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Research Paper

Cooperative stochastic energy management of networked energy hubs considering environmental perspectives

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ABSTRACT

Energy hubs (EHs) aim to increase the flexibility of energy systems by adopting different energy carriers and sources. This paper presents a cooperative stochastic framework for managing networked EHs (NEHs) from an economic-environmental perspective. Scenario preparation techniques, such as Monte Carlo simulation (MCS) and the k-means clustering algorithm, are used to develop scenarios for different sources of uncertainty. Furthermore, the Shapley value is used to allocate coalition gains among NEHs based on their contributions and performance. To distinguish the proposed model from existing literature, several case studies have been conducted to assess its effectiveness. Conducted simulations show that through cooperation, the total cost of EHs and CO2 emissions is reduced by approximately 3 % and 1.8 %, respectively. Moreover, the performed sensitivity analyses indicate the robustness and reliability of the model against input parameters.

1. Introduction

Energy consumption is rapidly increasing worldwide; providing new resources for consumers and efficiently using traditional sources motivate researchers to develop effective management tools for energy systems and grids in light of this trend (Masrur Ahmed et al., 2023). Over the past decades, considerable amount of research has been conducted regarding the cooperation of different energy providers, especially with regard to different energy supplies including gas, electricity, and renewable energy resources (RERs). The management of the simultaneous energy flow in multi-carrier energy systems formed the main focus of this research (Abbà et al., 2024). By co-optimizing gas and electricity flow, the reliability and efficiency of energy systems could be improved as the flexibility of providing demand will be increased in both normal and abnormal conditions (Lasemi et al., 2023). In multi-carrier energy systems, the energy hubs (EHs) is one of the frameworks used for integrated energy management (Zhang and Pirouzi, 2024). By utilizing multiple energy sources along with energy conversion facilities, EHs can supply various types of loads namely electrical and thermal loads. Today, EHs have been studied widely, and models have been developed for residential, commercial, and industrial systems, deploying Energy Storage Systems (ESSs) and RERs (Kluczek and Buczacki, 2023). These models are directly applicable to Energy Management Systems (EMS) (Nebey, 2024). In addition to monitoring and controlling energy use, EMS provide strategies for reducing cost and environmental impact while reducing energy consumption (Hafeez et al., 2020a).

The concept of networked EHs (NEH) is established through interconnecting several EHs, while many benefits can be derived (Akbari et al., 2021). Through interconnection schemes in NEH, the flexibility of EHs remarkably increases through the availability of multiple sources (Akbari et al., 2024). Further, NEH can leverage the strengths of each member to balance the weaknesses of others, which helps the system manage energy more efficiently. By deploying local energy sources more effectively, NEH enhances the system's reliability (Buonomano et al., 2023). Because of this, NEH enhances the performance of each EH as well as the system as a whole (Zadehbagheri et al., 2023).

Inexhaustible and clean energy is produced by RERs (Buonomano et al., 2022). Furthermore, these energy resources can be applied to eliminate rising concerns over the high cost of fossil fuel energy (Chang et al., 2020). Since the output power of RER has a stochastic nature, modeling associated uncertainty is vital to energy system analysis both

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Nomenclature

Indices

t Time index ($t \epsilon T$)
i,j Bus index ($j=i$, $i \epsilon I$)
l Scenario index within the k-means algorithm ($l=1:m$)
r Index for photovoltaic (PV) power output scenarios ($r \epsilon R$)
w Index of electricity price scenario ($w \epsilon W$)
v Cluster index within the clustering algorithm ($v=1:k$)

Parameters

λ Price
ρ_w and ρ_r Probabilities of scenario of the electricity price and PV generation
λ_t^{elec} and λ_t^{gas} Electricity and gas price
$H_i^{l,up,dr}$,$H_i^{l,dwn,dr}$ Maximum upward/downward variation of heating load
$P_i^{es,ch,max}$, $H_i^{hs,ch,max}$, and $C_i^{cs,ch,max}$ Maximum charging capacity of the electricity, heat, and ice storage units
$SOE_i^{es,min}$, $SOE_i^{hs,min}$, and $SOE_i^{cs,min}$ The lower bound of state of energy for the electricity, heat, and ice storage units
σ_i^{hs} and σ_i^{cs} Self-discharge factors for the heat and ice storage units
$\eta_i^{hs,ch}$ and $\eta_i^{hs,dch}$ The efficiency of charge and discharge for heat storages
ε unit treatment cost of the pollutant emission CO_2
LHV Low calorific value of natural gas
OM^{pv} Maintenance cost coefficient of PV units
β^{grid}, β^{gas} CO_2 emission coefficients for electricity and natural gas
$P_i^{grid,max}$, $G_i^{grid,max}$ Maximum capacity of exchanging power and gas
$\eta^{g2p,chp}$, $\eta^{g2h,chp}$ Gas to electricity/heat coefficient for combined heat and power (CHP)
$\eta^{g2h,br}$ Gas to heat coefficient for boiler units
V^{MPP}, I^{MPP} The voltage and current at the maximum power point for PV modules
$P_{i,r,t}^{pv}$ Output power of the PV unit
$P_{i,t}^{l}$, $H_{i,t}^{l}$, and $C_{i,t}^{l}$ Electrical, heating, and cooling loads
$P_i^{l,up,dr}$,$P_i^{l,dwn,dr}$ Maximum upward/downward variation of electrical load
$P_i^{es,dch,max}$, $H_i^{hs,dch,max}$, and $C_i^{cs,dch,max}$ Maximum discharging capacity of the electricity, heat, and ice storage units
$SOE_i^{es,max}$, $SOE_i^{hs,max}$, and $SOE_i^{cs,max}$ The upper bound of the state of energy for the electricity, heat, and ice storages
$\eta_i^{es,ch}$ and $\eta_i^{es,dch}$ Charging and discharging efficiency for the electricity storages
$\eta_i^{cs,ch}$ and $\eta_i^{cs,dch}$ The efficiency of charge and discharge for ice storages
OM^{hs} maintenance cost factor of heat storages
OM^{br} Maintenance cost factor of boiler
OM^{CHP} Maintenance cost factor of CHP unit
$B_{i,j}$, $P_{i,j}^{max}$ Susceptance & capacity of line i-j
COP^{ac}, COP^{ec}, and COP^{ice} Performance coefficients of absorption chiller (AC), electric chiller (EC), and ice storage
$G_i^{max,br}$, $G_i^{max,CHP}$ Maximum input of boiler and CHP
$P_i^{ice,max}$, $P_i^{ec,max}$ Maximum input power of ice storage and EC

Variables

$P_{i,w,r,t}^{grid,purc}$, $P_{i,w,r,t}^{grid,sold}$ Purchased/sold power from the upstream power grid
$G_{i,w,r,t}^{gas,purc}$ Purchased natural gas
$P_{i,w,r,t}^{CHP}$,$H_{i,w,r,t}^{CHP}$ Output electrical and heat power of CHP
$SOE_{i,w,r,t}^{es}$, $SOE_{i,w,r,t}^{hs}$, and $SOE_{i,w,r,t}^{cs}$ State of energy of the electricity, heat, and ice storages
$H_{i,w,r,t}^{ac}$ Input heat power of AC
$\theta_{i,w,r,t}$ Voltage angle of the i-th bus at the t-th interval
$C_{i,w,r,t}^{hs,ch}$, $C_{i,w,r,t}^{hs,dch}$ Charge/discharge power of ice storage
$H_{i,w,r,t}^{hs,ch}$, $H_{i,w,r,t}^{hs,dch}$ Charge/discharge power of heat storage
$P_{i,w,r,t}^{l,up}$, $P_{i,w,r,t}^{l,dwn}$ Demand variation upward/downward for electrical loads at each interval and cluster
$a_{i,w,r,t}^{cs,ch}$, $a_{i,w,r,t}^{cs,dch}$ Charging/discharging status of ice storage
$a_{i,w,r,t}^{hs,ch}$, $a_{i,w,r,t}^{hs,dch}$ Charging/discharging status of heat storage
$P_{i,w,r,t}^{grid}$ Exchanged power with the upstream power grid
$G_{i,w,r,t}^{gas,br}$, $G_{i,w,r,t}^{gas,chp}$ Input gas of boiler and CHP units
$P_{i,w,r,t}^{ec}$, $P_{i,w,r,t}^{ice}$ Consumed power by EC and ice storage
$C_{i,w,r,t}^{ac}$,$C_{i,w,r,t}^{ec}$, and $C_{i,w,r,t}^{cs,dch}$ Output cooling power of AC, EC, and ice storage
$H_{i,w,r,t}^{br}$ Output of boiler unit
$P_{i,w,r,t}^{hs,ch}$, $P_{i,w,r,t}^{hs,dch}$ Charge/discharge power of electricity storage
$P_{i,w,r,t}^{l,DR}$, $H_{i,w,r,t}^{l,DR}$ Electrical and heating load after implementing DR programs
$\alpha_{i,w,r,t}^{p,up,DR}$, $\alpha_{i,w,r,t}^{p,dwn,DR}$ Binary variables indicating the electrical demand shifting status
$H_{i,w,r,t}^{l,up}$, $H_{i,w,r,t}^{l,dwn}$ Demand variation upward/downward for heating loads at each interval and cluster
$\alpha_{i,w,r,t}^{h,up,DR}$, $\alpha_{i,w,r,t}^{h,dwn,DR}$ Binary variables indicating the heat demand shifting status
$a_{i,w,r,t}^{es,ch}$, $a_{i,w,r,t}^{es,dch}$ Charging/discharging status of electricity storage

from a scheduling and management perspective (Prabawa and Choi, 2024). Additionally, electricity price is a key parameter in energy systems. Uncertainty in electricity prices can cause challenges for EHs in order to schedule their sources and supply their loads optimally (Lin et al., 2023). Hence, having a viable approach to dealing with different sources of uncertainties is a crucial issue for energy systems research instead of deterministic approaches. One of the most effective techniques for handling uncertainty in the related literature is scenario-based stochastic programming approaches (Hu et al., 2021). Under high-level uncertainties resulting from RER and energy prices, a more realistic model of energy systems operation can be established by modeling the multiple-source of uncertainties through generating scenarios (Lu et al., 2023).

As a result of excessive CO_2 emissions, human society has faced challenges. This has led to a growing interest in calculating and managing carbon emissions (Farooq et al., 2023). In order to calculate and analyze carbon emissions, various methods exist, such as statistical methods (Wang et al., 2012), network-based models (Kang et al., 2015), and analytic life cycle approaches (Weisser, 2007). Moreover, to manage and control carbon emission, a variety of technologies and techniques exist, including carbon capture technologies (Sharifzadeh et al., 2019), RER technologies (Ghorbani et al., 2022), demand-side management models (Kang et al., 2015), and carbon-constrained models (Olsen et al., 2018). As part of the energy management in energy systems, reducing carbon emissions is also an important scheduling goal (Teso et al., 2022). Hence, scheduling models should consider the CO_2 emission treatment cost of energy systems. Also, Hoseinzadeh and Garcia investigates AI's ability to predict greenhouse emissions and consumption

Table 1
Summary of literature in NEHs.

