; $|\mathcal{N}|$ denotes the number of months in the annual horizon.

3.2. Intra-month rolling dispatch model

3.2.1. Scenario generation

Distinct from the monthly typical days obtained by clustering, a residual-based moving block bootstrap (MBB) method is employed to generate daily scenarios, enhancing the robustness of the intra-month rolling dispatch against low-probability extreme events. Historical residuals between actual values and baseline forecasts for PV generation and loads are divided into consecutive blocks of length L and resampled with replacement to construct disturbance sequences that preserve short-term autocorrelation and extreme fluctuations [47,48]. The

generated scenario values $\tilde{x}_k(t)$ for scenario k are obtained by superimposing the bootstrapped residuals onto the baseline forecast $\bar{x}(t)$, as expressed in Eq. (50).

$$\tilde{x}_k(t) = \max(0, \bar{x}(t) + \gamma_k \cdot \varepsilon_k(t)) \quad \varepsilon_k(t) \sim \text{MBB}(\mathcal{R}, L) \quad (50)$$

where $x \in \{P^{PV}, P^{Load}, Q^{Load}\}$; γ_k is a severity scaling factor that adjusts the magnitude of extreme events; ε_k is the bootstrapped disturbance; $\mathcal{R}$ denotes the historical residual set; and L is the block length.

To ensure that the generated scenarios capture high-impact deviations, the residuals are separated directionally. Specifically, negative PV errors form $\mathcal{R}^{PV-}$ to represent PV under-generation, and positive load errors form $\mathcal{R}^{Load+}$ to represent load surges [49]. This procedure produces a set of $\mathcal{N}$ scenarios, including one nominal baseline scenario indexed as $k = 0$ and multiple extreme scenarios indexed from $k = 1$ to $\mathcal{N} - 1$, which are subsequently fed into the MSMPC rolling dispatch. By considering these scenarios, the controller adaptively adjusts the energy and hydrogen storage schedules while accounting for both normal and extreme conditions.

3.2.2. Objective function

For each rolling step, the MPC problem minimizes the operating cost over the prediction horizon Ω under the scenario set $\mathcal{N}$. The objective includes energy purchase costs, O&M costs, environmental costs, penalty costs and electricity sales revenue, as given in Eqs. (51)–(56).

$$\min C^\Omega = \sum_{k \in \mathcal{N}} \pi_k \sum_{t \in \Omega} (C_k^{Buy}(t) + C_k^{Run}(t) + C_k^{Env}(t) + C_k^{Pen}(t) - C_k^{Sell}(t)) \Delta t \quad (51)$$

$$C_k^{Buy}(t) = c^{E,Buy}(t) P_k^{Grid}(t) + c^{Q,Buy}(t) Q_k^{Grid}(t) \quad (52)$$

$$C_k^{Run}(t) = c^{EL} P_k^{EL}(t) + c^{CMP} P_k^{CMP}(t) + c^{FC} P_k^{FC}(t) + c^{EB} P_k^{EB}(t) + c^{REC} Q_k^{REC}(t) \quad (53)$$

$$C_k^{Env}(t) = c^{Env} (\lambda^E P_k^{Grid}(t) + \lambda^Q Q_k^{Grid}(t)) \quad (54)$$

$$C_k^{Pen}(t) = c^{E,Pen} P_k^{Curt}(t) + c^{H,Pen} H_k^{Curt}(t) \quad (55)$$

$$C_k^{Sell}(t) = c^{E,Sell}(t) P_k^{Sell}(t) \quad (56)$$

where $k \in \mathcal{N}$ denotes the scenario index with probability π_k ; $t \in \Omega$ denotes the time index over the prediction horizon.

3.2.3. Constraints

In the intra-month rolling dispatch model, the operational constraints of each component, i.e., Eqs. (1)–(23), and the multi-energy supply-demand balance constraints, i.e., Eqs. (24)–(28), are enforced for each scenario $k \in \mathcal{N}$ over the prediction horizon $t \in \Omega$. To implement the MSMPC and couple it with the monthly hydrogen target, the states of energy storage systems, including battery SOC and hydrogen storage levels, are updated at each rolling step. Eq. (57) determines the target hydrogen change for the current rolling horizon based on the remaining monthly target. The expected change in hydrogen storage across all scenarios is then constrained to match the allocated target, as expressed in Eq. (58), and Eq. (59) ensures identical control variables across all scenarios in the first execution segment [50].

$$\Delta HS_{tar} = \frac{|\Omega|}{T_{rem}} \Delta HS_{rem} \quad (57)$$

$$\sum_{k \in \mathcal{N}} \pi_k (HS_k(|\Omega|) - HS_k(0)) = \Delta HS_{tar} \quad (58)$$

$$u_k(t) = u_0(t) \quad \forall k \in \mathcal{N} \setminus \{0\}, \forall t \in \Omega_{exe} \quad (59)$$

where ΔHS_{tar} is the target net hydrogen storage change allocated to the current rolling horizon; $|\Omega|$ represents the number of time steps in the rolling horizon; T_{rem} is the remaining number of time steps in the current

Table 1
Electricity purchase and selling prices.

