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Energy scheduling for a three-level integrated energy system based on energy hub models: A hierarchical Stackelberg game approach

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ABSTRACT

With the rapid development of information and energy generation technologies, the multi-level integrated energy system (IES) with multiple energy suppliers and end users has been vigorously promoted globally. In this study, the energy scheduling for a three-level IES is investigated by applying the hierarchical Stackelberg game approach. The IES is composed of one electricity utility company and one natural gas utility company (upper level), multiple same-structured smart energy hubs (S.E. hubs) that can produce electricity and heat simultaneously (middle level), and multiple users (lower level). By applying the Lagrange's function, the operation strategies of all market participants are derived with analytical solutions, which are verified by a decentralized algorithm developed in this study. Simulation results show that the increase in the number of S.E. hubs decreases the energy prices received by users, increases the energy demands, and decreases the profit of each S.E. hub; therefore, each S.E. hub strives to crowd out other S.E. hubs as much as possible. Technological advancement is an effective strategy for S.E. hubs to rise above the market competition; therefore, S.E. hubs whose technological levels are lower than those of others are at an obvious disadvantage.

1. Introduction

1.1. Motivation

With the continuous promotion of market reforms and rapid development of information technologies, the traditional monopolistic energy supply system, in which only one utility company supplies energy to meet the corresponding energy demands of all users, is gradually being replaced by hierarchical integrated energy systems (IESs). The IES is a multi-network that incorporates generation, storage, transportation, and conversion of multiple forms of energy in a single framework (Zhang et al., 2019). In a hierarchical IES, more suppliers, more users, and more energy generation facilities converge in one system at different levels to create a highly active and competitive energy market. Although traditional utility companies still exist, new energy supply companies with built-in distributed energy facilities have emerged as intermediaries between utility companies and users to provide a relatively wide range of options on energy procurement and consumption. On the one hand, these new companies act as the retailers and agents that distribute energy to users. On the other hand, the built-in distributed energy facilities enable the new companies to generate multiple forms of energy for users in more flexible ways. However, the addition of these new market participants, which can be modeled as smart energy hubs (S.E. hubs), has also contributed to the problems in the operation and coordination of the IES. Therefore, it is necessary and essential to investigate the energy scheduling of each market participant in the hierarchical IES integrated with S.E. hubs.

1.2. Literature survey

Energy scheduling has always been a crucial issue associated with IESs. In related studies, Wang et al. (2019a) studied the cogeneration mode for an IES, where a combined heat and power unit and a concentrating solar power plant were assembled. Using a game-theory planning method, Zhang et al. presented a planning model for an IES consisting of a natural gas system, an electricity system, and power-to-gas stations (Zhang et al., 2019). To find an efficient framework that combined sustainable design, reliable operation, and minimal lifetime cost for society, customers, and investors, a multi-objective optimization model for the design of an IES with an electric, thermal, and cooling subsystem was established by Wang et al. (2019b). Different from the multi-objective optimization that balances several variables at the same level (Aghaei & Alizadeh, 2013; Chen et al., 2018; Jing et al., 2012; Motevasel et al., 2013; Wu et al., 2017; Zhang et al., 2015; Zheng

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Nomenclature

Symbols

F	Objective function value ($)
C	Cost ($)
U	Utility ($)
S	Operation strategy
P	Electrical energy (MWh)
Q	Thermal energy (MWh)
G	Calorific value of natural gas (MWh)
P	Energy price ($/MWh)
η	Efficiency
a	Generation coefficient of electricity utility company ($/MWh^2)
b	Generation coefficient of electricity utility company ($/MWh)
c	Generation coefficient of electricity utility company ($)
d	Generation coefficient of natural gas utility company ($/MWh)
e	Generation coefficient of natural gas utility company ($)
cc	Generation coefficient of smart energy hub ($/MWh)
α	Preference coefficient of user ($/MWh^2)
β	Preference coefficient of user ($/MWh)
I	Number of smart energy hubs
K	Number of users
n	Number of iterations
θ	Threshold value ($/MWh)
σ	Constant value (MWh/$)
φ	Constant value (MWh/$)

Subscripts

EUC	Electricity utility company
GUC	Natural gas utility company
SEH	Smart energy hub
i	Index of smart energy hub
k	Index of user
MT	Microturbine
F	Furnace
T	Transformer
in	In
out	Out
e	Electricity
g	Gas
h	Heat

