



Consensus-based multi-stage distributed optimal control for electricity-hydrogen integrated station clusters

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ARTICLE INFO

Keywords:

Electricity-hydrogen integrated station clusters
Multi-stage distributed optimal control strategy
Electricity and hydrogen imbalance values
Consensus-based distributed trading mechanism

ABSTRACT

The rapid growth of new energy vehicles is making electricity-hydrogen integrated station (EHIS) critical infrastructure for future transportation energy systems. However, existing studies mainly focus on centralized optimization-based control framework which may lead to high computational burden on central node. In addition, existing distributed optimization methods may suffer from repeated iterative optimization or expensive infrastructure costs. To address these limitations, this study proposes a consensus-based multi-stage distributed optimal control strategy for EHIS clusters. The proposed strategy consists of intra-station supply-demand assessment, inter-station trading decision, and station-grid collaborative optimization. Specifically, each EHIS first determines operating schedule, net electricity and hydrogen requirements. Then, electricity and hydrogen imbalance values are calculated, and peer-to-peer trading actions are determined through consensus-based distributed trading mechanism. Finally, each EHIS optimizes interaction with the utility grid according to the inter-station trading results. Simulations on the EHIS clusters demonstrate that the proposed strategy effectively improves operational economy, reduces centralized computation pressure and enhances scalability.

1. Introduction

In recent years, driven by the pursuit of low-carbon and sustainable development, the installed capacity of renewable energy sources such as photovoltaic (PV) and wind power has increased markedly, and clean energy has gained growing global recognition. The International Energy Agency [1] reported that renewable energy, e.g., PV, wind, and hydrogen, is an essential component in achieving an affordable and secure energy transition. This transition necessitates the development of integrated energy infrastructure capable of efficiently managing and delivering diverse energy forms to meet evolving demand [2,3]. Electricity-hydrogen integrated station (EHIS) has attracted increasing attention, as the electricity-hydrogen coupling mechanism holds potential to provide crucial operational flexibility for managing complex energy supply and demand [4,5].

With the increasing deployment of EHIS, effective hydrogen transport network modeling and scheduling have become essential for secure and economic electricity-hydrogen system operation. The work in Refs. [6–8] involved model and optimization of hydrogen transport networks within EHIS, considering the representation of different transportation modes and network configurations. At present, hydrogen is mainly

transported by tube trailers for gaseous hydrogen, tanker trucks for liquid hydrogen and dedicated pipeline networks. Considering the operational constraints, e.g., transportation capacity and delivery distance, the work in Ref. [6] studied the scheduling strategy of gaseous hydrogen and tanker trucks to enhance the response ability of the power hydrogen energy grid in emergencies. The work in Ref. [7] provided a comprehensive review of hydrogen transport networks models and planning methods, highlighting the design and cost-effectiveness of pipeline networks for long-distance hydrogen delivery. The authors in Ref. [8] established an interactive optimization framework considering hydrogen pipeline pressure-differential characteristics to minimize operational cost of electricity and hydrogen suppliers.

Beyond hydrogen transport network scheduling, the rapid development of the hydrogen industry and hydrogen fuel cell vehicles has further promoted research on the modeling and operation of EHIS. The work in Refs. [9–11] focused on the modeling and operational optimization of EHIS, considering the coordination of multiple energy carriers, storage systems, and equipment health. The work in Ref. [9] proposed the wind-solar-hydrogen-storage optimization strategy of the single EHIS, implementing day-ahead to real-time multi-timescale scheduling. The authors in Ref. [10] developed a degradation modeling framework

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<https://doi.org/10.1016/j.energy.2026.141995>

Received 9 February 2026; Received in revised form 25 June 2026; Accepted 16 July 2026

Available online 21 July 2026

0360-5442/© 2026 Published by Elsevier Ltd.

for hydrogen equipment in EHIS, integrating model predictive control to establish an optimization framework considering the health status of equipment and system economy. The study in Ref. [11] established an electricity-heat-hydrogen multi-energy storage system to improve the reliability and economy of power supply considering the echelon utilization of batteries in EHIS. The work in Ref. [12] analyzed green hydrogen development using social life-cycle assessment, highlighting the social hotspots and geopolitical implications of the future hydrogen economy.

The EHIS operation is affected by multiple uncertainties, including renewable generation uncertainty, electricity and hydrogen demand fluctuations, source-load forecasting errors, and cyberattacks or data disturbances. To cope with source-load uncertainties, robust optimization, distributionally robust optimization, and chance-constrained scheduling methods have been developed for electricity-hydrogen integrated energy systems in work [13–15]. In addition, cyberattacks can be regarded as a special type of uncertainty that affects information exchange and system state estimation. The authors in Ref. [16] analyzed the resilience of grid-connected hydrogen refueling stations against distributed denial-of-service cyberattacks. The authors in Ref. [17] developed an adaptive feasibility-area estimation method to monitor abnormal operating states under potential cyberattacks. Related studies have further investigated feasibility-area-based cyberattack detection [18], false data injection attack detection [19], cybersecurity frameworks [20], and cyber protection for smart energy hubs with hydrogen storage [21]. These studies provide useful tools for resilience assessment, robust scheduling, uncertainty modeling, and cyber-resilient monitoring. However, most existing studies mainly address centralized control, single-station resilience, attack detection, or post-attack monitoring, with limited attention to distributed electricity-hydrogen trading and station-grid collaborative optimization in EHIS clusters.

The above optimizations of EHIS mainly adopt the centralized control framework. However, as EHIS networks expand, centralized control faces critical challenges in scalability and computational efficiency. The integration of new stations often requires reconfiguration of centralized optimization algorithms, which limits system scalability and further increases the computational burden on the central node. In addition, centralized algorithms are highly dependent on central controller, and a single point of failure may compromise the entire system. In contrast, distributed control framework can alleviate these limitations to a certain extent.

Distributed optimization in EHIS clusters focuses on coordinating electricity and hydrogen production, storage and trading to improve system economy. Existing studies have adopted various distributed solution methods, among which methods based on alternating direction method of multipliers (ADMM), Lagrangian-dual-based methods, gradient-based methods and blockchain-based decentralized trading methods. The works in Refs. [22–24] developed distributed gradient, subgradient, distributed gradient projection, and augmented Lagrange methods for multi-microgrid, multi-energy, and regional energy system optimization. The works in Refs. [25,26] investigated ADMM-based distributed optimization for distribution networks and integrated electricity-heat systems under communication packet loss. The work in Ref. [27] introduced an enhanced multi-agent consensus algorithm for islanded multi-microgrid energy dispatch. In addition, blockchain-based decentralized trading mechanisms have been explored in Refs. [28–33], including pool-structured auctions, Ethereum smart contracts, multi-class energy management, credit-value-based transactions, decentralized energy networks, and market-mechanism-integrated scheduling.

Existing studies still have several limitations when applied to EHIS clusters. Lagrangian-dual-based methods and ADMM-based methods may require extensive iterative optimization. As the number of EHISs increases, such iterative procedures may lead to a heavy computational burden, making scalability difficult to guarantee. Blockchain-based peer-to-peer trading methods may introduce expensive infrastructure cost and transaction verification complexity.

In addition to distributed optimization methods, various multi-energy trading mechanisms have been investigated, including price-based, contract-based, bartering-based and blockchain-enabled trading. Among them, P2P trading enables direct energy exchange through local information sharing, making it suitable for non-fully connected communication networks. Existing studies have explored different trading mechanisms. The work in Ref. [34] proposed an energy-community-based green hydrogen production mechanism with bartering-based exchange among prosumers, while the work in Ref. [35] investigated P2P electricity-hydrogen trading among multi-microgrids. From the perspective of multi-energy sharing and market design, the works in Refs. [36] and [37] studied residential multi-energy sharing and multi-market P2P trading in cooling-heating-power-hydrogen integrated systems. The works in Ref. [38] further explored decentralized multi-energy trading mechanisms. In addition, the work in Ref. [39] investigated the integration of renewable energy communities and hydrogen refueling stations for green hydrogen production. These studies show that P2P trading can provide flexible transaction structures for distributed energy systems. Therefore, this paper adopts a P2P trading mechanism for inter-station electricity and hydrogen trading among EHIS clusters.

To this end, this paper proposes a multi-stage distributed optimal control strategy for the EHIS clusters based on a consensus-based distributed trading mechanism, aiming to improve operational economy while reducing centralized computation pressure and enhancing scalability of the EHIS clusters. The proposed strategy consists of three stages: intra-station supply-demand assessment, inter-station trading decision, and station-grid collaborative optimization. During the intra-station supply-demand assessment stage, each EHIS quantifies its net electricity requirements, net hydrogen requirements and storage system state of charge (SOC) to minimize operational costs. During the inter-station trading decision stage, each EHIS computes electricity and hydrogen imbalance values and determines trading actions via a consensus-based distributed trading mechanism. During the station-grid collaborative optimization stage, each EHIS optimizes its trading schedule with the utility grid based on the inter-station trading result and verifies power flow security, aiming to minimize operational costs. The main contributions of this work are summarized as follows.

- (1) A multi-stage distributed optimal control framework is designed for the EHIS clusters, comprising intra-station supply-demand assessment, inter-station trading decision, and station-grid collaborative optimization, to coordinate the electricity and hydrogen energy within the EHIS clusters.
- (2) A consensus-based distributed electricity-hydrogen trading mechanism is developed for inter-station coordination. By converting local electricity and hydrogen requirements into imbalance values, the proposed mechanism enables EHISs to determine trading actions through local information exchange, avoiding centralized information aggregation, repeated iterative optimization, and blockchain-based transaction clearing.
- (3) A comprehensive simulation studies are conducted to evaluate the economic performance, computational efficiency, and scalability of the proposed strategy. The proposed method is compared with independent local control, a Lagrangian-dual-based distributed optimization method, and centralized optimization under the same modeling assumptions. In addition, scalability tests on 6-node, 12-node, and 18-node EHIS clusters are performed to verify the effectiveness of the proposed strategy.

The remainder of this paper is organized as follows. Section 2 introduces the multi-stage distributed optimization framework for the EHIS clusters. Section 3 presents the multi-stage distributed optimization models and the consensus-based distributed trading mechanism. Section 4 presents simulation results and analysis. Finally, conclusions are given in section 5.

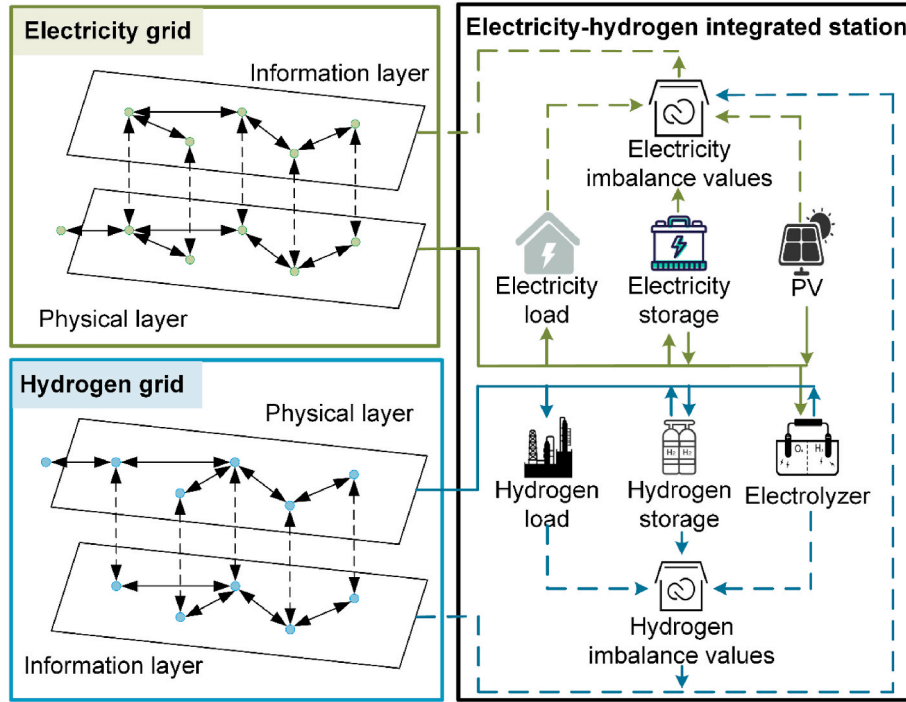


Fig. 1. Operation framework for EHIS clusters.

