IEEE TRANSACTIONS ON COMPUTATIONAL SOCIAL SYSTEMS, Volume 10, Issue 4, August 2023 pp. 1875-1887
10.1109/TCSS.2022.3200032

Two-Stage Co-Optimization for Utility-Social Systems with Social-Aware P2P Trading

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***Abstract*— Effective utility system management is fundamental and critical for ensuring the normal activities, operations, and services in cities and urban areas. In that regard, the advanced information and communication technologies underpinning smart cities enable close linkages and coordination of different sub-utility systems, which is now attracting research attention. To increase operational efficiency, we propose a two-stage optimal co-management model for an integrated urban utility system comprised of water, power, gas, and heating systems, namely integrated water-energy hubs (IWEHs). The proposed IWEH facilitates coordination between multi-energy and water sectors via close energy conversion, and can enhance the operational efficiency of an integrated urban utility system. In particular, we incorporate social-aware peer-to-peer (P2P) resource trading in the optimization model in which operators of an IWEH can trade energy and water with other interconnected IWEHs. To cope with renewable generation and load uncertainties and mitigate their negative impacts, a two-stage distributionally robust optimization is developed to capture the uncertainties, using a semidefinite programming reformulation. To demonstrate our model's effectiveness and practical values, we design representative case studies that simulate four interconnected IWEH communities. The results show that DRO is more effective than RO and SO for avoiding excessive conservativeness and rendering practical utilities, without requiring enormous data samples. This work reveals a desirable methodological approach to optimize the water-energy-social nexus for increased economic and system-usage efficiency for the entire (integrated) urban utility system. Furthermore, the proposed model incorporates social participations by citizens to engage in urban utility management for increased operation efficiency of cities and urban areas.**

***Index Terms*—Distributionally robust optimization, smart city, social-aware management, P2P trading, water-energy-social nexus.**

This work was supported in part by the National Natural Science Foundation of China (Grants No. 72025404 and No.71621002), the New Generation Artificial Intelligence Development Plan of China (2015–2030) (Grants No. 2021ZD0111205), Beijing Natural Science Foundation (L192012) and Beijing Nova Program (Z201100006820085). (*Pengfei Zhao and Shuangqi Li are first co-authors and contributed equally to this work.*)

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NOMENCLATURE

A. Sets

T	Set of time periods.
H	Set of integrated water energy hubs (IWEHs).

B. Parameters

λ_{h2g}^{P}	Cost coefficient of power selling to the external market.
$\lambda_{g2h}^{P}, \lambda_{g2h}^{G}, \lambda_{g2h}^{W}$	Cost coefficient of power, gas and water purchase from the external market.
$\lambda_{re}^{P}, \lambda_{re}^{G}, \lambda_{re}^{W}$	Reward cost coefficient of power, gas and water trading estimation.
$\lambda_{h2h}^{P}, \lambda_{h2h}^{H}, \lambda_{h2h}^{W}$	Cost Coefficient of power and heat trading among IWEHs.
$\lambda_{h}^{BS}, \lambda_{h}^{HS}, \lambda_{h}^{WS}$	Depreciation cost coefficient of battery, heat and water storage.
$\vartheta_{h2g}^{P}, \vartheta_{g2h}^{P}$	Penalty cost coefficient of power trading deviation between first and second stages.
$\vartheta_{g2h}^{G}, \vartheta_{g2h}^{W}$	Penalty cost coefficient of gas and water trading deviation between two stages.
$\vartheta_{h2h}^{P}, \vartheta_{h2h}^{H}, \vartheta_{h2h}^{W}$	Penalty cost coefficient of power, heat and water trading deviation between first and second stages for IWEHs.
η_{e}, η_{th}	Electric and thermal conversion efficiency of CHP.
η_{f}	Conversion efficiency of gas furnace.
η_{COP}	Coefficient of performance.
η_{p2g}^{g}	Electrical efficiency for electrolyser.
η_{EB}^{h}	Conversion efficiency of electric boiler.
$\eta_{p2g}^{w}, \eta_{cp}^{w}$	Water consumption efficiency of P2G and CHP.
$G_{cp,max}^{i}, P_{COP,max}^{i}$ $G_{GF,max}^{i}, P_{p2g,max}^{i}$	Maximum input limit of CHP, GSHP, gas furnace and P2G.
$G_{cp,min}^{i}, P_{COP,min}^{i}$ $G_{GF,min}^{i}, P_{p2g,max}^{i}$	Minimum input limit of CHP, GSHP gas furnace and P2G.
$P_{EB,max}^{i}, P_{EB,min}^{i}$	Maximum and minimum input limits of electric boiler.
$\Theta_{HS,max}^{s,ch}, \Theta_{HS,min}^{s,ch}$	Maximum and minimum limit of charging power of heat storage.
$\Theta_{HS,max}^{s,dch}, \Theta_{HS,min}^{s,dch}$	Maximum and minimum limit of discharging power of heat storage.

$E_{HS,min}$, $E_{HS,max}$	Minimum and maximum remaining heat for heat storage.
η_{HS}^{ch}, η_{HS}^{dch}	Charging and discharging efficiency of heat storage.
$P_{BS,max}^{s,ch}$, $P_{BS,min}^{s,ch}$	Maximum and minimum limit of charging power of battery.
$P_{BS,max}^{s,dch}$, $P_{BS,min}^{s,dch}$	Maximum and minimum limit of discharging power of battery.
$E_{BS,min}$, $E_{BS,max}$	Minimum and maximum energy for battery.
$\sigma_{WS,max}^{s,ch}$, $\sigma_{WS,min}^{s,ch}$	Maximum and minimum limit of charging water.
$\sigma_{WS,max}^{s,dch}$, $\sigma_{WS,min}^{s,dch}$	Maximum and minimum limit of discharging water.
$V_{WS,min}$, $V_{WS,max}$	Minimum and maximum remaining water.
η_{BS}^{ch}, η_{BS}^{dch}	Charging and discharging efficiency of battery.
P_{max}^{h2g}, P_{min}^{h2g}	Maximum and minimum limit of power purchase from external market.
P_{max}^{g2h}, P_{min}^{g2h}	Maximum and minimum limit of power selling to external market.
G_{max}^{g2h}, G_{min}^{g2h}	Maximum and minimum limit of gas purchase from external market.
σ_{max}^{g2h}, σ_{min}^{g2h}	Maximum and minimum limit of water purchase from external market.
$P_{p,max}^{h2h}$, $P_{p,min}^{h2h}$	Maximum and minimum limit of power purchase among IWEHs.
$P_{s,max}^{h2h}$, $P_{s,min}^{h2h}$	Maximum and minimum limit of power selling among IWEHs.
$\Theta_{p,max}^{h2h}$, $\Theta_{p,min}^{h2h}$	Maximum and minimum limit of heat purchase among IWEHs.
$\Theta_{s,max}^{h2h}$, $\Theta_{s,min}^{h2h}$	Maximum and minimum limit of heat selling among IWEHs.
$\sigma_{p,max}^{h2h}$, $\sigma_{p,min}^{h2h}$	Maximum and minimum limit of water purchase among IWEHs.
$\sigma_{s,max}^{h2h}$, $\sigma_{s,min}^{h2h}$	Maximum and minimum limit of water selling among IWEHs.
$\gamma_{h,t}$	PV generation forecast at time t.
$L_{h,ele}$, $L_{h,th}$, $L_{h,w}$	Power, heat and water demand at time t.