Ref. No.	Proposed framework	Considering		Facilities and sub-hub sections								Uncertainties	Scenario reduction technique
		Cost	Em	ESS			DRP		Power	Heating	Cooling		
				ES	HS	CS	EL	HL					
(Akbari et al., 2021)	A coordination MILP optimization model	✔		✔	✔		✔		✔	✔		✔	Kantorovich technique
(Cao et al., 2019)	A deterministic bi-objective MILP optimization model	✔	✔	✔	✔	✔	✔		✔	✔	✔		-
(Bahmani et al., 2021)	A cooperative deterministic MILP optimization model	✔		✔	✔	✔	✔	✔	✔	✔	✔		-
(Masrur et al., 2024)	A cooperative deterministic MILP model	✔	✔	✔	✔				✔	✔			-
(Lu et al., 2020)	A robust coordinated optimization model	✔	✔	✔	✔		✔	✔	✔	✔		✔	-
(Poursmaeil et al., 2021)	A robust coordinated optimization model	✔	✔	✔	✔		✔		✔	✔		✔	-
(Tian et al., 2021)	A robust optimization model	✔		✔	✔		✔	✔	✔	✔	✔	✔	-
(Nasiri et al., 2020)	A non-cooperative bi-level optimization model	✔							✔	✔			-
(Mirzapour-Kamanaj et al., 2020)	A non-cooperative bi-level optimization model	✔		✔					✔	✔		✔	-
(Dini et al., 2022)	A coordination MINLP optimization model	✔		✔	✔		✔		✔	✔		✔	Kantorovich technique
(Majidi and Zare, 2019)	A hybrid scenario-based / IGDT optimization model	✔		✔			✔		✔	✔		✔	Kantorovich technique
(Zhang et al., 2021)	A non-cooperative hierarchical strategy	✔		✔					✔	✔	✔	✔	Kantorovich technique
(Heidari et al., 2020)	A stochastic MINLP optimization model	✔		✔	✔	✔	✔		✔	✔	✔	✔	SCENRED/GAMS
(Salehi et al., 2019)	A coordination MILP optimization model	✔	✔	✔	✔	×	✔		✔	✔		✔	Kantorovich technique
(Rakipour and Barati, 2019)	A probabilistic MILP optimization model	✔		✔	✔	✔	✔		✔	✔	✔	✔	-
(Javadi et al., 2022)	A decentralized coordination MILP optimization model	✔		✔					✔	✔	✔		-
(Wang et al., 2020)	A decentralized coordination MINLP optimization model	✔		✔	✔				✔	✔			-
(Li et al., 2019)	A non-cooperative MIQCP optimization model	✔		✔	✔				✔	✔			-
(Jiang et al., 2021)	A cooperative game model	✔							✔	✔	✔		-
(Yan et al., 2024)	A non-cooperative stochastic model	✔	✔	✔	✔	✔	✔		✔	✔	✔	✔	-
(Zhong et al., 2022)	A non-cooperative model	✔	✔	✔	✔		✔	✔	✔	✔		✔	-
This paper	A cooperative cluster-based MILP model	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	K-means algorithm

*Table description, Em: Emission, ES: Electricity Storage, HS: Heat Storage, CL: Cooling Storage, EL: Electric Load, HL: Heat Load.

rates, establishing the basis for future research that focuses on both production and consumption parts.

The optimal operation of EHs and their energy management have already been the subject of various studies and research works. Cao et al. (2019), Masrur et al. (2024) have explored the optimal operation of EHs using a deterministic approach, which, although simple to employ, overlooks real-world variability and uncertainty. Through a robust optimization approach, Lu et al. (2020), Tian et al. (2021)) proposed optimal energy management models. However, robust approaches tend to oversimplify uncertainty by focusing primarily on worst-case scenarios, which can lead to overly conservative solutions that fail to optimize performance under more typical conditions while imposing considerable computing overhead. Through bi-level programming approaches, Nasiri et al. (2020), Mirzapour-Kamanaj et al. (2020) and investigated the optimal operation of EHs from just an economic view point. However, implementing demand response programs (DRPs), deploying a cooling system, as well as considering environmental issues have not been addressed. Through a stochastic scenario-based approach, Dini et al. (2022), Rakipour and Barati (2019) studied the energy management of EHs. However, the role of ice storage, applying a fair cost allocation, thermal DRPs implementation, as well as emission concerns have been ignored. A peer-to-peer trading method between several EHs with the aim of cost reduction for clients was presented by Javadi et al. (2022) and Wang et al. (2020). In addition, a decentralized power flow was addressed using alternating direction multipliers, resulting in total cost reduction under the coordination scheme of EHs. However, the role of thermal and cooling storage, emission concerns, and DR program application has not been studied. Benders decomposition has been applied in Li et al. (2019) for decentralizing the decision-making procedure, according to a hierarchy structure (leader-follower relationship) within integrated power-gas network and EHs. However, implementing DRPs and considering environmental issues were neglected. From an economically cooperative standpoint, the authors of Jiang et al. (2021) investigated the interactions among participants in a game according to the Nash bargaining theory, while the community energy manager encouraged the prosumers to take an active role in the energy management through an incentive mechanism. A multi-objective probabilistic model for microgrids is introduced in Ullah et al. (2021), in which the best optimal solution in the Pareto front is selected by a fuzzy min-max technique. Moreover, forecasting input parameters for the optimization models is essential and has been extensively studied in Hafeez et al. (2020b, 2020c) in the context of demand profiles. An artificial neural network (ANN) has been developed by the authors of Hafeez et al. (2020b) to

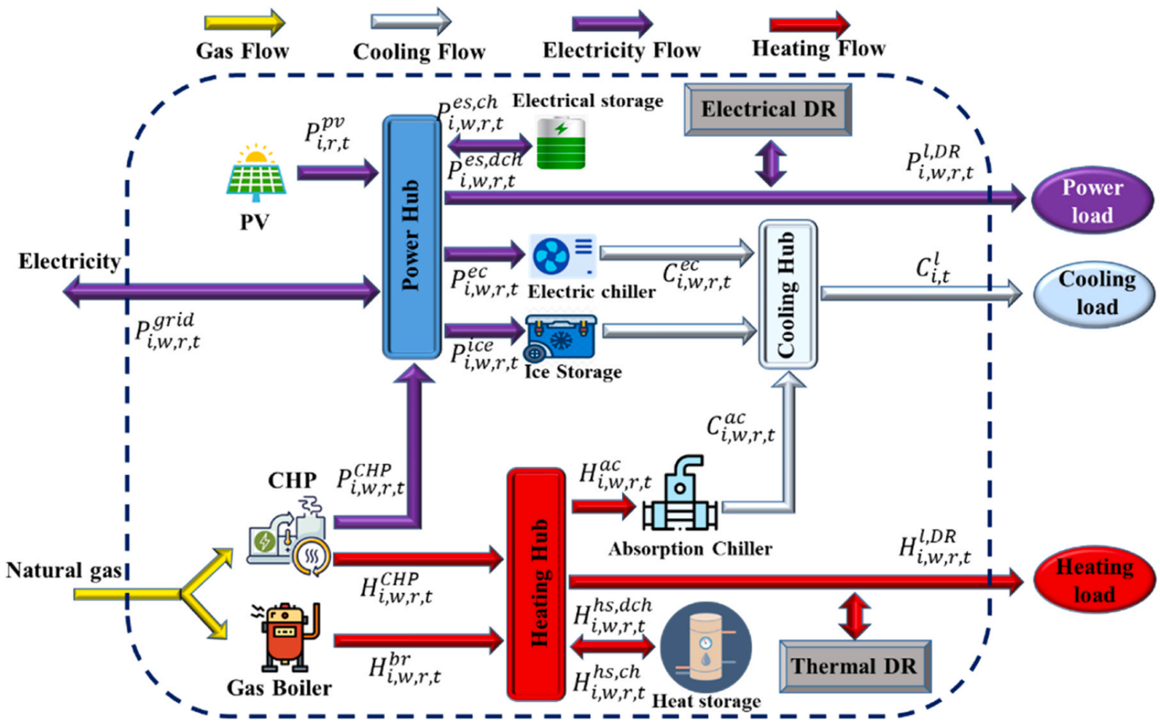


Fig. 1. The structure of proposed EHs.

forecast electricity prices and demand that has been optimized by a heuristic optimization framework for residential energy management controllers. To estimate the electric demand, Hafeez et al. (2020c) has implemented a deep learning model that combines the benefits of several methods, such as heuristic approaches, resulting in improved parameter accuracy and performance. The authors in Mardani et al. employed a data-driven approach to assess the impact of air pollution on PV generation through linear models. Another study in Hoseinzadeh et al. (2023) delves into the financial feasibility and environmental benefits of integrating various combinations of renewable energy technology such as hydropower, wind turbines, and solar panels at three different energy consumption levels. Their findings indicate that transitioning to renewable energy could considerably decrease costs and pollution in the region.

The literature review reveals several key findings. Firstly, some studies overlook various sources of uncertainty by adopting a deterministic approach. Secondly, in investigating cooperation among EHs, some research fail to establish a fair cost allocation method, which is critical for future collaboration. Furthermore, using non-cooperative games with Nash equilibrium methods does not guarantee optimal solutions, resulting in a less efficient economic plan for the system. Furthermore, in studies that use multi-criteria decision-making frameworks, particularly those that incorporate environmental and economic factors, hierarchical or optimal Pareto-front-based approaches are common. However, these methods pose challenges due to their significant computational burden, model complexity, and difficulties in determining the best solution concept. In the light of the mentioned description, in this paper, a cooperative framework has been presented in order to schedule the cooperation of multiple EHs, which takes into account the necessity of a fair cost allocation mechanism through applying Shapley value. In addition, considering energy storage systems as well as RER, the electrical and thermal DRPs are implemented on the loads. Furthermore, the uncertainty associated with RER and electricity price has been considered through a clustering-based approach. Hence, a Mixed-Integer Linear Programming (MILP) model is formulated stochastically, representing the energy flow of the EHs. It is worth mentioning that the suggested energy hub modeling approach seeks a compromise between computational efficiency and accuracy, giving priority to practicality. Although this approach might sound less complex than some current models, its emphasis on scalability guarantees that it can be applied in real-world situations. This study's suggested strategy provides an efficient solution while preserving important insights since it acknowledges the trade-off between complexities and practicality that has been observed in previous research. Furthermore, the proposed model advocates for establishing coalitions and sharing resources to optimize the system's cost. Furthermore, unlike existing research, the proposed paradigm improves the economic-environmental performance of NEHs by optimizing operational costs while reducing carbon emissions. This is obtained through the amalgamation of these two objectives into monetary metrics, resulting in simultaneous improvements. Additionally, by penalizing options with high emissions, the proposed model considers carbon costs and encourages the use of greener energy sources by incorporating distinct emission factors for various energy sources. It also prioritizes the integration of RERs and improves the consumption pattern through DRPs and ESSs, all of which contribute significantly to lessening the impact on the environment. In Table 1, a summary of the surveyed papers in NEHs has been given. It has been tried to compare different features of relevant existing references to illustrate the research gaps. The main contributions of this article to respond to research gaps can be briefly expressed as follows:

- A cooperative game theory-based model coordinates the functioning and interaction of EHs, assuring optimal financial results. The suggested model coordinates EH operations, allowing them to share their facilities and resources in order to save costs and enhance dependability as backup suppliers, while implementing a rational and fair cost allocation based on their efficiency and contribution.
- An environmentally-aware optimal scheduling model for NEHs has been developed that considers electricity and gas as energy carriers, as inputs, supplying both power and thermal demands. In addition, the impacts of coalitions, as well as DRPs upon CO_2 emission, have been evaluated.
- A stochastic clustering-based framework is proposed to handle uncertainties in PV generation and electricity price. Scenario

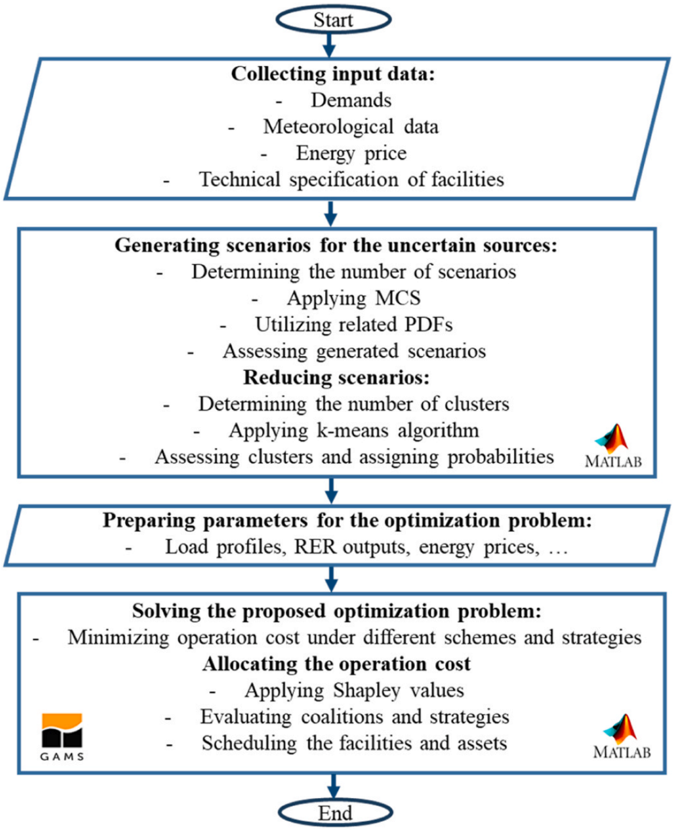


Fig. 2. The flowchart of the proposed energy management model.

preparation techniques such as MCS and k-means clustering are employed to analyze these uncertainties.