2. Multi-stage distributed optimization framework for EHIS clusters

2.1. EHIS clusters description

In this work, the EHIS clusters consists of multiple individual EHIS, and each EHIS incorporates three types of equipment: electricity-related equipment, hydrogen-related equipment, and electricity-hydrogen coupling equipment, as depicted in Fig. 1. The electricity-related equipment includes PV generation systems and electricity storage system (ESS), which serve local electrical loads. The hydrogen-related equipment includes the hydrogen storage system (HSS) and supplies hydrogen to hydrogen-consuming devices. The electric-hydrogen coupling equipment is the EL, which converts electricity into hydrogen via water electrolysis.

The EHIS clusters is supported by a utility grid that enables inter-station coordination of electricity and hydrogen energy. This utility grid consists of two parts, i.e., the electricity grid and the hydrogen grid. Each grid includes two layers: a physical layer and an information layer. The physical layer includes power transmission lines and hydrogen transmission pipelines. These infrastructures are responsible for the actual delivery of electricity and hydrogen across the EHIS clusters to meet the local energy demand and enable energy exchange across stations. The information layer can support distributed coordination by allowing each EHIS to share key information with its neighboring EHIS. This includes electricity and hydrogen imbalance values, trading power, trading hydrogen energy, and convergence results of the consensus-based inter-station energy trading algorithm. Based on the decisions in the information layer, the corresponding electricity and hydrogen transfers are executed via the physical layer.

In each EHIS, the electrical and hydrogen demands can be flexibly met through three approaches. The first is utilizing local resources, including on-site PV generation, ESS, HSS and EL. The second is purchasing electricity and hydrogen from the utility grid. The third approach involves inter-station energy exchange, where EHIS units coordinate with neighboring stations to balance supply and demand through electricity and hydrogen trading.

2.2. Multi-stage optimization framework of EHIS clusters

The deployment of EHIS clusters introduces new operational complexities: first, the inclusion of both electricity and hydrogen loads creates coupled demand; second, the power-to-hydrogen conversion capability introduces flexibility but also inter-temporal dependencies; and finally, inter-station communication allows for coordination but increases the dimensionality of the optimization problem. These factors collectively make a single-stage optimization approach inadequate. In addition, centralized frameworks are considered with the issues of scalability and complexity of the central controller.

To address these limitations in computational efficiency and cross-station coordination, a multi-stage distributed optimization framework is necessary. Hence, to enhance the overall coordination efficiency and operational economy of the EHIS clusters, this paper proposes such a framework, as illustrated in Fig. 2. The proposed framework consists of three stages: intra-station supply-demand assessment, inter-station trading decision, and station-grid collaborative optimization.

During the intra-station supply-demand assessment stage, each EHIS quantifies its net electricity requirements, net hydrogen requirements, storage system operating schedule and EL operating schedule to minimize operational costs.

During the inter-station trading decision stage, each EHIS computes electricity and hydrogen imbalance values and determines trading actions via a consensus-based distributed trading mechanism, where look-ahead weighting and storage system feasibility is considered to ensure feasible trading. In this stage, each EHIS exchanges its imbalance information to adjacent EHIS through the information layer of the utility grid and employs a consensus-based inter-station energy trading algorithm to perform distributed trading, resulting in the inter-station electricity and hydrogen trading results.

During the station-grid collaborative optimization stage, each EHIS optimizes its trading schedule with the utility grid based on the inter-station trading result and verifies power flow security, aiming to minimize operational costs.

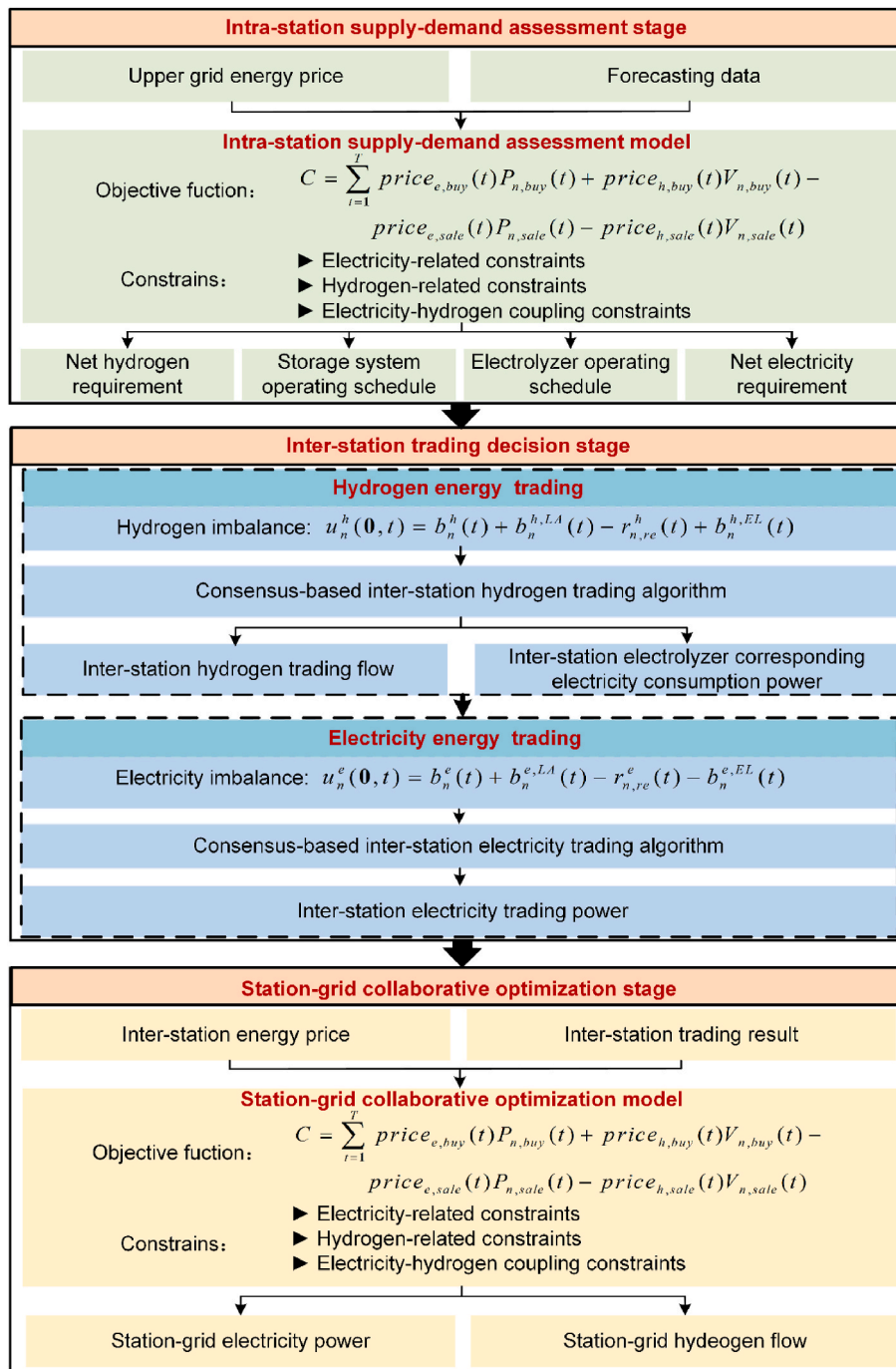


Fig. 2. Multi-stage optimization framework.

3. Multi-stage distributed optimization models and consensus-based distributed trading algorithm

This work mainly focuses on scheduling-oriented optimization decisions among different stations. To keep the model tractable, two assumptions are made. First, the degradation of ESS and HSS is not explicitly included in the objective function, and operation decisions are mainly evaluated from the perspective of short-term economic scheduling. Second, the hydrogen pipeline network is simplified, with hydrogen transportation represented in an aggregated manner. Detailed hydrogen gas network dynamics, such as pipeline pressure drops, pressure limits, and related flow constraints, are not explicitly represented.

3.1. Intra-station supply-demand assessment stage

During the supply-demand assessment stage, each EHIS employs an internal supply-demand assessment model to calculate its net electricity requirements, net hydrogen requirements, storage system operating schedule and EL operating schedule. This model is conducted based on the upper grid electricity and hydrogen prices, and the forecasting data of electricity load, hydrogen load and PV power generation. This internal model is a local optimization that does not consider electricity-hydrogen trading among different EHISs. It aims to minimize the operational cost subject to electricity-related constraints, hydrogen-related constraints and electricity-hydrogen coupling constraints. The internal supply-demand assessment model is as follows.

(1) Objective function

The objective function of the internal supply-demand assessment model can be expressed as Eq. (1).

$$\min C = \sum_{t \in T, n \in N} \text{price}_{e, \text{buy}}(t) P_{n, \text{buy}}(t) + \text{price}_{e, \text{sale}}(t) P_{n, \text{sale}}(t) - \text{price}_{h, \text{buy}}(t) V_{n, \text{buy}}(t) - \text{price}_{h, \text{sale}}(t) V_{n, \text{sale}}(t) \quad (1)$$

where C represents the cost of EHIS clusters in intra-station supply-demand assessment stage; T represents the set of time periods; N represents the set of EHIS clusters; $\text{price}_{e, \text{buy}}(t)$ and $\text{price}_{e, \text{sale}}(t)$ represents the electricity purchase and sale price of upper power grid; $\text{price}_{h, \text{buy}}(t)$ and $\text{price}_{h, \text{sale}}(t)$ represents the hydrogen purchase and sale price of upper hydrogen grid; $P_{n, \text{buy}}(t)$ and $P_{n, \text{sale}}(t)$ represent the electricity purchase and sale determined by EHIS n through its local optimization; $V_{n, \text{buy}}(t)$ and $V_{n, \text{sale}}(t)$ represent the hydrogen purchase and sale determined by EHIS n through its local optimization.

The net electricity and hydrogen requirements of EHIS can be calculated as Eq. (2).

$$\begin{cases} P_n(t) = P_{n, \text{buy}}(t) - P_{n, \text{sale}}(t), t \in T, n \in N \\ V_n(t) = V_{n, \text{buy}}(t) - V_{n, \text{sale}}(t), t \in T, n \in N \end{cases} \quad (2)$$

where $P_n(t)$ represents the net electricity requirements of the EHIS n ; $V_n(t)$ represents the net hydrogen requirements of the EHIS n .

(2) Electricity-related constraints

The electricity-related constraints of the internal supply-demand assessment model include power balance constraints, PV constraints, ESS constraints and distribution network power flow constraints.

Power balance constraints can be modeled as Eq. (3), which ensures the power demand can be satisfied.

$$P_{n, \text{load}}(t) + P_{n, \text{sale}}(t) + P_{n, \text{EL}}(t) + P_{n, \text{ch arg e}}(t) = P_{n, \text{PV}}(t) + P_{n, \text{buy}}(t) + P_{n, \text{disch arg e}}(t), t \in T, n \in N \quad (3)$$

where $P_{n, \text{EL}}(t)$ represents the input power of EL; $P_{n, \text{ch arg e}}(t)$ and $P_{n, \text{disch arg e}}(t)$ represent charge power and discharge power of ESS, respectively; $P_{n, \text{PV}}(t)$ represents the generation power of PV; $P_{n, \text{load}}(t)$ represents the electricity load.

