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Socially-Governed Energy Hub Trading Enabled by Blockchain-Based Transactions

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***Abstract*—Decentralized trading schemes involving energy prosumers have prevailed in recent years. Such schemes provide a pathway for increased energy efficiency and can be enhanced by the use of blockchain technology to address security concerns in decentralized trading. To improve transaction security and privacy protection while ensuring desirable social governance, this paper proposes a novel two-stage blockchain-based operation and trading mechanism to enhance energy hubs connected with integrated energy systems (IESs). This mechanism includes multi-energy aggregators that use a consortium blockchain and its enabled proof-of-work to transfer and audit transaction records, with social governance principles for guiding prosumers' decision-making in the peer-to-peer (P2P) transaction management process. The uncertain nature of renewable generation and load demand are adequately modeled in the two-stage Wasserstein-based distributionally robust optimization. The practicality of the proposed mechanism is illustrated by several case studies that jointly show its ability to handle an increased renewable generation capacity, achieves a 16.7% saving in the audit cost, and facilitates 2.4% more P2P interactions. Overall, the proposed two-stage blockchain-based trading mechanism provides a practical trading scheme and can reduce redundant trading amounts by 6.5%, leading to a further reduction of the overall operation cost. Compared to the state-of-the-art benchmark methods, our mechanism exhibits significant operation cost reduction and ensure social governance and transaction security for an IES and energy hubs.**

***Index Terms*—Blockchain, energy hubs, energy management, integrated energy systems, peer-to-peer trading, social governance.**

NOMENCLATURE

A. *Sets*

H	Energy hubs.
T	Time intervals.

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B. *Variables*

$P_{h,t}^{s,h-g}, P_{h,t}^{s,g-h}$	Power selling and purchase with the IES.
$G_{h,t}^{s,g-h}$	Gas purchase from the IES.
$P_{h,t,p}^{s,h-h}, P_{h,t,s}^{s,h-h}$	Power trading among energy hubs.
$\Theta_{h,t,p}^{s,h-h}, \Theta_{h,t,s}^{s,h-h}$	Heat trading among energy hubs.
$P_{h,cp,t}^{s,o}, \Theta_{h,cp,t}^{s,o}$	Conversion output of CHP.
$\Theta_{h,COP,t}^{s,o}, P_{h,GF,t}^{s,o}$	Conversion output of GSHP/natural gas furnace.
$P_{h,BS,t}^{s,ch}, P_{h,BS,t}^{s,dch}$	Charging/discharging amount of battery.
$\Theta_{h,HS,t}^{s,ch}, \Theta_{h,HS,t}^{s,dch}$	Charging/discharging amount of heat storage.
$E_{h,BS,t}^{s}, E_{h,HS,t}^{s}$	Residual energy storage.
$\xi_{h,t}$	Uncertain PV generation.
ζ_{ele}, ζ_{th}	Uncertain power and heat loads.

C. *Parameters*

λ_{h-g}^{P}	Unit price of selling electric power to the integrated energy system (IES).
$\lambda_{g-h}^{P}, \lambda_{g-h}^{G}$	Unit price of purchasing power/gas from IES.
$\lambda_{re}^{P}, \lambda_{re}^{G}$	Unit reward price of energy trading estimation.
$\lambda_{h-h}^{P}, \lambda_{h-h}^{H}$	Unit price of power/heating trading among hubs.
$\lambda_{h}^{BS}, \lambda_{h}^{HS}$	Depreciation cost coefficient of battery and heat storage.
$\vartheta_{h-g}^{P}, \vartheta_{g-h}^{P}$	Penalty of electric power trading caused by decision adjustment.
ϑ_{g-h}^{G}	Penalty of gas trading caused by decision adjustment.
$\vartheta_{h-h}^{P}, \vartheta_{h-h}^{H}$	Penalty of power/heat trading caused by decision adjustment.
ω_{PoW}^{P}	Cost coefficient of consensus process.
ρ_{e}, ρ_{th}	CHP's conversion efficiency: power and heating.
ρ_{f}	Gas furnace's conversion efficiency of.
ρ_{COP}	Coefficient of performance.
$\rho_{HS}^{ch}, \rho_{HS}^{dch}$	Charging and discharging efficiency of heat storage.
$\rho_{BS}^{ch}, \rho_{BS}^{dch}$	Charging and discharging efficiency of battery.
$P_{h,max}^{hg}, P_{h,min}^{hg}$	Max/min bound of IES power purchase.
$P_{h,max}^{gh}, P_{h,min}^{gh}$	Max/min bound of IES power selling.
$G_{h,max}^{gh}, G_{h,min}^{gh}$	Max/min bound of IES gas purchase.
$P_{h,p,max}^{hh}, P_{h,p,min}^{hh}$	Max/min bound of IES power purchase of hubs.
$P_{h,s,max}^{h-h}, P_{h,s,min}^{h-h}$	Max/min bound of IES power selling of hubs

$\Theta_{h,p,max}^{h-h}, \Theta_{h,p,min}^{h-h}$	Max/min bound of IES heat purchase of hubs.
$\Theta_{h,s,max}^{h-h}, \Theta_{h,s,min}^{h-h}$	Max/min bound of IES heat selling of hubs.
$\chi_{h,t}$	Generation forecast of PV.
D_{ele}, D_{th}	Power/heating demand.

I. INTRODUCTION

THE interaction among multi-energy vectors plays a vital role in ensuring efficient energy usage motivated by the promising energy conversion techniques, e.g., combined heat and power (CHP) and power-to-gas (P2G) [1, 2].

A. Peer-to-Peer Energy Hub Trading Management

Integrated energy systems (IESs) enable to comprehensively aggregate the integration of multi-energy vectors and achieve energy coordination and complementation via multi-energy infrastructures [3]. Energy hubs are recognized as a special form of IES [4], which realizes the energy conversion and comprehensive coordination in any scale systems with flexibility [5]. Paper [6] designs a distributed multi-period energy hub operation model considering power, gas and heating. A fully-distributed consensus-based method is used to solve the reformulated second-order cone programming problem. In [7], a distributed management algorithm for residential energy hubs is given. The monotone generalized Nash game realizes efficient energy coordination between the customers and energy providers.

Each energy hub with distributed generators can be regarded as a prosumer and participate in the market trading environment for addressing the local excessive energy consumption and promoting social welfare. Energy hub prosumers can actively participate in peer-to-peer (P2P) trading, which contributes to increasing the on-site consumption of renewable generation with reduced reliance on the grid [8]. A cooperative game-theoretical P2P operation for energy hubs is conducted to fairly allocate the payoff [8]. The balanced trading result demonstrates the sound stability of the energy hub grand coalition. In [9], a risk-averse stochastic programming (SP) is proposed for the market bidding problem of energy hubs. P2G is maximally utilized to mitigate the operational risk due to uncertainty from wind turbines. Paper [10] proposes a P2P coordination for home energy hub systems via optimally scheduling the home storage systems and shiftable appliances. The hierarchical framework includes the levels of selection and home appliance management. A bargaining-based cooperative game theoretical formulation is proposed for IESs in [11]. The participated energy hubs will bargain with each other in terms of the exchanged energy and payments. Paper [12] introduces a novel stochastic optimization framework that addresses resilient operation scheduling of interconnected energy hubs, incorporating P2P energy trading and energy storages during severe disturbances. The framework achieves significant reductions in load shedding, with P2P energy trading reducing load shedding by 64% leading to a 76% reduction in load shedding compared to scenarios without these strategies. A decentralized P2P electricity trading model using an alternating direction method of multipliers approach is proposed in [13], demonstrating its effectiveness in achieving least-cost operation of energy hubs, minimizing data exchange, and reducing overall costs and power losses in a transactive energy market. Paper [14] introduces a bi-level strategic energy trading framework that utilizes P2P transactive energy hubs and electric vehicles to minimize operation costs of the distribution network, demonstrating its effectiveness through numerical results on the IEEE 33-bus test system.

B. Grid-Connected Operation Schemes

In addition to the islanded energy hub, recent research investigates the coordinated optimization of district IES interconnected with energy hubs. A flexible energy demand control is given in [15] for providing additional balance for avoiding the wind power curtailment. The energy hub aggregator is authorized to purchase energy from IES for supplying residential customers in the most efficient way. Paper [16] develops a chance-constrained model for planning and operation of energy hubs networked with a distribution level IES. The reformulated second-order cone problem is efficiently solved with global optimality. The results show the relationship between the hub number and carbon emission. Paper [17] introduces an optimal scheduling model for energy grids and networked energy hubs, showcasing its ability to simultaneously improve economic status, reduce operating costs and energy losses, and enhance voltage profile and temperature in the networks. In [18], it addresses the issue of flexibility pricing in energy hubs by formulating a bilevel model that maximizes the expected profit of resources in the flexibility market, considering uncertain energy generation sources. The results demonstrate the effectiveness of the proposed approach in improving the operation, flexibility, and economic conditions of energy networks and energy hubs. Paper [19] presents a bi-level optimization model for flexible renewable energy hubs integrated with various storage systems, demonstrating their potential to improve the technical and economic conditions of energy networks while achieving high flexibility conditions and enhancing the economic status of the renewable hub, as validated by numerical results. Paper [20] introduces a two-stage optimization framework for grid-connected energy hubs' participation in day-ahead and real-time energy markets, demonstrating its ability to improve the operational and economic performance of energy networks while reducing computation time compared to single-layer management and achieving up to 18% and 26% enhancements in operating and economic indicators.