The rest of this article is structured as follows. Section 2 describes the structure of NEHs as well as contains the proposed mathematical optimization model. The case studies and the conducted simulations are introduced in Section 3. A sensitivity analysis is deliberated in Section 4. Finally, summarized conclusions are delivered in Section 5.

2. System modeling

Basically, an EH is a system that provides a variety of energy demands by interconnecting several energy carriers through the energy conversion facilities, e.g., CHPs, boilers, chillers, Energy Storage Systems (ESS), such as electricity, heating, and ice storage, and basic input-output interfaces. Fig. 1 shows the schematic of the proposed EHs. In addition, deploying RERs in energy systems necessitates considering the stochastic nature of their output power from a scheduling and operation point of view. The mathematical formulation of the proposed cooperative model and scenario preparation procedure handling the uncertainties are described in this section.

2.1. Uncertainties modeling

One of the most well-known methods is the application of stochastic process-based simulation techniques, such Monte Carlo Simulation (MCS). It is possible to study uncertainties accurately using the MCS-based approaches. However, their computational time poses a significant drawback. The MCS-based techniques' computing time is highlighted, especially when addressing optimization problems or making decisions in real time are required. Hence, there is a growing interest in novel, rapid techniques, including scenario-based or analytical approaches, for assessing the uncertainty in energy systems (Yaghoubi-Nia et al., 2021). Fig. 2 depicts the detailed flowchart of the proposed collaborative energy management framework for EHs, including the scenario preparation procedure.

2.1.1. Scenario generation

RERs, such as PV units, generate power probabilistically (Hafeez et al., 2021). The Beta distribution is a widely used to model the probability distribution function of solar irradiance, as seen in (1) (Hung et al., 2014).

$$f_b(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{\alpha-1}(1-s)^{\beta-1} & 0 \le s \le 1, \alpha,\beta \ge 0 \\ 0 \; otherwise \end{cases} \tag{1}$$

Γ is the gamma function, and s denotes solar irradiance. The characteristics of the Beta distribution are determined by the hourly mean (μ_s) and standard deviation (σ_s) from historical data using (2) and (3) (Ma et al., 2020).

$$\beta = (1-\mu_s)\left(\frac{\mu_s \; (1-\mu_s)}{\sigma_s^2} - 1\right) \tag{2}$$

$$\alpha = \frac{\mu_s \beta}{1-\mu_s} \tag{3}$$

According to the inverse of the cumulative density function of the beta distribution, the MCS technique is used to produce scenarios. Moreover, the output power of PV units is calculated according to the solar irradiance, the ambient temperature, as well as the characteristics of PV units, by (4)–(8) (Hakimi et al., 2021).

$$\theta = \theta^{am} + s * \left(\frac{N^{OT} - 20}{0.8}\right) \tag{4}$$

$$I^{PV} = s * [I^{sc} + K^c(\theta - 25)] \tag{5}$$

$$V^{PV} = V^{OC} - K^v * \theta \tag{6}$$

$$FF = \frac{V^{MPP} * I^{MPP}}{V^{OC} * I^{SC}} \tag{7}$$

$$P^{PV} = N^{PV} * FF * V^{PV} * I^{PV} \tag{8}$$

The facilities' schedule and operation are significantly affected by the price of electricity. The lognormal distribution is utilized to characterize electricity prices hourly as shown by (9):

$$f_p\left(\lambda, \mu_p, \sigma_p\right) = \frac{1}{\lambda \sigma_p \sqrt{2\pi}} \exp\left[-\frac{(\ln\lambda - \mu_p)^2}{2{\sigma_p}^2}\right] \tag{9}$$

where μ_p and σ_p denote the mean value and the standard deviation of the price series, respectively, derived from historical data.

2.1.2. Clustering and scenario reduction

As a scenario reduction method, the k-means algorithm was employed in this study to reduce the number of scenarios and, consequently, the optimization problem's execution time. A popular unsupervised data-partitioning classification technique for cluster analysis in data mining research is the K-means algorithm (Hosseinnia et al., 2022). The algorithm finds the partition of the cluster where objects with the greatest distance from each other and from objects in other clusters are located. Within a partition, objects are grouped according to their members and centroid. Cluster centroid points are the points from which the total distance between all objects within a cluster is minimized. Centroids prioritize assigning m samples/scenarios to distinct k clusters based on the k-means algorithm. For uncertain parameters, including the output power of PV and electricity price, the generated scenarios by

MCS are vectors that change with time. The mathematical formulation of simulated scenarios involving uncertain parameters and sub-systems is shown in (10). Additionally, (11) illustrates the dynamic vectors representing the centers of clusters, mirroring the dimensionality of their respective scenario sets. The distance between simulated scenarios and the centroids needs to be computed as the Objective Function (OF) of the algorithm, as outlined in (12) (Akbari et al., 2022).

$$x_l = [\quad x_{l,1},\quad x_{l,2},\quad \ldots,\quad x_{l,t},\ldots,\quad x_{l,23}, x_{l,24}\quad]\mathrm{t} = \quad 1,\ldots,\mathrm{T}\ \mathrm{l} = \quad 1,\quad \ldots,\mathrm{m} \tag{10}$$

$$C_v = [\quad C_{v,1},\quad C_{v,2},\quad \ldots,\quad C_{v,t},\quad \ldots,\quad C_{v,23},\quad C_{v,24}\quad]\mathrm{t} = \quad 1,\ldots,\mathrm{T}\ \mathrm{v} = 1,\ldots,\mathrm{k} \tag{11}$$

$$J = \sum_{v=1}^{k}\sum_{l=1}^{m}\left\|x_l^{(l)} - c_v\right\|^2 \tag{12}$$

2.2. The Clustering-based optimization formulation

2.2.1. Objective function

The objective function of the proposed MILP model, as outlined in Eqs. (13)–(16), involves minimizing the overall cost associated with the NEHs. Additionally, the constraints modeling the operation of facilities are presented in Eqs. (17)–(65). This cost encompasses various factors such as power transferred from the grid, input gas, CO_2 emission treatment expenses ($Cost^{EM}$), as well as the operational and maintenance costs ($Cost^{OM}$) of several facilities including photovoltaic (PV) systems, combined heat and power (CHP) units, electrical storage (ES), heat storage (HS), ice storage, and boiler units.

$$Min\ Cost = \quad Cost^{Energy} + Cost^{EM} + Cost^{OM} \tag{13}$$

$$Cost^{Energy} = \quad \sum_i\sum_w\sum_r\sum_t(\lambda_t^{elec}.P_{i,w,r,t}^{grid} + \lambda_t^{gas}.G_{i,w,r,t}^{gas,purc}).\rho_w.\rho_r.\Delta t \tag{14}$$

$$Cost^{EM} = \sum_i\sum_w\sum_r\sum_t \varepsilon.(\beta^{grid}.P_{i,w,r,t}^{grid,purc} + \beta^{gas}.LHV.G_{i,w,r,t}^{gas,purc}).\rho_w.\rho_r.\Delta t \tag{15}$$

$$Cost^{OM} = \quad \sum_i\sum_w\sum_r\sum_t\left\{\begin{array}{l}\left[OM^{pv}.P_{i,r,t}^{pv}\right] + [OM^{CHP}\left(P_{i,w,r,t}^{CHP} + H_{i,w,r,t}^{CHP}\quad\right)] + [OM^{br}.H_{i,w,r,t}^{br}\big) \\ +\left[OM^{es}\left(P_{i,w,r,t}^{es,dch} + P_{i,w,r,t}^{es,ch}\right)\right] + [OM^{hs}\left(H_{i,w,r,t}^{hs,dch} + H_{i,w,r,t}^{hs,ch}\right)]\end{array}\right\}.\rho_w.\rho_r.\Delta t \tag{16}$$

2.2.2. Energy balance constraints and energy conversion facilities model

The energy flow at each sub-EH should be in balance in each cluster and time step. The power balance is guaranteed by imposing (17). The electrical power at each EH could be supplied by the CHP unit, PV, the ES, and the transferred power with other EHs. In addition, the upstream power grid could exchange the dearth or excess energy. Constraint (18) and (19) formulate the limitations of line capacity and the angle of buses ($\theta_{i,w,r,t}$) (Feng et al., 2023).

$$P_{i,w,r,t}^{grid} + P_{i,w,r,t}^{CHP} + P_{i,r,t}^{pv} + P_{i,w,r,t}^{es,dch} = P_{i,w,r,t}^{l,DR} + P_{i,w,r,t}^{es,ch} + P_{i,w,r,t}^{ice} + P_{i,w,r,t}^{ec} + \sum_j \quad B_{i,j}.(\theta_{i,w,r,t} - \theta_{j,w,r,t})\quad \forall \quad i,w,r,t \tag{17}$$

$$-P_{i,j}^{\max} \le B_{i,j}.\left(\theta_{i,w,r,t} - \theta_{j,w,r,t}\right) < P_{i,j}^{\max}\quad \forall \quad i,j,w,r,t \tag{18}$$

$$-\pi \le \theta_{i,w,r,t} \le \pi\forall \quad i,w,r,t \tag{19}$$

In order to calculate accurately the share of pollution associated with the imported power from the upstream power grid, constraints (20)–(22) are used. In addition, the limitation of the maximum capacity of exchanging power is considered by (21) and (22). The binary variable $\alpha_{i,w,r,t}^{grid}$, representing the state of purchasing energy, is used to prevent simultaneous sale and purchase of electricity.

$$P_{i,w,r,t}^{grid} = (\frac{P_{i,w,r,t}^{grid,purc}}{\eta_i^{trans}}) - \left(P_{i,w,r,t}^{grid,sold}.\eta_i^{trans}\right)\forall \quad i,w,r,t \tag{20}$$

$$0 \le P_{i,w,r,t}^{grid,purc} \le \alpha_{i,w,r,t}^{grid}.\quad P_i^{grid,\max}\quad \forall \quad i,w,r,t \tag{21}$$

$$0 \le P_{i,w,r,t}^{grid,sold} \le (1 - \alpha_{i,w,r,t}^{grid}).\quad P_i^{grid,\max}\quad \forall \quad i,w,r,t \tag{22}$$

The amount of purchased gas, by the i-th EH at the t-th time interval, w-th cluster for electricity price, and the r-th PV clusters, as well as the limitation of maximum purchasing capacity, is considered by (23) and (24), respectively.

$$G_{i,w,r,t}^{gas,purc} = G_{i,w,r,t}^{gas,br} + G_{i,w,r,t}^{gas,chp}\quad \forall \quad i,w,r,t \tag{23}$$

$$G_{i,w,r,t}^{gas,purc} \le G_i^{grid,\max}\quad \forall \quad i,w,r,t \tag{24}$$

By consuming natural gas, the CHP units can generate electrical power and co-generate heat, according to their technical parameters, formulated by constraints (25) and (26) (Liang et al., 2022). In addition, a portion of heat can be supplied by boilers. (28) models the relationship between the boiler's intake gas and output heat power. Also, the limits of input gas for boilers and CHP units are satisfied by constraints (27) and (29), respectively.

$$P_{i,w,r,t}^{CHP} = G_{i,w,r,t}^{gas,chp}.\eta^{g2p,chp}.LHV\Big/\Delta t\quad \forall \quad i,w,r,t \tag{25}$$

$$H_{i,w,r,t}^{CHP} = G_{i,w,r,t}^{gas,chp}.\eta^{g2h,chp}.LHV\Big/\Delta t\quad \forall \quad i,w,r,t \tag{26}$$

$$0 \le G_{i,w,r,t}^{gas,chp} \le G_i^{\max,chp}\quad \forall \quad i,w,r,t \tag{27}$$

$$H_{i,w,r,t}^{br} = G_{i,w,r,t}^{gas,br}.\eta^{g2h,br}.LHV\Big/\Delta t\quad \forall \quad i,w,r,t \tag{28}$$

$$0 \le G_{i,w,r,t}^{gas,br} \le G_i^{\max,br}\quad \forall \quad i,w,r,t \tag{29}$$