The PV constraints in Eq. (4) ensure that the utilized PV power $P_{n, \text{PV}}(t)$ cannot exceed the forecasted PV generation power $P_{n, \text{PV}}^{\text{forecast}}(t)$.

$$0 \leq P_{n, \text{PV}}(t) \leq P_{n, \text{PV}}^{\text{forecast}}(t), t \in T, n \in N \quad (4)$$

ESS constraints can be modeled as Eq. (5), which ensures ESS cannot be charged and discharged at the same time.

$$\begin{cases} \alpha_{n, \text{disch arg e}}(t) + \alpha_{n, \text{ch arg e}}(t) \leq 1, t \in T, n \in N \\ 0 \leq P_{n, \text{disch arg e}}(t) \leq \alpha_{n, \text{disch arg e}}(t) P_{n, \text{disch arg e}}^{\text{up}}, t \in T, n \in N \\ 0 \leq P_{n, \text{ch arg e}}(t) \leq \alpha_{n, \text{ch arg e}}(t) P_{n, \text{ch arg e}}^{\text{up}}, t \in T, n \in N \end{cases} \quad (5)$$

where $\alpha_{n, \text{disch arg e}}(t)$ and $\alpha_{n, \text{ch arg e}}(t)$ represent binary variables that signify the charging and discharging states of ESS, respectively; $P_{n, \text{ch arg e}}^{\text{up}}$ and $P_{n, \text{disch arg e}}^{\text{up}}$ represent the power upper limits of charge and discharge, respectively. The constraints of SOC can be expressed as Eq. (6).

$$\begin{cases} \text{SOC}_{\text{low}} \leq \text{SOC}_n(t) \leq \text{SOC}_{\text{up}}, t \in T, n \in N \\ \text{SOC}_n(t+1) = \text{SOC}_n(t) - \frac{P_{n, \text{disch arg e}}(t) \Delta t}{\eta_{\text{disch arg e}} C_n^{\text{elec}}} + \frac{P_{n, \text{ch arg e}}(t) \Delta t \eta_{\text{ch arg e}}}{C_n^{\text{elec}}}, t \in T, n \in N \\ \text{SOC}_n(0) = \text{SOC}_n(T), n \in N \end{cases} \quad (6)$$

where $\text{SOC}_n(t)$ represents SOC configured with ESS; SOC_{up} and SOC_{low} represent the upper and lower limits of SOC configured with ESS, respectively; C_n^{elec} represents the capacity of ESS; $\eta_{\text{ch arg e}}$ and $\eta_{\text{disch arg e}}$ are the charge and discharge efficiency of ESS.

Distribution network power flow constraints can be modeled as Eq. (7).

$$\begin{cases} 0 \leq P_{n, \text{buy}}(t) \leq P_{n, \text{buy}}^{\text{up}}, t \in T, n \in N \\ 0 \leq P_{n, \text{sale}}(t) \leq P_{n, \text{sale}}^{\text{up}}, t \in T, n \in N \end{cases} \quad (7)$$

where $P_{n, \text{buy}}^{\text{up}}$ and $P_{n, \text{sale}}^{\text{up}}$ represent the upper limit of purchased and sold electricity power, respectively.

(3) Hydrogen-related constraints

The hydrogen-related constraints of the internal supply-demand assessment model include hydrogen flow balance constraints, HSS constraints and hydrogen pipeline flow constraints.

Hydrogen flow balance constraints can be modeled as Eq. (8).

$$V_{n, \text{load}}(t) + V_{n, \text{ch arg e}}(t) + V_{n, \text{sale}}(t) = V_{n, \text{buy}}(t) + V_{n, \text{disch arg e}}(t) + V_{n, \text{EL}}(t), t \in T, n \in N \quad (8)$$

where $V_{n, \text{EL}}(t)$ represents the hydrogen output flow of EL; $V_{n, \text{ch arg e}}(t)$ and $V_{n, \text{disch arg e}}(t)$ represent charge flow and discharge flow of HSS, respectively; $V_{n, \text{load}}(t)$ represents the hydrogen load.

HSS constraints can be modeled as Eq. (9), which ensures HSS cannot be charged and discharged at the same time.

$$\begin{cases} \beta_{n, \text{disch arg e}}(t) + \beta_{n, \text{ch arg e}}(t) \leq 1, t \in T, n \in N \\ 0 \leq V_{n, \text{disch arg e}}(t) \leq \beta_{n, \text{disch arg e}}(t) V_{n, \text{disch arg e}}^{\text{up}}, t \in T, n \in N \\ 0 \leq V_{n, \text{ch arg e}}(t) \leq \beta_{n, \text{ch arg e}}(t) V_{n, \text{ch arg e}}^{\text{up}}, t \in T, n \in N \end{cases} \quad (9)$$

where $\beta_{n, \text{disch arg e}}(t)$ and $\beta_{n, \text{ch arg e}}(t)$ represent binary variables that signify the charging and discharging states of HSS, respectively; $V_{n, \text{ch arg e}}(t)$ and $V_{n, \text{disch arg e}}(t)$ represent the flow upper limits of charge and discharge of HSS, respectively. The constraints of hydrogen stored in HSS can be modeled as Eq. (10).

$$\begin{cases} 0 \leq E_n(t) < C_n^{\text{hydrogen}}, t \in T, n \in N \\ E_n(t+1) = E_n(t) - V_{n, \text{disch arg e}}(t) + V_{n, \text{ch arg e}}(t), t \in T, n \in N \\ E_n(0) = E_n(T), n \in N \end{cases} \quad (10)$$

where $E_n(t)$ represents the total hydrogen stored in HSS; C_n^{hydrogen} represents the capacity of HSS.

Hydrogen pipeline flow constraints can be modeled as Eq. (11).

$$\begin{cases} 0 \leq V_{n, m}^{\text{buy}}(t) \leq V_{n, m}^{\text{max, buy}}, t \in T, n \in N \\ 0 \leq V_{n, m}^{\text{sale}}(t) \leq V_{n, m}^{\text{max, sale}}, t \in T, n \in N \\ V_n^{\text{buy}}(t) = \sum V_{n, m}^{\text{buy}}(t), n \in N, m \in N \\ V_n^{\text{sale}}(t) = \sum V_{n, m}^{\text{sale}}(t), n \in N, m \in N \end{cases} \quad (11)$$

where $V_{n, m}^{\text{max, buy}}$ and $V_{n, m}^{\text{max, sale}}$ represent the upper limit of hydrogen pipeline flow, respectively; $V_{n, m}^{\text{buy}}(t)$ and $V_{n, m}^{\text{sale}}(t)$ represent the purchase and sale hydrogen flow from EHIS n to EHIS m , respectively.

(4) Electricity-hydrogen coupling constraints

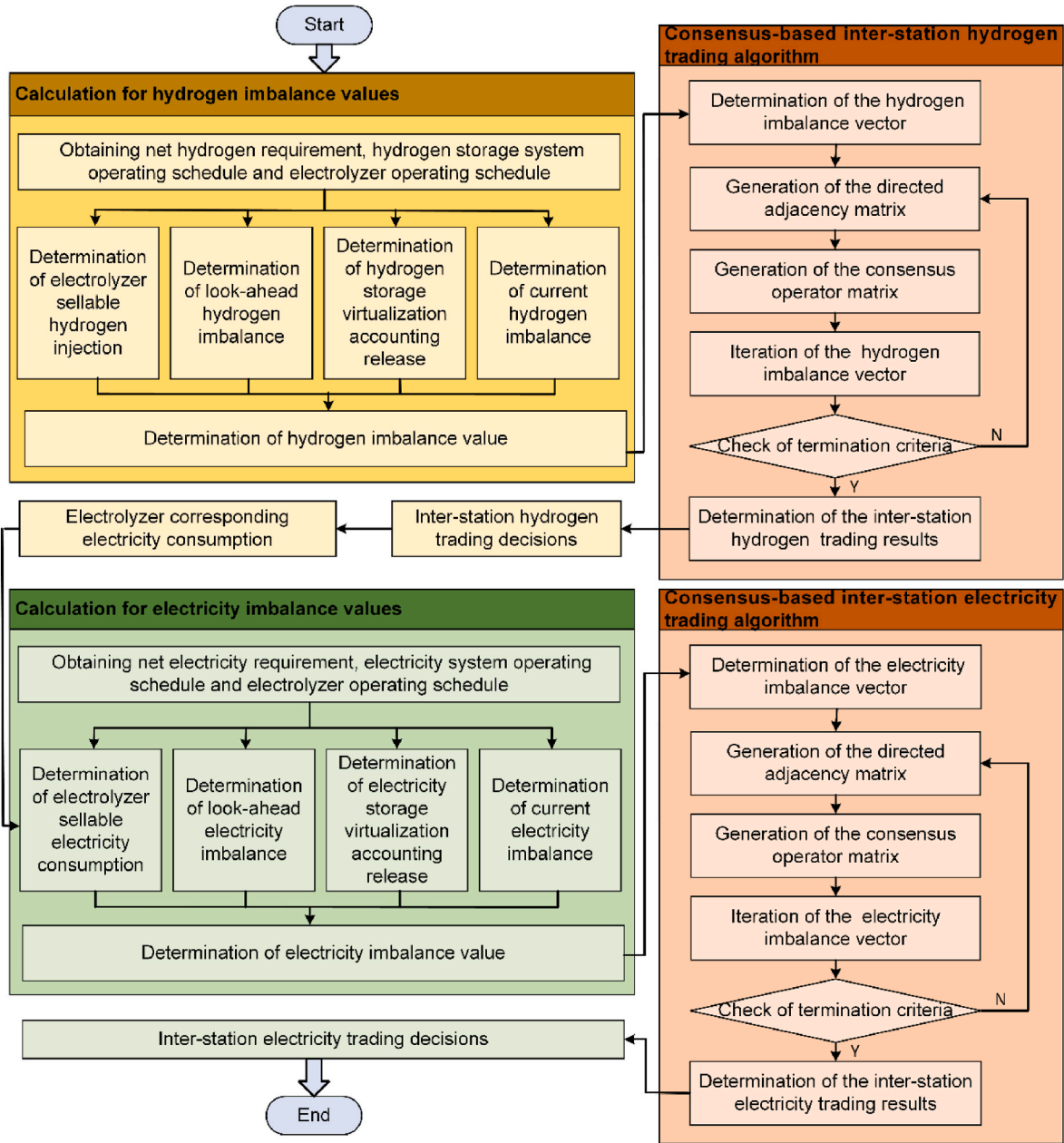


Fig. 3. The procedure of the inter-station trading.

The electricity-hydrogen coupling constraints include the EL constraints, where the EL produces hydrogen via water electrolysis, as expressed in Eq. (12).

$$\begin{cases} P_{n,EL}(t)\eta_{EL}\alpha_{trans} = V_{n,EL}(t), t \in T, n \in N \\ 0 \leq P_{n,EL}(t) \leq P_{n,EL}^{up}, t \in T, n \in N \end{cases} \quad (12)$$

where η_{EL} is the efficiency of EL; α_{trans} is the efficiency conversion coefficient of energy; $P_{n,EL}^{up}$ represents the input power upper limits of EL.

3.2. Inter-station trading decision stage

During the inter-station trading decision stage, based on the topology of the physical and information layer as well as net electricity requirements, net hydrogen requirements, storage system operating schedule and EL operating schedule, each EHIS applies a distributed trading mechanism and consensus-based inter-station energy trading

algorithm to calculate electricity and hydrogen imbalance values and the corresponding inter-station trading decisions. The inter-station trading procedure is shown in Fig. 3.