C. Variables

$P_{h,t}^{s,h2g}$, $P_{h,t}^{s,g2h}$	Power selling and purchase with markets
$G_{h,t}^{s,g2h}$	Gas purchase from the market.
$\sigma_{h,t}^{s,g2h}$	Water purchase from the market.
$P_{h,t,p}^{s,h2h}$, $P_{h,t,s}^{s,h2h}$	Power trading among IWEHs.
$\Theta_{h,t,p}^{s,h2h}$, $\Theta_{h,t,s}^{s,h2h}$	Heat trading among IWEHs.
$\sigma_{h,t,p}^{s,h2h}$, $\sigma_{h,t,s}^{s,h2h}$	Water trading among IWEHs.
$G_{h,cp,t}^{s,i}$, $P_{h,COP,t}^{s,i}$ $G_{h,GF,t}^{s,i}$	Input of CHP, GSHP and gas furnace.
$P_{h,p2g,t}^{s,i}$, $P_{h,EB,t}^{s,i}$	Input of P2G and electric boiler.
$P_{h,cp,t}^{s,o}$, $\Theta_{h,cp,t}^{s,o}$	Power and heat output of CHP.
$\Theta_{h,COP,t}^{s,o}$, $P_{h,GF,t}^{s,o}$	Output of GSHP and gas furnace.
$G_{h,p2g,t}^{s,o}$, $\Theta_{h,EB,t}^{s,o}$	Output of P2G and electric boiler.
$\sigma_{h,p2g,t}^{s,i}$, $\sigma_{h,cp,t}^{s,i}$	Water consumption of P2G and CHP.
$P_{h,BS,t}^{s,ch}$, $P_{h,BS,t}^{s,dch}$	Charging and discharging power of battery storage.
$\Theta_{h,HS,t}^{s,ch}$, $\Theta_{h,HS,t}^{s,dch}$	Charging and discharging of heat storage.
$\sigma_{h,WS,t}^{s,ch}$, $\sigma_{h,WS,t}^{s,dch}$	Charging and discharging of water storage.
$E_{h,BS,t}^{s}$, $E_{h,HS,t}^{s}$, $V_{h,WS,t}^{s}$	Remaining capacity of battery, heat and water storage.
$\xi_{h,t}$	Uncertain PV generation.
$\zeta_{h,ele}$, $\zeta_{h,th}$, $\zeta_{h,w}$	Uncertain power, heat and water loads.
x	Vector of first-stage variables.
y	Vector of second-stage variables.

I. INTRODUCTION

SMART city management leverages advanced information and communication technologies (ICTs) to ensure sustainable, efficient urban operations that are central to quality services to citizens and support their normal activities [1, 2]. These technologies make the effective coordination of multiple heterogeneous utility systems viable and promise greater efficiency and reliability [3, 4]. For instance, Lei et al. [5] design a planning scheme for charging infrastructures, which considers the coupling relationships between power and traffic systems to support smart cities. Shi et al. [6] study a water-food-land ecosystem and examine the impacts of urbanization on the sustainability of a major city in China. Zuloaga and Vittal [7] suggest a coordination strategy for power-water distribution systems in extreme drought scenarios.

Urban energy system management is fundamental and critical to the highly demanding operations and services in a city, due to its system complexity and importance to energy usage [8]. Energy hubs enable optimal, flexible management of multi-energy infrastructures to meet the fast-growing energy demands efficiently and reliably [9]. The overall efficiency in an energy hub can be enhanced through close couplings and conversion, such as power-to-gas (P2G), combined heat and power (CHP), gas furnace, ground source heat pump (GSHP), and electric boiler [10]. With the increasing prevalence of intermittent renewable energy sources (RES), energy hubs have received a growing attention that seeks to offset the intermittency of RES through conversion of distinct, multi-energy systems [11, 12].

Existing research on energy hub operation usually targets system operation cost minimization or social welfare maximization, while considering heterogeneous uncertainties [13]. For example, Dolatabadi et al. [14] take a hybrid approach to combine stochastic optimization and information gap decision theory (IGDT) for energy hub scheduling, with the consideration of risk-cognizant dispatch of RES. The suggested model offers risk-averse and risk-seeker strategies in the presence of price uncertainty. Sheikhi et al. [15] design a smart energy hub operation scheme that employs a cloud computing framework to achieve efficient data processing and support integrated demand-side management. Oskouei et al. [16] develop an operation model for energy markets consisted of multiple (virtual) industrial energy hubs. To support the energy market management in both day-ahead and real-time stages, a two-stage robust optimization (RO) is employed to minimize the operation costs and compensate for operational risks. Shao et al [17] develop an integrated demand response program for integrated energy systems that are linked by energy hubs, according to a formulated two-level optimization model that allows flexible adjustments to changing energy demands.

Energy and water resources are intrinsically interdependent. Conceivably, water resources are of great significance to power industries, especially in energy transmission and conversion [7]. For example, the converted heat of CHP typically exists in the form of steam or hot water. As Pan et al. [18] explain, P2G facilities consume water and often use electrolyzers to separate it into hydrogen and oxygen. Hydrogen can be injected into gas pipelines or storage directly, as well as participating in the methanation process to absorb carbon emissions and produce methane [19]. Meanwhile, water facilities (e.g., wastewater treatment plants) consume approximately 3% of the overall electricity in the United Sates [20], and around 80% of the electricity consumed by water distribution systems is used to pump and distribute water in urban areas. Traditionally, power and water resources are modelled and operated separately, which obviously ignores their interdependencies and therefore restricts the overall efficiency.

Water-power nexus entails effective and efficient use of water and power resources and facilities in a holistic and comprehensive manner [21]. Existing research mostly focuses on co-optimization of water and power systems by minimizing overall operation costs or carbon emissions. For example, Moazeni et al. [22] design an economic dispatch for integrated water and power systems and suggests economic dispatch of thermal energy and water demand management for buildings in smart cities. Specifically, the thermal equilibrium of buildings is incorporated in the system modelling to improve the residential comfort level. To address the challenge of low spatial dimensions, Wang et al. [23] use clustering maps to model a large-scale urban IWPS with spatial resolutions. To enhance the operational efficiency of IWPSs, Mehrjerdi [24] develops a joint optimization for an IWPS in a remote island by considering different desalination procedures that include multi-stage flash and reverse-osmosis. Liu et al. [25] design an optimal operational scheme of IWPS, which includes PVs, diesel generators, and pumped water reservoirs, and suggest a manta ray optimization approach to determine a global optimum with acceptable robustness.

Instead of designing self-operation schemes for independent energy hubs, a peer-to-peer (P2P) trading environment can be created to coordinate proactive consumers toward mutually beneficiary and satisfying partnerships [26]. Facilitated by distributed generators, energy hubs can be viewed as prosumers that enable active participations in a P2P energy market, rather than totally relying on the wholesale energy market. As a result, energy generation, trading, and consumption can be coordinated at the local level to establish a highly efficient energy hub community jointly [27]. For example, Xu et al. [28] design a P2P transactive multi-resource trading framework for energy hubs by reorganizing the original model as a Nash bargaining problem that features subsequent social multi-resource and payoff allocation subproblems. Ali et al. [29] suggests a multi-objective energy trading and planning model for gird-connected microgrids. Fan et al. [30] propose a bargaining cooperative game model with Pareto-optimal balance for energy hubs. In this model, participating energy hubs bargain with one regarding the exchanged energy and payments. Wang et al. [31] considers a risk-averse stochastic optimization for market clearing of energy hubs, which uses P2G extensively to reduce the financial risk created by stochastic wind generation. Ma et al. [32] design a real-time rolling horizon cooperative P2P trading model for community-level energy hubs, together with the stochastic nature of PV generation and conditional value-at-risk. Chen et al. [33] develop a P2P trading scheme for industrial, residential, and commercial energy hubs, using a multi-agent deep reinforcement learning approach to handle the associated complex uncertainties. Gu et al. [34] analyze an optimal charging strategy for microgrid prosumers, in light of the energy router-based sharing mechanism, and apply a multi-objective evolutionary algorithm.

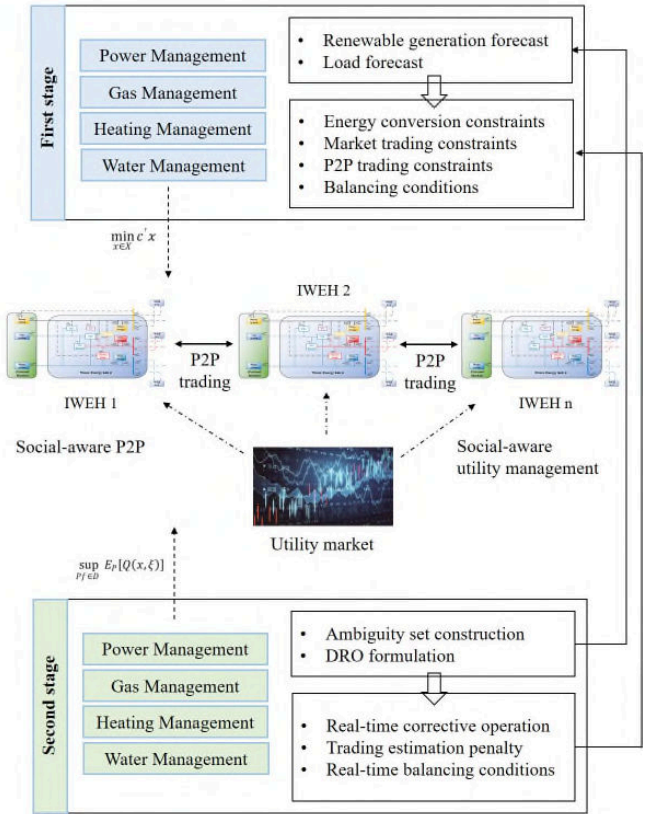


Fig. 1. Schematic of the proposed TS-IHM.