The produced heat by the facilities at each EH should be equal to the heat demand, which is considered by the constraint (30). Also, constraints (31)–(37) are used to model the energy flow in the cooling section of each EH. Eq. (31) guarantees the energy balance at the cooling sub-EH. A portion of the cooling load can be provided by the Absorption Chiller (AC). ACs convert the received heat into cooling energy which can be modeled by constraint (32). Constraint (33) indicates the AC's limits. Also, ECs generate cooling power by consuming electrical energy. Constraints (34) and (35) are used to formulate the Electric Chiller (EC) performance and capacity. In addition, the power consumed by the ice storage in order to make ice is modeled by Eq. (36). The capacity of producing ice is limited by the constraint shown in (37).

$$H^{CHP}_{i,w,r,t} + H^{br}_{i,w,r,t} + H^{hs,dch}_{i,w,r,t} = H^{l,DR}_{i,w,r,t} + H^{hs,ch}_{i,w,r,t} + H^{ac}_{i,w,r,t} \quad \forall \quad i,w,r,t \tag{30}$$

$$C^{ac}_{i,w,r,t} + C^{ec}_{i,w,r,t} + C^{cs,dch}_{i,w,r,t} = C^{l}_{i,t} \quad \forall \quad i,w,r,t \tag{31}$$

$$C^{ac}_{i,w,r,t} = H^{ac}_{i,w,r,t}. \quad \mathrm{COP}^{ac} \quad \forall \quad i,w,r,t \tag{32}$$

$$H^{ac}_{i,w,r,t} \le H^{ac,\max}_{i} \quad \forall \quad i,w,r,t \tag{33}$$

$$C^{ec}_{i,w,r,t} = P^{ec}_{i,w,r,t}. \quad \mathrm{COP}^{ec} \quad \forall \quad i,w,r,t \tag{34}$$

$$P^{ec}_{i,w,r,t} \le P^{ec,\max}_{i} \quad \forall \quad i,w,r,t \tag{35}$$

$$C^{cs,ch}_{i,w,r,t} = P^{ice}_{i,w,r,t}. \quad \mathrm{COP}^{ice} \quad \forall \quad i,w,r,t \tag{36}$$

$$P^{ice}_{i,w,r,t} \le P^{ice,\max}_{i} \quad \forall \quad i,w,r,t \tag{37}$$

2.2.3. DRPs modeling

The DRPs can enhance the operation of energy systems from a techno-economic point of view since they can provide higher flexibility. In this paper, two types of demands, including power and heat loads, can participate in DRPs. Constraints (38)–(42) describe the mathematical model of the implemented DRPs. The total load demand after participation in DRPs can be calculated by (38). The maximum allowed load that can participate in DRPs is limited using constraints as shown in (39) and (40). Simultaneous changes, such as upward and downward variations, in the loads, are avoided by constraint (41) (Zeynali et al., 2021). All demand increases should be equal to all demand decreases over the optimization interval, satisfied by (42).

$$P^{l,DR}_{i,w,r,t} = P^{l}_{i,t} + \quad P^{l,up}_{i,w,r,t} - P^{l,dwn}_{i,w,r,t} \quad \forall \quad i,w,r,t \tag{38}$$

$$0 \le P^{l,up}_{i,w,r,t} \le P^{l,up,dr}_{i}.P^{l}_{i,t}.a^{p,up,DR}_{i,w,r,t} \quad \forall \quad i,w,r,t \tag{39}$$

$$0 \le P^{l,dwn}_{i,w,r,t} \le P^{l,dwn,dr}_{i}.P^{l}_{i,t}.a^{p,dwn,DR}_{i,w,r,t} \quad \forall \quad i,w,r,t \tag{40}$$

$$a^{p,up,DR}_{i,w,r,t} + a^{p,dwn,DR}_{i,w,r,t} \le 1 \quad \forall \quad i,w,r,t \tag{41}$$

$$\sum_t P^{l,up}_{i,w,r,t} = \sum_t P^{l,dwn}_{i,w,r,t} \quad \forall \quad i,w,r \tag{42}$$

Similar to the description of electrical DRPs, the heat DRPs should be applied to the proposed model according to (43)–(47).

$$H^{l,DR}_{i,w,r,t} = H^{l}_{i,t} + \quad H^{l,up}_{i,w,r,t} - H^{l,dwn}_{i,w,r,t} \quad \forall \quad i,w,r,t \tag{43}$$

$$0 \le H^{l,up}_{i,w,r,t} \le H^{l,up,dr}_{i}.H^{l}_{i,t}.a^{h,up,DR}_{i,w,r,t} \quad \forall \quad i,w,r,t \tag{44}$$

$$0 \le H^{l,dwn}_{i,w,r,t} \le H^{l,dwn,dr}_{i}.H^{l}_{i,t}.a^{h,dwn,DR}_{i,w,r,t} \quad \forall \quad i,w,r,t \tag{45}$$

$$a^{h,up,DR}_{i,w,r,t} + a^{h,up,DR}_{i,w,r,t} \le 1 \quad \forall \quad i,w,r,t \tag{46}$$

$$\sum_t H^{l,up}_{i,w,r,t} = \sum_t H^{l,dwn}_{i,w,r,t} \forall \quad i,w,r \tag{47}$$

2.2.4. Energy storage systems (ESSs) modeling

Modern systems are fitted with ESSs that can be used in a variety of applications. By providing more flexibility, ESSs play a significant role in optimal energy management for the EHs. With regard to the technical parameters of the ESS, multiple constraints have been used to formulate ESS's performance, listed in Eqs. (48)–(53).

Electricity storage unit: The relation between the state of energy at the previous interval (t-1) and the current time (t), in clusters w and r, is shown in (48) (Nikolaidis and Poullikkas, 2022). Constraints (49)–(50) limit the charging and discharging power of the Electricity Storage (ES) (Emrani-Rahaghi and Hashemi-Dezaki, 2021). In addition, preventing the charging and discharging of the ES simultaneously, $a^{es,ch}_{i,w,r,t}$ and $a^{es,dch}_{i,w,r,t}$, binary variables representing the state of charging and discharging of the ES, are used in (51) (Akbari and Fazel, 2022). The initial and final conditions for the state of the energy are guaranteed by (52) (Mirzaei et al., 2020). Also, constraint (53) bounds the stored energy in the ES in a particular range.

$$\mathrm{SOE}^{es}_{i,w,r,t} = \mathrm{SOE}^{es}_{i,w,r,t-1} - \left(\frac{P^{es,dch}_{i,w,r,t}}{\eta^{es,dch}_{i}}.\Delta t\right) + \left(\eta^{es,ch}_{i}. \quad P^{es,ch}_{i,w,r,t}.\Delta t\right) \quad \forall i,w,r,t \tag{48}$$

$$0 \le P^{es,ch}_{i,w,r,t} \le P^{es,ch,\max}_{i}.a^{es,c}_{i,w,r,t} \; \forall i,w,r,t \tag{49}$$

$$0 \le P^{es,dch}_{i,w,r,t} \le P^{es,dch,\max}_{i}.a^{es,dch}_{i,w,r,t} \; \forall i,w,r,t \tag{50}$$

$$a^{es,c}_{i,w,r,t} + a^{es,dch}_{i,w,r,t} \le 1 \; \forall i,w,r,t \tag{51}$$

$$\mathrm{SOE}^{es}_{i,w,r,initial} = \mathrm{SOE}^{es}_{i,w,r,end} \; \forall i,w,r \tag{52}$$

$$\mathrm{SOE}^{es,\min}_{i} \le \mathrm{SOE}^{es}_{i,w,r,t} \le \mathrm{SOE}^{es,\max}_{i} \; \forall i,w,r,t \tag{53}$$

Heat storage unit: At each time interval t, the heat balance constraint for the HS is shown in (54) (Zhang et al., 2019). Constraints (55) and (56) bound the charging and discharging thermal power of the HS to their maximum amounts. The HS cannot be charged and discharged at the same, guaranteed by constraint (57). Similar to the ES for the HS, the initial and final conditions for the state of energy are satisfied by (58). Constraint (59) narrows the state of energy of the HS into the allowed upper and lower limits.

$$\mathrm{SOE}^{hs}_{i,w,r,t} = \left(1 - \sigma^{hs}_{i}\right).\mathrm{SOE}^{hs}_{i,w,r,t-1} - \left(\frac{H^{hs,dch}_{i,w,r,t}}{\eta^{hs,dch}_{i}}.\Delta t\right) + \left(\eta^{hs,ch}_{i}. \quad H^{hs,ch}_{i,w,r,t}.\Delta t\right) \forall i,w,r,t \tag{54}$$

$$0 \le H^{hs,ch}_{i,w,r,t} \le H^{hs,ch,\max}_{i}.a^{hs,ch}_{i,w,r,t} \; \forall i,w,r,t \tag{55}$$

$$0 \le H^{hs,dch}_{i,w,r,t} \le H^{hs,dch,\max}_{i}.a^{hs,dch}_{i,w,r,t} \; \forall i,w,r,t \tag{56}$$

$$a^{hs,ch}_{i,w,r,t} + \; a^{hs,dch}_{i,w,r,t} \le 1 \; \forall i,w,r,t \tag{57}$$

$$\mathrm{SOE}^{hs}_{i,w,r,initial} = \mathrm{SOE}^{hs}_{i,w,r,end} \; \forall i,w,r \tag{58}$$

$$\mathrm{SOE}^{hs,\min}_{i} \le \mathrm{SOE}^{hs}_{i,w,r,t} \le \mathrm{SOE}^{hs,\max}_{i} \; \forall i,w,r,t \tag{59}$$

Ice storage unit: The ice storage systems can improve the performance of the sub-cooling hub as well as the costs (Afsharpanah et al., 2022). During a day when the electricity price is relatively low, ice storage can be charged to provide cooling demand when required. Similar to the description of the HS operation, constraints in (60)–(65) present the ice storage modeling (Heidari et al., 2020).

$$\mathrm{SOE}^{cs}_{i,w,r,t} = \left(1 - \sigma^{cs}_{i}\right).\mathrm{SOE}^{cs}_{i,w,r,t-1} - \left(\frac{C^{cs,dch}_{i,w,r,t}}{\eta^{hs,dch}_{i}}.\Delta t\right) + \left(\eta^{cs,ch}_{i}. \quad C^{cs,ch}_{i,w,r,t}.\Delta t\right) \quad \forall i,w,r,t \tag{60}$$

$$0 \le C^{cs,ch}_{i,w,r,t} \le C^{cs,ch,\max}_{i}.a^{cs,ch}_{i,w,r,t} \; \forall i,w,r,t \tag{61}$$

$$0 \le C^{cs,dch}_{i,w,r,t} \le C^{cs,dch,\max}_{i}.a^{cs,dch}_{i,w,r,t} \; \forall i,w,r,t \tag{62}$$

$$a^{cs,ch}_{i,w,r,t} + a^{cs,dch}_{i,w,r,t} \le 1 \quad \forall i,w,r,t \tag{63}$$

$$\mathrm{SOE}^{cs}_{i,w,r,initial} = \mathrm{SOE}^{cs}_{i,w,r,end} \; \forall i,w,r \tag{64}$$

$$\mathrm{SOE}^{cs,\min}_{i} \le \mathrm{SOE}^{cs}_{i,w,r,t} \le \mathrm{SOE}^{cs,\max}_{i} \; \forall i,w,r,t \tag{65}$$

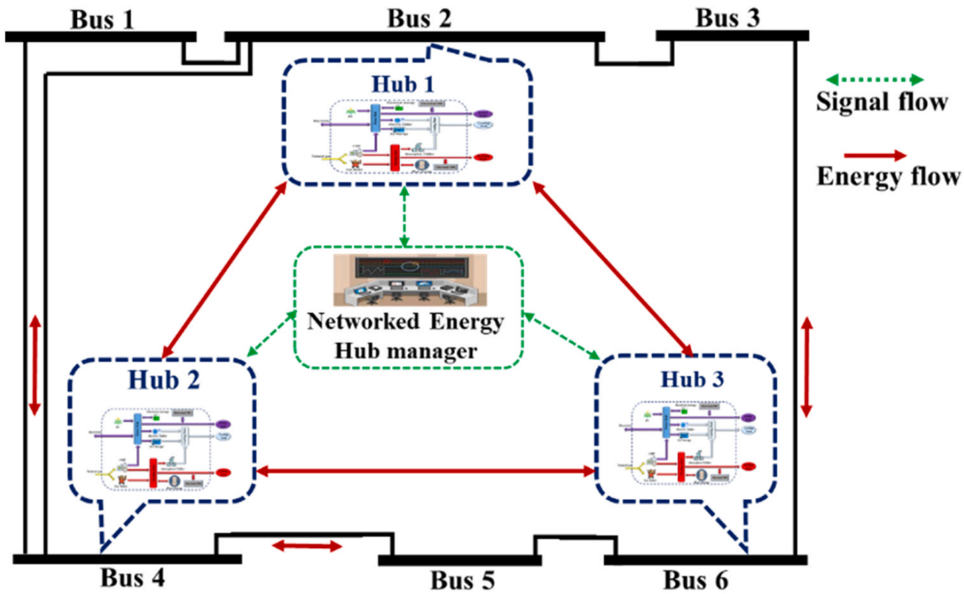


Fig. 3. The system architecture of the NEH.