C. System Uncertainties

The uncertainties in the energy hub management include uncertain renewable generation output, load demand, and energy pricing, etc. The major measure to smooth the adverse effects of uncertainties and prediction limitation is taking the uncertainty impacts into account when coordinating the energy components to avoid suboptimal solutions [21]. Two traditional approaches have been substantially applied in the existing research to cope with the uncertainties, namely robust optimization (RO) and SP. Paper [22] proposes an optimal load dispatch scheme for energy hub communities. Monte Carlo simulation is applied to model the electric vehicle uncertainty and RO is adopted to model the electricity price uncertainty.

The uncertainty set contains the upper and lower bounds of the prices and the robustness level can be controlled by a robustness parameter. An optimal economic dispatch model of energy hubs considering the ramping product in the energy market is given in [23]. RO is used to hedge against the price uncertainties. An interval prediction-based method considering a long short-term memory learning program is incorporated to select the uncertainty intervals. Paper [24] deals with the electricity market uncertainties for a self-scheduling energy hub, where the RO is combined with an information gap decision theory approach. The results demonstrate the 8.6% increase in the operation cost. Paper [25] presents a min max min robust framework for the short-term operation of microgrids with natural gas networks, effectively addressing the challenges posed by renewable resource uncertainty and electrical/thermal loads, while demonstrating improved system robustness and flexibility in the presence of uncertainties. Paper [26] introduces a distributed algorithm based on the alternating direction method of multipliers to coordinate the operation of interconnected energy hubs in networked microgrids, effectively resolving power exchange conflicts between microgrids and the distribution network while considering uncertainties through a distributed robust model. SP is exploited in [27] to capture the ambient temperature uncertainty in adiabatic compressed air energy storage management for energy hubs. The Kernel regression is helpful to estimate the conditional distributional information of uncertainties. Paper [28] designs a multi-objective optimization scheme for energy hubs considering the uncertain renewable generation output, load, and market prices. SP is applied using the scenario generation of Normal, Beta, and Weibull distributions. The research of [29] designs a two-stage stochastic model for operating energy hubs in conjunction with day-ahead and real-time electricity markets, incorporating value-at-risk to mitigate high operation costs in worst-case scenarios. The results demonstrate the trade-off between expected cost and value-at-risk, as well as the impact of confidence level on value-at-risk. Paper [30] proposes a robust chance-constrained optimization framework for the optimal operation management of an energy hub, considering electrical, heating, and cooling demands as well as renewable power generation.

D. Decentralized Energy Trading and Blockchain Technology

The increasing promotion of trading among energy hubs imposes security challenges, e.g., privacy leakage and forgery. The traditional centralized trading mechanism relies on a trusted third party, which inevitably causes a lack of privacy and misconduct behaviours for benefits [31]. To create a transparent and auditable trading environment, blockchain technology has been exploited widely in the finance domain, e.g., the application of BitCoin [32]. The consensus mechanism is the core part of blockchain, which audits and maintains the information from nodes [33, 34]. Then the traceable transaction data is verified and stored as blocks and added into the existing blockchain with a unique hash value. Paper [35] creates a blockchain-empowered energy transaction platform for individual households and is tested on hardware internet of things (IoT) devices, which reduces the overall energy purchase cost from the traditional energy purchase patterns. A residential power trading system is established in [36] and tested in real-world cases in Canada. The homeowners enable to select bidding strategies based on the Hyperledger Fabric platform. To investigate how blockchain disables dishonest participants in energy P2P trading, a combined blockchain and distributed optimization are proposed [37]. Paper [38] explores a homomorphic encryption-based P2P trading model for energy blockchain systems. The real identity of the blockchain participants is retrieved by machine learning techniques. The majority of blockchain-based energy management has extensively applied blockchain technology for securing transactions of P2P trading of electric vehicles and microgrids. A hierarchical and zonal scheduling model for electric vehicles using consortium blockchain is proposed in [39]. The overall load variance is minimized via an iterative two-layer optimization model. The underutilization of gaming competition among microgrids is mitigated in [40] via a blockchain-based particle swarm optimization model. Paper [41] designs a demand side load management for industrial users with a secure market structure. The users can directly control their own loads without relying on demand aggregators. Accordingly, inaccurate estimations are avoided. A comprehensive model for the economic and technical management of microgrids with ancillary services is given in [42]. A blockchain client-server architecture toward prosumers is developed for transparent tradings. Paper [43] proposes a contract-based EV charging strategy for the internet of energy. The delegated Byzantine fault tolerance consensus scheme provides an efficient platform for audit and sharing the transaction records.

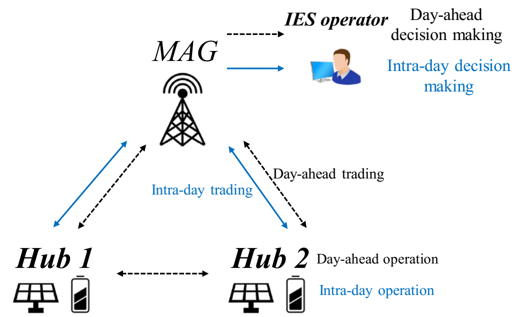


Fig. 1. The proposed operation process.

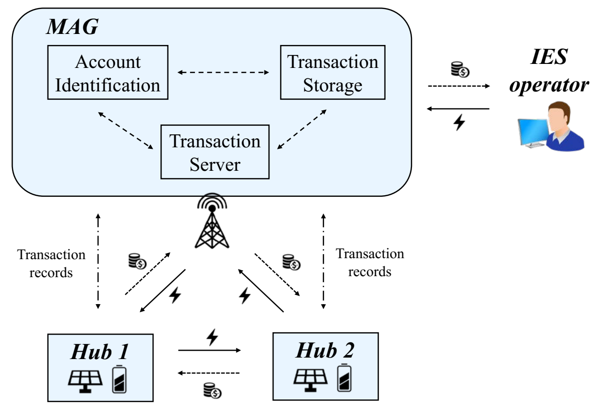


Fig. 2. The proposed trading process.

E. Motivations

Our research is motivated by the intersection of several key trends and challenges in the field of energy systems, particularly in the social implications of these developments, as they relate to the decentralization of energy systems, the application of blockchain technology, the integration of energy hubs, the handling of uncertainty in renewable generation and load demand, and the need for new forms of social governance in energy trading. The key motivations of this paper are:

Decentralized Energy Trading: In recent years, decentralized trading schemes among energy prosumers have gained significant popularity. These schemes provide a pathway for improving energy efficiency by allowing direct energy exchange between producers and consumers. However, the decentralized nature of these schemes presents new challenges in terms of transaction security and privacy protection.

Blockchain Technology: Blockchain technology has emerged as a promising solution to these challenges. By providing a secure and transparent platform for transactions, blockchain technology enhances trust and cooperation among participants in decentralized energy trading. However, the application of blockchain technology in this context is still a relatively new area of research, and there are many unresolved issues and potential improvements to explore.

Integration of Energy Hubs and Blockchain: Existing research has often treated energy hubs and blockchain technology as separate areas of investigation. There is a significant gap in the literature for a comprehensive approach that integrates these two areas. Our research is motivated by the need to bridge this gap and develop a unified framework for blockchain-based energy trading.

Two-Stage Consortium Blockchain-Based Framework: In response to this need, we propose a two-stage consortium blockchain-based framework for socially-governed multi-energy trading. This framework models the interdependencies among power, gas, and heating in energy hubs with multiple conversion technologies. It also provides a preparatory plan for IES operators and energy hub owners, leading to more reliable and economic system operation.

Social Implications and Governance: The transition towards decentralized energy systems has profound social implications. It shifts the power dynamics in energy markets, empowering individual prosumers and local communities. However, this shift also requires new forms of governance to ensure fair and efficient operation of the energy system. Our research addresses this need by proposing a socially-governed multi-energy trading framework. This framework leverages blockchain technology to enable transparent, secure, and democratic decision-making processes in energy trading. It allows all participants to verify transactions, enhancing trust and cooperation in the energy community. Furthermore, the two-stage trading mechanism provides a preparatory plan for IES operators and energy hub owners, ensuring that the operational decisions are socially optimal and economically beneficial. This socially-governed approach to energy trading represents a significant contribution to the field of computational social systems, offering new insights into how technology can be used to facilitate social coordination and cooperation in decentralized energy systems.

F. Research Gaps

A review of previous research suggests several important research gaps.

1. *Energy hubs and blockchain applications in power systems have been investigated separately.* Although prior studies, such as [6] and [7], have examined issues related to operational efficiency, social welfare, and environmental friendliness of the energy hub management, few efforts are devoted to the operational security of energy hubs. For instance, Xu et al. [6] design a distributed multi-period energy hub operation model that includes power, gas, and heating, but does not consider the security challenges in P2P trading. Similarly, Liang et al. [7] develop a distributed management algorithm for residential energy hubs, which also does not consider the potential security risks associated with decentralized trading. Meanwhile, blockchain applications in energy systems also have been explored, as exemplified by [8] and [9], but mostly separate from energy hubs. Despite blockchain's potential for enhancing trust and cooperation among participants in decentralized energy trading, its integration with energy hubs' operations and management received little attention. Fruitful opportunities remain to leverage the security and transparency benefits of blockchain, and require a comprehensive approach to integrate energy hubs' operations and management and blockchain-based trading. In response to this need, the current research aims to develop a secure, efficient blockchain-based energy hub trading and management mechanism that bridges the gap in previous studies of energy hubs and blockchain applications in power systems.