3.2.1. Consensus-based inter-station energy trading algorithm

This paper develops a consensus-based inter-station energy trading algorithm, inspired by water waves equilibrium, diffusion strategy [40] and consensus theory [41] [42]. The algorithm treats the energy imbalance values as a "fluctuation" and simulates the interaction of water flow through a dynamic adjacency mechanism. Through this algorithm, the energy surplus and deficit at each station are balanced within the EHIS clusters, enabling clusters-level supply-demand matching. After the algorithm converges, the inter-station trading results, including the inter-station hydrogen trading flows or the inter-station electricity trading powers, are obtained. The algorithm implementation steps is given as follows.

(1) Determination of the imbalance vector

The imbalance vector $U(k)$ is defined as a vector representing EHS imbalance values, which can be expressed as Eq. (13).

$$U(k) = [u_1(k), u_2(k) \dots u_n(k)]^T \quad (13)$$

where $u_n(k)$ represents the EHS imbalance values. In the imbalance vector $U(k)$, positive values denote surplus and negative values denote deficit. The initial imbalance vector $U(0)$ is derived from the input data, such as electricity or hydrogen imbalance values, acquired by the distributed trading mechanism.

(2) Generation of the directed adjacency matrix

Inspired by water flowing from high to low potential energy, the directed adjacency matrix $M'(k)$ is dynamically regenerated based on the topological relationship of the EHS clusters and imbalance value differences among EHS, where each link is directed from an EHS with a higher imbalance value to an EHS with a lower imbalance value. The element $m'_{nm}(k)$ in the matrix $M'(k)$ can be expressed Eq. (14).

$$m'_{nm}(k) = \begin{cases} 1, & \text{if } u_n(k) \geq u_m(k) \text{ and } u_n(k) > 0 \\ 0, & \text{if } u_n(k) < u_m(k) \end{cases} \quad (14)$$

where n represents the EHS of the EHS clusters; m represents the EHS linked with EHS n ; k represents the iteration times. It should be noted that $m'_{nm}(k)$ equals 1 when n equals m , which means EHS n is linked by itself.

(3) Generation of the consensus operator matrix

The consensus operator matrix $T(k)$ determines the proportion of imbalance values that are allocated to the EHS with higher imbalance values to their connected EHSs with lower imbalance values. The element $t_{nm}(k)$ in the consensus operator matrix $T(k)$ can be calculated as Eq. (15).

$$t_{nm}(k) = \begin{cases} c_n(k), & \text{if } m'_{nm}(k) = 1 \\ 0, & \text{if } m'_{nm}(k) = 0 \end{cases} \quad (15)$$

where $c_n(k)$ is the EHS weight, which can be expressed Eq. (16).

$$c_n(k) = \frac{1}{\sum_{m=1} m'_{nm}(k)} \quad (16)$$

(4) Iteration of imbalance vector

Imbalance vector $U(k)$ can be iterated as Eq. (17),

$$U(k+1) = T(k) \cdot U(k) \quad (17)$$

(5) Check of termination criteria

Four termination criteria, i.e., global energy balance, collective surplus state, collective deficit state and maximum iterations reached, are defined for the inter-station energy trading algorithm, and the iteration stops once any one of them is satisfied.

First, the algorithm is considered to have reached global energy balance when the imbalance of every EHS is reduced below a permissible tolerance band, meaning that all elements $u(k)$ are sufficiently close to zero. This condition is given by Eq. (18).

$$|u_n(k)| < \varepsilon, \forall n \quad (18)$$

where ε is a small positive value that represents the permissible tolerance band.

Second, the algorithm is considered to have reached a collective surplus state when all elements $u(k)$ are no less than a preset tolerance threshold. In this case, the imbalance values of EHS indicate surplus energy available for sale, which can be expressed as Eq. (19).

$$u_n(k) \geq -\varepsilon, \forall n \quad (19)$$

Third, the algorithm is considered to have reached a collective deficit state when all elements $u(k)$ are no larger than a preset tolerance threshold. In this case, the imbalance values of EHS indicate a deficit energy that requires external purchase, which can be expressed as Eq. (20).

$$u_n(k) \leq \varepsilon, \forall n \quad (20)$$

Finally, to guarantee finite-time termination, the iteration stops when the iteration index reaches the preset maximum number of iterations k_{up} , as given by Eq. (21).

$$k = k_{up} \quad (21)$$

(6) Determination of the inter-station trading results

After the algorithm converges, the inter-station trading results vector U_{trd} is obtained. The elements u_n^{trd} in vector U_{trd} can be expressed as Eq. (22).

$$u_n^{trd} = u_n(0) - u_n(k_{ter}) \quad (22)$$

where k_{ter} represents the number of iterations to convergence. For U_{trd} , the positive and negative values denote sale and purchase, respectively. Moreover, according to the energy type of input data, the inter-station trading results vector U_{trd} represents the inter-station hydrogen trading flows or the inter-station electricity trading powers.

3.2.2. Distributed trading mechanism

A distributed trading mechanism is proposed for the EHS clusters, which includes two main steps. First, hydrogen imbalance values and the inter-station hydrogen trading are determined. Second, according to EL corresponding electricity consumption resulting from the inter-station hydrogen trading decisions, electricity imbalance values and inter-station electricity trading are determined.

It should be noted that, in the following distributed trading mechanism, energy trading costs are not explicitly considered. This simplification is justified by the pricing scheme, where selling energy to other stations is more profitable than selling to the grid, and purchasing energy from other stations is cheaper than purchasing from the grid. Therefore, inter-station trading is always economically favorable. As a result, the mechanism focuses solely on promoting energy exchange among stations, rather than evaluating precise cost impacts.

3.2.2.1. Storage virtualization accounting mechanism. To effectively incorporate storage feasibility and temporal flexibility into the imbalance values calculation, a lot-based storage virtualization accounting mechanism is introduced, which is designed to record future delivery requirements and facilitate inter-station coordination.

The lot-based storage virtualization accounting inventory partitions the storage inventory of each station into discrete energy lots, thereby explicitly modeling the amount of discharging while reserving specific lots for a designated future release. The discrete energy lots in the lot-based storage virtualization accounting inventory can be expressed as Eq. (23).

$$s_{n,\tau-t}^x \geq 0, 0 \leq \tau \leq t \leq T_0 \quad (23)$$

where x represents the energy carrier, $x = h$ represents hydrogen and $x = e$ represents electricity.; $s_{n,\tau-t}^x$ represents the energy lots of carrier x virtually stored at time slot τ and reserved to be released at time slot t ; T_0

represents the total number of time slots in the scheduling horizon. Accordingly, the aggregated inventory release amount $S_n^{x,agg}(t)$ is expressed as Eq. (24).

$$S_n^{x,agg}(t) = \sum_{\tau=0}^{t-1} S_{n,\tau \rightarrow t}^x \quad (24)$$

Based on this structure, the details of the storage virtualization accounting mechanism consist of the following procedures:

(a) Storage virtualization accounting effective release amount determination

The storage virtualization accounting effective release amount is the energy discharge for deficit, which represents the aggregated inventory release amount constrained by physical discharge limits. It is determined by matching the storage virtualization accounting feasible release amount with the deficit magnitude, thereby quantifying the actual energy supply available to cover the deficit.

The deficit magnitude $D_n^x(t)$ represents the portion of energy demand that cannot be met by local storage or generation and therefore must be supplied through inter-station trading or grid import which can be expressed as Eq. (25).

$$D_n^x(t) = \max(0, Q_n^x(t)) \quad (25)$$

where $Q_n^x(t)$ represents the energy requirement from the intra-station supply-demand assessment stage, which can be calculated as Eq. (26).

$$\begin{cases} Q_n^h(t) = -V_n(t) \\ Q_n^e(t) = -P_n(t) \end{cases} \quad (26)$$

where the negative sign indicates energy consumption to meet the station's load.

The storage virtualization accounting feasible release amount $r_{n,pl}^x(t)$ can be calculated as Eq. (27).

$$r_{n,pl}^x(t) = \begin{cases} \min(S_n^{h,agg}(t), V_{n,ch \arg e}^{up}), x = h \\ \min(S_n^{e,agg}(t), P_{n,ch \arg e}^{up}), x = e \end{cases} \quad (27)$$

where $r_{n,pl}^x(t)$ is the feasible release amount of energy carrier x constrained by the aggregated inventory release amount $S_n^{x,agg}(t)$ and the physical maximum discharge limit ($V_{n,ch \arg e}^{up}$ for hydrogen and $P_{n,ch \arg e}^{up}$ for electricity). This ensures that the energy dispatched does not exceed the storage capability or the physical limits of the system.

The storage virtualization accounting feasible release amount $r_{n,re}^x(t)$ represents the maximum storage virtualization accounting releasable energy under discharge constraints, which can be calculated as Eq. (28).

$$r_{n,re}^x(t) = \min(r_{n,pl}^x(t), D_n^x(t)) \quad (28)$$

where $r_{n,re}^x(t)$ is the effective release amount of energy carrier x , calculated as the minimum of the feasible release $S_n^{x,agg}(t)$ and the physical maximum discharge limit ($V_{n,ch \arg e}^{up}$ for hydrogen and $P_{n,ch \arg e}^{up}$ for electricity). This represents the actual energy dispatched to cover the deficit, ensuring that the station neither releases more than required nor exceeds storage constraints.

(b) Storage virtualization accounting stored amount determination

After the distributed trading, the storage virtualization accounting stored amount should be determined. The storage virtualization accounting stored amount necessitates considering the distributed trading result, the deficit magnitude, and the charging upper limit.

The storage virtualization accounting stored amount $c_n^x(t)$ represents

the actual energy that can be stored in the station's inventory, ensuring that storage constraints and charging limits are respected. The storage virtualization accounting stored amount $c_n^x(t)$ can be expressed as Eq. (29).

$$c_n^x(t) = \min(\max(0, u_n^x(k^*, t) - D_n^x(t)), cap_n^x(t), S_{n,ch \arg e}^{up,x}) \quad (29)$$

where $u_n^x(k^*, t)$ represents the trading result; $S_{n,ch \arg e}^{up,x}$ represents the charging upper limit; $cap_n^x(t)$ represents the storage virtualization accounting available capacity, which is determined by the remaining available capacity of the physical storage system.

The storage virtualization accounting stored amount $c_n^x(t)$ is then allocated into future release time slots via the lot-based inventory. The lot allocated release amount $lot_{n,t,k}^x$ can be expressed as Eq. (30).

$$lot_{n,t,k}^x = \min(c_n^x(t) \varpi_{n,t}^x(k), \Gamma_{n,t \rightarrow (t+k)}^x) \quad (30)$$

where $\varpi_{n,t}^x(k)$ denote the normalized allocation weight for storage virtualization accounting stored; $lot_{n,t,k}^x$ denotes the lot allocated release amount reserved at time slot t for release at $t+k$; $\Gamma_{n,t \rightarrow (t+k)}^x$ represents the minimum storage virtualization accounting available capacity over the subsequent time window $[t, t+k]$. If the lot allocated release amount cannot be fully utilized at the corresponding time slot, the unreleased part is rolled forward to subsequent time slots. The lot allocated release amount $lot_{n,t,k}^x$ represents the actual energy portion assigned to each future release time slot, ensuring that energy release respects capacity constraints while maintaining temporal flexibility.

(c) Storage virtualization accounting inventory state update

To ensure the temporal continuity of the simulation, the storage virtualization accounting inventory state must be updated. The storage virtualization accounting inventory state represents the total stored amount of storage virtualization accounting inventory, whose initial value is determined by the storage system operating schedule from the intra-station supply-demand assessment stage.