Period	$c^{E,Buy}$ (\$/kWh)	$c^{E,Sell}$ (\$/kWh)
Peak (10:00-14:59, 18:00-21:59)	0.15	0.03
Flat (7:00-9:59, 15:00-17:59)	0.10	0.02
Valley (0:00-6:59, 22:00-23:59)	0.05	0.01

month; ΔHS_{rem} is the remaining monthly net hydrogen storage target, initialized as ΔHS_m at the beginning of the month and updated after each execution segment; and u_k collects the control variables implemented in Ω_{exe} , e.g., hydrogen and power charging/discharging rates and the associated binary indicators.

Upon completion of the execution segment, the realized SOC and hydrogen storage levels are used as the initial conditions for the next rolling step. Simultaneously, the remaining monthly net hydrogen storage target is dynamically updated based on the actual storage changes. The rolling horizon then shifts forward, and the rolling procedure continues until the end of the month. Specifically, the initialization constraints for the SOC and hydrogen storage states are formulated in Eqs. (60)–(62).

$$SOC_k(0) = SOC_{init} \quad (60)$$

$$SOC_k(|\Omega_{exe}|) = SOC_{init} \quad (61)$$

$$HS_k(0) = HS_{sta} \quad (62)$$

where SOC_{init} is the SOC at the beginning of the current rolling optimization; $\Omega_{exe} \subseteq \Omega$ denotes the execution segment; $|\Omega_{exe}|$ represent the numbers of time steps in the execution segment; HS_{sta} represents the hydrogen storage states at the beginning of the current rolling dispatch,

Table 2
Modeling parameters for components.

EL unit
$\eta^{EL} = 0.8$, $c^{EL} = 0.01$ \$/kW, $P_{min}^{EL} = 0$ kW, $P_{max}^{EL} = 3000$ kW
CMP unit
$\eta^{CMP} = 0.6$, $c^{CMP} = 0.02$ \$/kW, $\Pi^{CMP} = 3.74$ kWh/kg
FC unit
$\eta^{FC} = 0.7$, $c^{FC} = 0.001$ \$/kW, $P_{max}^{FC} = 1500$ kW, $LHV_{H_2} = 33.3$ kWh/kg
EB unit
$\eta^{EB} = 0.98$, $c^{EB} = 0.005$ \$/kW, $Q_{max}^{EB} = 1000$ kW
Heat recovery unit
$\eta^{REC} = 0.8$, $c^{REC} = 0.02$ \$/kW, $Q_{max}^{REC} = 3000$ kW
BESS unit
$CAP^{Bat} = 10$ MW, $SOC_{min} = 0.2$, $SOC_{max} = 0.8$, $SOC_{init} = 0.5$
$\eta^{loss} = 0.002$, $\eta^{ch} = 0.85$, $\eta^{dch} = 0.85$, $P_{max}^{ch} = 4$ MW, $P_{max}^{dch} = 4$ MW
Hydrogen storage unit
$HS_{min} = 1800$ kg, $HS_{max} = 18000$ kg, $HS_{init} = 10800$ kg
$H_{max}^{ch} = 20$ kg/h, $H_{max}^{dch} = 15$ kg/h

i.e., the realized storage level at the end of the previous execution segment.

4. Simulation results and analysis

4.1. Simulation setup

To validate the proposed monthly-daily rolling operational optimization framework, simulations are conducted on an EHHIES equipped with BESS and SHS. In the test system, the electricity purchase and selling prices are listed in Table 1 [51]. For the monthly aggregated optimization model, $c^{E,Buy} = 0.10$ \$/kWh and $c^{E,Sell} = 0.02$ \$/kWh. The heat purchase price is set to $c^{Q,Buy} = 0.07$ \$/kWh. Environmental parameters are $c^{Env} = 0.06$ \$/kW, $\lambda^E = 0.05$, and $\lambda^Q = 0.03$. Penalty coefficients are set to $c^{E,Pen} = 1.0$ \$/kWh, and $c^{H,Pen} = 10$ \$/kg. In the intra-month rolling dispatch model, the execution segment is set to $|\Omega_{exe}| = 24$ h and the prediction horizon is set to $|\Omega| = 168$ h. The modeling parameters for components in the EHHIES are listed in Table 2.

To construct the monthly aggregated optimization model, multi-year historical hourly PV and load data are aggregated using the K-medoids clustering method to obtain monthly total energies as model inputs. The number of clusters K for each month is determined via silhouette analysis, with K = 4 for spring and autumn months and K = 7 for summer and winter months. Fig. 4 shows the aggregated monthly curves that characterize seasonal patterns. Moreover, to account for extreme events, e.g., PV shortages and load surges, in the rolling dispatch, multi-scenario source-load data are generated by superimposing residual-based disturbances onto the baseline forecast. Fig. 5 illustrates the scenario envelopes of PV generation as well as electricity and heat loads at selected time periods, representing the possible ranges of these inputs under