2. Despite existing models of bi-level or tri-level optimization reflect the interactive relationships between P2P energy producers and customers, effective two-stage blockchain-based P2P trading mechanisms for modelling day-ahead and corrective trading behaviours are still lacking. Day-ahead decision-making is essential for preparing the next-day trading and management schemes, and can result in efficient, rigorous, and optimal trading practices. For example, [8] and [9] propose cooperative game-theoretical P2P operations and risk-averse stochastic programming, respectively. These studies do not offer any comprehensive two-stage blockchain-based P2P trading mechanisms. Gan et al. [8] suggest a cooperative game-theoretical P2P operation model for energy hubs to increase on-site consumptions of renewable generation while reducing the reliance on the power grid. This model however does not consider day-ahead and corrective trading behaviours that are crucial for preparing the next-day trading and management schemes. Similarly, Wang et al. [9] propose a risk-averse stochastic programming to address the market bidding problem that involve energy hubs. While this work addresses the operational risk, due to the uncertainty from wind turbines, it does not incorporate any two-stage blockchain-based P2P trading mechanisms. Lacking such a mechanism in [8] and [9] underscores an important gap that needs to be addressed.

Moreover, [10] and [11] design P2P coordination for home energy hub systems and a bargaining-based cooperative game theoretical formulation for IESs, respectively. Yet thy do not offer a comprehensive two-stage blockchain-based P2P trading mechanism. This further reveals the need for effective two-stage blockchain-based P2P trading mechanisms.

3. *Traditional RO and SP have been extensively applied for uncertainty modeling in operations research, but each has its own limitations.* For example, RO has been criticized for over-conservativeness, as evident in [22] and [23] that uses RO to model uncertainties in optimal load dispatch scheme for energy hub communities and optimal economic dispatch model of energy hubs, respectively. Although it can model uncertainties, RO suffers over-conservativeness, which in turn can lead to excessively cautious decisions that are suboptimal in practice. On the other hand, SP has been challenged for high computational requirements, large samples, and inaccurate results, desite its frequent use in uncertainty modeling. In [27] and [28], SP is applied to capture the ambient temperature uncertainty in adiabatic compressed air energy storage management for energy hubs or design a multi-objective optimization scheme for energy hubs with consideration of the uncertain renewable generation output, load, and market prices. While these studies illustrate the use of SP in uncertainty modelling with some insights, they fail to address its high computational requirements, which represents a significant, practical barrier especially in large-scale problems that involve large samples. It is crucial to mitigate the limitations of these two traditional methods, which calls for new methods capable of modeling uncertainties while avoiding the over-conservativeness of RO and high computational requirements of SP. We address this gap by proposing a two-stage Wasserstein-based DRO model that can effectively handle load and renewable uncertainties. Specifically, we adopt a Wasserstein-based ambiguity set (WAS) and use a linear decision rule to obtain a tractable robust counterpart. This approach retains the advantages of both RO and SP, can mitigate their respective limitations, and thus provides a more practical and efficient solution for uncertainty modelling in energy systems.

G. Contributions

This paper introduces a two-stage consortium blockchain-based framework for socially-governed multi-energy trading. "Socially governed" entails democratic decision-making processes enabled by the proposed blockchain-based framework which allows all participants to verify transactions with enhanced trust and cooperation in the energy community. In addition, its two-stage trading mechanism provides IES operators and energy hub owners with a preparatory plan to ensure socially optimal and economically beneficial operational decisions. This paper proposes a two-stage coordinated privacy-preserving operation and trading mechanism between energy hubs and the distribution level IES based on a consortium blockchain. The interdependencies among power, gas and heating are modelled in energy hubs with multiple conversion technologies. Each energy hub is a prosumer which can both produce and consume multi-energy. Compared with the previous blockchain-based trading works, this paper further models the interaction between energy hubs and the IES operator. A registered energy hub with unique keys and certificate enables to trade power, gas, and heating with IES and other interconnected energy hubs using multi-energy coins (MECs) based on the secure consortium blockchain-based trading environment. The two-stage mechanism realizes trading in both day-ahead and intra-day markets. Multi-energy aggregators (MAGs) are responsible for auditing transaction records openly without the cooperation of any trusted third parties. The inherent renewable and load uncertainties of energy hubs are captured by the innovative Distributionally robust optimization (DRO), inheriting the advantages of RO and SP [44-46]. The WAS is adopted and a linear decision rule is utilized to obtain a tractable robust counterpart. Our framework is 'practical' in the sense that it can be effectively implemented in real-world energy systems. Our case studies demonstrate that our framework can handle increased renewable generation capacity, save audit costs, and facilitate more P2P interaction. Moreover, our framework reduces the redundant trading amount by 6.5%, leading to further reductions in the overall operation cost.

For simplicity and ease of communications, we refer this work blockchain-based coordinated operation and trading scheme for energy hubs (BOTH). Based on the existing literature, the key novelties of this paper are three-fold:

- This paper develops a blockchain-based multi-energy trading environment for networked energy hubs. A consortium-based blockchain is applied to securely audit and verify transaction records.
- A hierarchical two-stage operation and trading framework is developed for energy hubs, which strengthens the operational flexibility.
- A two-stage Wasserstein-based DRO model is deployed for effectively handling load and renewable uncertainties. The ambiguity set can be flexibly adjusted.

H. Paper Organization

The remainder of the paper is organized as follows. In section II, the blockchain-based operation and trading scheme are given. Section III proposes system modelling and objective functions. Section IV presents the methodology for solving the proposed problem. The case evaluation is demonstrated in section V. The conclusion is finally given in section VI.

II. Blockchain-Based Operation and Trading Scheme

This section presents the operation and trading mechanisms of BOTH, respectively. The multi-energy trading can be conducted not only between different energy hubs but between energy hubs and MAGs. The consortium blockchain is exploited in this paper to share and audit transaction records publicly without trusting any third parties.

A. Blockchain-Based Operation

The two-stage blockchain-based operation scheme for IES and energy hubs, which we refer to as a socially-governed operation scheme, is given in Fig. 1. At the first stage, the IES operator makes the initial system operation plan based on the estimated energy trading amount uploaded by energy hub owners. In this socially-governed scheme, energy hub owners are encouraged and rewarded to share the estimated next-day trading plan with MAG. This collective participation and decision-making process is crucial for achieving an accurate and optimal day-ahead operation scheme made by the IES operator. The intended trading plan is encrypted and signed with digital signatures for transaction security. The pseudonym information is transferred from MAGs to the IES operator. Then the IES operator enables to schedule generators' reserve capacity with obtained predicted energy trading plan with MAGs. In the second stage, energy hub owners send energy exchange request again owing to the uncertain load characteristics under the real practice. The IES operator makes corrective adaptive operation considering the uncertain energy exchange behaviour based on the request transferred via MAGs. Meanwhile, secure energy trading is implemented between MAGs and energy hubs.

B. Blockchain-Based Trading

MAGs provide wireless communication services for energy hubs and the IES. MAGs process the trading request from energy hubs and work as brokers to broadcast the requests to all energy hub owners and the IES operator. During the second-stage operation, a consensus process is required for auditing transactions, which is implemented prior to the newly created block is connected to the existing blockchain, i.e., a new transaction is formed. All the authorized MAGs are responsible for the consensus process, which forms the proposed consortium blockchain structure.

The blockchain-based trading scheme is shown in Fig. 2. A MAG consists of a transaction server, a transaction storage and an account identification. The transaction server is adopted for collecting trading requests from energy hubs and match trading pairings among all the connected energy hubs. It also bridges the energy exchange between energy hubs and the IES. The account information of energy hubs is managed by the account identification. Furthermore, it encrypts and structures transactions into blocks and transmits to all the MAGs for audit. All the transaction records are stored in the transaction storage.

The schematic of the proposed energy hub is given in Fig. 3. Each energy hub is registered through a trusted authority, e.g., an associated department of government, and accordingly is legitimate for secure energy trading. Each energy hub has a unique identity I_h with public and private keys (π_h and ρ_h) as well as a corresponding certificate cer_h. The trading among energy hubs and IES relies on a MECs. A digital wallet is attached to each I_h with pre-saved MEC. The registration authority provides a digital wallet address for each I_h as W_h and a mapping list $\{\pi_h, \rho_h, cer_h, W_h\}$. As shown in Fig. 2, an energy hub owner can decide trading with other energy hubs, IES or being in self-operation status. During each transaction, pseudonyms are created for trading participators. The associated data and transaction records are encrypted with timestamps. Digital signatures are required to ensure the security and accuracy of transactions.

The step-by-step blockchain-based trading mechanism, forming the core of our socially-governed approach, is illustrated in Fig. 4. WEH owners are able to submit trading timestamps. Digital signatures are required to ensure the security and accuracy of transactions. This socially-governed mechanism ensures that all participants have a say in the trading process, enhancing trust and cooperation among them. We compile smart contracts via Solidity 0.8.7 with the code shown in Fig. 5. After the successful trading, the energy buying energy hub pays for the purchased energy via MECs, which is transferred from its own wallet address to the energy seller's wallet address. The transaction record is provided by the energy buyer and the seller then verifies and

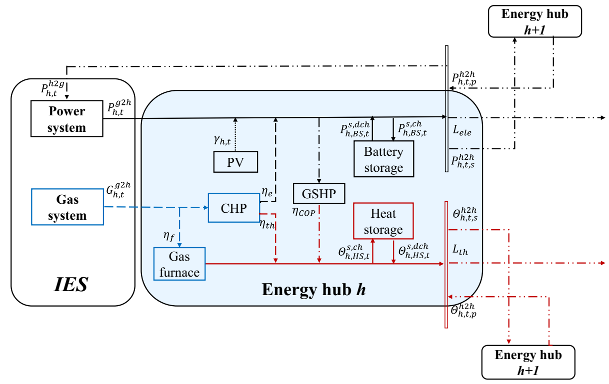


Fig. 3. The proposed energy hub model.

```
pragma solidity ^0.8.7;

contract FeeCollector { // 0xA182D684c4e930142b97986Eb7fe0Cb40D1D929d
    address public owner;
    uint256 public balance;

    constructor() {
        owner = msg.sender; // store information who deployed contrac
    }

    receive() payable external {
        balance += msg.value; // keep track of balance (in WEI)
    }


    function withdraw(uint amount, address payable destAddr) public {
        require(msg.sender == owner, "Only owner can withdraw");
        require(amount <= balance, "Insufficient funds");

        destAddr.transfer(amount); // send funds to given address
        balance -= amount;
    }
}
```

Fig. 4. Deployed smart contract code via Solidity.