The storage virtualization accounting inventory state $s_n^x(t)$ is updated as Eq. (31).

$$s_n^x(t+1) = s_n^x(t) + S_{n,ch \arg e}^x(t) - S_{n,disch \arg e}^x(t) \quad (31)$$

where $S_{n,ch \arg e}^x(t)$ represents net storage virtualization accounting charge amounts; $S_{n,disch \arg e}^x(t)$ represents net storage virtualization accounting discharge amounts. They are given by Eq. (32).

$$\begin{cases} S_{n,ch \arg e}^x(t) = \max(0, c_n^x(t) - r_{n,re}^x(t)) \\ S_{n,disch \arg e}^x(t) = \max(0, r_{n,re}^x(t) - c_n^x(t)) \end{cases} \quad (32)$$

The storage virtualization accounting inventory state $s_n^x(t)$ denotes the total energy available in the station's storage after considering all charging and discharging actions, ensuring temporal continuity of the storage state.

3.2.2.2. Calculation for hydrogen imbalance values. In the inter-station hydrogen trading decision process, each EHIS determines a hydrogen trading imbalance value $u_t^h(0, t)$ and exchanges it to perform distributed hydrogen trading.

The hydrogen trading imbalance value $u_t^h(0, t)$ is composed of four terms, which can be expressed as Eq. (33):

$$u_t^h(0, t) = b_n^h(t) + b_n^{h,LA}(t) - r_{n,re}^h(t) + b_n^{h,EL}(t) \quad (33)$$

where $b_n^h(t)$ represents the current hydrogen imbalance mapping from the intra-station supply-demand assessment stage net hydrogen

requirement; $b_n^{h,LA}(t)$ represents the look-ahead hydrogen imbalance considering future deficit pressure; $r_{n,re}^h(t)$ represents the hydrogen storage virtualization accounting release amount; $b_n^{h,EL}(t)$ represents EL sellable hydrogen injection from the EL capacity.

The details of the hydrogen trading imbalance value components are below:

(a) Current hydrogen imbalance

The current imbalance $b_n^h(t)$ represents the net hydrogen requirement obtained from the intra-station supply-demand assessment stage, which can be expressed as Eq. (34).

$$b_n^h(t) = -V_n(t) \quad (34)$$

where $V_n(t)$ represents the net hydrogen requirement.

(b) Look-ahead hydrogen imbalance

To anticipate future deficit pressure, the look-ahead hydrogen imbalance $b_n^{h,LA}(t)$ is considered, which adjusts the future imbalance to reflect future deficit pressure, and provides a quantitative basis for inter-station trading decisions. Considering future hydrogen imbalances and available storage virtualization accounting capacity, the look-ahead hydrogen imbalance $b_n^{h,LA}(t)$ is calculated as Eq. (35).

$$b_n^{h,LA}(t) = \gamma_n^h(t) b_n^{h,future}(t) \quad (35)$$

where $b_n^{h,future}(t)$ represents the deficit part of the weighted future imbalance; $\gamma_n^h(t)$ represents available storage virtualization accounting capacity scaling, which can be expressed as Eq. (36).

$$\gamma_n^h(t) = \min\left(1, \frac{cap_n^h(t)}{|b_n^{h,future}(t)| + \varepsilon}\right) \quad (36)$$

where $cap_n^h(t)$ represents the hydrogen storage virtualization accounting available capacity. The available storage virtualization accounting capacity scaling $\gamma_n^h(t)$ limits the contribution of future hydrogen deficits to the current look-ahead imbalance, ensuring that the station does not over-anticipate shortages beyond what its storage can feasibly cover.

The deficit part of the weighted future imbalance $b_n^{h,future}(t)$ quantifies the expected impact of future shortages on hydrogen imbalance, guiding storage release and inter-station trading to anticipate deficits. The deficit part of the weighted future imbalance $b_n^{h,future}(t)$ is calculated as Eq. (37).

$$b_n^{h,future}(t) = \sum_{\tau=1}^L \nu_{n,t}(\tau) b_{n,def}^h(t+\tau) \quad (37)$$

where $b_{n,def}^h(t+\tau)$ represents the deficit part of the current imbalance of EHIS n at time slot $t+\tau$; $\nu_{n,t}(\tau)$ represents the normalized look-ahead weight, which can be expressed as Eq. (38).

$$\begin{cases} \nu_{n,t}(\tau) = \frac{\varpi_t(\tau) \sigma_{n,t}(\tau)}{\sum_{l=1}^L \varpi_t(l) \sigma_{n,t}(l)} \\ \varpi_t(\tau) = \alpha^\tau (1 + \beta_e \text{price}_e(t+\tau)) \\ \sigma_{n,t}(\tau) = \varepsilon + (1-\varepsilon) \frac{D_n^h(t+\tau)}{\max_{l=1,\dots,L} D_n^h(t+l)} \\ D_n^h(t+\tau) = \max(0, -b_n^h(t+\tau)) \\ L = \min(H, T-t) \end{cases} \quad (38)$$

where $\varpi_t(\tau)$ represents time-price base weight; α and β_e respectively

represent discount factor and price sensitivity coefficient; $\sigma_{n,t}(\tau)$ represents deficit intensity factor; $D_n^h(t)$ represents the deficit magnitude; L represents the forward step. These weights prioritize future deficits based on temporal urgency, economic price signals, and shortage severity, allowing the look-ahead imbalance to effectively guide inter-station trading while anticipating system conditions.

(c) Hydrogen storage virtualization accounting release amount

As previously described, the hydrogen storage virtualization accounting release amount is calculated according to Eq. (28).

(d) EL sellable hydrogen injection

EL sellable hydrogen injection is activated when either local electricity is surplus, or producing hydrogen is economically attractive. EL sellable hydrogen injection can be expressed as Eq. (39).

$$\begin{cases} b_n^{h,EL}(t) = \frac{P_{n,EL}^{sp}(t)}{\eta_{EC} \alpha_{trans}}, Q_n^e(t) > 0 \text{ or } \text{price}_e(t) < \text{price}_h(t) / \eta_{EC} \alpha_{trans} \\ P_{n,EL}^{sp}(t) = \max(0, P_{n,EC}^{sp}(t) - P_{n,EL}(t)) \end{cases} \quad (39)$$

where $P_{n,EL}^{sp}(t)$ represents the sellable hydrogen input power considering the EL capacity. EL sellable hydrogen injection $b_n^{h,EL}(t)$ ensures that hydrogen injection occurs whenever there is surplus electricity or economic incentives to produce, while respecting physical capacity limits of the EL. In this way, the station maximizes the utilization of available electricity for hydrogen production and facilitates profitable hydrogen trading.

Based on the hydrogen imbalance values, the proposed consensus-based inter-station energy trading algorithm is executed, and then, the inter-station hydrogen trading flows are derived. The inter-station hydrogen trading flows include the inter-station hydrogen purchase flow $V_{n,trd}^{buy}(t)$ and the inter-station hydrogen sale flow $V_{n,trd}^{sell}(t)$.

3.2.2.3. Calculation for electricity imbalance values. According to the inter-station hydrogen trading results, the electricity exchanges are performed among the EHIS clusters. The electricity trading procedure follows the same distributed trading mechanism as the hydrogen trading.

The electricity trading imbalance value $u_n^h(0, t)$ is composed of four terms, which can be expressed as Eq. (40).

$$u_n^e(0, t) = b_n^e(t) + b_n^{e,LA}(t) - r_{n,re}^e(t) - b_n^{e,EL}(t) \quad (40)$$

where $b_n^e(t)$ represents the current electricity imbalance mapping from the intra-station supply-demand assessment stage net electricity requirement; $b_n^{e,LA}(t)$ represents the look-ahead electricity imbalance; $r_{n,re}^e(t)$ represents the electricity storage virtualization accounting release amount; $b_n^{e,EL}(t)$ represents the EL sellable electricity consumption, which is equal to the EL corresponding electricity consumption $P_{n,sell}^{EL}(t)$, which can be expressed as Eq. (41).

$$P_{n,sell}^{EL}(t) = \frac{V_{n,trd}^{sell}(t) b_n^{h,EL}(t)}{(u_n^h(0, t) + \varepsilon_0) \eta_{EC} \alpha_{trans}} \quad (41)$$

where ε_0 represents a small positive value. EL sellable electricity consumption quantifies the actual electrical energy required by the EL to produce the sellable hydrogen traded via the inter-station hydrogen sale flow $V_{n,trd}^{sell}(t)$.

Based on the electricity imbalance values, the proposed consensus-based inter-station energy trading algorithm is executed, and then, the inter-station electricity trading power is derived. The inter-station electricity trading power includes inter-station electricity purchase

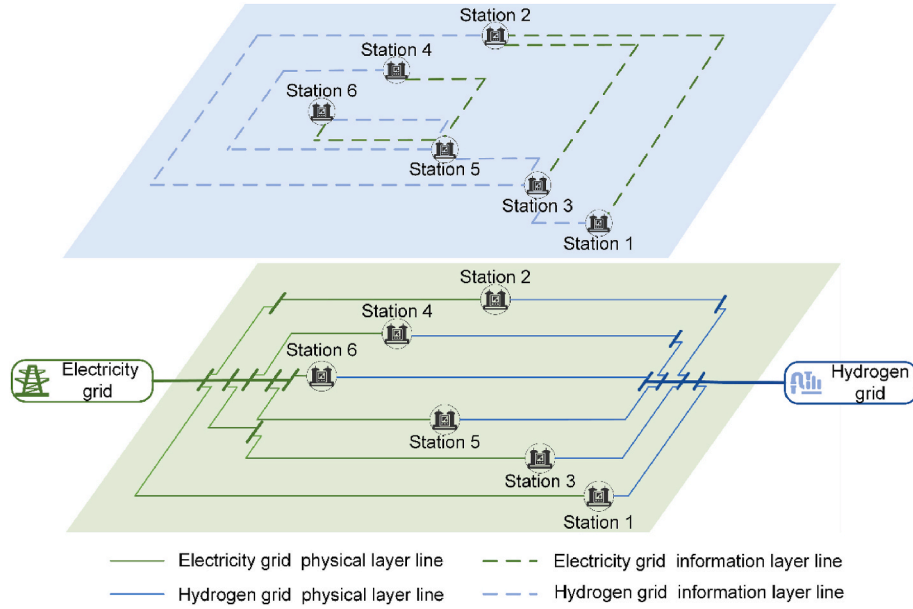


Fig. 4. Physical and information systems of a 6-node EHIS clusters.

power $V_{n,td}^{buy}(t)$ and inter-station electricity sale power $V_{n,td}^{sell}(t)$.

3.3. Station-grid collaborative optimization stage

During station-grid collaborative optimization stage, each EHIS employs a station-grid collaborative optimization model to determine its optimal dispatch. This model is conducted based on the outcomes of the inter-station trading decision, the inter station electricity and hydrogen prices, the upper grid electricity and hydrogen prices, as well as the forecasting data of electricity load, hydrogen load, and PV power generation. After the station-grid collaborative optimization, the obtained dispatch is checked against the distribution network power flow constraints using the forward-backward sweep method. The branch currents I_{ij} and bus voltages V_i are calculated as:

$$\begin{cases} V_i(t) = V_0(t) - \sum_{(ij)} Z_{ij}(t) I_{ij}(t), t \in T, i \in N, j \in N \\ I_{ij}(t) = \frac{P_{ij}(t) - jQ_{ij}(t)}{V_i^*(t)}, t \in T, i \in N, j \in N \end{cases} \quad (42)$$

where V_0 is the slack bus voltage, Z_{ij} is the line impedance, and P_{ij} , Q_{ij} are the active and reactive power flows. If all bus voltages and branch currents satisfy the security limits $V_i^{\min} \leq V_i \leq V_i^{\max}$ and $|I_{ij}| \leq I_{ij}^{\max}$, the results can be obtained. Otherwise, the algorithm returns to the intra-station supply-demand assessment stage to update parameters.