Typically, renewable energy generation is uncertain and volatile, due to the unpredictable and complex weather conditions [35]. Prior studies of energy system operation usually employ SO or RO to mitigate the suboptimal operation results associated with renewable energy uncertainties [36-39]. In general, SO requires the *priori* information of uncertainty distributions with sufficiently large data sets, which suffers computational intractability and is not practical due to the data availability constraint. In contrast, RO requires much less

TABLE I
COMPARING THE PROPOSED WORK WITH PREVIOUS STUDIES

Reference No.	Multi-energy	**Water-energy nexus**	Two-stage model	Optimization method
[24]	✓	-	-	Deterministic
[25]	-	-	-	Deterministic
[26]	✓	-	-	Deterministic
[27]	✓	-	-	SO
[28]	✓	-	✓	SO
[29]	✓	-	-	Learning-based
[30]	-	-	-	Learning-based
Proposed	✓	✓	✓	DRO

information to construct uncertainty sets, such as estimating values with fluctuation boundaries. Yet its emphasis on the worst-case scenario often yields excessively conservative results. To address this limitation, the use of distributionally robust optimization (DRO) is appealing. It represents an effective uncertain programming method for energy system operation problems [40-43], rather than relying on a voluminous data set or sacrificing computational effectiveness. For example, Liu et al. [40] design a real-time economic dispatch for power transmission systems by considering frequency regulations and using DRO to cope with inaccurate renewable energy forecasts. Dehghan et al. [41] develop a unit commitment model by taking the DRO approach to solve non-convex AC power flow equations. The training-based ambiguity set can be controlled by altering the number of training scenarios. Zhao et al. [42] propose a DRO-based hardening plan to address the unreliable planning in catastrophic natural disasters. Ryu et al. [44] design an optimal distributionally robust AC power flow model that considers the uncertain electric field caused by geomagnetic disturbances. Li et al. [45] propose an optimal P2P trading scheme for three-phase unbalanced microgrid networks by adopting a Wasserstein metric-based DRO to capture the uncertainties in load consumptions and renewable energy generations. To create a reliable and resilient microgrid operation, Ding et al. [46] study DRO-based joint chance constraints to mimic extreme weather conditions. Rayati et al. [47] suggest a distributionally robust chance constrained optimization for distribution power systems by considering the uncertain PV generations and customer consumptions.

We summarize several research gaps identified in our literature review.

- Notwithstanding that the operation problems under the water-power nexus have been extensively studied, the water-multi-energy nexus has received relatively less research attention, especially small-scale water-energy systems in urban areas.
- Unlike the well-explored centralized management of the urban utility system, social participations in utility management remain mostly understudied.
- The load of energy and water systems can significantly fluctuate, partly due to unpredictable consumptions by energy users. In addition, substantial uncertainties exist in renewable energy generation because of changing weather conditions. These uncertainties are important to urban energy system management and should be considered properly.

This study seeks to address these gaps. We summarize the significance of our work as follows. First, multi-energy systems constitute a crucial topic in energy system management and has received increasing attention from both researchers and practitioners. In that regard, incorporating multi-energy systems in water-energy nexus can further contribute to increased overall system efficiency than considering the power sector only. Without considering gas and heat sectors in the water-energy nexus modelling, energy coupling, device coordination, and energy conversion are overlooked, which leads to energy losses and sub-optimal results. Second, voluntary participations of energy customers via P2P trading is valuable to public resource allocation, because it allows additional flexibility and provides a new perspective toward urban energy system management. Existing utility systems have limited resources, which can be augmented by and thus benefiting from the social side of the utility-social system perspective. Third, uncertainties in the utility systems lead to uneconomic operations and erroneous decisions. A deterministic approach is not appropriate for the stochastic nature of renewable energy generation and load uncertainties, and its use likely results in less practical, sub-optimal decisions in terms of economic efficiency and resource utilization.

This paper proposes a two-stage DRO model for interconnected integrated water-energy hubs (IWEHs) with the consideration of social-aware P2P trading, as well as the close couplings and extensive conversions in the water-multi-energy that allows the water system and energy systems to operate in a coordinated and complementary manner via converters. Moreover, we incorporate social participations in the form of P2P trading of power, heat and water. The proposed model contains day-ahead and real-time stages to support decision making prior to and immediate after the realization of uncertain renewable energy and load. We use the moment information with a semidefinite programming (SDP) reformulation to construct an ambiguity set, and apply column-and-constraint generation algorithm (C&CG) to solve the SDP problem. We design four case studies and implement them in a 4-IWEH community to evaluate the effectiveness of the **t**wo-**s**tage **i**ntegrated water-energy **h**ub **m**anagement (TS-IHM) problem. TABLE I compares representative previous studies and the proposed TS-IHM that is illustrated in Fig. 1 schematically.

This study makes several important contributions, highlighted as follows.

1) It develops an innovative IWEH model for a water-energy nexus of power, gas, heat, and water, together with the uncertainties in renewable energy and load. This model considers close energy conversions and inter-system complementation, and can enhance the operational efficiency of an integrated urban utility system.

2) A social-aware P2P trading platform is incorporated to exchange excessive local energy and water resources, which can mitigate the daily operation cost of a single IWEH and the entire water-energy system. In addition to the P2P trading, operators of each IWEH can trade with external power, gas, and water markets.

3) A two-stage DRO model is developed to optimize day-ahead and real-time operation schemes. The day-ahead stage determines the preparatory operation scheme and the real-time stage takes recourse actions to adjust the initial decisions for

responses. The results of several case studies show that DRO is more effective than RO and SO for avoiding excessive conservatism and rendering practical without requiring enormous data samples.

The remainder of this paper is organized as follows. Section II elaborate the IWEH structure and its modelling. Section III presents the methodology for solving TS-IHM. Section IV details the case studies conducted to demonstrate the effectiveness and practical values of IWEH. This paper is concluded in Section V with a summary and several promising future research directions.

II. System Modelling

In this section, we provide an overview of IWEH and elaborate the structure and mathematical modelling of IWEH with formally defined constraints and objective functions. Then, we illustrate the problem interpretation.

A. Overview of IWEH

The proposed model investigates the transactive management of IWEH for water-energy nexus. An IWEH is a small-scale utility management system that connect and coordinate electricity, gas, heat, and water. In this study, energy refers to a mix of electricity, gas, and heat. These energy vectors are closely linked and tightly coupled. As a result, P2P trading involves electricity, heat, and water. Fig. 2 illustrates our P2P trading scheme. As shown, stakeholders of TS-IHM include external market operators and IWEH operators. External market operators are responsible for connecting different utility systems (such as power, gas, and water systems) and IWEH operators can perform resource exchanges (e.g., purchasing, selling). The operation and trading incentives of distinct utility systems pertains to a fundamentally different topic which is outside the scope of this study. Multiple IWEHs are connected with one another, with each IWEH operator responsible for operating a distinct system while trading with external market operators and other IWEHs. Each IWEH has generators, converters, and storage systems. Previous research has considered P2P trading for microgrids [40, 43]. Several studies examine multiple interconnected microgrids [44, 45]. Fig. 2 illustrates our P2P trading scheme among IWEHs.

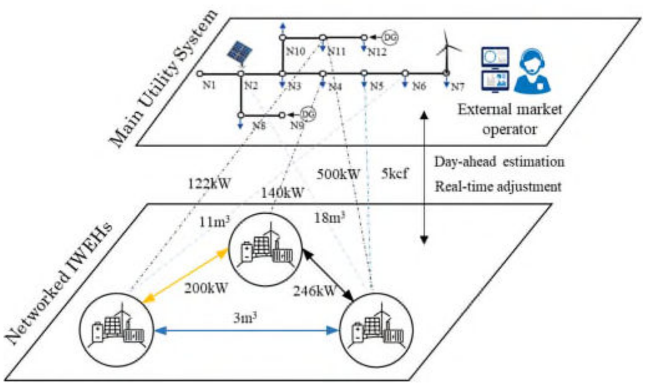


Fig. 2. The proposed P2P trading scheme.