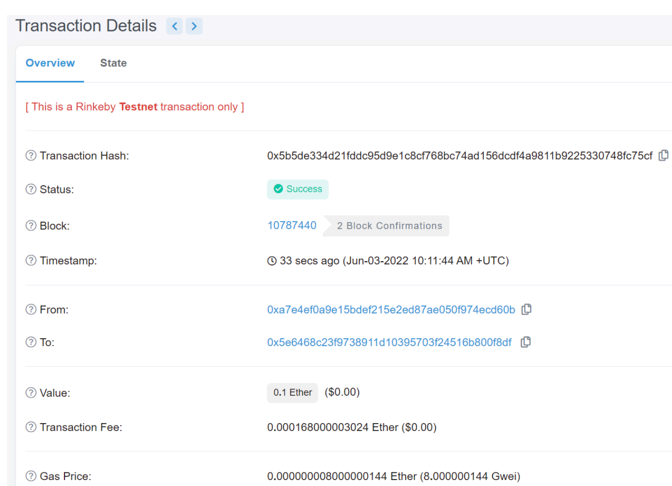


Fig. 5. Submitted water-energy request from WEH1.

signs the transaction record, followed by the uploading process to MAGs for audit.

When a transaction is generated, it is facing an audit by all the authorized MAGs, which is considered as a proof-of-work (PoW) mechanism. The PoW generates a unique hash for each block, which can be seen as a fingerprint identifying each block with corresponding content. The cryptographic hash provides the main secure guarantee for the blockchain as the linkage between each block. To tamper the block's content, the hash with difficulty needs to be disconnected first. After a transaction is successfully added to the consortium blockchain, it is structured into a block and linked with the existing blockchain. The record is publicly visible to all the energy hubs and MAGs.

III. System Modelling

A. Day-Ahead Modelling of BOTH

In the first stage, the trading and operation cost among energy hubs are to be minimized. In (1), the first term represents the benefit of power selling to the IES, where λ_{h-g}^{P} represents the cost coefficient; $P_{h,t}^{s,h-g}$ represents the amount of power selling to the IES. The second and third terms show the day-ahead estimation of power and gas purchase cost, where λ_{g-h}^{P} and λ_{g-h}^{G} are the corresponding cost coefficients; $P_{h,t}^{s,g-h}$ and $G_{h,t}^{s,g-h}$ are the power and gas purchase. In the day-ahead market, each energy hub owner estimates the trading amount for the next 24 hours and request the energy exchange with IES through the closest MAG. This manner is encouraged since a trading and operation preparatory dispatch can be obtained and mitigates the IES operation difficulties for the second stage. Accordingly, the energy purchase price from IES in the day-ahead market is cheaper than the intra-day market. The associated reward is given in the fourth and fifth terms, where λ_{re}^{P} and λ_{re}^{G} are the reward coefficients of the energy estimation. The sixth and seventh terms depict the trading cost with other connected energy hubs, where λ_{h-h}^{P} and λ_{h-h}^{H} are the power and heating trading coefficiencies; $P_{h,t,p/s}^{s,h-h}$ and $\Theta_{h,t,p/s}^{s,h-h}$ denote the power and heating P2P trading amount. The depreciation cost of battery and heat storage is given in the rest of (1), where λ_{h}^{BS} and λ_{h}^{HS} are the degradation coefficients of power and heating storage; $P_{h,BS,t}^{s,ch/dch}$ and $\Theta_{h,HS,t}^{s,ch/dch}$ denote the charging and discharging power and heating of the storage system.

$$\begin{aligned}\Gamma_1 = \min \sum_{h\in H, t\in T} & -\lambda_{h-g}^{P} P_{h,t}^{s,h-g} + \lambda_{g-h}^{P} P_{h,t}^{s,g-h} + \lambda_{g-h}^{G} G_{h,t}^{s,g-h} \\ & -\lambda_{re}^{P}\left(P_{h,t}^{s,h-g} + P_{h,t}^{s,g-h}\right) - \lambda_{re}^{G} G_{h,t}^{s,g-h} + \lambda_{h-h}^{P}\left(P_{h,t,p}^{s,h-h} - P_{h,t,s}^{s,h-h}\right) \\ & +\lambda_{h-h}^{H}\left(\Theta_{h,t,p}^{s,h-h} - \Theta_{h,t,s}^{s,h-h}\right) + \lambda_{h}^{BS}\left(P_{h,BS,t}^{s,ch} + P_{h,BS,t}^{s,dch}\right) \\ & +\lambda_{h}^{HS}\left(\Theta_{h,HS,t}^{s,ch} + \Theta_{h,HS,t}^{s,dch}\right) \end{aligned} \tag{1}$$

The technical constraints of the first-stage BOTH are presented in (2)-(15), which are categorized into 1) power and gas constraints, and 2) thermal constraints. Multiple energy converters are utilized to collectively consume gas and power.

1) Power and Gas Constraints

Equations (2)-(6) constrain the conversion of GSHP, gas furnace and CHP. Constraint (2) regulates the input of GSHP, i.e., $P_{h,COP,t}^{s,i}$. Constraints (3) and (4) are used to limit the gas furnace, where $G_{h,GF,t}^{s,i}$ and $P_{h,GF,t}^{s,o}$ are the input and output; η_{GF} is the conversion efficiency. In equations (5) and (6), the power output of the CHP $P_{h,cp\ ,t}^{s,o}$ is constrained, where $G_{h,cp\ ,t}^{s,i}$ is the gas input; ρ_{cp^e} represent the conversion efficiency.

$$P_{COP,min}^{i} \le P_{h,COP,t}^{s,i} \le P_{COP,max}^{i} \tag{2}$$

$$P_{h,GF,t}^{s,o} = \rho_{GF} G_{h,GF,t}^{s,i} \tag{3}$$

$$P_{GF,min}^{i} \le P_{h,GF,t}^{s,i} \le P_{GF,max}^{i} \tag{4}$$

$$P_{h,cp\ ,t}^{s,o} = \rho_{cp^e} G_{h,cp\ ,t}^{s,i} \tag{5}$$

$$P_{cp,min}^{i} \le P_{h,cp,t}^{s,i} \le P_{cp,max}^{i} \tag{6}$$

The charging and dischargeng power of battery storage should be limited. In (7) and (8), the remaining capacity of battery storage $E_{h,BS,t}^{s}$ is presented, where ρ_{BS}^{ch} and ρ_{BS}^{dch} are the charging and discharging efficiencies.

$$E_{h,BS,t}^{s} = E_{h,BS,t-1}^{s} + \sum\nolimits_{1}^{t} P_{h,BS,t}^{s,ch}\rho_{BS}^{ch} - P_{h,BS,t}^{s,dch}/\rho_{BS}^{dch} \tag{7}$$

$$E_{BS,min} \le E_{h,BS,t}^{s} \le E_{BS,max} \tag{8}$$

The trading amount ($P_{h,t}^{s,h-g}$, $P_{h,t}^{s,g-h}$, $G_{h,t}^{s,g-h}$, $P_{h,t,p}^{s,h-h}$, and $P_{h,t,s}^{s,h-h}$) should be limited by upper and lower bounds. Equations (9) and (10) are the input-output balancing constraints of power and gas, where $\chi_{h,t}$ is the PV generation forecast and D_{ele} is the power load demand.

$$\begin{aligned} P_{h,t}^{s,g-h} + \sum_{h\in H} P_{h,t,p}^{s,h-h} + P_{h,cp\ ,t}^{s,o} + P_{h,BS,t}^{s,dch} + \chi_{h,t} = \\ P_{h,COP,t}^{s,o} + \sum_{h\in H} P_{h,t,s}^{s,h-h} + P_{h,BS,t}^{s,ch} + P_{h,t}^{s,h-g} + D_{ele} \end{aligned} \tag{9}$$

$$G_{h,t}^{s,g-h} = G_{h,GF,t}^{s,i} + G_{h,cp,t}^{s,i} \tag{10}$$

2) Thermal Constraints

Constraints (11) and (12) define the thermal output of GSHP and CHP, i.e., $\Theta_{h,COP,t}^{s,o}$ and $\Theta_{h,cp\ ,t}^{s,o}$, where $P_{h,COP,t}^{s,i}$ and $G_{h,cp\ ,t}^{s,i}$ are the power and gas input.

$$\Theta_{h,COP,t}^{s,o} = \rho_{COP} P_{h,COP,t}^{s,i} \tag{11}$$

$$\Theta_{h,cp\ ,t}^{s,o} = \rho_{cp^h} G_{h,cp\ ,t}^{s,i} \tag{12}$$

We need to limit the magnitude of charging and discharging heat $\Theta_{h,HS,t}^{s,ch/dch}$. The remaining thermal energy $E_{h,HS,t}^{s}$ is modelled and limited in (13) and (14), where $\rho_{HS}^{ch/dch}$ is the efficiency.