The station-grid collaborative optimization model aims to minimize the operational cost, which can be expressed as Eq. (43).

$$\begin{aligned} \min C_{coll} = & \sum_{t=1}^T \sum_{n=1}^N \text{price}_{e,td}^{trade}(t) P_{n,td}^{buy}(t) + \text{price}_{h,td}^{trade}(t) V_{n,td}^{buy}(t) - \text{price}_{e,td}^{trade}(t) P_{n,td}^{sell}(t) \\ & - \text{price}_{h,td}^{trade}(t) V_{n,td}^{sell}(t) + \text{price}_{e,buy}(t) P_{n,buy}(t) + \text{price}_{h,buy}(t) V_{n,buy}(t) \\ & - \text{price}_{e,sale}(t) P_{n,sale}(t) - \text{price}_{h,sale}(t) V_{n,sale}(t) \end{aligned} \quad (43)$$

where C_{coll} represents the cost of EHIS clusters in station-grid collaborative optimization stage; $\text{price}_{e,td}^{trade}(t)$ and $\text{price}_{h,td}^{trade}(t)$ represent the inter-station electricity purchase and sale price, respectively; $\text{price}_{e,buy}^{trade}(t)$ and $\text{price}_{h,buy}^{trade}(t)$ represent the inter-station hydrogen purchase and sale price, respectively.

Table 1

Time-of-use electricity price.

Time	Inter-station purchase price/\$	Inter-station sale price/\$	Station-grid purchase price/\$	Station-grid sale price/\$
11:00-17:59, 22:00-23:59	0.10	0.09	0.12	0.06
8:00-10:59, 18:00-21:59	0.15	0.12	0.18	0.02
0:00-7:59	0.07	0.05	0.08	0.04

The station-grid collaborative optimization model follows the electricity-related constraints in Eqs. (4)–(7), the hydrogen-related constraints in Eqs. (9) and (10). Additional balance constraints for electricity power, hydrogen flow and electricity-hydrogen coupling are given in Eqs. (44)–(46), respectively.

$$\begin{aligned} P_{n,load}(t) + P_{n,sale}(t) + P_{n,EL}(t) + P_{n,ch \arg e}(t) + P_{n,td}^{sell}(t) = P_{n,pv}(t) + P_{n,buy}(t) + \\ P_{n,disch \arg e}(t) + P_{n,td}^{buy}(t), t \in T, n \in N \end{aligned} \quad (44)$$

$$\begin{aligned} V_{n,load}(t) + V_{n,ch \arg e}(t) + V_{n,sale}(t) + V_{n,td}^{sell}(t) = V_{n,buy}(t) + V_{n,disch \arg e}(t) \\ + V_{n,EL}(t) + V_{n,td}^{buy}(t), t \in T, n \in N \end{aligned} \quad (45)$$

$$\begin{cases} P_{n,EL}(t) \eta_{EL} = V_{n,EL}(t), t \in T, n \in N \\ P_{n,sell}^{EL}(t) \leq P_{n,EL}(t) \leq P_{up,EL}, t \in T, n \in N \end{cases} \quad (46)$$

Table 2

Time-of-use inter-station hydrogen price.

Time	Inter-station purchase price/\$	Inter-station sale price/\$
11:00-17:59, 22:00-23:59	3.5	3.0
8:00-10:59, 18:00-21:59	5.5	5.0
0:00-7:59	2.5	2.2

Table 3

Key parameters for each EHIS.

EHIS	ESS capacity/kW	HSS capacity/kg	EL power upper limits/kW
Station 1	400	90	180
Station 2	800	20	420
Station 3	1100	60	360
Station 4	300	90	240
Station 5	400	80	220
Station 6	900	30	420

4. Simulation analysis

4.1. Simulation setup

To validate the effectiveness of the proposed multi-stage distributed optimal control strategy, a 6-node EHIS clusters is used. The physical layer topology and information layer topology of the 6-node EHIS clusters are depicted in Fig. 4. The electricity prices for inter-station trading and station-grid interaction are listed in Table 1. The hydrogen pricing is set as follows: for station-grid interaction, the purchase and sale prices are 9.0 \$/kg and 2.0 \$/kg [43], respectively; for inter-station distributed hydrogen trading, the prices are listed in Table 2. The key parameters for each EHIS are given in Table 3.

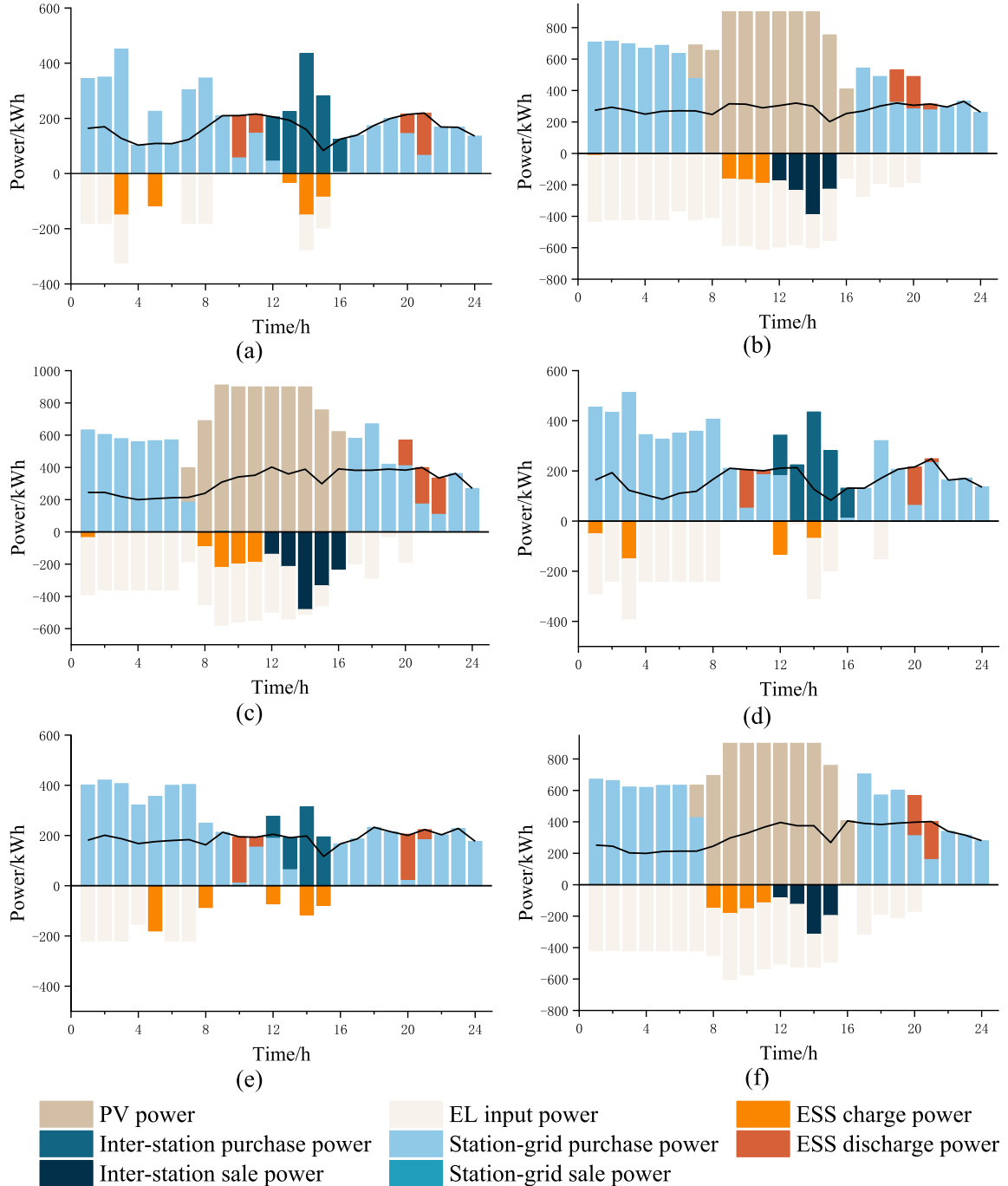


Fig. 5. Electricity balance results of EHIS clusters: (a) Station 1, (b) Station 2, (c) Station 3, (d) Station 4, (e) Station 5, (f) Station 6.

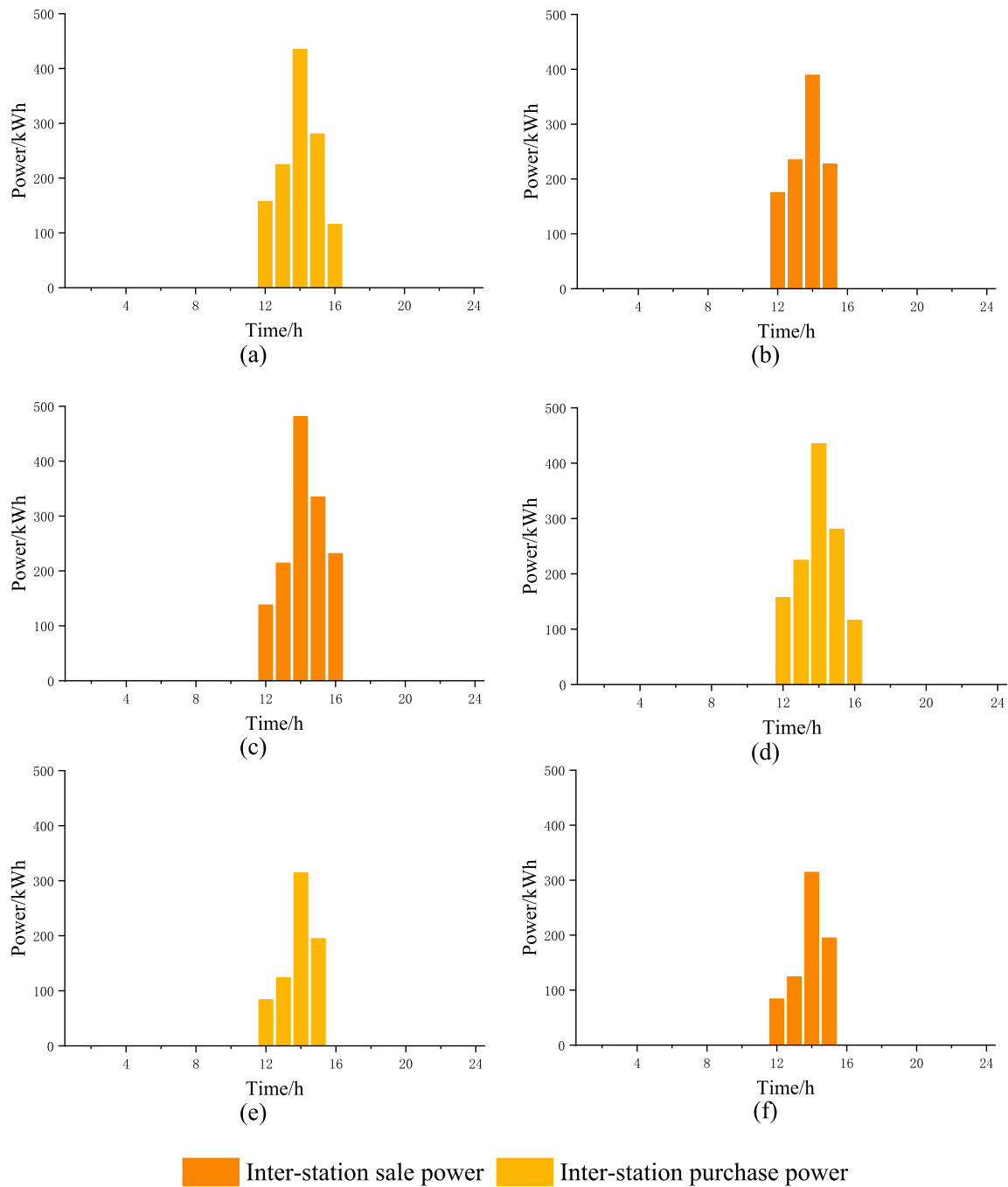


Fig. 6. Distributed electricity trading results of EHIS clusters: (a) Station 1, (b) Station 2, (c) Station 3, (d) Station 4, (e) Station 5, (f) Station 6.