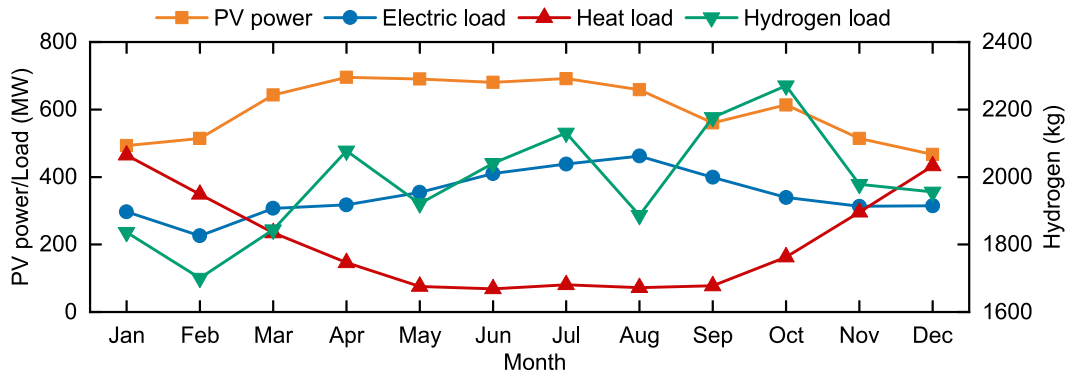


Fig. 4. Monthly aggregated PV power and load data.

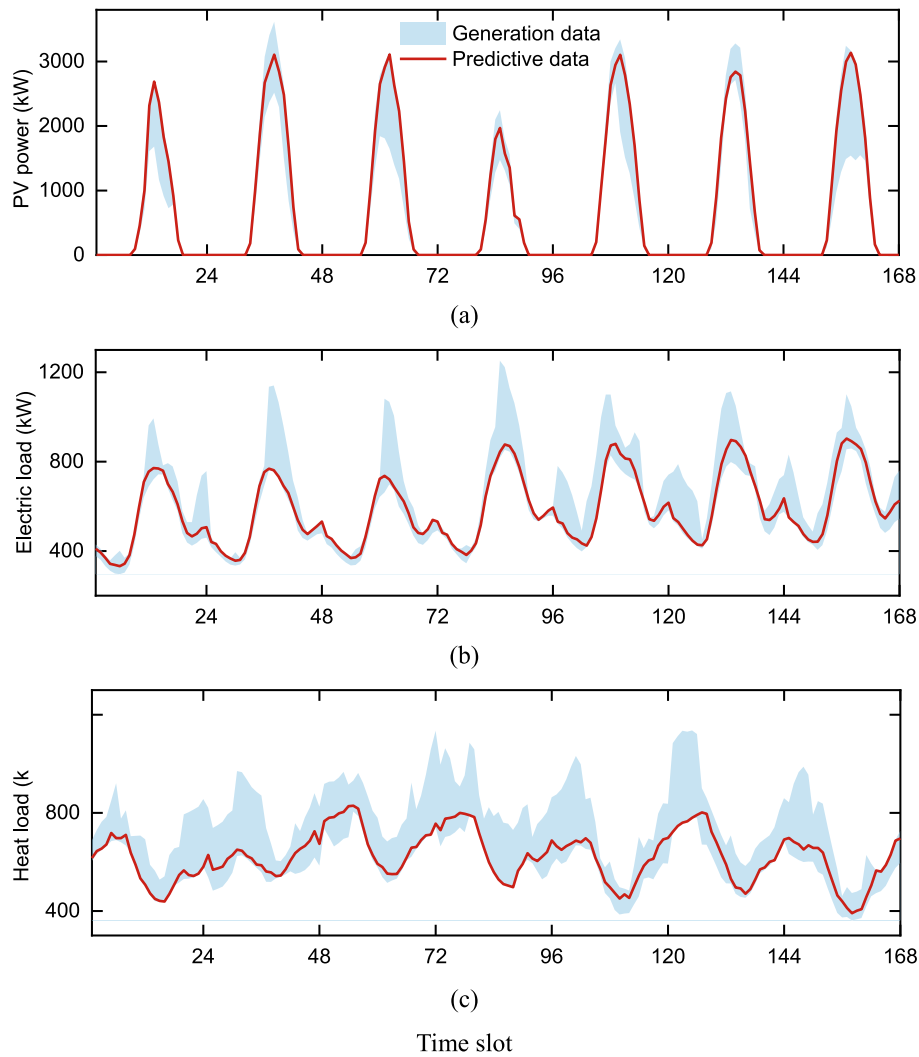


Fig. 5. Multi-scenario source-load data: (a) PV power, (b) electric load, and (c) heat load.

extreme conditions.

All the programs are developed in Python, solved using the Gurobi solver, and executed on a personal computer equipped with a 2.00 GHz Intel Core i7-12800HX CPU and 16 GB of RAM. The execution time for the monthly aggregated optimization is 1.23 s, and the total execution time of the intra-month rolling dispatch model for the entire year is 413.63 s.

4.2. Simulation results

Fig. 6 presents the energy balance results of the monthly aggregated optimization model for electricity, heat and hydrogen. Positive values primarily represent power generation, while negative values correspond to energy consumption or demand. Specifically, the system predominantly stores hydrogen when the power exceeds the demand. During high-demand seasons with limited PV generation, the stored hydrogen is converted to electricity to supply the electric demand, while recovered heat is used to meet the heating demand, thus achieving energy balance on a monthly timescale. Fig. 7 illustrates the monthly net hydrogen storage targets derived from the monthly aggregated optimization model. The MSMPC is then applied in the intra-month dispatch model to optimize the hydrogen storage strategy throughout the year, considering various scenarios and the hydrogen targets. This rolling optimization approach ensures effective coordination of hydrogen charge and discharge across different timescales to meet both seasonal and

operational demands.