$$E_{h,HS,t}^{s} = E_{h,HS,t-1}^{s} + \sum\nolimits_{1}^{t} \Theta_{h,HS,t}^{s,ch}\rho_{HS}^{ch} - \Theta_{h,HS,t}^{s,dch}/\rho_{HS}^{dch} \tag{13}$$

$$E_{HS,min} \le E_{h,HS,t}^{s} \le E_{HS,max} \tag{14}$$

Finally, we apply (15) to balance the thermal input and output, where D_h denotes the thermal load demand.

$$\begin{aligned} \sum_{h\in H} \Theta_{h,t,p}^{s,h-h} + \Theta_{h,cp\ ,t}^{s,o} + \Theta_{h,COP,t}^{s,o} + \Theta_{h,HS,t}^{s,dch} = \\ \sum_{h\in H} \Theta_{h,t,s}^{s,h-h} + \Theta_{h,HS,t}^{s,ch} + D_h \end{aligned} \tag{15}$$

B. Recourse Actions of BOTH

The second-stage objective function is shown in (16), which includes i) penalty cost of the trading deviation between the second and first stages and ii) cost of the consensus process, i.e., PoW. The penalty cost coefficients of trading deviation for power and gas are represented by ϑ_{h-g}^{P}, ϑ_{g-h}^{P}, and ϑ_{g-h}^{G}; ϑ_{h-h}^{P}

and ϑ_{h-h}^{P} denote the penalty coefficient of P2P trading; the cost coefficient of consensus process for power and heating are represented by ω_{PoW}^{P} and ω_{PoW}^{H}.

$$\begin{aligned}\Gamma_2 = \min \sum_{h\in H, t\in T} & \vartheta_{h-h}^{P}\left|P_{h,t,p}^{s,h-h} - P_{h,t,p}^{r,h-h}\right| + \vartheta_{h-h}^{P}\left|P_{h,t,s}^{s,h-h} - P_{h,t,s}^{r,h-h}\right| \\ & + \vartheta_{h-h}^{H}\left|\Theta_{h,t,p}^{s,h-h} - \Theta_{h,t,p}^{r,h-h}\right| + \vartheta_{h-h}^{H}\left|\Theta_{h,t,s}^{s,h-h} - \Theta_{h,t,s}^{r,h-h}\right| \\ & + \vartheta_{h-g}^{P}\left|P_{h,t}^{s,h-g} - P_{h,t}^{r,h-g}\right| + \vartheta_{g-h}^{P}\left|P_{h,t}^{s,g-h} - P_{h,t}^{r,g-h}\right| \\ & + \vartheta_{g-h}^{G}\left|G_{h,t}^{s,g-h} - G_{h,t}^{r,g-h}\right| \\ & + \omega_{PoW}^{P}\left(P_{h,t}^{r,h-g} + P_{h,t}^{r,g-h} + P_{h,t,p}^{r,h-h} + P_{h,t,s}^{r,h-h}\right) + \omega_{PoW}^{H} \\ & \left(+\Theta_{h,t,p}^{r,h-h} + \Theta_{h,t,s}^{r,h-h}\right) + \omega_{PoW}^{H} G_{h,t}^{s,g-h} \end{aligned} \tag{16}$$

The inherent renewable uncertainty is considered following the day-ahead decisions. In addition, the intra-day corrective BOTH is used to adjust on trading strategies and energy conversion scheduling. The second-stage energy balance constraints are given in (17)-(19), where $\xi_{h,t}$ and ζ_{ele}, ζ_{th} are the uncertain renewable generation output and uncertain load demand. Please notice that the reminder of the second-stage constraints are ignored for space limitation, but are the same as the first-stage formulation shown in section III-A by replacing superscript 's' with 'r'.

$$\begin{aligned} & P_{h,t}^{r,g-h} + \sum_{h\in H} P_{h,t,p}^{r,h-h} + P_{h,cp,t}^{r,o} + P_{h,BS,t}^{r,dch} + \xi_{h,t} = \\ & P_{h,COP,t}^{r,o} + \sum_{h\in H} P_{h,t,s}^{r,h-h} + P_{h,BS,t}^{r,ch} + P_{h,t}^{r,h-g} + \zeta_{ele} \end{aligned} \tag{17}$$

$$G_{h,t}^{r,g-h} = G_{h,GF,t}^{r,i} + G_{h,cp,t}^{r,i} \tag{18}$$

$$\begin{aligned} & \sum_{h\in H} \Theta_{h,t,p}^{r,h-h} + \Theta_{h,cp,t}^{r,o} + \Theta_{h,COP,t}^{r,o} + \Theta_{h,HS,t}^{r,dch} = \\ & \sum_{h\in H} \Theta_{h,t,s}^{r,h-h} + \Theta_{h,HS,t}^{r,ch} + \zeta_{th} \end{aligned} \tag{19}$$

IV. Methodology

This section proposes the methodology for the BOTH modelling via a two-stage framework and the solution procedures. The illustration of the two-stage BOTH model is given in Fig. 6. In addition, we illustrate the Wasserstein-based DRO approach in Fig. 7.

A. Abstract Formulation

The initial formulation is presented as a dense matrix formulation. Equations (20) and (21) represent the objective function and constraints of the first stage, and the corresponding variables are denoted as vector *x*.

$$\min_{x\in X} c^T x + \sup_{\mathbb{P}\in WS} E_{\mathbb{P}}[\Omega(x,\xi)] \tag{20}$$

$$\text{s.t. } Cx \le d, x \in \mathbb{R}^{V_1} \tag{21}$$

Equations (22) and (23) model the second-stage problem, where y represents the variables. Equations (2)-(15) with '*re*' superscript and (17)-(19) are summarized by (23). In (24), vector $\upsilon(\xi)$ includes the constant/random vectors, denoted as υ^0 and υ_i^{ξ}, respectively.

$$\Omega(x,\xi) = \min_{y} f'y, y \in \mathbb{R}^{V_2} \tag{22}$$

$$\text{s.t. } Wx + Ty \le \upsilon(\xi), y \in \mathbb{R}^{V_2} \tag{23}$$

$$\upsilon(\xi) = \upsilon^0 + \upsilon_i^{\xi}\xi_i \tag{24}$$

B. Wasserstein Distance-Based Ambiguity Set

The Wasserstein metric between the variable and reference distributions is shown in (25) [47]. The random variables are denoted as ξ and $\xi^{\dagger}$. We use $\rho(\xi,\xi^{\dagger})$ to represent the distance metric. Equation (26) presents the ambiguity set. $\boldsymbol{P}$ is used to represent a variety of possible distributions.

$$d\left(\mathbb{P},\widehat{\mathbb{P}}\right) = \inf E_{\mathbb{Q}}[\rho(\xi,\xi^{\dagger})], \xi\sim\mathbb{P}, \xi^{\dagger}\sim\widehat{\mathbb{P}} \tag{25}$$

$$\mathscr{S} = \left\{\mathbb{P}\in\boldsymbol{P}(\mathbb{R}^i)\left|\begin{matrix}\xi\sim\mathbb{P}\\ d\left(\mathbb{P},\widehat{\mathbb{P}}\right)\le\eta\end{matrix}\right.\right\} \tag{26}$$

The specific conditional WAS is shown in (27) and we use $\tilde{s}$ to denote the scenarios. The WAS includes the following requirements: i) the uncertain variable is within the WAS-generated distribution; ii) the expectation of ξ is a fixed value (μ_s); iii) the auxiliary variable φ is applied to constrain the distance between distributions and iv) the uncertain variable ξ

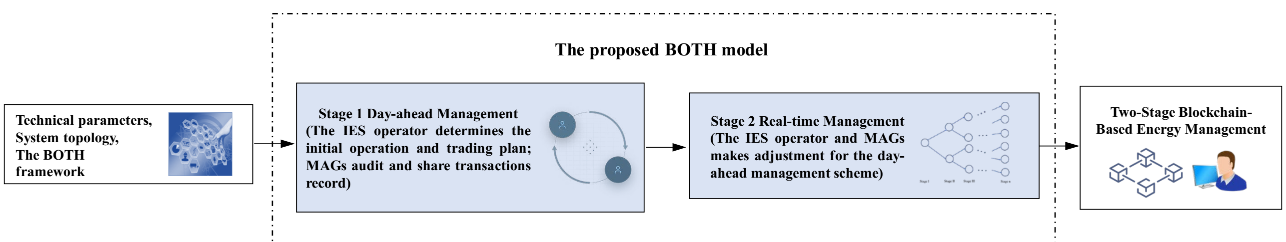


Fig. 6. The proposed two-stage BOTH model.