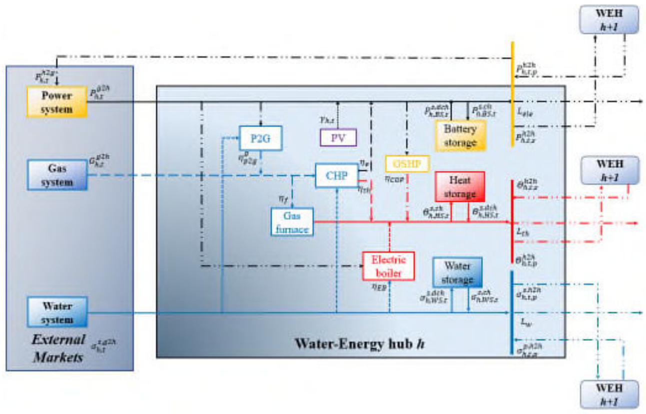


Fig. 3. Structure of the proposed IWEH.

B. Structure of IWEH

In Fig. 3, the IWEH structure is given, which contains the coordination between power, gas, heat and water. The external markets supply power, gas and water to IWEH. The PV generation can be directly consumed by power load or converted to heat. Enormous energy conversions are based on P2G, CHP, gas furnace, GSHP, and electric boiler, which realizes the conversion between power, heat and gas. The energy storage system incorporates battery, heat and water storage for storing surplus multi-energy and water. Each IWEH is allowed to trade power, heat and water with other IWEH and trade power with the power system.

C. Day-ahead Operation of IWEH

The first stage objective aims to minimize the day-ahead operation cost based on the PV and load forecast. Each IWEH operator is encouraged to estimate the next-day load information and trading plans, which simplifies the real-time operational decision making for both upper-level markets and IWEH operators with more accurate operation schemes. This behaviour is rewarded by the upper-level market. In addition, the day-ahead energy and water purchase cost is assumed to be cheaper than the real-time cost for encouragement and stimulation. Equation (1) includes i) the benefit of power selling to the power market, ii) day-ahead estimated power, gas and water purchase from the power market, iii) reward of estimating load and trading plans, iv) trading cost with other IWEHs and v) the operation and maintenance cost of the water-energy storage system.

$$
\begin{aligned}
\Gamma_1 = \min \sum_{h\in H, t\in T} & -\lambda_{h2g}^{P} P_{h,t}^{s,h2g} \\
& + \lambda_{g2h}^{P} P_{h,t}^{s,g2h} + \lambda_{g2h}^{G} G_{h,t}^{s,g2h} + \lambda_{g2h}^{W} \sigma_{h,t}^{s,g2h} \\
& - \lambda_{re}^{P}\left(P_{h,t}^{s,h2g} + P_{h,t}^{s,g2h}\right) - \lambda_{re}^{G} G_{h,t}^{s,g2h} - \lambda_{re}^{W} \sigma_{h,t}^{s,g2h} \\
& + \lambda_{h2h}^{P}\left(P_{h,t,p}^{s,h2h} - P_{h,t,s}^{s,h2h}\right) \\
& + \lambda_{h2h}^{H}\left(\Theta_{h,t,p}^{s,h2h} - \Theta_{h,t,s}^{s,h2h}\right) + \lambda_{h2h}^{W}\left(\sigma_{h,t,p}^{s,h2h} - \sigma_{h,t,s}^{s,h2h}\right) \\
& + \lambda_{h}^{BS}\left(P_{h,BS,t}^{s,ch} + P_{h,BS,t}^{s,dch}\right) \\
& + \lambda_{h}^{HS}\left(P_{h,HS,t}^{s,ch} + P_{h,HS,t}^{s,dch}\right) + \lambda_{h}^{WS}\left(\sigma_{h,WS,t}^{s,ch} + \sigma_{h,WS,t}^{s,dch}\right) \qquad (1)
\end{aligned}
$$

The first-stage constraints of TS-IHM are specified in (2)–(29). Equation (2) regulates the GSHP conversion. Constraints (3)–(4) indicate P2G modelling with the associated water consumptions. The gas-to-heat conversion for a gas furnace is restricted by (5). Constraints (6)–(7) confine the input and output of an electric boiler as well as its water consumptions. In

(8)–(9), we model the gas-power and gas-heat conversions of CHP, followed by the CHP water consumption modeling in (10). Constraint (11) specifies the limit of conversion input of GSHP, P2G, CHP, gas furnace, and electric boiler, and constraints (12)–(13) confine the charging and discharging power of battery and heat storage. The remaining energy is indicated by (14)–(17). Similarly, water storage modelling are detailed in (18)–(20), and constraints (21)–(25) regulate the trading amount of power, gas, heat and water, respectively. Finally, the balancing constraints of power, gas, heat and water are presented in (26)–(29).

$$\Theta_{h,COP,t}^{s,o} = \eta_{COP} P_{h,COP,t}^{s,i} \tag{2}$$

$$G_{h,p2g,t}^{s,o} = \eta_{p2g}^{g} \frac{P_{h,p2g,t}^{s,i}}{\Omega_{hy}} \tag{3}$$

$$\sigma_{h,p2g,t}^{s,i} = \eta_{p2g}^{w} P_{h,p2g,t}^{s,i} \tag{4}$$

$$P_{h,GF,t}^{s,o} = \eta_{GF} G_{h,GF,t}^{s,i} \tag{5}$$

$$\Theta_{h,EB,t}^{s,o} = \eta_{EB}^{h} P_{h,EB,t}^{s,i} \tag{6}$$

$$\sigma_{h,EB,t}^{s,i} = \eta_{EB}^{w} P_{h,EB,t}^{s,i} \tag{7}$$

$$P_{h,cp,t}^{s,o} = \eta_{cp}^{e} G_{h,cp,t}^{s,i} \tag{8}$$

$$\Theta_{h,cp,t}^{s,o} = \eta_{cp}^{h} G_{h,cp,t}^{s,i} \tag{9}$$

$$\sigma_{h,cp,t}^{s,i} = \eta_{cp}^{w} G_{h,cp,t}^{s,i} \tag{10}$$

$$P_{\{\cdot\},min}^{i} \le P_{h,\{\cdot\},t}^{s,i} \le P_{\{\cdot\},max}^{i}, \quad \{\cdot\} = COP, p2g, GF, EB, cp \tag{11}$$

$$\{\cdot\}_{BS/HS,min}^{s,ch} \le \{\cdot\}_{h,BS/HS,t}^{s,ch} \le \{\cdot\}_{h,BS/HS,max}^{s,ch} \tag{12}$$

$$\{\cdot\}_{BS/HS,min}^{s,dch} \le \{\cdot\}_{h,BS/HS,t}^{s,dch} \le \{\cdot\}_{h,BS/HS,max}^{s,dch} \tag{13}$$

$$E_{h,BS,t}^{s} = E_{h,BS,t-1}^{s} + \sum_{1}^{t} P_{h,BS,t}^{s,ch} \eta_{BS}^{ch} - P_{h,BS,t}^{s,dch} / \eta_{BS}^{dch} \tag{14}$$

$$E_{BS,min} \le E_{h,BS,t}^{s} \le E_{BS,max} \tag{15}$$

$$E_{h,HS,t}^{s} = E_{h,HS,t-1}^{s} + \sum_{1}^{t} \Theta_{h,HS,t}^{s,ch} \eta_{HS}^{ch} - \Theta_{h,HS,t}^{s,dch} / \eta_{HS}^{dch} \tag{16}$$

$$E_{BS/HS,min} \le E_{h,BS/HS,t}^{s} \le E_{BS/HS,max} \tag{17}$$

$$\sigma_{WS,min}^{s,ch/dch} \le \sigma_{h,WS,t}^{s,ch/dch} \le \sigma_{WS,max}^{s,ch/dch} \tag{18}$$

$$V_{h,WS,t}^{s} = V_{h,WS,t-1}^{s} + \sum_{1}^{t} \sigma_{h,WS,t}^{s,ch} - \sigma_{h,WS,t}^{s,dch} \tag{19}$$