The simulation was implemented using Python 3.9.13 and Gurobi 10.0.3 and executed on a standard computer equipped with an Intel® Core™ i5-10300H processor and 16 GB RAM, achieving an average total computation time of 1.37 s.

4.2. Simulation results

Fig. 5 presents the electricity balance results of the EHIS clusters, while Fig. 6 shows the distributed inter-station electricity trading results of the EHIS clusters. During the PV peak window, the electricity purchases of the non-PV-equipped stations (Stations 1, 4, and 5) are mainly supplied through inter-station trading from PV-equipped stations (Stations 2, 3, and 6), which substantially reduces their reliance on electricity purchased from the external electricity grid and facilitates intra-

clusters utilization of PV generation. Consistently, Fig. 6 indicates that the electricity trading is concentrated in the high-PV-output periods (approximately 11:00–16:00), indicating that inter-station trading is primarily activated to allocate PV surplus and achieve intra-clusters supply–demand matching. In addition, the ESS is primarily charged within the PV window and discharged when PV weakens or demand rises, supporting intra-station electricity balancing. The EL is preferentially scheduled to operate when electricity prices are low and PV output is high, indicating coordinated electricity-to-hydrogen conversion driven by both price signals and renewable availability.

Fig. 7 presents the hydrogen balance results of the EHIS clusters, while Fig. 8 shows the inter-station hydrogen trading results. The PV-equipped stations (Stations 2, 3, and 6) produce hydrogen when electricity prices are low and PV output is available; the produced hydrogen

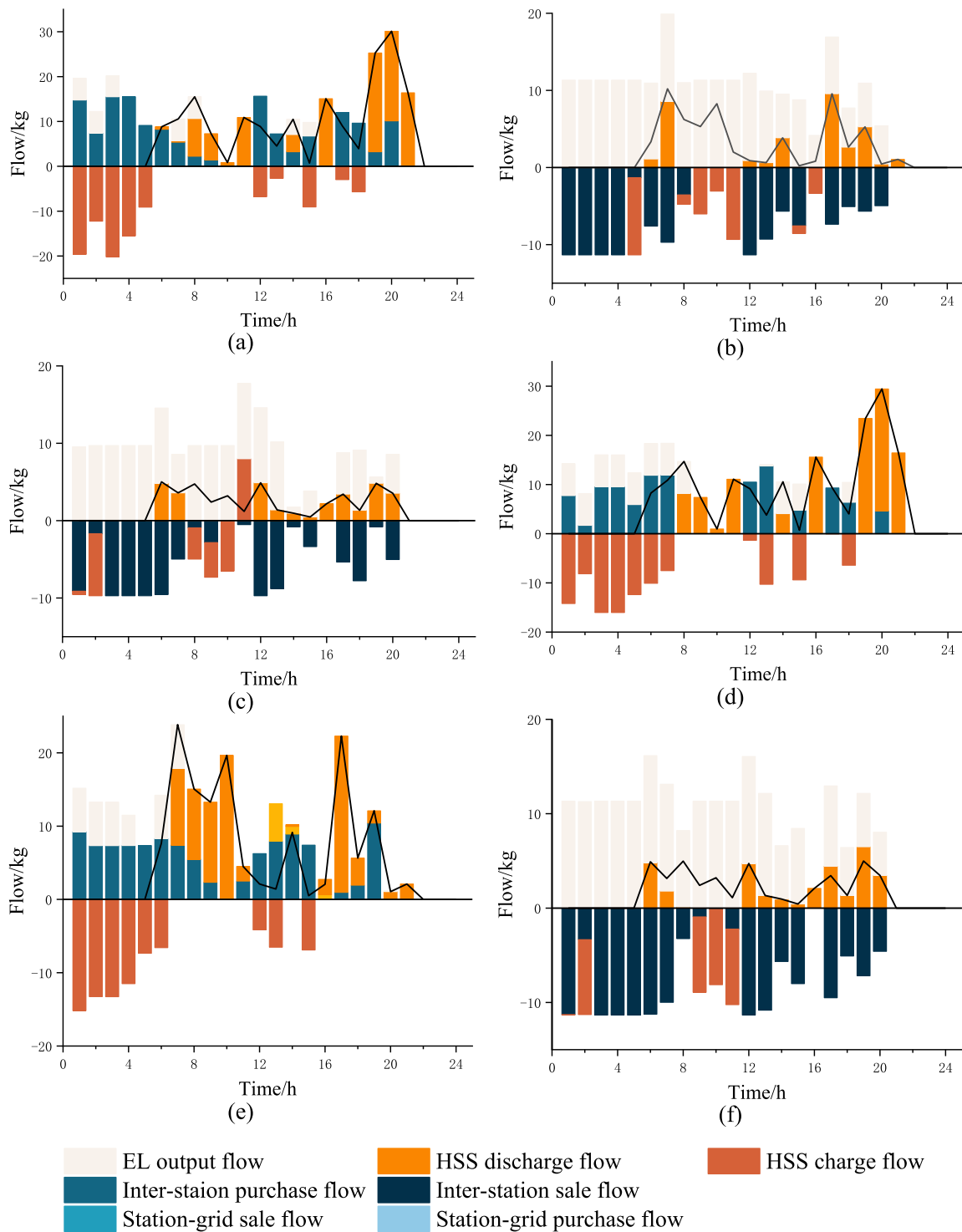


Fig. 7. Hydrogen balance results of EHIS clusters: (a) Station 1, (b) Station 2, (c) Station 3, (d) Station 4, (e) Station 5, (f) Station 6.

is either sold to the non-PV-equipped stations (Stations 1, 4, and 5) via inter-station trading or stored in the HSS for later use. Meanwhile, the non-PV-equipped stations produce hydrogen during the low-price window, e.g., 0:00–7:59, by purchasing electricity from the electricity grid, and they also purchase hydrogen from PV-equipped stations for storage, so that the stored hydrogen can be released to meet the hydrogen demand in later hours. Consistently, Fig. 8 indicates that inter-station hydrogen transactions are mainly triggered when the hydrogen purchase price is low and PV output is high. These results confirm that inter-

station hydrogen sharing combined with HSS effectively strengthens intra-clusters coordination and reduces reliance on external hydrogen procurement.

4.3. Comparison analysis of the 6-node EHIS cluster

Further, to verify the economic performance of the proposed strategy over an extended horizon, Latin hypercube sampling is used to sample scenes throughout a year and 7 typical days are selected. These selected

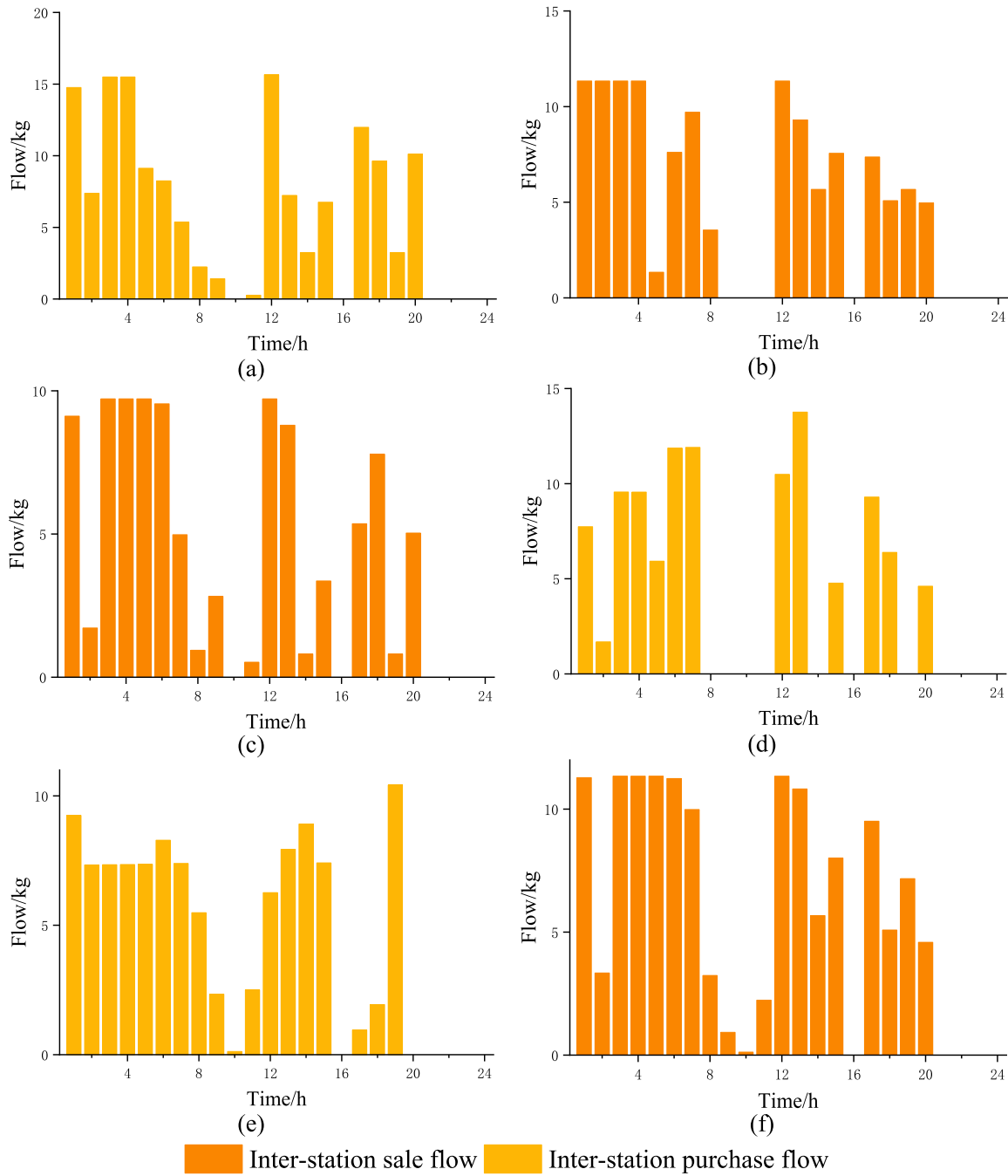


Fig. 8. Distributed hydrogen trading results of EHIS clusters: (a) Station 1, (b) Station 2, (c) Station 3, (d) Station 4, (e) Station 5, (f) Station 6.

days serve as test cases for assessing and comparing the against four benchmark strategy described as follows.

Benchmark 1: EHIS clusters optimized through a distributed trading mechanism with inter-station energy trading (this work).

Benchmark 2: EHIS clusters optimized through independent local control without inter-station energy trading.

Benchmark 3: EHIS clusters optimized through a Lagrangian-dual-based distributed optimization method, where coupling constraints are relaxed by Lagrange multipliers [44].

Benchmark 4: EHIS clusters optimized through centralized optimization where all EHISs are coordinated by a central controller using global system information.