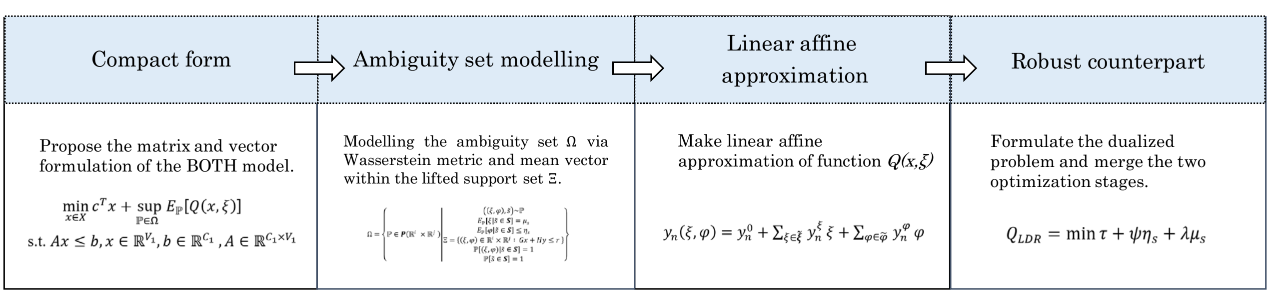


Fig. 7. Illustration of the DRO method.

and auxiliary variable φ are constrained inside the lifted support set Ξ.

$$WAS = \left\{ \mathbb{P} \in \boldsymbol{P}(\mathbb{R}^i \times \mathbb{R}^j) \;\middle|\; \begin{array}{c} ((\xi,\varphi),\tilde{s}) \sim \mathbb{P} \\ E_{\mathbb{P}}[\xi | \tilde{s} \in \boldsymbol{S}] = \mu_s \\ E_{\mathbb{P}}[\varphi | \tilde{s} \in \boldsymbol{S}] \le \eta_s \\ \Xi = \{(\xi,\varphi) \in \mathbb{R}^i \times \mathbb{R}^j : \; Wx + Ty \le r\} \\ \mathbb{P}[(\xi,\varphi) | \tilde{s} \in \boldsymbol{S}] = 1 \\ \mathbb{P}[\tilde{s} \in \boldsymbol{S}] = 1 \end{array} \right\} \tag{27}$$

C. *Affine Approximation and Robust Counterpart*

Equation (28) is equivalent to $\Omega(x,\xi)$. It is intractable to determine the worst-case expected formulation because we consider all the possible realizations involving the uncertainties [48]. We apply the LDR in (30) to tackle the problem [49], approximating $y(\xi)$ by its linearized affine functions.

$$\Omega(x,\xi) = \sup_{\mathbb{P} \in WS} E_{\mathbb{P}}[\Omega(x,\xi)] = \sup_{\mathbb{P} \in WS} E_{\mathbb{P}}[f' y(\xi)] \tag{28}$$

$$y(\xi) \in \arg\min\{f'y: \; Wx + Ty \le \upsilon(\xi)\} \tag{29}$$

$$y_j(\xi,\varphi) = y_j^0 + \textstyle\sum_{\xi \in \tilde{\xi}} y_n^{\xi} \, \xi + \sum_{\varphi \in \tilde{\varphi}} y_n^{\varphi} \, \varphi \tag{30}$$

We replace the recouse decision $y(\xi)$ by the below LDR formulation to approximate $\Omega(x,\xi)$, represented by $\Omega_{LDR}(x,\xi)$.

$$\Omega_{LDR}(x,\xi,\varphi,\tilde{s}) = \min \sup_{\mathbb{P} \in \Omega} E_{\mathbb{P}}[f' y(\xi,\varphi,\tilde{s})] \tag{31}$$

$$\text{s.t. } Wx + Ty(\xi,\varphi,\tilde{s}) \le \upsilon(\xi), \; \forall (\xi,\varphi) \in \Xi \tag{32}$$

In order to transform the second-stage min-sup structure to a pure minimization problem to merge with the first-stage problem, we thus obtain its dual reformulation [50] in (33)-(36), where dual variables are denoted by ψ and λ.

$$\Omega_{LDR} = \min \tau + \psi\eta_s + \lambda\mu_s \tag{33}$$

$$\text{s.t.} \quad \tau + \xi'\lambda + \varphi'\psi \ge f' y(\xi,\varphi,\tilde{s}), \; \forall (\xi,\varphi) \in \Xi \tag{34}$$

$$Wx + Ty(\xi,\varphi,\tilde{s}) \le \upsilon(\xi), \forall (\xi,\varphi) \in \Xi \tag{35}$$

$$\psi \ge 0, \psi \in \mathbb{R}^j, \tau \in \mathbb{R}, \lambda \in \mathbb{R}^i \tag{36}$$

Equations (33)-(36) is a linearized robust linear problem. And its robust counterpart can be written in (37)-(42).

$$\Omega_{LDR} = \min \tau + \psi\eta_s + \lambda\mu_s \tag{37}$$

$$\text{s.t.} \quad \tau - f' y^{0s} + \chi_0' r \ge 0 \tag{38}$$

$$\chi_{0s}'\{\cdot\}_{si/j} = \sum_j q_j y_{ji}^{\xi/\varphi,s} - \lambda_i, \forall i \in I, \forall j \in J, \forall s \in S, \{\cdot\} = W,T \tag{39}$$

$$\chi_{ms}'\{\cdot\}_{si/j} = \sum_k C_{jk} y_{ki}^{\xi/\varphi,s} - \upsilon_{ji}^{\xi}, \forall i \in I, \forall s \in S, \{\cdot\} = W,T \tag{40}$$

$$W_j' x + T_j' y^{0s} - \upsilon_j^0 + r' \chi_{js}, \forall s \in S \tag{41}$$

$$\psi \ge 0, \alpha_0 \ge 0, \alpha_j \ge 0 \tag{42}$$

Additional dual variables are given as α_0 and α_j. Eventually, we derive the tractable approximated formulation of the initial two-stage BOTH in (37)-(42).

V. Case Evaluation

The performance of the proposed BOTH framework for secure trading among energy hubs and IES is evaluated in a regional test system including four interconnected energy hubs. The parameters of the energy hubs are given in TABLE I [51, 52]. In addition, the penalty coefficients of the P2P trading is from [53]. To test the model effectiveness under different market and capacity conditions, comparison between 5 cases is considered [51, 52, 54]:

Case 1: Baseline case.

Case 2: When considering twice PV capacity.

Case 3: When considering twice power trading unit cost.

Case 4: When considering twice power&heat trading cost.

Case 5: When considering twice PoW unit cost.

We conduct the above 5 cases as the sensitivity analysis to test the performance of our BOTH model. We set case 2 for testing the impact of the renewable generator capacity on the objective result. Cases 3 and 4 are planned to investigate the P2P trading cost coefficients on the economic performance. Case 5 is used to test the effect of consensus charging on the operation cost and scheduling results.

A. *Security and Economic Analysis*

The proposed two-stage secure trading framework including preparatory trading and intra-day real trading is compared with the single-stage trading framework (SSTM). In TABLE II, the P2P trading amount between energy hubs (both power and heat) is analysed under BOTH and the SSTM. Since the load and renewable uncertainties affect the secure and economic trading of energy hubs, RO is adopted to capture the uncertainties. Overall, BOTH yields a lower trading amount compared with SSTM since the conservatism caused by worst-case oriented SSTM is mitigated by incorporating moment information and Wasserstein-based distance. The P2P trading amount of case 2 under BOTH is the highest, i.e., 17568 kWh, with the twice PV capacity as case 1. When the twice of power trading unit cost is considered in case 3, the P2P trading amount decreases by 2199 kWh. However, when the twice heat trading cost is considered, case 4 yields 16625 kWh trading amount, which is 11% higher than that of case 3. The reason is that the doubled heat trading price stimulates the heat trading among energy hubs for gaining profit by selling excessive generated heat. For SSTM, the similar result shows that case 4 is 8.5% higher than that of case 3. In case 5, when PoW unit cost is doubled, the trading amount under BOTH is dramatically reduced by 4362 kWh, which is the lowest trading amount for all the cases. This indicates that

TABLE I
PARAMETERS OF ENERGY HUBS

System parameters	
CHP	η_e=0.33, η_{th}=0.57, $G_{h,cp,max}^i$=600, $G_{h,cp,min}^i$=0
GSHP	COP=3, $P_{h,COP,max}^i$=900, $P_{h,COP,min}^i$ =0
GF	η_f=0.7, $G_{h,GF,max}^i$=900, $G_{h,GF,min}^i$=0
Water tank	$0 \le E_{h,HS,t}^s \le$ 100kWh, η_{HS}^{ch}= 0.85, η_{HS}^{dch}= 0.85, λ_h^{BS} =0.02$/kWh
Battery	$0 \le E_{h,BS,t}^s \le$ 200kWh, η_{BS}^{ch}= 0.88, η_{BS}^{dch}= 0.88, λ_h^{HS} =0.02$/kWh
Power trading	$0 \le P_{h,t}^{s,h2g} \le$ 300kW, $0 \le P_{h,t}^{s,g2h} \le$ 600kW
Gas trading	$0 \le G_{h,t}^{s,g2h} \le$ 2kcf

TABLE II
P2P TRADING AMOUNT

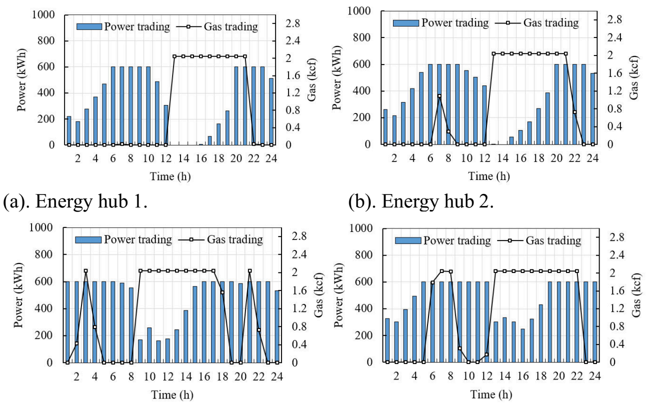
Trading amount (kWh)	Case 1	Case 2	Case 3	Case 4	Case 5
Single-stage framework	18244	18894	16098	17471	13532
BOTH framework	17151	17568	14952	16625	12789

TABLE III
COST OF CONSENSUS PROCESS

PoW cost ($)	Case 1	Case 2	Case 3	Case 4	Case 5
Single-stage framework	183.05	172.41	199.20	214.38	358.42
BOTH framework	168.88	152.43	177.16	186.10	311.79

TABLE IV
ECONOMIC PERFORMANCE FOR ALL CASES

Economic result ($)	Case 1	Case 2	Case 3	Case 4	Case 5
First-stage cost	2786	1940	4466	4289	2794
Expected second-stage cost	702	924	706	818	871
Total cost	3488	2864	5172	5107	3665



(a). Energy hub 1. (b). Energy hub 2.
(c). Energy hub 3. (d). Energy hub 4.