Figs. 8 and 9 present the energy balance results for electricity, heat and hydrogen over several days in January and July, respectively, from the rolling dispatch optimization model. Since the model operates on an intra-month rolling dispatch with a timescale of 1 h, it considers BESS as a short-term storage solution to regulate daily supply and demand. Based on the hydrogen targets from the monthly aggregated optimization model, it is evident that January is primarily a hydrogen discharge month. PV generation is relatively low during this period, and heating demand is high, so hydrogen is discharged from the hydrogen storage tank to balance supply and demand. In contrast, in July, PV generation is higher, and demand is relatively low, so the overall trend is hydrogen storage to meet future demand. Additionally, it can be observed that under the rolling dispatch model, considering predictions and multiple scenarios, hydrogen storage does not follow a linear growth pattern but fluctuates according to actual conditions.

Fig. 10 illustrates the energy balance results of four typical days under the MSMPC rolling dispatch model. Subfigures (a)-(c) represent summer days with excess PV generation, while (d)-(f) show summer days with insufficient PV, (g)-(i) depict winter days with low PV, and (j)-(l) illustrate autumn days with balanced supply and demand. During the summer, the system stores surplus electricity as hydrogen when PV generation exceeds demand. However, on days with lower PV generation, the system does not blindly store hydrogen to meet the monthly hydrogen targets, demonstrating its ability to balance fluctuations

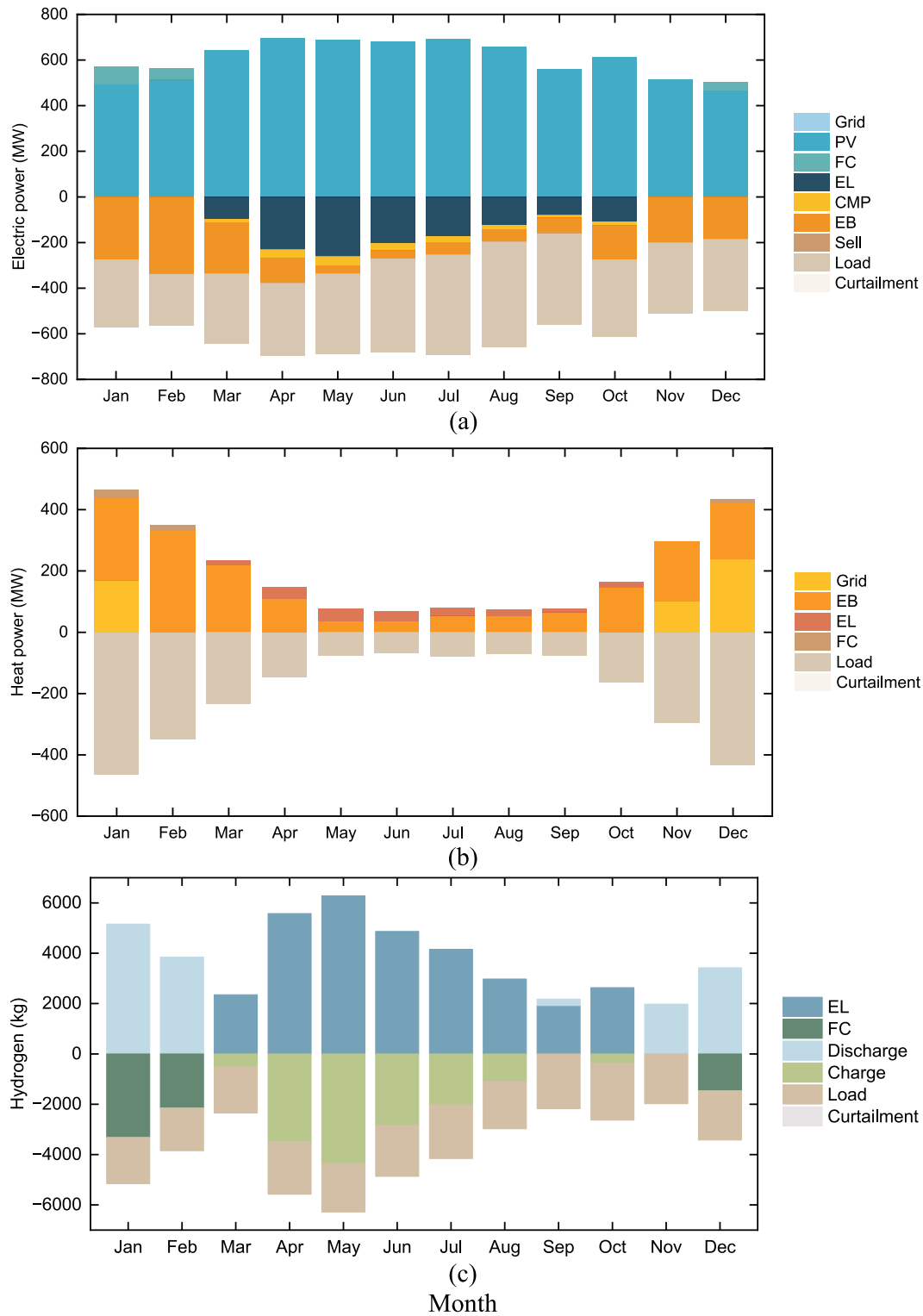


Fig. 6. Energy balance for the monthly aggregated optimization model: (a) electricity, (b) heat, and (c) hydrogen.

between renewable generation and demand. In winter, hydrogen is mainly discharged to meet electricity and heating needs. When supply and demand are more balanced, the system operates stably, charging or discharging hydrogen as required to maintain equilibrium. This highlights the flexibility of the MSMPC in optimizing hydrogen storage strategies across different seasonal and operational conditions.