2.3. The fairly cost allocation method

In a complex decision-making environment, rational decisions can encompass several conflicts of interest. Additionally, certain strategies might be required to maximize utility in a cooperative game. A coalition is shaped when a set of players cooperates together. There are several cost allocation methods, as solution concepts, in cooperative game theory-based frameworks, such as Nucleolus and Shapley value. Shaley value describes the payoff of players in coalitional games according to their contribution, bargaining power of players, as well as their efficacy. Accordingly, Eq. (66) indicates the payment of i-th player:

$$\varphi_i = \sum_{S\subseteq N/\{i\}} \frac{|S|!(n-|s|-1)!}{n!}[\nu(S\cup\{i\})-\nu(S)] \tag{66}$$

where, $N = \{1,2,\ldots,n\}$ and S are the set of whole players/EHs and the subset of N, respectively. In (66), $\nu(S)$, denoting the characteristic function of coalition S, is called the worth of coalition, which reveals information about the competitive condition. Also, $|S|$ is the cardinal number of set S, denotes the number of participants in coalition S. It is worth mentioning that since (66) is valid for $n \geq 1$, the proposed cooperative energy management strategy can be implemented by single-owner systems.

3. Simulation results

In addition, the following three case studies have been considered to assess the effectiveness of the proposed cooperative energy management model:

- Case 1: Similar to the approach of Cao et al. (2019), Lu et al. (2020), Heidari et al. (2020), Rakipour and Barati (2019), each EH optimizes its operation costs through autonomous scheduling. In this case study, the EHs will not cooperate and share their facilities, and it is considered as the base case;
- Case 2: In this case, based on cooperative strategies, the EHs cooperate with each other aiming to minimize total operation cost in the form of coalitions. Moreover, similar to the approach of Bahmani et al. (2021), Jiang et al. (2021), the EHs can just exchange electricity. In addition, according to their efficiency and contribution, the overall profit in a coalition is divided among participants;

Table 2
Technical parameters of heat and ice storage units (Lu et al., 2020; Salehi et al., 2019).

Parameter	Values			Parameter	Values		
	$i=2$	$i=4$	$i=6$		$i=2$	$i=4$	$i=6$
$SOE_i^{cs,\max}$ [kWh]	100	360	250	$SOE_i^{hs,\max}$ [kWh]	500	400	500
$SOE_i^{cs,\min}$ [kWh]	10	36	25	$SOE_i^{hs,\min}$ [kWh]	50	40	50
$C_i^{cs,ch,\max}$ [kW]	50	120	100	$H_i^{hs,ch,\max}$ [kW]	200	170	220
$C_i^{cs,dch,\max}$ [kW]	50	120	100	$H_i^{hs,dch,\max}$ [kW]	200	170	220
$\eta_i^{cs,ch}$ [%]	97	97	97	$\eta_i^{hs,ch}$ [%]	90	90	90
$\eta_i^{cs,dch}$ [%]	95	95	95	$\eta_i^{hs,dch}$ [%]	90	90	90
σ_i^{cs} [%]	2	2	2	σ_i^{hs} [%]	2	2	2

Table 3
Technical parameters of electricity storage units and the other facilities (Ma et al., 2020).

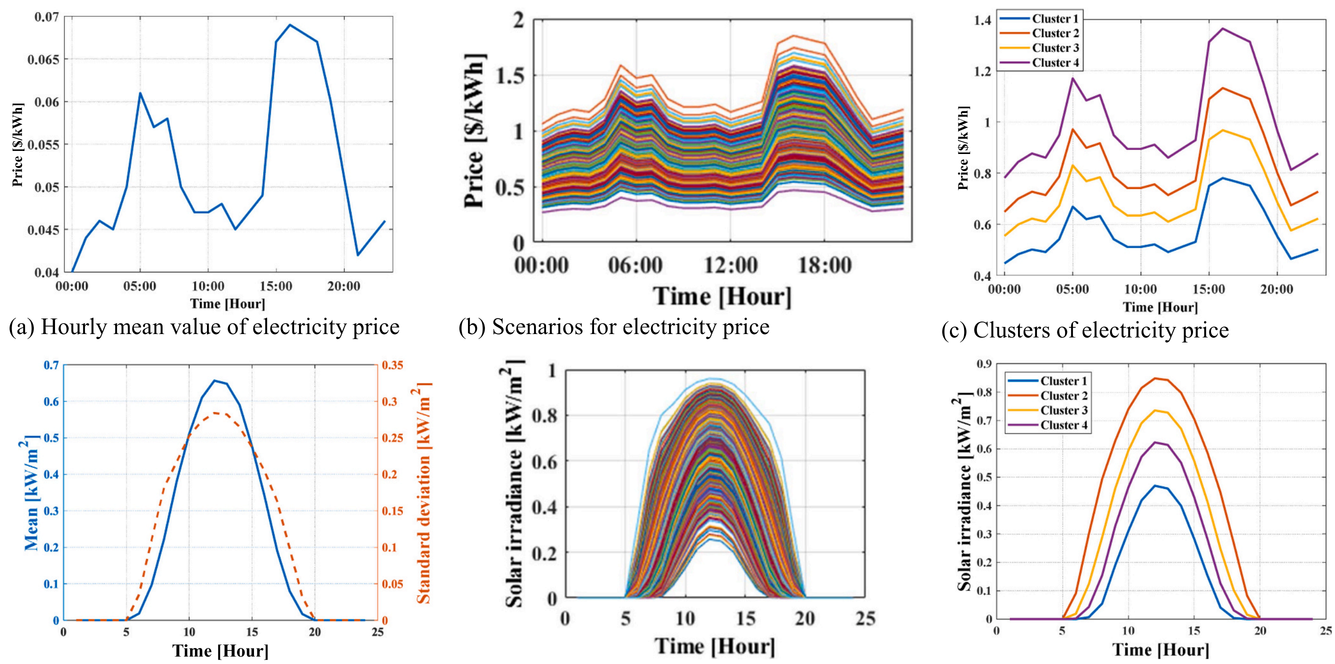
Parameter	Values			Parameter	Values		
	$i=2$	$i=4$	$i=6$		$i=2$	$i=4$	$i=6$
$SOE_i^{es,\max}$ [kWh]	500	600	500	$G_i^{\max,chp}$ [m^3]	85	100	70
$SOE_i^{es,\min}$ [kWh]	50	60	50	$G_i^{\max,br}$ [m^3]	100	200	90
$P_i^{es,ch,\max}$ [kW]	180	220	200	$P_i^{ec,\max}$ [kW]	180	100	95
$P_i^{es,dch,\max}$ [kW]	180	220	200	$P_i^{ice,\max}$ [kW]	100	100	250
$\eta_i^{es,ch}$ and $\eta_i^{es,ch}$ [%]	96	96	96	$H_i^{ac,\max}$ [kW]	150	180	220
$H_i^{l,up,dr}$ and $H_i^{l,dwn,dr}$ [%]	0	5	10	$P_i^{l,up,dr}$ and $P_i^{l,dwn,dr}$ [%]	5	10	10

- Case 3:In this case, the EHs not only can exchange electrical power but also heat power. Hence, they will share their resources in coalitions aiming to optimize their costs.

A 6-bus test system, as shown in Fig. 3, is used to apply the proposed cooperative energy management model for NEHs. The specifications for

Table 4
The other parameters of the optimization problem (Lu et al., 2020).

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
COP^{ice}	3.5	OM^{pv} [cent/kWh]	1.6	OM^{br} [cent/kWh]	2.7	β^{gas} [kg/kWh]	0.177
COP^{ec}	4	OM^{es} [cent/kWh]	0.2	ε [cent/kg]	3.36	$P_i^{grid,max}$ [kW]	1000
COP^{ac}	1.2	OM^{hs} [cent/kWh]	0.5	LHV [kWh/m^3]	9.7	η_l^{trans} [%]	98
λ_t^{gas} [cent/m^3]	35	OM^{chp} [cent/kWh]	2	β^{grid} [kg/kWh]	0.187	$G_i^{grid,max}$ [kW]	2000



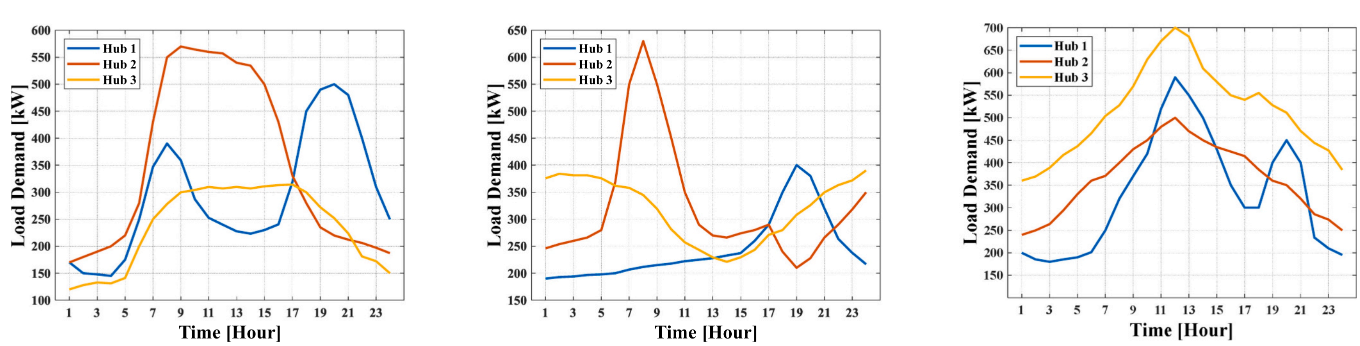
(a) Hourly mean value of electricity price
(b) Scenarios for electricity price
(c) Clusters of electricity price
(d) Hourly mean value for solar irradiance
(e) Scenarios for solar irradiance
(f) Clusters of solar irradiance

Fig. 4. Mean value of historical data, MCS-based simulated scenarios, and k-means clusters for electricity price and solar irradiance.

Table 5
The probabilities of electricity price and solar irradiance clusters.

Electricity price	Cluster number	w_1	w_2	w_3	w_4
	Probability	0.210	0.153	0.298	0.339
Solar irradiance	Cluster No.	r_1	r_2	r_3	r_4
	Probability	0.206	0.308	0.135	0.351

the understudy 6-bus test system have been assumed based on data of benchmark distribution systems, such as Dolatabadi et al. (2021). The resistance and reactance of all distribution lines connecting different segments have been assumed to be 1.5042 and 1.3554 Ohm. The segmentation concept (Hariri et al., 2020) has been used in this study. Indeed, each bus represents a segment, including internal buses and branches. The EHs 1, 2, and 3 have been modeled as a segment, which is connecting to other EHs as a single bus. As depicted, the understudy EHs have been located at buses 2, 4, and 6, respectively. The simulation parameters, specifications, and input data are presented in Tables 2–4. Table 2 contains the technical parameters of heat and ice energy storage systems (Lu et al., 2020; Salehi et al., 2019). In Table 3, the parameters of electricity storage and the other assets' capacities are shown (Ma et al., 2020). The other simulation parameters are listed in Table 4 (Bahmani et al., 2021; Lu et al., 2020). In addition, the size of PV modules deployed in EHs 1, 2, and 3 are assumed to be 125 kW, 200 kW,



(a) Electrical load demand
(b) Heat load demand
(c) Cooling load demand

Fig. 5. The electrical, thermal, and cooling demand of EHs.