Fig. 8. Power and gas trading with IES.

the higher consensus process cost paid by energy hub owners directly impacts on the P2P trading desire. Instead, energy hub owners intend to consume more energy purchased from the IES with more utilization of energy storage.

In TABLE III, the PoW cost result is given, which reflects the total trading amount of energy hubs. Noted that all the transactions are ensured with security based on the consensus mechanism. In general, SSTM shows a higher PoW cost than that under BOTH. Since SSTM considers the worst-case uncertain scenario of renewable and load uncertainties. The PoW cost of case 2 is the lowest under BOTH and SSTM since twice of PV capacity is utilized, which greatly reduces the trading amount. In case 2, the PoW cost is 5% higher than that of case 1, which shows the opposite result with TABLE II with a reduced P2P trading amount. This result indicates that the twice power trading unit cost stimulates the trading between IES and energy hubs whilst reduce the P2P trading among energy hubs. Moreover, case 4 presents an even higher PoW cost when twice of heat trading unit cost is additionally considered. In case 5, the PoW cost is $311.79 under BOTH and $358.42 under SSTM due to the twice PoW unit cost setting.

The economic performance of operation cost of the overall energy hub community is given in TABLE IV. Case 1 shows $2786 and $702 in the two stages, respectively. In comparison, case 2 shows lower total operation cost owing to the twice PV capacity. However, the second-stage operation cost is $222 higher than baseline case 1 since the larger PV capacity results in higher output fluctuation, which requires a larger power imbalance. Case 3 and 4 yields higher operation cost ($5172 and $5107) when power and heat trading unit cost are considered. However, the operation cost of case 4 is lower than that of case 3 when twice the heat trading cost is additionally considered. Since the twice of heat trading cost encourages more heat selling. Energy hub owners can choose to produce more heat based on the conversion from power and gas. In case 5, the doubled audit cost results in a slightly higher operation cost than case 1, i.e., $3665.

B. Trading Analysis

The power and gas trading scheduling between IES and energy hubs are given in Fig. 8. Noted that the power trading indicates the power purchase from IES minus the power selling to IES and the gas trading is simply the gas purchase from IES. In Fig. 8 (a), the power trading is mainly scheduled at 1:00-12:00 and 16:00-24:00. PV enables to provide power support between 12:00 and 16:00. In comparison, gas purchase from IES is only scheduled between 13:00 and 21:00. For energy hubs 2-4, similar trading scheduling is obtained. In Fig. 8 (d), energy hub 4 shows an overall higher trading amount with IES due to the higher load consumption profile. Apart from the two power trading peaks at 5:00-12:00 and 19:00-24:00 (600kWh), it also shows distinct power trading between 13:00 and 18:00 compared with energy hub 1. Furthermore, a new gas trading peak between 6:00-9:00 is scheduled.

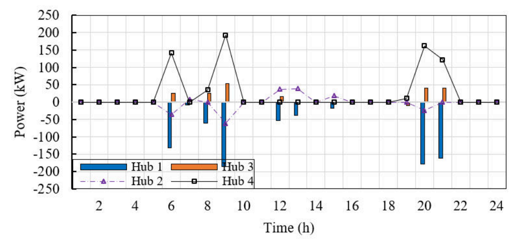


Fig. 9. Power P2P trading under case 1.

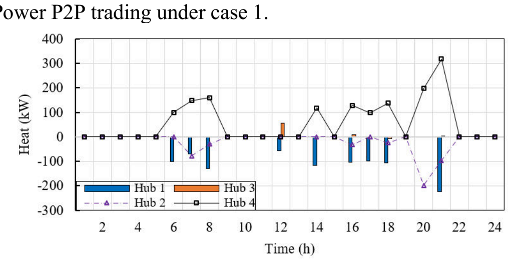


Fig. 10. Heat P2P trading under case 1.

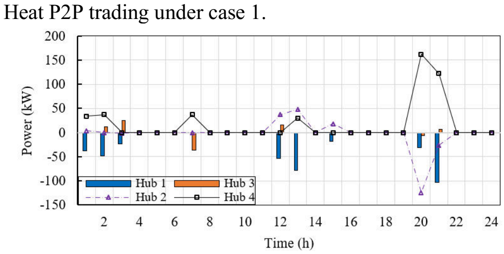


Fig.11. Power P2P trading under case 3.

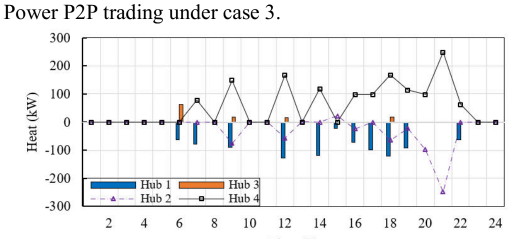


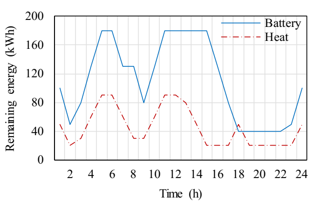
Fig. 12. Heat P2P trading under case 3.

The P2P trading scheduling under cases 1 and 3 are given in Figs. 9-12. In case 1, the power trading is concentrated in the morning and the peak load time periods. At 20:00, energy hubs

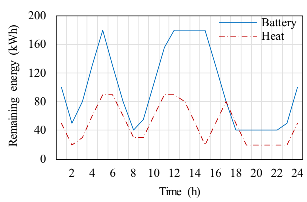
1 and 4 yield 178kW power selling and 162 purchase. In comparison, under case 3, the power P2P trading reduces, particularly during the morning time periods due to the twice of power trading cost. On the contrary, in Fig. 12, the heat P2P trading amount among energy hubs is higher than that of case 1.

C. Scheduling Result of Energy Storage and Conversion

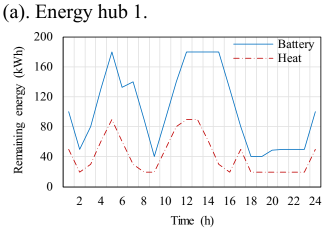
In Fig. 13, the results of remaining storage capacity are presented. For energy hub 1, the battery storage is charging before 5:00, followed by a short idle period. Then it is discharging and charging between 7:00 and 10:00. The remaining capacity of the battery reaches 180kWh between 11:00 and 15:00 during the low demand period. During the evening time, it remains at a low capacity level. Notwithstanding the load profile of power and heat are different, the heat storage shows similar usage curve with two distinct idle usage periods. Since the extensive energy conversion realizes the energy complementation, i.e., heat storage can be used to support power load and battery storage enables to supply heat load. In addition, the scheduling curve of energy hubs 2-4 show similar results. Compared with energy hub 1, energy hub 4 shows less usage on the storage system even with a higher demand profile. The reason is that more trading is scheduled instead of storing excessive energy for later self-usage.



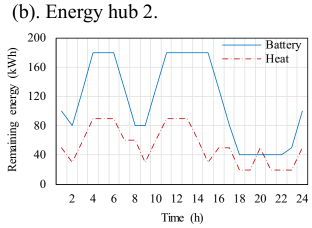
(a). Energy hub 1.



(b). Energy hub 2.



(c). Energy hub 3.



(d). Energy hub 4.

Fig. 13. Remaining capacity of battery and heat storage.

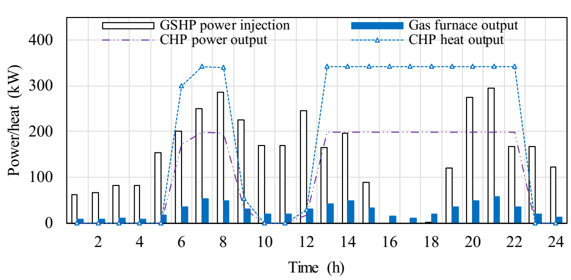


Fig. 14. Converter scheduling result of case 1.

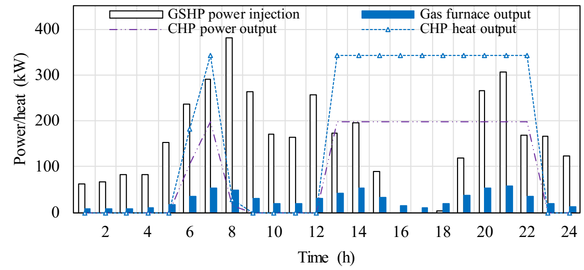
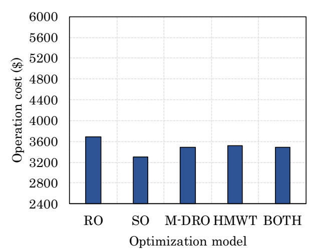
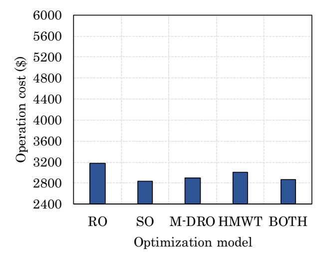


Fig. 15. Converter scheduling result of case 2.