4.3. Comparison analysis

To further verify the effectiveness of the proposed method, two benchmarks are designed for comparative studies.

Benchmark 1: A multi-scenario MILP (MSMILP) method is adopted under the same monthly net hydrogen storage targets, but without the MPC-based rolling optimization mechanism.

Benchmark 2: A single-scenario MPC (SSMPC) method is employed,

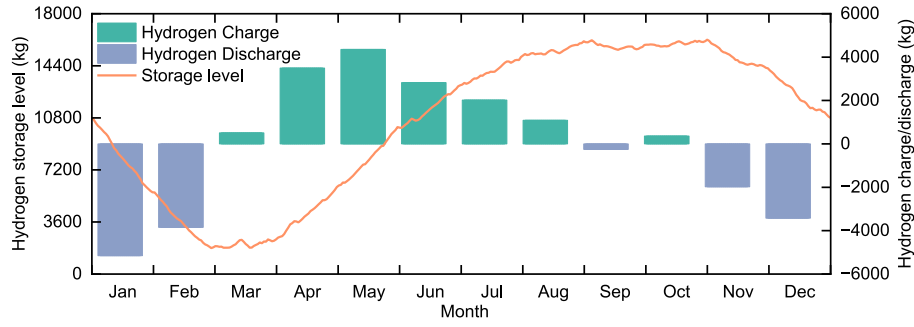


Fig. 7. Annual hydrogen storage level from the intra-month rolling dispatch model.