$$V_{WS,min} \le V_{h,WS,t}^{s} \le V_{WS,max} \tag{20}$$

$$P_{h,min}^{h2g/g2h} \le P_{h,t}^{s,h2g/g2h} \le P_{h,max}^{h2g/g2h} \tag{21}$$

$$G_{h,min}^{g2h} \le G_{h,t}^{s,g2h} \le G_{h,max}^{g2h} \tag{22}$$

$$P_{h,p/s,min}^{h2h} \le P_{h,t,p/s}^{s,h2h} \le P_{h,p/s,max}^{h2h} \tag{23}$$

$$\Theta_{h,p/s,min}^{h2h} \le \Theta_{h,t,p/s}^{s,h2h} \le \Theta_{h,p/s,max}^{h2h} \tag{24}$$

$$\sigma_{h,p/s,min}^{h2h} \le \sigma_{h,t,p/s}^{s,h2h} \le \sigma_{h,p/s,max}^{h2h} \tag{25}$$

$$\begin{aligned} P_{h,t}^{s,g2h} + \sum_{h\in H} P_{h,t,p}^{s,h2h} + P_{h,cp,t}^{s,o} + P_{h,BS,t}^{s,dch} + \gamma_{h,t} = \\ P_{h,COP,t}^{s,o} + \sum_{h\in H} P_{h,t,s}^{s,h2h} + P_{h,BS,t}^{s,ch} \\ + P_{h,t}^{s,h2g} + P_{h,p2g,t}^{s,i} + P_{h,EB,t}^{s,i} + L_{h,ele} \end{aligned} \tag{26}$$

$$G_{h,t}^{s,g2h} + G_{h,p2g,t}^{s,o} = G_{h,GF,t}^{s,i} + G_{h,cp,t}^{s,i} \tag{27}$$

$$\begin{aligned} \sum_{h\in H} \Theta_{h,t,p}^{s,h2h} + \Theta_{h,cp,t}^{s,o} + \Theta_{h,COP,t}^{s,o} + \Theta_{h,HS,t}^{s,dch} + \Theta_{h,EB,t}^{s,o} = \\ \sum_{h\in H} \Theta_{h,t,s}^{s,h2h} + \Theta_{h,HS,t}^{s,ch} + L_{h,th} \end{aligned} \tag{28}$$

$$\begin{aligned} \sigma_{h,t}^{s,g2h} + \sum_{h\in H} \sigma_{h,t,p}^{s,h2h} + \sigma_{h,WS,t}^{s,dch} \\ = \sum_{h\in H} \sigma_{h,t,s}^{s,h2h} + \sigma_{h,WS,t}^{s,ch} + L_{h,w} \\ + \sigma_{h,p2g,t}^{s,i} + \sigma_{h,cp,t}^{s,i} + \sigma_{h,EB,t}^{s,i} \end{aligned} \tag{29}$$

D. Real-time Operation of IWEH

The real-time objective function of IWEH operation is given in (30) including the penalty cost caused by estimation errors of trading plans of power, gas, heat and water with external markets and other interconnected IWEH in the community.

$$\begin{aligned} \Gamma_2 = \min \sum_{h\in H, t\in T} \vartheta_{h2g}^{P} \left| P_{h,t}^{s,h2g} - P_{h,t}^{r,h2g} \right| \\ + \vartheta_{g2h}^{P} \left| P_{h,t}^{s,g2h} - P_{h,t}^{r,g2h} \right| \\ + \vartheta_{g2h}^{G} \left| G_{h,t}^{s,g2h} - G_{h,t}^{r,g2h} \right| + \vartheta_{g2h}^{W} \left| \sigma_{h,t}^{s,g2h} - \sigma_{h,t}^{r,g2h} \right| \\ + \vartheta_{h2h}^{P} \left| P_{h,t,p}^{s,h2h} - P_{h,t,p}^{r,h2h} \right| \\ \vartheta_{h2h}^{P} \left| P_{h,t,s}^{s,h2h} - P_{h,t,s}^{r,h2h} \right| + \vartheta_{h2h}^{H} \left| \Theta_{h,t,p}^{s,h2h} - \Theta_{h,t,p}^{r,h2h} \right| \\ + \vartheta_{h2h}^{H} \left| \Theta_{h,t,s}^{s,h2h} - \Theta_{h,t,s}^{r,h2h} \right| + \\ \vartheta_{h2h}^{W} \left| \sigma_{h,t,p}^{s,h2h} - \sigma_{h,t,p}^{r,h2h} \right| + \\ \vartheta_{h2h}^{W} \left| \sigma_{h,t,p}^{s,h2h} - \sigma_{h,t,p}^{r,h2h} \right| \end{aligned} \tag{30}$$

After the day-ahead decision making, the endogenous renewable and load uncertainties are revealed. Accordingly, adaptive recourse actions are required for making adjustment of conversions, operation and trading strategies. The majority of the second-stage constraints are the same as the first-stage constraints except (31)-(34), representing new balancing conditions for power, gas, heat and water with the realization of uncertainties. It is to be noted that the superscript ‘s’ is represented by ‘r’ denoted as ‘scheduled’ and ‘regulated’.

$$\begin{aligned} P_{h,t}^{r,g2h} + \sum_{h\in H} P_{h,t,p}^{r,h2h} + P_{h,cp,t}^{r,o} + P_{h,BS,t}^{r,dch} + \xi_{h,t} = \\ P_{h,COP,t}^{r,o} + \sum_{h\in H} P_{h,t,s}^{r,h2h} + P_{h,BS,t}^{r,ch} + P_{h,t}^{r,h2g} + \zeta_{h,ele} \end{aligned} \tag{31}$$

$$G_{h,t}^{r,g2h} = G_{h,GF,t}^{r,i} + G_{h,cp,t}^{r,i} \tag{32}$$

$$\begin{aligned} \sum_{h\in H} \Theta_{h,t,p}^{r,h2h} + \Theta_{h,cp,t}^{r,o} + \Theta_{h,COP,t}^{r,o} + \Theta_{h,HS,t}^{r,dch} = \\ \sum_{h\in H} \Theta_{h,t,s}^{r,h2h} + \Theta_{h,HS,t}^{r,ch} + \zeta_{h,th} \end{aligned} \tag{33}$$

$$\begin{aligned} \sigma_{h,t}^{r,g2h} + \sum_{h\in H} \sigma_{h,t,p}^{r,h2h} + \sigma_{h,WS,t}^{r,dch} \\ = \sum_{h\in H} \sigma_{h,t,s}^{r,h2h} + \sigma_{h,WS,t}^{r,ch} + \zeta_{h,w} \\ + \sigma_{h,p2g,t}^{r,i} + \sigma_{h,cp,t}^{r,i} + \sigma_{h,EB,t}^{r,i} \end{aligned} \tag{34}$$

E. Interpretation of the TS-IHM

Equations (1)–(34) provide details of the mathematical formulation of TS-IHM. We can conceptualize the formulation as an optimization problem, with (1) and (30) as the objective functions and the rest of the formulation as constraints. The optimization objective is to minimize the total operation cost of IWEHs and the constraints are used to model and regulate the transactive management of IWEHs. We operationalize the problem using codes in a MATLAB environment. For example, we demonstrate partial mathematical formulation in Fig. 4, which represents the modelling of equations (12)–(15) and (17) explicitly.

```
%% Battery modelling
Ev(1,:)=100; % initial state of battery

for k = 1:nHours
    for j=1:4
  Constraints = [Constraints, uv_ch(k,j)+uv_dch(k,j)<=1]; % Avoid simultaneous charging and discharging
  Constraints = [Constraints, uv_ch(k,j).*0.0001 <= Pv_ch(k,j) <= uv_ch(k,j).*50]; % Charging limits
  Constraints = [Constraints, uv_dch(k,j).*0.0001 <= Pv_dch(k,j) <= uv_dch(k,j).*50]; % Discharging limits
  Constraints = [Constraints,40<=Ev(k,j)<=180]; % Total capacity limits
    end
end

for k = 2:nHours
     for j=1:4
    Ev(k,j)=Ev(k-1,j)+Pv_ch(k,j)-Pv_dch(k,j); % Formulate the remaining capacity
     Constraints = [Constraints,40<=Ev(k,j)<=180];   % Full capacity is 200kWh
     end
end
```

Fig. 4. Battery modelling as an exemplar problem interpretation.