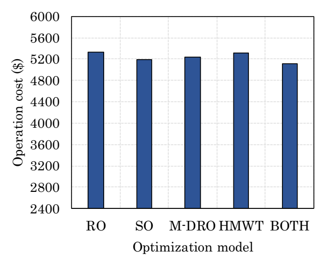
Converter scheduling results of cases 1 and 2 for energy hub 4 are given in Figs. 14 and 15. In case 1, the CHP usage is focused at 6:00-9:00 and 13:00-23:00, where the power and heat output of CHP reaches the maximum limits 350kW and 200kW for 12 hours. In comparison, gas furnace shows much lower conversion usage with an average output of 28kW. The reason is that instead of converting gas to only heat, CHP is utilized more frequently with both power and heat output. GSHP shows three usage peaks at 8:00, 12:00 and 21:00, respectively, which are approximately 300kW. In Fig. 15, the twice of PV capacity directly results in higher power injection of GSHP whilst the CHP usage is reduced. Between 6:00 and 9:00, the CHP power output is averagely 150kW while it is 106kW under case 2. Since the higher reliance on PV reduces the gas purchase and consumption by CHP and gas furnace.



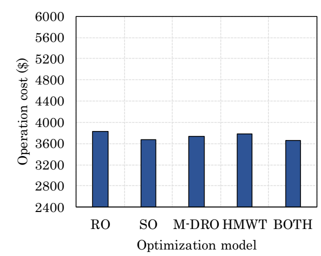
(a). Model comparison under case 1.



(b). Model comparison under case 2.



(c). Model comparison under case 4.



(d). Model comparison under case 5.

Fig. 16. Ojective cost comparison with the existing works.

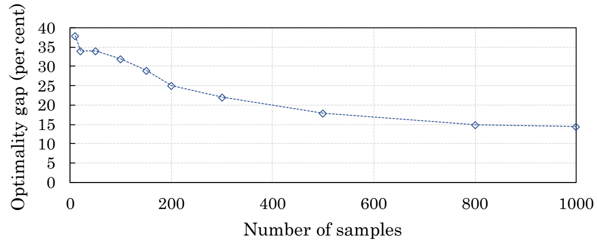


Fig. 17. Convergence characteristics of the MDRTH model.

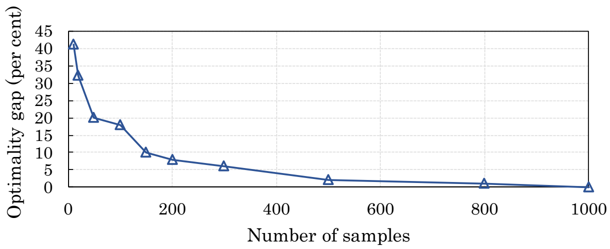
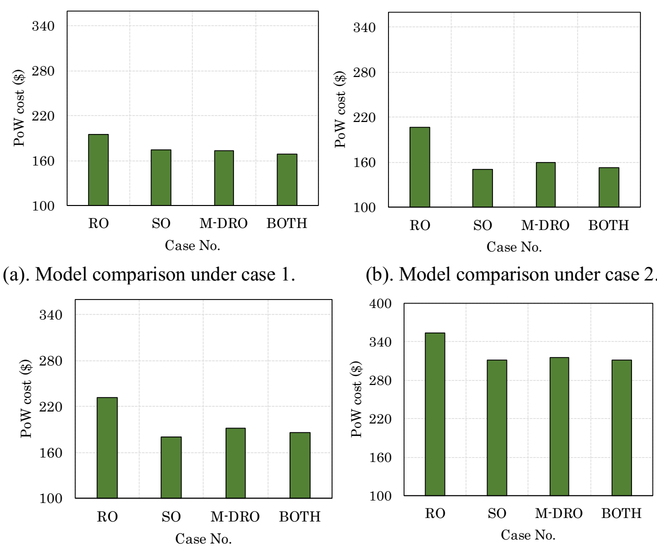


Fig. 18. Convergence characteristics of the proposed BOTH model.

D. Comparison with The Existing Works

To demonstrate the effectiveness of the proposed blockchain-based trading mechanism and the optimization framework, this section illustrates the comparisons between the proposed BOTH model and the existing state-of-the-art works, including the P2P **t**rading and management of energy **h**ubs (TH) considering renewable and load uncertainties handled by RO (denoted as RTH) [55], SP [56] (denoted as STH), and moment-based DRO (denoted as MDRTH) [57, 58]; and networked energy hub management without P2P trading which is denoted as HMWT [59]. To evaluate the performance of the abovementioned 4 benchmark methods and the proposed BOTH, the comparisons of operation costs, convergence characteristics, and PoW costs are conducted.



(a). Model comparison under case 1.
(b). Model comparison under case 2.
(c). Model comparison under case 4.
(d). Model comparison under case 5.

Fig. 19. Comparison of cost for the consensus scheme.

In Fig. 16, the results show that RTH yields the highest operation costs in all the cases. In case 1, the \$3694 modelled by RTH is 5.9% higher than that of the proposed BOTH. In case 2, the cost reduction of the proposed BOTH compared with RTH is distinct with a 10.9% cost reduction. The reason is that when considering twice the PV capacity, the PV output fluctuation is increased. BOTH characterized by Wasserstein-DRO exploits a mitigated computational conservativeness with the lower operation cost result than RTH. We apply the sample-based SP with 1000 PV generation and hub load samples generated by Gaussian distribution with mean value μ=0 and standard deviation σ=0.02. The results of STH are comparable with BOTH. In case 1, STH yields \$3306 of operation cost, which is 94.8% of BOTH. However, the proposed BOTH under cases 4 and 5 shows 1.6% and 0.4% lower operation cost compared with STH. Despite the STH shows comparable economic efficiency with BOTH, the intrinsic stochastic characteristic leads to low computational efficiency with huge amount of sample numbers. When STH is modelled by insufficient samples, the computational burden will be addressed, the real uncertainty distribution will probably not be captured. MDRTH adopts the second moment information , i.e., mean vectors and covariance matrices, which is transformed into a semidefinite programming model and solved by a constraint generation algorithm. In case 1, MDRTH yields \$3495 of operation cost, which is 0.2% higher than that of BOTH. Overall, the operation cost of MDRTH is generally 1.6% higher than that of BOTH. The interconnections and complementation of energy hubs are not considered in HMWT. Fig. 16 shows the average operation cost of HMWT is 3.3% higher than that of BOTH and 2.5% lower than that of RTH. The results indicate that the P2P trading scheme is beneficial for improve the energy operational efficiency via optimally coordinating, converting and exchanging the abundant energy, rather than self supplying and consuming the energy.

The convergence rate results of MDRTH and the proposed BOTH are demonstrated in Figs. 17 and 18, where the optimality gap ($\tilde{\gamma}$) is defined as $\frac{r-s}{r} \times 100\%$. We define r as the optimal objective value of MDRTH and BOTH, and s as the result obtained by sample average approximation with 1000 samples. With 10 samples, the $\tilde{\gamma}$ of MDRTH and BOTH are 41% and 38%, respectively. The $\tilde{\gamma}$ of BOTH decreases sharply with the growth of sample amount. When the number of samples reaches 1000, BOTH converges whilst the $\tilde{\gamma}$ MDRTH is still 14.5%. This result indicates that MDRTH cannot converge with the growth of the sample size relying on the second moment information.

To investigate the utilization of the decentralized consensus under different models, we compare the PoW costs in Fig. 19. The results clearly show that the PoW cost of RTH is the highest among all the cases. In case 2, the PoW cost of RTH is 35.8% higher than that of BOTH. Similar to the operation cost in Fig. 16, STH and BOTH show comparable results whilst MDRTH shows higher PoW utilization.

VI. Conclusion

We propose a two-stage secure and economic trading mechanism for interconnected energy hubs, which is underpinned by a socially governed consortium blockchain. The illustrated socially governed approach enables democratic decision-making processes and can elevate the trust and cooperation among energy hub owners and IES operators. The results of multiple case studies provide compelling evidence suggesting its effectiveness and practical values. Take Case 1 for example, the proposed BOTH model has a total operation cost of \$3,488, representing a 5.2% reduction from that of the STH model. Its total operation cost in Case 2 that features twice the PV capacity further decreases to \$2,864, demonstrating our model's adaptability to increasing renewable generation capacities. Jointly, these empirical results highlight the proposed model's pragmatic utilities and values, and reveal its advantageous capability to handle increasing renewable generation capacity, lower audit costs, and facilitate P2P interactions. At a broader level, the proposed two-stage blockchain-based trading framework not only provides a practical trading scheme but also decreases the redundant trading volume by 6.5%, which should lead to further reductions of the overall operation cost. It achieves up to a 6% reduction in operation cost, while assuring social governance and transaction security for both IES and energy hubs, and allows significant improvements in trading volume and overall system efficiency. Furthermore, this paper sheds light on practical guidelines for P2P trading and operations of in a multi-energy community that is socially governed, with increased security and fairness.

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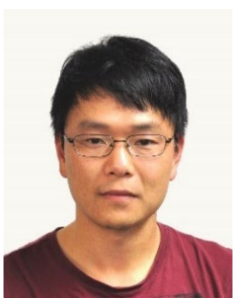

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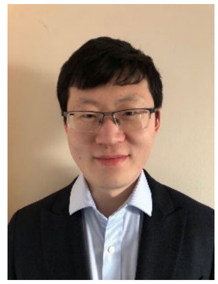

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