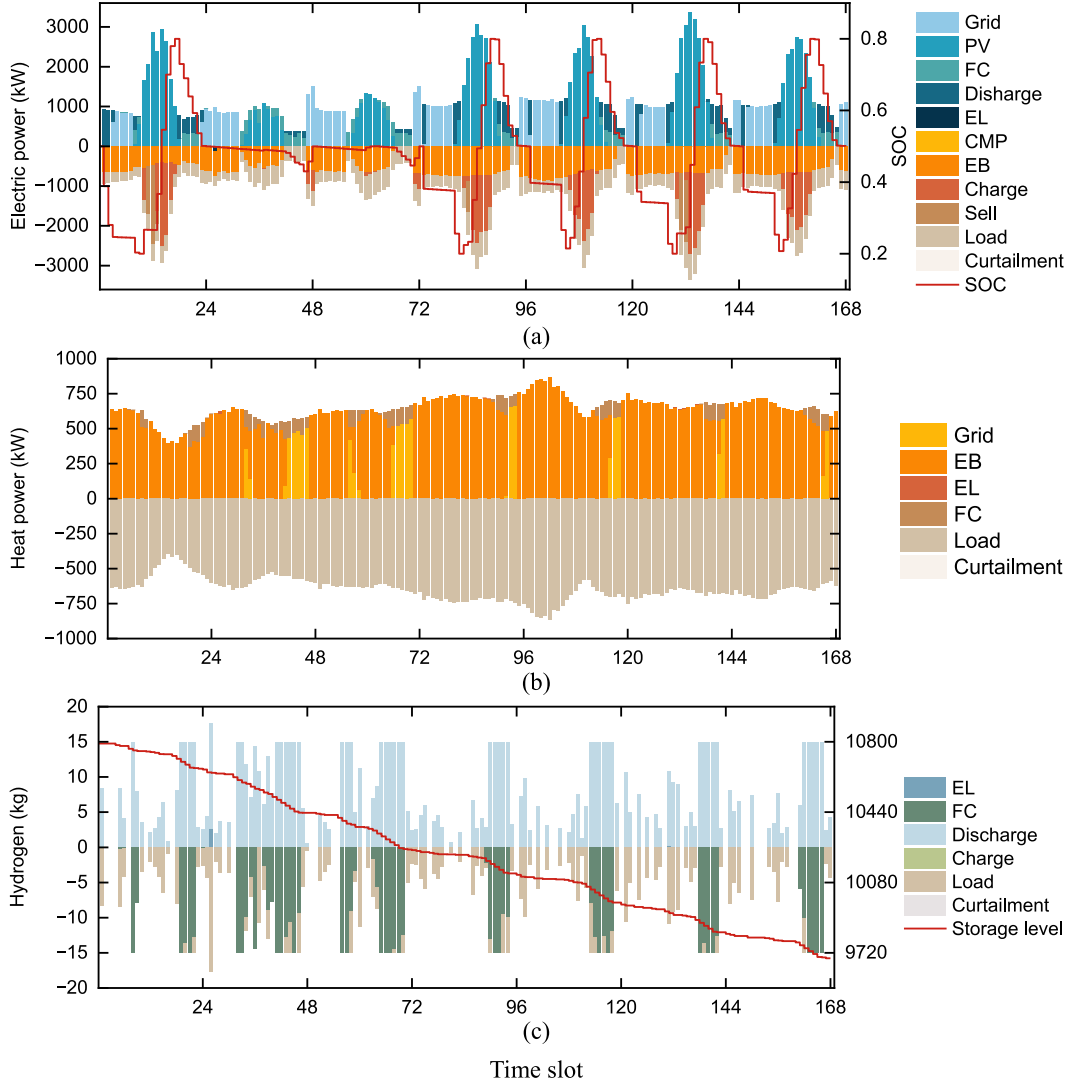


Fig. 8. Energy balance for several days in January: (a) electricity, (b) heat, and (c) hydrogen.

in which rolling optimization is performed only under a nominal scenario, representing a deterministic MPC approach without consideration of extreme events or scenario uncertainties.

Fig. 11 compares the annual hydrogen storage trajectories obtained by the proposed MSMPC method and benchmark 1, i.e., MSMILP method. Although MSMILP considers multiple scenarios, it lacks a prediction horizon to adapt the daily hydrogen schedule to forthcoming conditions. Therefore, the monthly hydrogen targets are essentially distributed evenly across days, leading to an almost linear storage

trajectory with limited flexibility. In contrast, MSMPC considers multiple scenarios over a prediction horizon, enabling adaptive adjustments of the hydrogen charging/discharging strategy while progressively tracking the hydrogen targets, thereby enhancing the coordination between long-term planning and short-term operation. As a result, the proposed MSMPC achieves a lower annual operating cost of \$116,761.19, saving \$3253.54 compared with MSMILP, corresponding to a 2.71% cost reduction. This demonstrates the effectiveness of the proposed rolling optimization framework in improving both operational

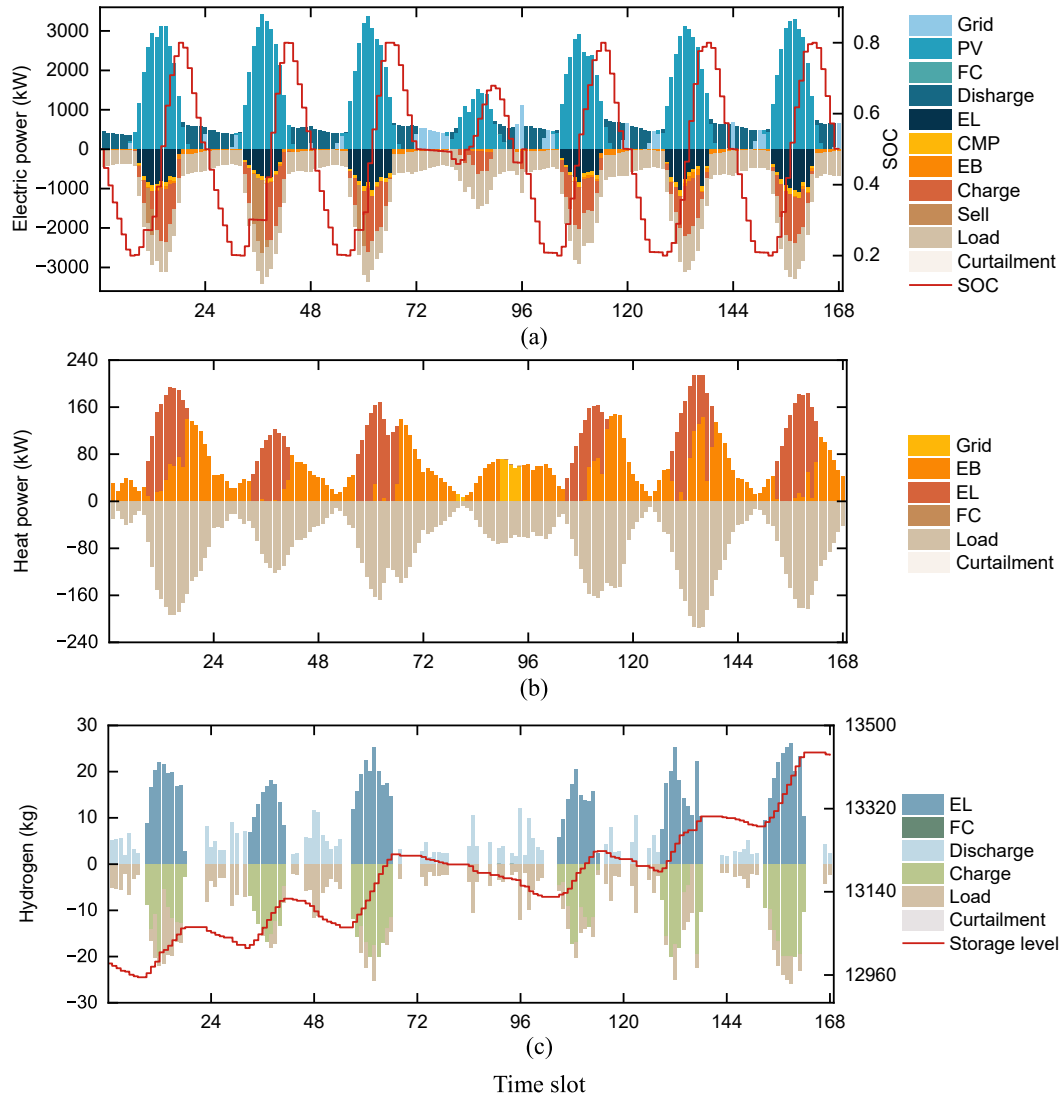


Fig. 9. Energy balance for several days in July: (a) electricity, (b) heat, and (c) hydrogen.

flexibility and economic performance.