As shown in Fig. 9, the operational costs of four benchmark strategies are compared over seven representative days. The average operational

costs of Benchmark 1, Benchmark 2, Benchmark 3, and Benchmark 4 are \$ 4015.60, \$ 5265.96, \$ 4034.71, and \$ 3800.71, respectively. Compared with the independent local control in Benchmark 2, the proposed strategy in Benchmark 1 reduces the average operational cost by \$1250.36, corresponding to a 23.74% cost reduction. This result indicates that inter-station electricity and hydrogen trading can effectively improve the economic performance of EHIS clusters. In addition, the proposed strategy is 0.47% lower than that of the Lagrangian-dual-based distributed optimization method in Benchmark 3. Although the cost of the proposed strategy is 5.65% higher than that of the centralized optimization method in Benchmark 4, this is mainly because Benchmark 4 relies on global system information. Overall, these results demonstrate that the proposed strategy can achieve near-centralized economic performance while maintaining a distributed and decentralized structure.

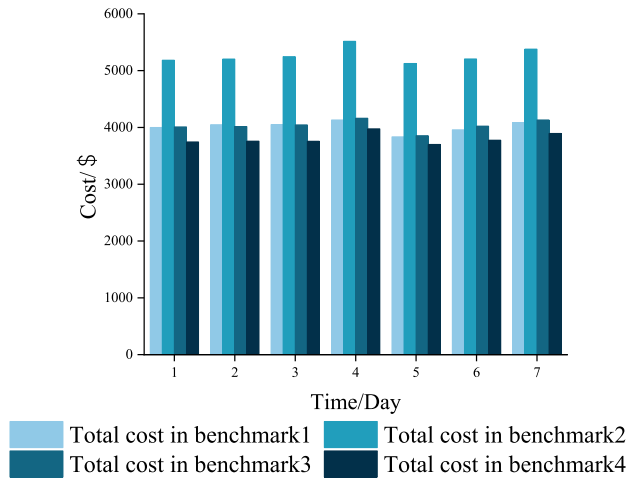


Fig. 9. Total cost of EHIS clusters comparison over 7 test days.

Table 4

Calculation time of EHIS clusters comparison over 7 test days.

Time	Calculation time of the proposed method/Second	Calculation time of the Lagrangian-dual-based distributed optimization/Second
Day 1	0.52	14.78
Day 2	0.53	16.20
Day 3	0.49	15.01
Day 4	1.54	15.41
Day 5	0.47	15.86
Day 6	0.39	16.16
Day 7	0.46	15.78

As shown in Table 4, the computational times of the proposed method and the Lagrangian-dual-based distributed optimization method are compared over seven representative days. The average computational times of the proposed method and the Lagrangian-dual-based distributed optimization method are 0.63 s and 15.59 s, respectively. The Lagrangian-dual-based distributed optimization method requires repeated local subproblem optimization and multiplier updates, which leads to a relatively high computational burden. In contrast, the proposed method avoids repeated optimization iterations by using the consensus-based inter-station trading mechanism. These results indicate that the proposed method can effectively reduce the computational burden caused by iterative distributed optimization.

4.4. Scalability analysis

To further evaluate the scalability of the proposed multi-stage distributed optimal control strategy, additional test systems with 12-node and 18-node EHISs are considered. Fig. 10 compares the proposed strategy with Benchmark 1, i.e., the independent operation strategy, over seven representative days for the 6-node, 12-node, and 18-node EHIS clusters. The average node operational costs are reduced from \$877.66, \$926.86, and \$911.25 to \$669.27, \$698.95, and \$692.28 for the 6-node, 12-node, and 18-node systems, respectively. The corresponding cost reduction ratios are 23.74%, 24.59%, and 24.03%. These results indicate that the proposed strategy can maintain economic performance across EHIS clusters of different scales.

Calculation time of the proposed method for 6-node, 12-node and 18-

node scale EHIS clusters scenarios over 7 test days are illustrated in Table 5. The average calculation times of the 6-node, 12-node, and 18-node systems are 0.48 s, 1.47 s, and 3.22 s, respectively. Even for the 18-node system, the maximum calculation time over the seven test days is only 4.06 s. The calculation time increases moderately with the system scale because the proposed method only solves local subproblems and determines inter-station trading through the consensus-based mechanism, avoiding repeated optimization iterations, multiplier updates. Therefore, the proposed strategy can avoid centralized information aggregation and large-scale global optimization, showing good computational scalability for larger EHIS clusters.

5. Conclusions

This paper proposes a consensus-based multi-stage distributed optimal control strategy for EHIS clusters. The proposed strategy consists of intra-station supply-demand assessment, inter-station trading decision, and station-grid collaborative optimization. In the intra-station supply-demand assessment stage, each EHIS independently determines its net electricity and hydrogen requirements. In the inter-station trading decision stage, electricity and hydrogen imbalance values are calculated, and inter-station trading decisions are determined through a consensus-based distributed trading mechanism. In the station-grid collaborative optimization stage, each EHIS optimizes its interaction with the utility grid based on the inter-station trading results.

Simulation results demonstrate that the proposed strategy improves operational economy, computational efficiency, and scalability while promoting inter-station electricity and hydrogen sharing. In the 6-node EHIS cluster, the proposed strategy reduces the average operational cost by 23.74% compared with independent local control, indicating that inter-station electricity-hydrogen trading can effectively improve the economic performance of EHIS clusters. Compared with the Lagrangian-dual-based distributed optimization method, the proposed strategy achieves comparable economic performance, while significantly reducing the average computational time from 15.59 s to 0.63 s. Furthermore, scalability tests on 6-node, 12-node, and 18-node EHIS clusters show that the proposed strategy achieves stable cost reduction ratios of 23.74%, 24.59%, and 24.03%, respectively. The corresponding average calculation times are 0.48 s, 1.47 s, and 3.22 s. These results verify that the proposed strategy can maintain stable economic benefits and acceptable computational burden under larger system scales.

For future work, the following research directions are worthy of further exploitation:

- (1) Although degradation is not explicitly modeled, deep cycling, frequent operation, and aging-induced performance variation may affect component lifetime, State of Health (SoH), and long-term operational decisions. Neglecting these effects may underestimate life-cycle operating costs and influence the optimal storage scheduling strategy. Therefore, degradation constraints, nonlinear aging models, SoH evolution, and degradation costs will be incorporated into long-term optimization to improve the accuracy of operating cost assessment and the practical applicability of the proposed framework.
- (2) Future work will investigate uncertainty-aware and cyber-resilient distributed scheduling methods, considering renewable generation uncertainty, electricity and hydrogen demand fluctuations, communication disturbances, and cyberattack uncertainties, thereby further enhancing the resilience, stability, and secure operation of EHIS clusters.
- (3) In the present framework, hydrogen delivery is simplified, and detailed gas network dynamics are not explicitly modeled. This may reduce the physical accuracy of hydrogen transportation scheduling when pipeline pressure limits, flow capacity, and pressure drops are significant. Future work will incorporate physical flow constraints, such as the Weymouth equation,

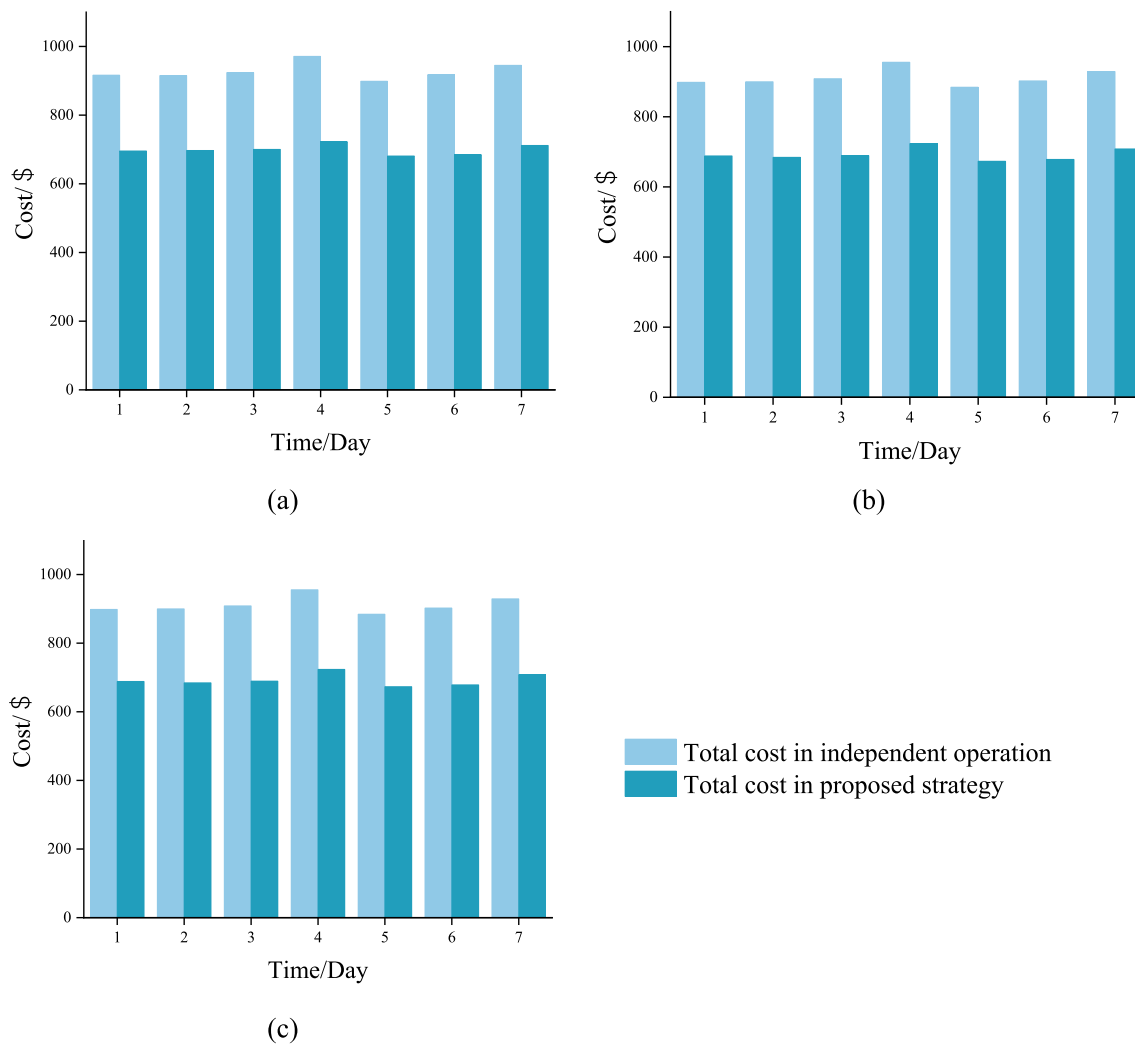


Fig. 10. Node average operational cost of different EHIS clusters over 7 test days: (a) 6-node system (b) 12-node system, (c) 18-node system.

Table 5

Calculation time of the proposed method for different scale EHIS clusters over 7 test days.

Time	Calculation time of 6-node EHIS clusters/ Second	Calculation time of 12-node EHIS clusters/ Second	Calculation time of 18-node EHIS clusters/ Second
Day 1	0.52	1.70	4.04
Day 2	0.53	1.41	1.93
Day 3	0.49	1.66	2.25
Day 4	1.54	1.01	4.06
Day 5	0.47	1.78	3.56
Day 6	0.39	1.24	2.74
Day 7	0.46	1.52	3.97

together with nodal pressure and pipeline capacity constraints, to support safer and more physically consistent hydrogen network operation.

CRediT authorship contribution statement

Haorui Zhu: Writing – original draft, Methodology. **Xiaolun Fang:** Writing – review & editing, Funding acquisition, Conceptualization. **Jian Zhang:** Investigation. **Qiang Yang:** Supervision, Funding acquisition.

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.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (62403176) and the Natural Science Foundation of Zhejiang Province (LBMHD25E070001).

Data availability

No data was used for the research described in the article.

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