Table 6
The optimal results for operation cost in various case studies.

Case study	Entities in coalition S	Operation cost							
		First EH connected to bus No. $i = 2$		Second EH connected to bus No. $i = 4$		Third EH connected to bus No. $i = 6$		Total cost	
		Amount [$]	Reduction [%]	Amount [$]	Reduction [%]	Amount [$]	Reduction [%]	Amount [$]	Reduction [%]
Case 1	Without coalition	1927.5	-	2205.6	-	1987.1	-	6120.2	-
Case 2	$C_{2,4}$	1921.6	0.3	2199.7	0.3	1987.1	0.0	6108.4	0.2
	$C_{2,6}$	1924.6	0.2	2205.6	0.0	1984.2	0.1	6114.4	0.1
	$C_{4,6}$	1927.5	0.0	2199.9	0.3	1981.4	0.3	6108.7	0.2
	$C_{2,4,6}$	1922.8	0.2	2198.1	0.3	1982.6	0.2	6103.6	0.3
Case 3	$C_{2,4}$	1900.8	1.4	2178.9	1.2	1987.1	0.0	6066.8	0.9
	$C_{2,6}$	1864.3	3.3	2205.6	0.0	1923.9	3.2	5993.8	2.1
	$C_{4,6}$	1927.5	0.0	2124.3	3.7	1905.8	4.1	5957.6	2.7
	$C_{2,4,6}$	1889.8	2.0	2149.8	2.5	1894.8	4.6	5934.5	3.0

and 250 kW, respectively (Ma et al., 2020). To study the validity and performance of the proposed MILP model, GAMS optimization software is used along with the CPLEX solver.

3.1. Scenario generation and reduction

The hourly statistical data in Hung et al. (2014) have been used for simulating the solar irradiance/PV output power and electricity prices. In Fig. 4, the mean value for hourly historical data for electricity price and solar irradiance have been depicted. Applying the MCS, 1000 scenarios have been produced separately for the different sources of uncertainty namely the solar irradiance and the electricity price. The simulated scenarios for solar irradiance and electricity price using the MCS have been shown in Fig. 4. Examining whether simulated scenarios follow actual historical data and associated statistical indices is an essential issue. In this study, it has been concluded based on examinations and statistical analyses that 1000 scenarios are adequate to represent the discussed parameters.

Afterward, the two sets of generated scenarios have been clustered by using the k-means algorithms. A sensitivity analysis has been performed to determine the most appropriate number of clusters. Accordingly, 4 clusters have been selected to represent the generated scenarios of each scenario set. The clusters have also been presented in Fig. 4. In addition, Table 5 describes the probability of the clusters. Also, Fig. 5 shows the loads' profile of the EHs based on data from Cao et al. (2019), Lu et al. (2020), Javadi et al. (2022).

3.2. Optimization results

Table 6 presents the optimal solutions for the operating cost of the case studies. In addition, in Cases 2 and 3, different combinations of participants in coalitions are investigated. Also, C_S denotes the coalition of the members of S. According to Table 6, the operation cost of all EHs

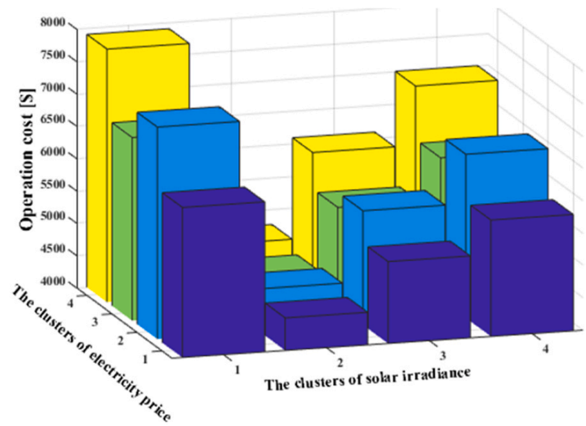


Fig. 6. Comparison of the total operation cost in Case 3 based on various clusters.

will decrease in cooperative strategies. Specifically, in Case 2, when all EHs share their facilities and cooperate with each other in $C_{2,4,6}$, the operation cost of the first EH (connected to bus No. $i = 2$), the second EH (connected to bus No. $i = 4$) , and the third one (connected to bus $i = 6$) reduce 4.7, 7.5, 4.5 $, respectively. In other words, the proposed model improves the operation cost for EHs 1, 2, and 3 by about 0.2 %, 0.3 %, and 0.2 %, respectively. Also, by comparing the total cost of the NEH, the most reduction belongs to coalition $C_{2,4,6}$, where the operating cost improves 0.3 % or 16.6 $. In addition, most of the overall gain in this coalition, determined by the efficacy and contribution of all participants, accrues to the second EH. Furthermore, the reduction in the operating cost depends on the members of the coalition. Hence, selecting the most profitable coalition for each EH through an effective selection mechanism is crucial, specifically in large-scale systems with a great

Table 7
Comparison of CO_2 emission in various case studies.

Case study	Entities in coalition S	Emission							
		First EH connected to bus No. $i = 2$		Second EH connected to bus No. $i = 4$		Third EH connected to bus No. $i = 6$		Total emission	
		Amount [kg]	Reduction [%]	Amount [kg]	Reduction [%]	Amount [kg]	Reduction [%]	Amount [kg]	Reduction [%]
Case 1	Without coalition	6649.5	0.0	7872.2	0.0	5987.9	0.0	20,509.6	0.0
Case 2	$C_{2,4}$	6482.3	2.5	7705.1	2.1	5987.9	0.0	20,175.3	1.6
	$C_{2,6}$	6633.6	0.2	7872.2	0.0	5972.0	0.3	20,477.9	0.2
	$C_{4,6}$	6649.5	0.0	7769.6	1.3	5885.3	1.7	20,304.4	1.0
	$C_{2,4,6}$	6528.9	1.8	7664.9	2.6	5931.9	0.9	20,125.7	1.9
Case 3	$C_{2,4}$	6483.2	2.5	7706.0	2.1	5987.9	0.0	20,177.1	1.6
	$C_{2,6}$	6638.4	0.2	7872.2	0.0	5976.9	0.2	20,487.6	0.1
	$C_{4,6}$	6649.5	0.0	7798.7	0.9	5914.4	1.2	20,362.5	0.7
	$C_{2,4,6}$	6518.2	2.0	7678.4	2.5	5949.3	0.6	20,145.9	1.8

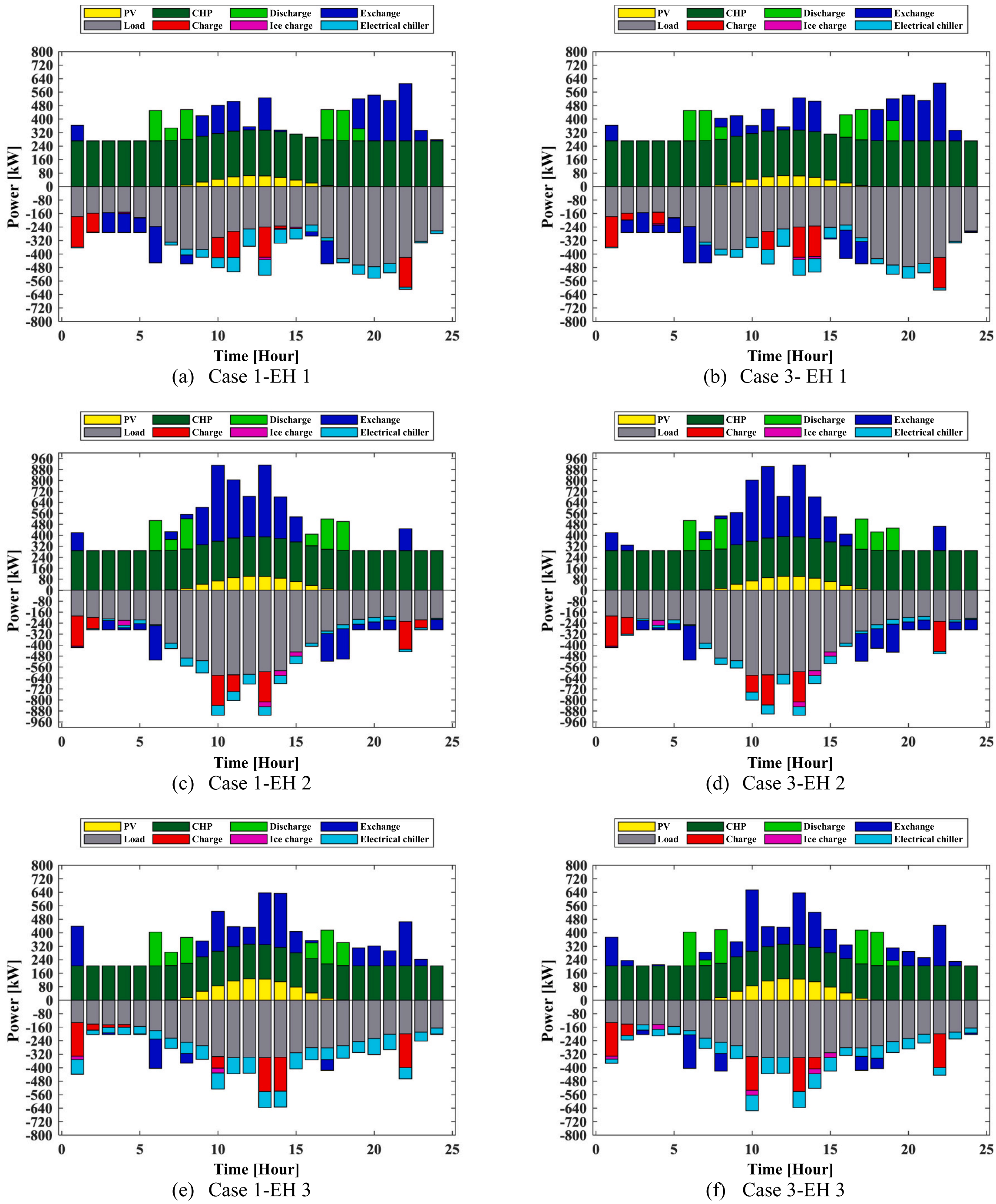


Fig. 7. Optimal scheduling of electrical generations/consumptions in Cases 1 and 3 under the first cluster of PV output power and the fourth cluster for electricity price.

number of players. For instance, by comparing the results of $C_{2,4}$ and $C_{2,6}$, it can be concluded that the operation cost of the second EH in coalition $C_{2,4}$ decreased 590 cents or 0.3 %, while in coalition $C_{2,6}$ has been improved by 0.2 %.

In Case 3, it has been assumed that EHs can simultaneously exchange heat and electricity power. Accordingly, comparing the costs in Cases 2 and 3, it can be concluded under the Case 3 scheme, through exchanging heat and electrical power among EHs, the coalitions are more profitable since more facilities can act in coalition to serve the loads optimally. For instance, comparing the results of $C_{2,4,6}$, in Cases 2 and 3, 169.1 $ more could be saved under Case 3. Useful comparisons can be deliberated upon the other coalitions. Particularly, in Case 2, $C_{2,4}$ is more profitable than $C_{2,6}$, while in Case 3, $C_{2,6}$ could be more effective in reducing operation costs.