III. Methodology

A. Distributionally Robust Optimization

To solve the utility management problem, the certainty of future states and uncertainty estimates for stochastic approaches are not always guaranteed, due to the data availability constraint. In general, DRO mitigate the over-fitting issue common to SO by considering a set of distributions rather than a deterministic one. It can be viewed as a data-driven stochastic robust optimization model. The ambiguity set incorporates a classification of candidate distributions. The worst case is then selected to solve the optimization problem. Pragmatically, DRO is robust and can use limited historical data to generate reliable distribution estimates. We describe the proposed method for solving TS-IHM in this section by detailing the compact form of the original problem, construction of the ambiguity set, dual reformulations, and C&CG algorithm. We conduct dual reformulations twice to eliminate the *min-max* structure as well as exploring the finite dimension of variables.

B. Abstract Formulation and Ambiguity Set

For the concise and clear presentation of the proposed method, the abstract formulation of the objective functions and constraints is shown in (35)-(38). Equations (35) and (37) represent the overall and second-stage objective functions and equations (36) and (38) represent the constraints of the first and second stages.

$$\min_{x\in X} c'x + \sup_{Pf\in D} E_P[Q(x,\xi)] \tag{35}$$

$$\text{s.t. } Ax \le b, \tag{36}$$

$$Q(x,\xi) = \min_{y} f'y \tag{37}$$

$$\text{s.t. } Ex + Fy + G\xi \le h, \tag{38}$$

Similar to the uncertainty set of RO, the ambiguity set of DRO enables to capture the uncertainties with predetermined bounds. In addition, distributional information is incorporated and thus a set of possible uncertainty distributions is considered, which mitigates the robustness. Moment information is adopted in this paper for constructing the ambiguity set. In (39), the mean vector and covariance matrix are employed.

C&CG algorithm

STEP 1: Initialize set of vertices, denoted as VS, and set tolerance ε.

STEP 2: Solve the master problem in (53). Record the optimal value O^* and solution x^*.

$$\min_{x,\Psi,\psi,\psi_0} c'x + \langle \Psi'\Theta \rangle + \psi'\mu + \psi_0$$

$$\begin{bmatrix}\xi\\1\end{bmatrix}' \begin{bmatrix}\Psi & \frac{1}{2}(\psi + G'\tau^i)\\ \frac{1}{2}(\psi + G'\tau^i)' & \psi_0 - (h-Ex)'\tau^i\end{bmatrix} \begin{bmatrix}\xi\\1\end{bmatrix} \ge 0$$

$$\forall\xi \in \Xi, i=1,2,\dots,N_v, x\in X, \forall\tau^i \in VS$$

STEP 3: Solve the subproblem in (54). Record the optimal objective value o^* and optimal solution τ^*.

$$(\xi_s)'\Psi\xi_s + \psi'\xi_s + \psi_0 - (h - Ex - G\xi_s)'\tau \ge 0$$

STEP 4: Stop the algorithm when $o^* \ge 0$. And thus obtain O^* and x^*. When $o^* < 0$, $VS = VS \cup \tau^*$ and then return to STEP 2.

STEP 5: Solve the second stage problem after ξ is revealed

$$Q(x,\xi) = \min_{y} f'y$$

Fig. 5. Flowchart of C&CG.

$$D = \left\{ f(\xi) \,\middle|\, \begin{array}{c} \mathrm{P}\{\xi\} = 1 \\ \mathrm{E}\{\xi\} = \mu \\ \mathrm{E}\{\xi(\xi)'\} = \Sigma + \mu(\mu)' \end{array} \right\} \tag{39}$$

C. Second-stage Dual Formulation

The '*sup min*' framework in the second stage requires to be changed to '*min*' and thus the two sub-objectives can be mutually merged with dual formulations. The explicit form of $\sup_{Pf\in D} E_P[Q(x,\xi)]$ is shown as (40)-(44). The probability density function is denoted as $Pf(\xi)$.

$$S(x)^{primal} = \max_{Pf\in D_\xi} \int_{\Xi} Q(x,\xi)\, Pf(\xi) d\xi \tag{40}$$

$$\text{s.t. } Pf(\xi) \ge 0, \forall\xi \in \Xi \tag{41}$$

$$\int_{\Xi} Pf(\xi) d\xi = 1 \tag{42}$$

$$\int_{\Xi} \xi^m Pf(\xi) d\xi = \mu_m,\ m=1,2,\dots,\Xi \tag{43}$$

$$\int_{\Xi} \xi^m \xi^n Pf(\xi) d\xi = \Sigma_{mn} + \mu_m\mu_n,\ m, n=1,2,\dots,\Xi \tag{44}$$

There is an infinite number of variables owing to the decision variable of (40)-(44) is $Pf(\xi)$ since the constructed ambiguity set enables to characterize all the possible distributions which share the same moment information. Based on the strong duality theory [48], the dual reformulation is required to transform the primal form to a tractable dual form in (45) and (46). Thus, the infinite-dimensional primal form can be replaced by the finite-dimensional dual form. The new dualized objective function ψ_0, ψ_j and Ψ_{jk}. with dual variables is to be minimized.

Lemma: When the covariance matrix is strictly positive and considering the strong duality theory, the results of (45) are equal to results of (40) [49].

Therefore, the infinite number of variables are transformed into a finite number when the primal form is transformed into the dual form. The new compact form of TS-IHM is presented in (47). It is to be noted that $\Theta = \Sigma + \mu(\mu)'$

$$S(x)^{dual} = \min_{\Psi,\psi,\psi_0} \langle \Psi'\Theta \rangle + \psi'\mu + \psi_0 \tag{45}$$

$$\text{s.t. } (\xi)'\Psi\xi + \psi'\xi + \psi_0 \geq Q(x,\xi), \forall \xi \in \Xi \tag{46}$$

$$\min_{x \in X} c'x + S(x)^{dual} \tag{47}$$

D. Semidefinite Programming and Solution

Equation (47) is still not in closed form as it has an infinite number of constraints. A closed form of (47) is required to obtain the computational tractability [50]. Equations (48) and (49) are the new dual reformulation with new dual variable τ. The polyhedral uncertainty set VS is used to accommodate extreme points. The original $Q(x,\xi)$ in (37) is replaced by the positive quadratic function in (50). The optimal solution of $Q(x,\xi)$ is determined among extreme points in VS, where N_v represents the set of vertex existing in the feasible region of VS. When (46) is substituted by (50), equations (51) and (52) can be thus obtained. Equation (53) is the compact matrix form of (52).

$$\max_{u \in VS} \tau'(h - Ex - G\xi) \tag{48}$$

$$VS = \{\tau | F'\tau = f, \tau \leq 0\} \tag{49}$$

$$\exists \tau \in VS: Q(x,\xi) = (h - Ex - G\xi)'\tau \tag{50}$$

$$(\xi)'\Psi\xi + \psi'\xi + \psi_0 \geq (h - Ex - G\xi)'\tau \quad \forall \xi \in \Xi, i = 1,2,\ldots,N_v \tag{51}$$

$$(\xi)'\Psi\xi + (\psi + G'\tau^i)'\xi + \psi_0 - (h - Ex)\tau^i \geq 0 \quad \forall \xi \in \Xi, i = 1,2,\ldots,N_v \tag{52}$$

$$\min_{x,\Psi,\psi,\psi_0} c'x + \langle \Psi'\Theta \rangle + \psi'\mu + \psi_0$$
$$\begin{bmatrix} \xi \\ 1 \end{bmatrix}' \begin{bmatrix} \Psi & \frac{1}{2}(\psi + G'\tau^i) \\ \frac{1}{2}(\psi + G'\tau^i)' & \psi_0 - (h - Ex)'\tau^i \end{bmatrix} \begin{bmatrix} \xi \\ 1 \end{bmatrix} \geq 0 \tag{53}$$
$$\forall \xi \in \Xi, i = 1,2,\ldots,N_v, x \in X, \forall \tau^i \in VS$$

The vast number of constraints with the large cardinality of VS leads to a high computational burden even though the SDP (53) is tractable. Accordingly, the proposed C&CG can be utilized to solve large-scale linear problems [51]. The principle of C&CG is to relax part of the constraints and incorporate more vertices at each step. The detailed process of C&CG is shown in Fig. 5. Equation (54) is the subproblem of the final TS-IHM problems.

$$(\xi_s)'\Psi\xi_s + \psi'\xi_s + \psi_0 - (h - Ex - G\xi_s)'\tau \geq 0 \tag{54}$$

IV. CASE STUDIES

We examine the effectiveness of the proposed TS-IHM by conducting four case studies based on a water-energy system that contains four interconnected IWEHs. Each IWEH can trade energy and water with other IWEHs or external markets. TABLEs II and III present the converter efficiency and trading limits, respectively. Fig. 6 depicts the average load profile of power, heat and water across the different IWEHs. The cases included in the evaluation are as follows.