Fig. 12 compares the daily operating costs of the proposed MSMPC method and benchmark 2, i.e., SSMPC method, over 16 selected test days with realized extreme events. Since SSMPC optimizes the schedule only under a deterministic scenario, its daily hydrogen operation tends to be overly idealized. As a result, when extreme PV shortages or load surges materialize, additional corrective actions are needed to maintain feasibility, leading to both higher costs and reduced operational robustness. In contrast, MSMPC considers multiple scenarios, including low-probability extremes, within the prediction horizon, allowing the rolling optimization to proactively adjust the hydrogen charging and discharging schedule and better anticipate uncertain conditions. Consequently, MSMPC achieves consistently lower costs on all 16 test days, with the average daily operating cost decreasing from \$376.04 to \$310.51. This 17.43% reduction under extreme conditions further highlighting the advantage of the proposed method in balancing operational robustness and economic efficiency under uncertainty.

5. Conclusions and future work

This paper presents a monthly-daily rolling operational optimization framework for the dispatch of an EHHIES, considering the supply-demand balance of electricity, heat, and hydrogen. The proposed

approach enables the synergistic operation of long-term SHS and short-term BESS, effectively resolving seasonal and short-term supply-demand mismatches. Moreover, the framework consists of a monthly aggregated optimization stage and an intra-month rolling dispatch stage. In the monthly stage, monthly total energy inputs derived from clustering-based typical days are used to capture seasonal supply-demand characteristics and determine the monthly net hydrogen storage targets. In the intra-month stage, a MSMPC-based rolling strategy is employed to track the monthly hydrogen target while accounting for multiple scenarios, including extreme events, thereby improving operational robustness. By linking monthly targets with intra-month rolling dispatch and explicitly considering multi-timescale uncertainties, the framework provides a coordinated mechanism for adapting hybrid storage operation to both seasonal energy shifting and short-term stochastic fluctuations.

The proposed MSMPC method was validated on an EHHIES test system and comparatively evaluated against two benchmark methods. Compared with Benchmark 1, i.e., MSMILP, the proposed method reduces the annual operating cost by 2.71% under the same monthly hydrogen targets, thereby demonstrating its improved economic performance. Compared with Benchmark 2, i.e., SSMPC, the proposed method decreases the average daily operating cost by 17.43% under extreme conditions, which verifies its enhanced operational robustness