Considering environmental issues, Unlike Bahmani et al. (2021), Jiang et al. (2021), the CO_2 emission treatment cost has been considered in the proposed model. In addition, although Lu et al. (2020), Poursmaeil et al. (2021) have studied the emission pollution cost in their model, just the amount of emission associated with the useful portion of natural gas has been considered, and the emission corresponds to the total purchased gas has not been concerned. For the sake of clarity, the emission has been calculated based on the output power of energy conversion facilities instead of input gas. Table 7 presents the optimization results for the emission of the case studies. As revealed by test

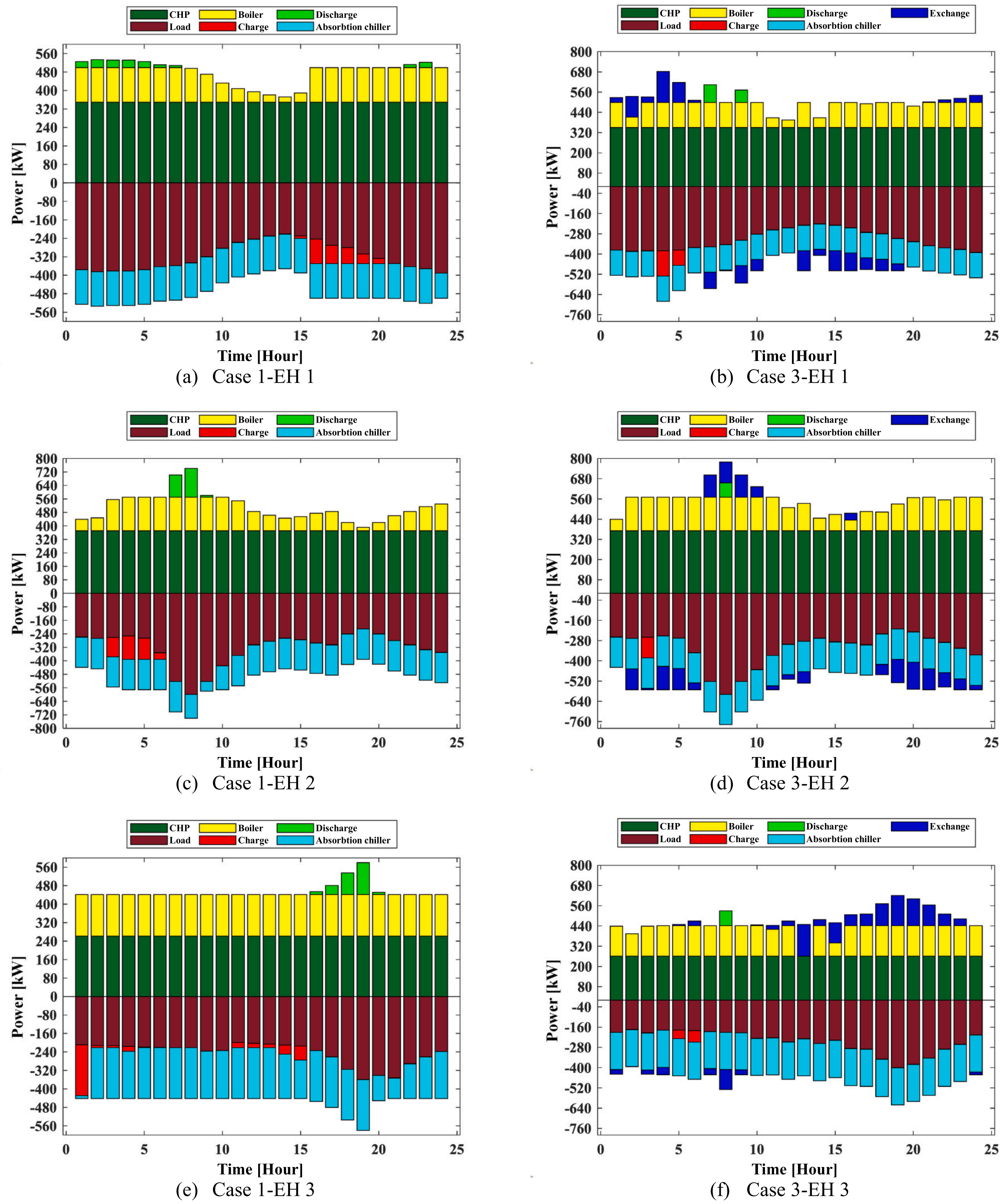
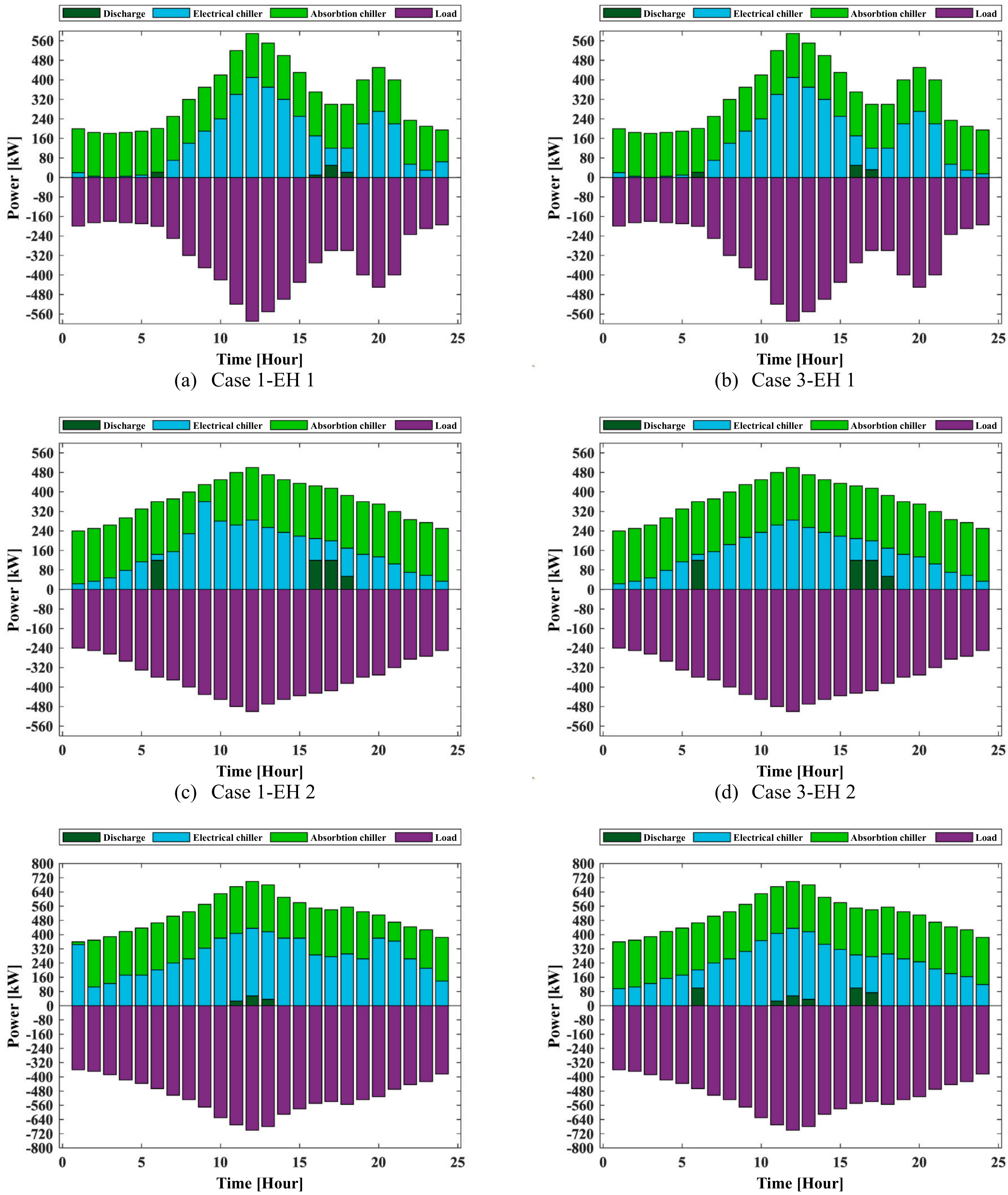


Fig. 8. Scheduling results of heat generations/consumptions in Cases 1 and 3 under the first cluster of PV output power and the fourth cluster for electricity price.

results shown in Table 7, the emission of understudy NEH has been reduced in cooperative strategies. For instance, under Case 2, in $C_{2,4,6}$, the emission of the first EH (connected to bus No. $i = 2$), the second EH (connected to bus No. $i = 4$), and the third one (connected to bus $i = 6$) has reduced 120.6, 207.3, 56 kg, or about 1.8 %, 2.6 %, and 0.9 %, respectively. In addition, comparing the results under case studies, it can be concluded that Case 3 is more environmentally-friendly for all coalitions. Specifically, by $C_{2,4,6}$ in Case 3, around 20 kg CO_2 decreases compared to Case 2.

Fig. 6 shows the total operation cost of EHs in different clusters of PV power generation and electricity price. By comparing the simulation results of clusters, it could be concluded that the optimal solution can drastically variate due to the uncertainties. Hence, applying the simplified deterministic formulation is not accurate enough to determine outcomes for the cooperation scheme. Moreover, from an operational perspective, inaccurate scheduling can incur additional costs or cause interruptions for the system. Accordingly, coping with uncertainties through an appropriate approach is crucial for managing energy in the EHs.

The optimum scheduling of electrical, heat, and cooling power in case studies one and three, in clusters r_1 and w_4, are shown in Figs. 7–9. It should be mentioned that clusters r_1 and w_4, among their related clusters set, has the least PV power generation and the highest electricity price, respectively. The optimization results of the electricity generation and consumption by the power sources, energy storage units as well as power consumers, including electrical chiller and ice storage unit, are



(a) Case 1-EH 1   (b) Case 3-EH 1

(c) Case 1-EH 2   (d) Case 3-EH 2

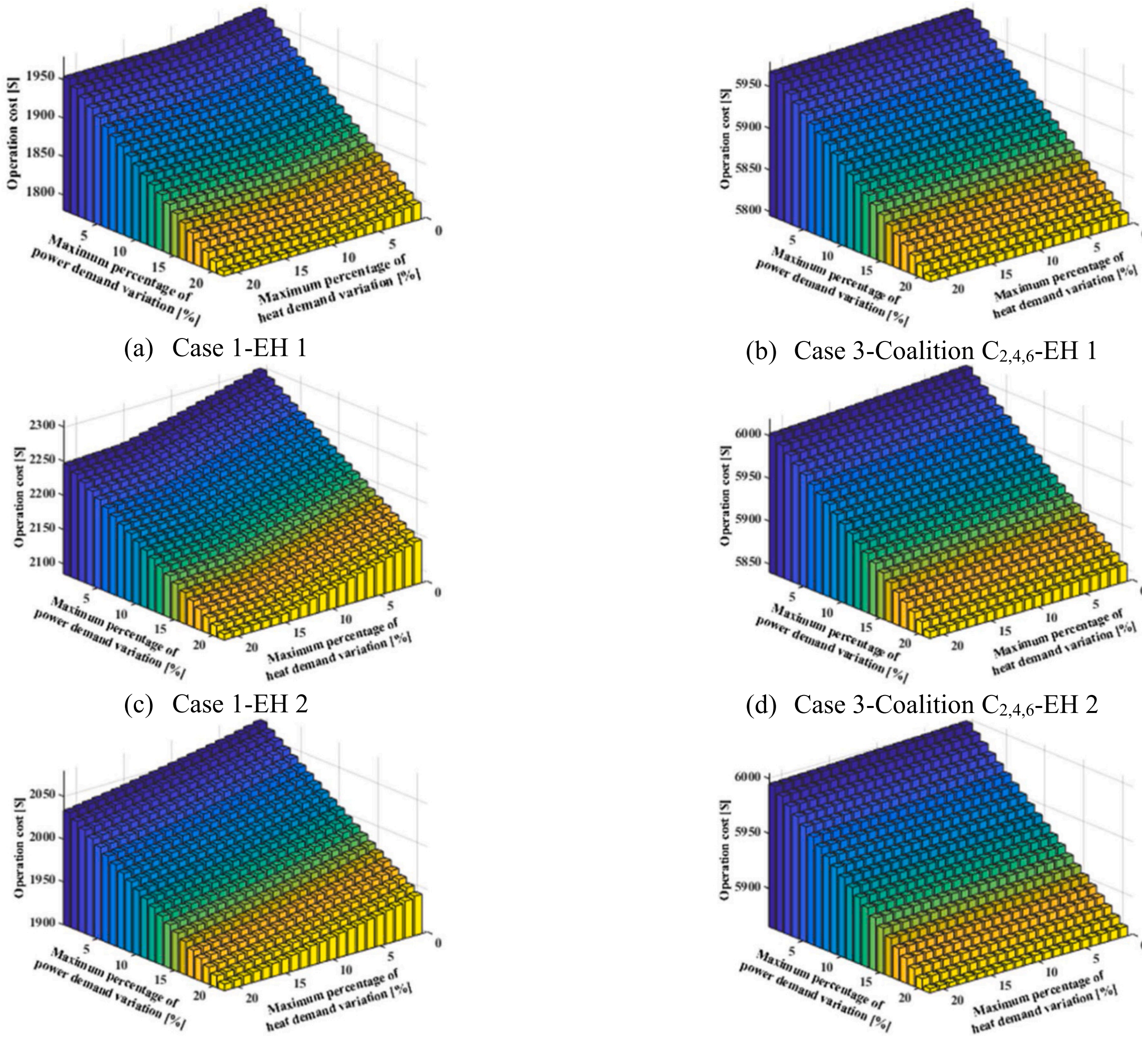
(e) Case 1-EH 3   (f) Case 3-EH 3

Fig. 9. Scheduling results of cooling generations/consumptions in Cases 1 and 3 under the first cluster of PV output power and the fourth cluster for electricity price.