Case 1: Baseline case.

Case 2: Doubling the PV capacity of the baseline case.

Case 3: Doubling the power trading unit cost of the baseline case.

Case 4: Doubling each trading unit cost of the baseline base.

TABLE II
CONVERSION EFFICIENCY

Converters	CHP (η_e)	CHP (η_{th})	GSHP	Gas furnace	P2G	Electric boiler
Efficiency	33%	57%	300%	70%	80%	99%

TABLE III
TRADING PARAMETERS

Limit	P^{h2g}_{max}	P^{g2h}_{max}	G^{g2h}_{max}	σ^{g2h}_{max}	P^{h2h}_{max}	Θ^{h2h}_{max}	$\sigma^{h2h}_{p,max}$
Max	600kWh	400kWh	500kWh	5m^3	500kWh	200kWh	5m^3

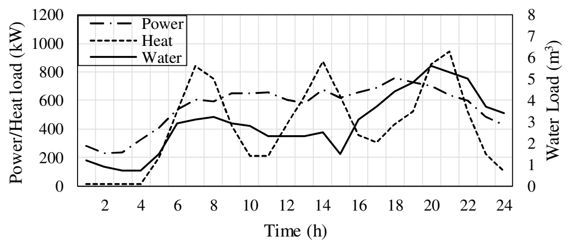


FIG. 6. AVERAGE POWER, HEAT AND WATER

TABLE IV
ECONOMIC PERFORMANCE FOR ALL CASES

Economic result ($)	Case 1	Case 2	Case 3	Case 4
First-stage cost	3911	2893	6364	7823
Expected second-stage cost	814	856	732	827
Total cost	4725	3749	7096	8650

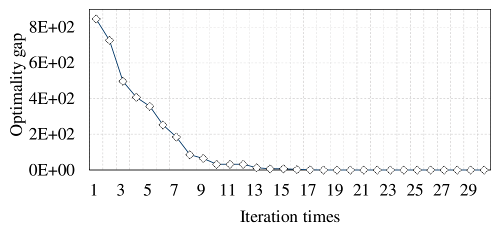


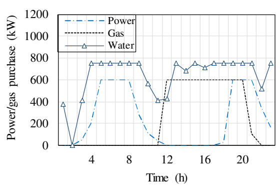
Fig. 7. Convergence performance of the C&CG.

A. Economic Performance and Trading Analysis

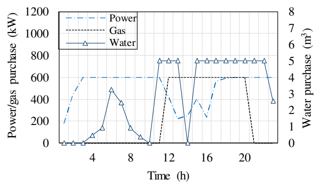
TABLE IV summarizes the economic efficiency in each investigated case, including the first-stage operation cost, second-stage expected operation cost, and the total cost. As a baseline case, Case 1 has a day-ahead operation cost of $3,911 and a real-time operation cost of $814. Case 2 features twice the PV capacity and has a total operation cost of $3,749, equivalent to 79.3% of Case 1's total cost. The real-time stage of Case 2 has a cost higher than that of Case 1, because a greater PV capacity increases both operational flexibility and generation fluctuation risks. The resulting (greater) PV output variability leads to a larger range of decision difference between the two stages, with a higher penalty cost. In Case 3, the total operation cost is $7,096, approximately 50% higher than that of Case 1 but the expected real-time operation cost is lower than that of Case 1, due to its reduced reliance on power supply as a higher power trading unit cost and greater PV fluctuations can be mitigated by the storage system. Case 4 has the highest operation cost, because it features twice of the unit trading cost of power, heat and water than the baseline case. The total operation cost is \$8,650, which is 83% higher than that of Case 1. Fig. 7 shows the convergence result of the proposed C&CG solution algorithm. Equation (54) is a biconvex problem, so we need to solve it using an alternative direction oracle to solve convex quadratic and linear programming independently. As shown, the optimality gap is 8.5E+02 at the first iteration, and the algorithm is mostly converged with optimality gap=3.68E-07 at the 20th iteration.

TABLE V
P2P TRADING AMOUNT

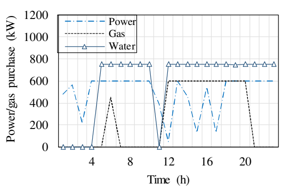
Trading amount	Case 1	Case 2	Case 3	Case 4
Power (kWh)	16536	16084	14312	16557
Heat (kWh)	11253	11162	10767	11227
Water (m^3)	307	313	315	316



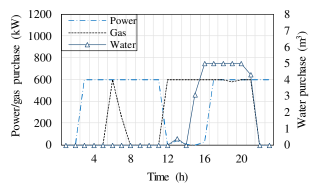
(a). IWEH 1.



(b). IWEH 2.



(c). IWEH 3.



(d). IWEH 4.

Fig. 8. Power, gas and water trading with external markets.

TABLE V presents the P2P trading amount of power, heat and water. In Case 1, the trading amount of power, heat and water reaches 16536kWh, 11253kWh and 307 m^3, respectively. Case 2 has a PV capacity twice of that of Case 1, and exhibits lower power and heat trading, but higher in water trading than Case 1. This can be attributed to the abundant power supply by the additional PV output yielding greater energy conversions and consequently P2G and electric boiler consume more water resources. Comparatively, when the power unit trading cost is doubled, power trading is decreased by 2224kWh. The heat trading amount is influenced too, which is reduced by 486kWh in comparison with Case 1. Additionally, the doubled power trading cost leads to a higher demand for gas supply. With the P2P trading cost of all the vectors considered, Case 4 has a trading amount similar to that of the baseline case.

Fig. 8 illustrates the trading scheduling with external markers for IWEHs 1-4 in Case 1. For IWEH 1, power purchases mainly happen 5:00 – 8:00 and 18:00 – 21:00. During the midday periods, PV generator supports power load partially. Gas purchases are scheduled 12:00 – 21:00 at 600kWh. In contrast, water purchases from the water market spreads across the entire time period, showing an average of 4.06 m^3. The load profiles

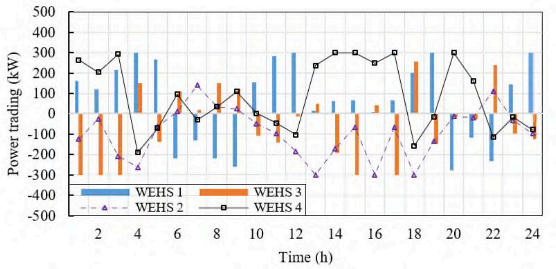


Fig. 9. Power trading with other IWEHs.

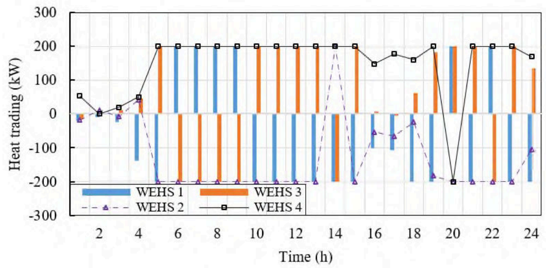


Fig. 10. Heat trading with other IWEHs.

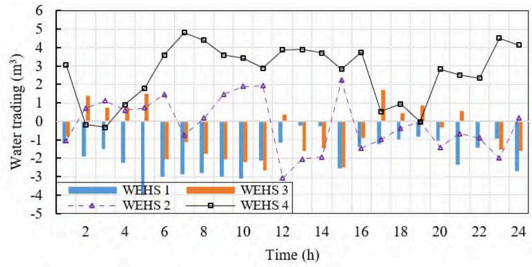
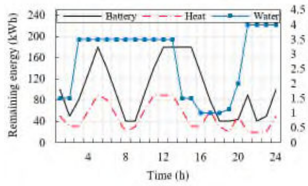
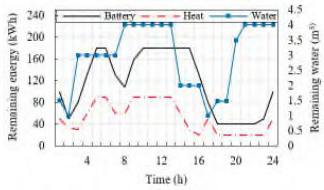


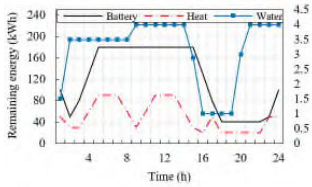
Fig. 11. Water trading with other IWEHs.