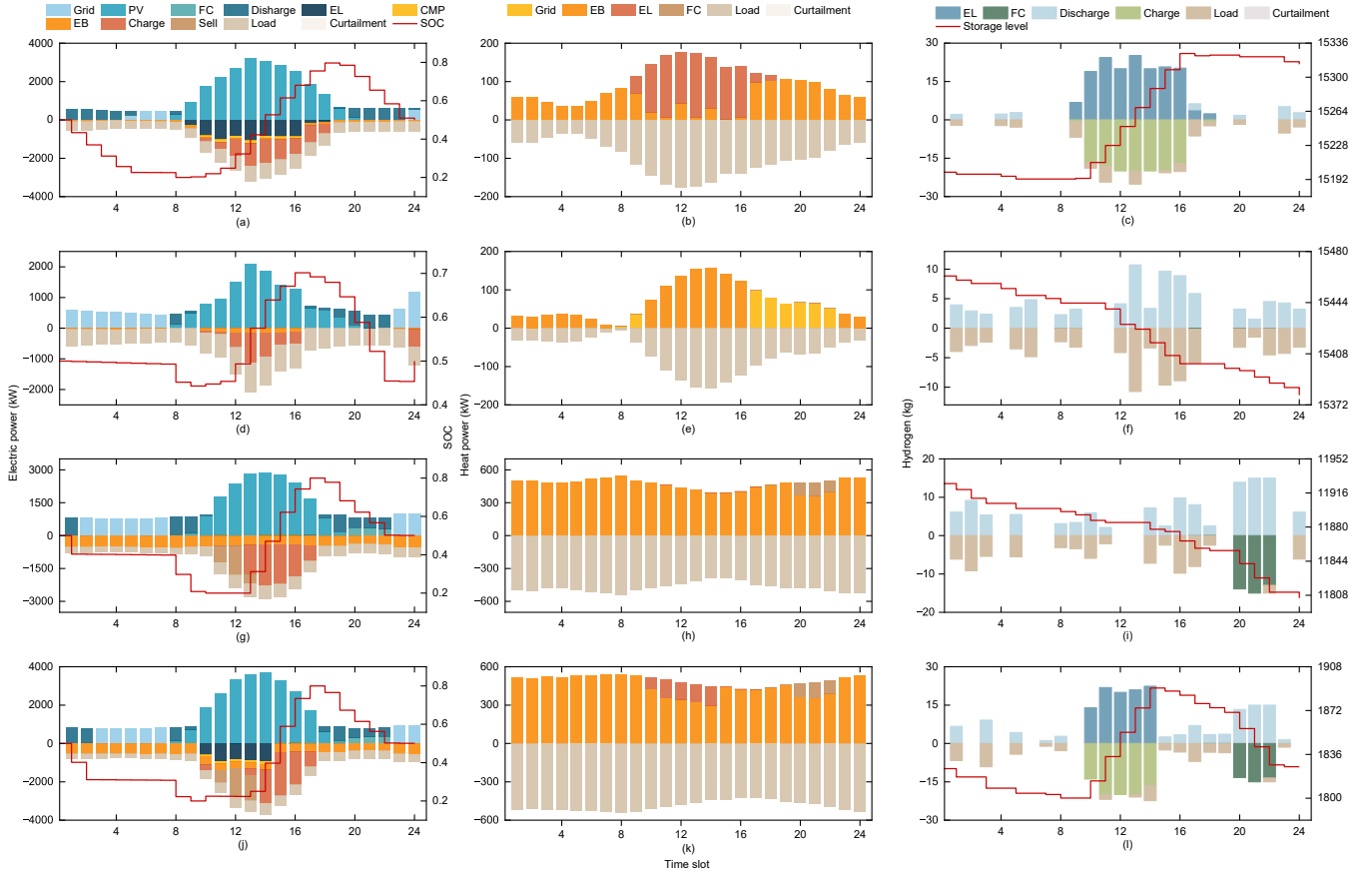


Fig. 10. Energy balance for four typical days: (a)(d)(g)(j) electricity, (b)(e)(h)(k) heat, and (c)(f)(i)(l) hydrogen.

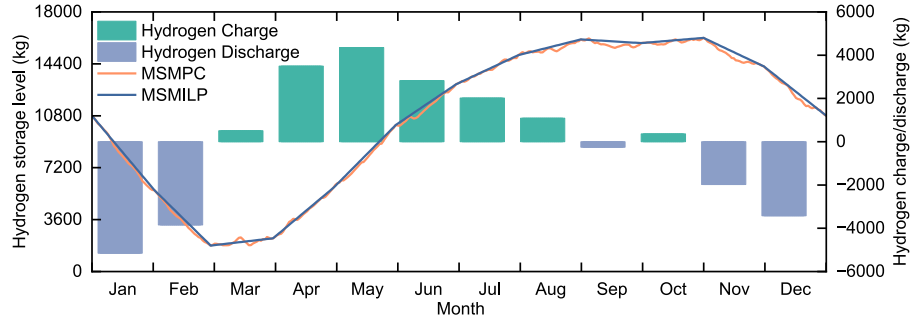


Fig. 11. Annual hydrogen storage trajectory comparison using the proposed MSMPC and MSMILP methods.

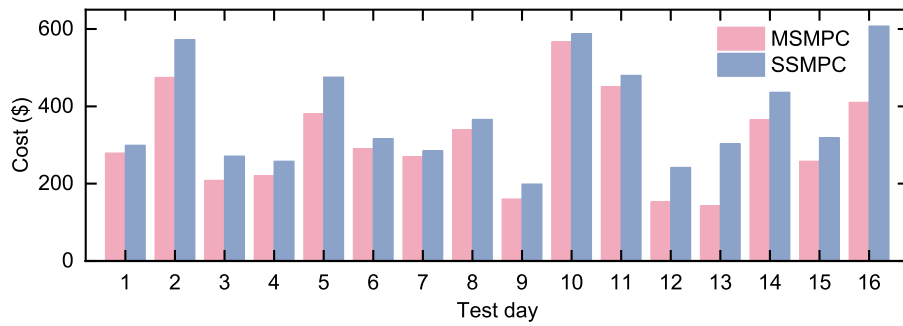


Fig. 12. Daily operating cost comparison under extreme events using the proposed MSMPC and SSMPC methods.

against severe uncertainties. Compared with conventional multi- scenario planning, the proposed rolling framework further avoids

deterministic day-ahead scheduling by enabling adaptive tracking through a prediction horizon. These results indicate that the proposed method effectively coordinates monthly aggregated optimization and intra-month rolling dispatch, achieving a trade-off between economic efficiency and operational robustness.

For future work, the following research directions are considered worth further investigation.

- (1) The proposed framework considers the coupling of electricity, heat, and hydrogen. However, other energy carriers, such as natural gas or cooling loads, could be integrated to further enhance system flexibility and better accommodate multi-energy supply-demand dynamics.
- (2) The current framework primarily focuses on temporal coordination. Further studies could extend the model to multi-node networks, incorporating electrical network constraints, the thermal inertia of district heating networks, and the fluid dynamics of hydrogen pipelines, to handle more complex spatial distribution requirements.

CRedit authorship contribution statement

Hao Shen: Methodology, Writing – original draft. **Xiaolun Fang:** Conceptualization, Funding acquisition, Supervision, Writing – review & editing. **Zhangping Chen:** Investigation, Visualization. **Xiaotong Niu:** Data curation. **Qiang Yang:** Funding acquisition, Writing – review & editing.

Declaration of competing interest

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

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