depicted in Fig. 7. As can be seen, CHP units provided most of the demand during the day for all hubs, since the relatively lower gas price and the ability to co-generating heat and power. Moreover, by deploying energy storage units, the EHs import power at the relatively low-price intervals, during 9:00–14:00, which reduces their dependency on the upstream grid and makes a profit at the high-price intervals 15:00–19:00. Furthermore, EHs implement DRPs to shift the load, improving their ability to meet the demands.

Fig. 8 illustrates the power balance in the heat sub-EHs. In Case 1, under the autonomous strategy, the CHP units, the boilers, and the heat storage units contribute the most in providing heat load, respectively. In addition, the heat storages provide the demand on the on-peak load hours as an auxiliary supplier. Moreover, by comparing the result of Cases 1 and 3 in Fig. 8, it can be concluded that under Case 3 and the cooperative strategy, the EHs tend to transfer heating power with each other instead of utilizing their heat storage units which can reduce costs. Particularly, in 1:00–4:00 for EH 1, 6:00–7:00 for EH 2, and 17:00–19:00 for EH 3, the heat exchanges and related cost reductions appear in Case 3. As a result of exchanging heat energy through sharing the facilities, the EHs have more options and resources to supply their load more economical. In addition, by implementing heat DRPs, EHs have more flexibility to provide the required heat demands, and by shifting the heat load, they can reduce their operating costs.

The optimization results for the cooling sections are depicted in Fig. 9. The cooling loads are mainly supplied by ACs and ECs. In addition, by charging the ice storage units at low-price periods, a portion of



(a) Case 1-EH 1
(b) Case 3-Coalition $C_{2,4,6}$-EH 1
(c) Case 1-EH 2
(d) Case 3-Coalition $C_{2,4,6}$-EH 2
(e) Case 1-EH 3
(f) Case 3-Coalition $C_{2,4,6}$-EH 3

Fig. 10. Sensitivity analysis on operation cost for the autonomous strategy (Case 1) and Cooperative strategy (Coalition $C_{2,4,6}$ in Case 3).

stored ice is melted to supply the cooling demand at the on-peak loads resulting in reducing operating costs. By comparing the results of Cases 1 and 3, it can be concluded that under the cooperative scheme by exchanging heat and power (Case 3), the role of ACs, in all EHs, as well as ice storage unit, specifically in the third EH, has increased during the day resulting in more flexibility for the EHs under the cooperative energy management strategy.

4. Sensitivity analysis

To evaluate the impacts of maximum participation ratio for increasing/decreasing demand, including electricity and heat loads, in the DRPs on the corresponding total costs as well as emission, a sensitivity analysis is performed. Hence, the maximum participation ratios for loads in each EH are assumed to be changed from 0 % to 20 %, and the effect of changes in the operating costs and CO_2 emission of the EH in Case 1 as well as the operating costs and emissions of coalition $C_{2,4,6}$ in Case 3, are shown in Figs. 10 and 11. It should be mentioned that the participation ratio for increasing or decreasing demand has been considered equal ($P_i^{l,up,dr}=P_i^{l,dwn,dr}$ and $H_i^{l,up,dr}=H_i^{l,dwn,dr}$).

As shown in Figs. 10–11, regardless of the type of demand, raising the maximum participation ratio for heat and electricity loads results in a decrease in the total cost for EHs. Furthermore, by comparing the effectiveness of two different types of DRPs, it can be concluded that the electrical DRP is more efficient in reducing costs and emissions regardless of whether the EHs are in cooperative or autonomous schemes considering the higher electricity price as the most important factor. Also, considering $P_2^{l,up,dr}=0$ and $H_2^{l,up,dr}=20$, the operating cost of the first EH in Case 1 is reduced 15.6 $ or 0.7 %, while in coalition $C_{2,4,6}$ in Case 3, the operating cost of the EHs has decreased by 7.9$ or 0.1 %. Hence, it can be concluded that the thermal DRP can be more effective in autonomous strategy for the first EH in understudy NEH. By considering $P_2^{l,up,dr}=20$ and $H_2^{l,up,dr}=0$, the operating cost of the first EH in Case a has been decreased by 167.7 $ or 8.5 %, whereas for EH 1 participation in coalition $C_{2,4,6}$, the operating cost of the EHs has decreased by 166.6 $ or 2.7 %. Hence, in autonomous strategy (Case 1), it can be concluded that electrical DRP is more useful for EH 1.

In addition, the operating costs almost change linearly by the maximum participation ratio for electricity and heat loads in cooperative strategy, while there are some breaking points in the cost variations on the maximum participation ratio axis for heat loads in autonomous strategy. It has been highlighted, particularly for EHs 1 and 2 in Fig. 10, with the maximum percentage of heat demand participation of 9 % and 15 %, respectively. Furthermore, regardless of the type of demand, the DRPs bring about a reduction in emission for EHs under the cooperative strategy. However, implementing thermal DRP by EH 2 in a certain range of maximum demand participation, under autonomous operation, can increase the emission since the DRP is executed from an economic

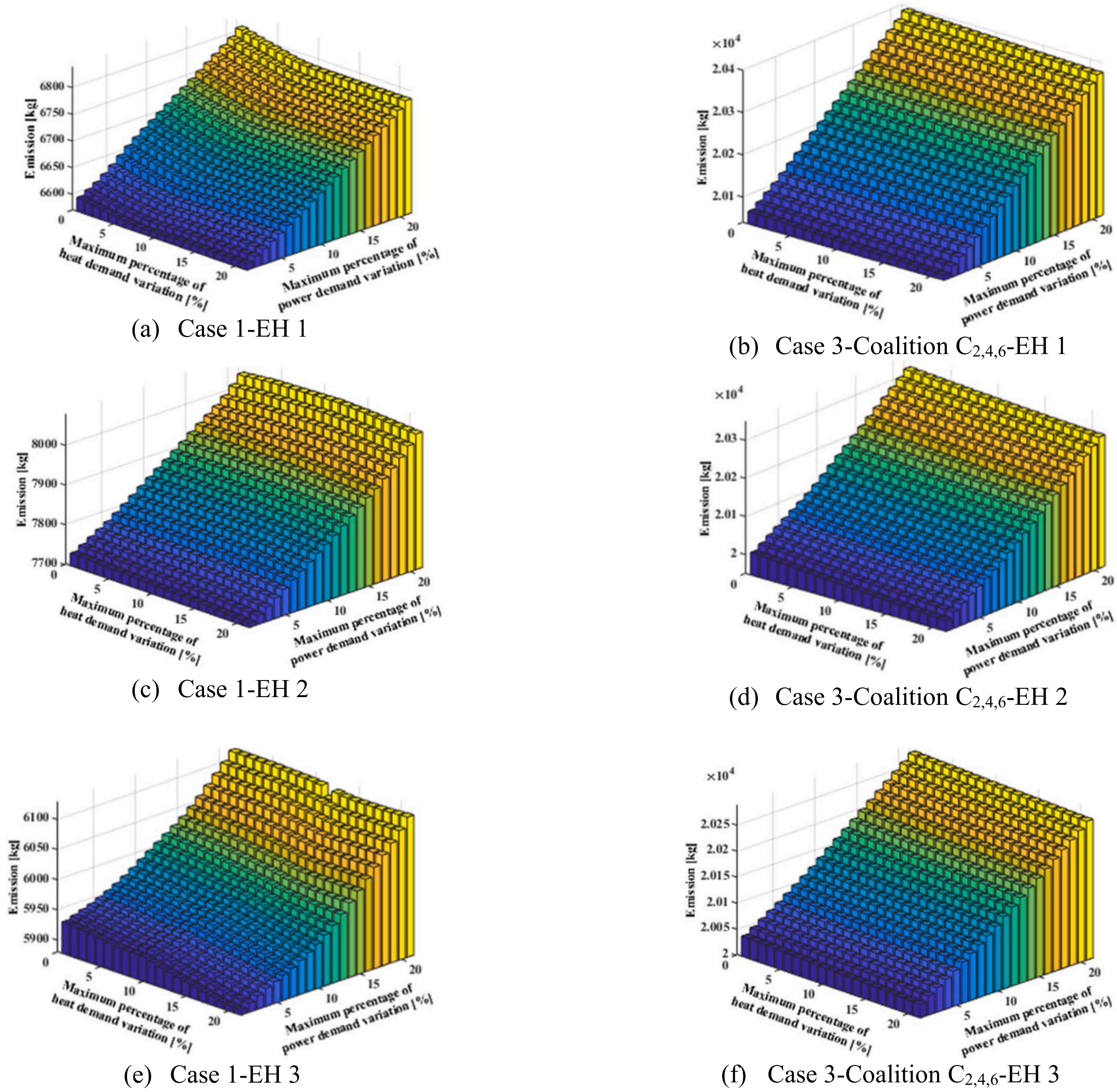


Fig. 11. Sensitivity analysis on emission for the autonomous strategy (Case 1) and Cooperative strategy (Coalition $C_{2,4,6}$ in Case 3).

viewpoint although the emission cost is considered (Fig. 11, EH 2). In addition, similar to the operating costs, the emissions almost change linearly by the maximum participation ratio for electricity and heating loads in cooperative strategy, whereas the emissions vary more chaotically by thermal DRP under the autonomous strategy, since the optimization problem aims to deploy the facilities with total minimum operating costs which may produce more pollutants. It should be noted that the emission of the EHs is more sensitive to the electrical DRP than the thermal DRP.

5. Conclusion

Different studies and methods have been developed to optimize the NEH operation. However, a research gap exists in proposing a new cooperative stochastic energy management for NEHs, considering techno-environmental prospectives, besides uncertainties modeling. This research has tried to fill such a research gap by proposing a new clustering-based cooperative energy management for NEHs. The EHs, by forming coalitions and sharing their resources, aims to reduce the total operation cost of the coalition. In the proposed cooperative framework, through a cost allocation method and based on the contribution and efficiency of EHs, the overall gain of cooperation is fairly divided among participants. In order to deal with uncertainties, including PV power output and electricity price, a cluster-based approach has been applied, utilizing the k-means algorithm. In addition, the role of energy storage systems and DRPs in EHs operation has been studied. Several case studies were considered and evaluated, investigating the autonomous and cooperative strategies with different operating modes, including transferring electricity and heat power among the EHs. Simulation results indicate that through cooperative strategies in the form of coalitions, the total cost of EHs, as well as CO_2 emission, will reduce by about 3 % and 1.8 %, respectively. Moreover, assessing the total cost and emission reduction of EHs in different coalitions reveals the necessity of a multi-criteria decision-making framework for EH owners, which is considered for future work by considering multi-objective models.

CRediT authorship contribution statement

Hamed Hashemi-Dezaki: Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Data curation. **Saeed Akbari:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **João Martins:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Data curation.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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