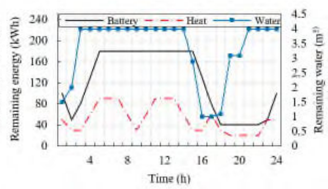
(a). Case 1.



(b). Case 2.



(c). Case 3.



(d). Case 4.

Fig. 12. Remaining capacity of battery and heat storage.

of IWEHs 2-4 are higher than that of IWEH 1; specifically, the load profile of IWEH 4 is the highest among all the IWEHs. Yet heat and water purchases from external markets are the lowest as the majority supply comes from P2P trading with other IWEHs.

Figs. 9–11 present P2P trading of power, heat and water in Case 1. As Fig. 9 shows, IWEH 4 mainly purchases power whilst IWEHs 1-3 are scheduled to sell power for profits. Due to the lower P2P trading cost, power P2P trading appears more frequently than power trading with external power markets, see

Fig. 8. The trading peaks (300kW) in many time periods. Heat P2P trading has a more active exchange schedule than does power P2P trading. The trading peaks (200kWh) during 5:00 – 15:00 and 19:00 – 23:00, because there are no heat purchases from external markets and thus IWEHs rely on energy conversions to heat vector or P2P heat purchases for the increased heat consumptions. However, power-heat and gas-heat conversions inevitably cause energy losses due to conversion efficiency. As Fig. 10 shows, IWEHs 3 and 4, which feature higher heat loads, are scheduled to purchase heat from IWEHs 1 and 2 in most of the time periods. According to Fig. 11, water P2P trading exhibits an exchange trend completely different from that of power or heat trading scheduling curve; that is, IWEH 4 purchases water whilst IWEHs 1-3 supplies water. The energy conversion in IWEH 4 is more frequent than that of IWEHs 1-3. The water purchases by IWEH 4 remains at a high level over the entire time horizon with the exceptions of 2:00 – 4:00 and 17:00 – 19:00. The water load is low between 2:00 and 4:00, which does not have sufficient water supply. During 17:00 – 19:00, water storage is extensively utilized to discharge the pre-stored water.

B. *Scheduling Results of Storage and Converters*

Fig. 12 shows each case's remaining storage capacity of battery, heat and water for IWEH 1. In Case 1, the battery storage is charging during low-tariff periods before 6:00, followed by a discharging period until 10:00. Another charging and discharging cycle takes place between 6:00 and 19:00. In general, heat storages occur with more frequently with charging and discharging cycles. The utilization of water storage is the least, compared with power and heat storages. In addition to 15:00 – 19:00, we observe other time periods in which the water storage capacity remains at a high level; i.e., greater than 3.5 m^3. Case 2 has a PV capacity twice that of baseline case and its battery storage scheduling exhibits secluding results similar to those of Case 1. Yet the water storage is used more extensively, because P2G and electric boiler are scheduled for more conversions from power. Cases 3 and 4 show much less battery usage than Cases 1 and 2. In both scenarios, power P2P trading cost is doubled, so direct power consumptions or conversions decrease.

TABLE VI depicts converter water consumptions. As shown, CHP consumes most of the water in each case. As shown, CHP consumes 51.25% of the total water in Case 1 and P2G consumes 5.52 m^3, which accounts for 8% of the total water usage. Case 3 exhibits different water consumptions, compared with other cases. Its total water consumption reaches 74.68 m^3 and the consumption by CHP accounts for 66.44% of the total water usage. This result indicates that gas purchases from external gas markets decrease with the power trading cost more prominently than other cases. For Cases 1 and 2, the converter scheduling curve over a 24-hour window is shown in Figs. 13 and 14, respectively. Overall, GSHP has the highest utilization, due to the high conversion efficiency, and CHP is scheduled with both heat and power output after 9:00. Electric boiler has the maximum conversion output: 500kW at 7:00. With the PV capacity doubled, Case 2 shows higher P2G usage and less CHP usage, see Fig. 14.

TABLE VI
WATER CONSUMPTION BY CONVERTERS

Water (m^3)	Case 1	Case 2	Case 3	Case 4
CHP	35.14	35.10	49.62	35.21
P2G	5.52	5.52	5.06	5.53
Electric boiler	27.90	27.83	20.00	27.84
Total	68.56	68.45	74.68	68.58

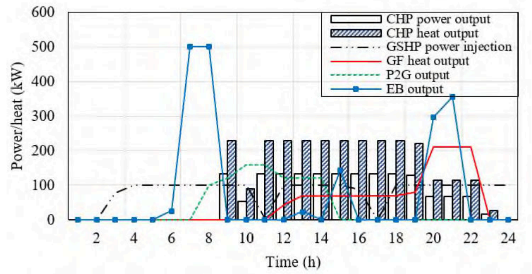


Fig. 13. Converter scheduling result of case 1.

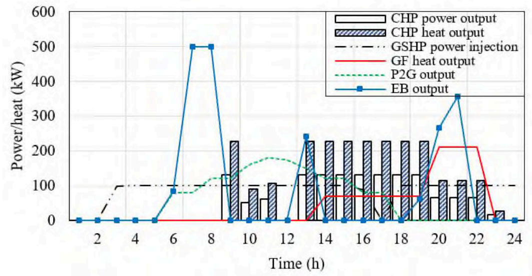


Fig. 14. Converter scheduling result of case 2.

V. CONCLUSION

This study develops an innovative IWEH operation scheme that considers P2P resource trading by voluntary participations for increased operation efficiency of an integrated urban utility system that is underpinned by the water-energy-social nexus. The effective coordination and complementation via energy converters facilitate an economically efficient and reliable IWEH operation scheme. A social-aware P2P trading mechanism is designed for all the interconnected IWEHs, which supports their exchanges of power, heat and water for surplus energy and water. To address the uncertainties in renewable energy generation and load, we develop a moment-based ambiguity set of DRO to characterize PVs and load uncertainties, using a tractable SDP reformulation. Moreover, the proposed two-stage trading model benefits both IWEH operators and external market players by offering greater flexibility in a preparatory plan at the day-ahead stage. The second stage allows system operators and market players to make corrective operations by adjusting exchanges and converter scheduling. We design distinct case studies to mimic common urban utility environments and conduct simulations to evaluate the effectiveness of our proposed TS-IHM. The results suggest that IWEH operators, supported by the proposed model, can achieve greater economic efficiency and reliability for the entire integrated urban utility system through enhanced water-energy-social nexus. Particularly, we explore a new energy management paradigm that involves P2P-based social participations to further increase resource utilization efficiency. The main achievements of this paper include:

i) We innovatively examine the water-energy nexus for small-scale water-energy systems at a residential level.

ii) Our social-aware P2P trading framework contributes to maximal resource utilization in a decentralized manner.

iii) The proposed two-stage DRO approach is capable of addressing the over-fitting issue common to SO.

This study can inform the related research by offering a valuable insight into joint management of IWEHs and considering the maximal social welfare through P2P trading, instead of managing the operations of water and energy hubs separately. Practice-wise, this study indicate that smart utility systems can be designed and managed for residential areas to satisfy energy and water demands more effectively.

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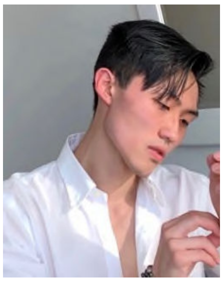

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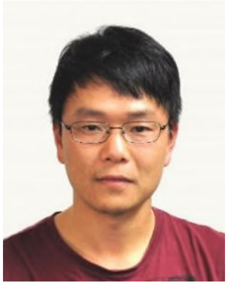

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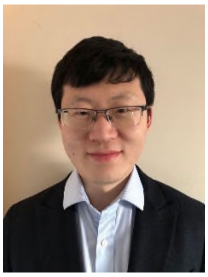

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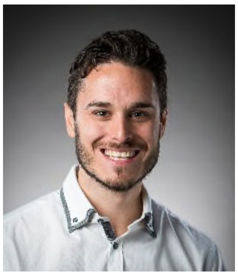

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