Acronyms

IES	Integrated energy system
S.E.	*Hub* smart energy hub
SLMF	Single-leader multi-follower
MLMF	Multi-leader multi-follower
SE	Stackelberg equilibrium

et al., 2018), the multi-level optimization could better reflect the actual hierarchical decision-making relationship in practical engineering (Bahramara et al., 2016; Han et al., 2016; Jin et al., 2018; Shi et al., 2005; White & Anandalingam, 1993; Wu et al., 2018). In multi–level optimization, Evins proposed a methodology to address the design and operation of a building and its energy system in three levels: building design, system design, and system operation (Evins, 2015). Bahramara et al. modeled a hierarchical decision–making framework to optimize the operation of a distribution company and microgrids (Bahramara et al., 2016). Stojiljković presented a methodology to formulate the multi–objective bi–level optimization of an energy supply system, where the upper–level decision makers decided the design and policy, while the plant operation was defined at a lower level (Stojiljković, 2017). Luo et al. utilized the bi-level optimization models to design and operate IESs at a neighborhood scale on isolated islands (Luo et al., 2018, 2019). In Ref. Wang et al. (2019c) presented a two-stage optimization method for a coupled capacity planning and operation problem, cast within the economical operation of an IES.

Multi-level optimization provides a basic feasible method to analyze hierarchical IESs, but it faces a challenge when dealing with the interactions between multiple same-type participants, where each participant strives to maximize his/her own benefit. To analyze the situations in which the decision variables of different participants are independently controlled, the game model is gradually introduced and applied in IESs (Andoni et al., 2017; Banez-Chicharro et al., 2017). The Stackelberg game model, in which the different status of players and the different order of players' actions are considered (Chen & Jing, 2019), can be established to investigate the supply and demand of energy in a hierarchical IES with multiple participants (Luh et al., 1982; Maharjan et al., 2013; Motalleb et al., 2018; Soliman & Leon-Garcia, 2014). Basically, these Stackelberg game models can be classified into single-leader multi-follower (SLMF) models and multi-leader multi-follower (MLMF) models. In terms of SLMF models, Yu et al. described a Stackelberg game model for electricity trading between one utility company and multiple users, which was aimed at balancing supply and demand and smoothing the aggregated load in the system (Yu & Hong, 2016). Meng et al. modeled the interactions between one utility company and its electricity customers as a 1-leader M-follower Stackelberg game. The authors adopted genetic algorithms to maximize the profit of the utility company, while the analytical solution on the side of customers was developed by the linear programming method (Meng & Zeng, 2013). Despite the electrical demand, Wang et al. studied the demand response of thermostatically controlled loads to control their set-point temperatures by considering the tradeoff between the electricity payment and user comfort preference; the specific energy trading process was formulated as a 1-leader M-follower Stackelberg game (Wang et al., 2018). Compared to the case of the SLMF models, the MLMF models could better simulate the real energy market transactions. In terms of the MLMF models, Paudel et al. proposed an MLMF Stackelberg model for peer-to-peer energy trading among the prosumers in a community micro-grid (Paudel et al., 2019). Yu et al. proposed a novel incentive-based demand response model to enable the electricity dispatch between three levels of participants, which included a grid operator, multiple service providers, and the corresponding customer (Yu & Hong, 2017). In Ref. Sheikhi et al. (2015a, 2015b) formulated the interaction between multiple S.E. hubs as a non-cooperative game. In that study, customers in S.E. hubs employed the energy management system to access the electricity and natural gas price data, to wisely manage their daily energy consumption. With energy hubs integrated in the system, but not on the side of users, Wei et al. proposed a hierarchical MLMF Stackelberg game model for analyzing the multiple energy trading problem in an IES, wherein distributed energy stations led the game to decide the unit prices of electricity and cooling energies they generated, while energy users performed as followers determining the amounts of energies to consume (Wei et al., 2017). To maximize the total payoff of all the participants, Zhang et al. employed a virtual leader-follower Stackelberg game model to achieve a reliable collaboration among the agents in an IES, and Q-learning was adopted for the knowledge learning for each participant (Zhang et al., 2017).

1.3. Contributions

A considerable number of MLMF Stackelberg game models have been developed to study the energy interactions between market participants in multi-level IESs; however, most of these models were only concerned with the energy pricing and energy interactions between the utility companies and users (Paudel et al., 2019; Sheikhi et al., 2015a, 2015b; Yu & Hong, 2016), or between the distributed energy facilities and users (Amrollahi & Bathaee, 2017; Bahramara et al., 2019; Das & Al-Abdeli, 2017; Luo et al., 2018). In some studies wherein utility companies, distributed energy facilities, and users were all taken into consideration, either the distributed energy facilities were owned and operated by the users (Karmellos & Mavrotas, 2019; Karmellos et al., 2019; Paudel et al., 2019), or the energy pricing scheme was fixed (Chen & Jing, 2019; Wei et al., 2017); therefore, the market participation and market influence of grid companies and distributed energy facilities were always underestimated. Besides, in most of the aforementioned MLMF Stackelberg game models, the system parameters of different energy providers, e.g., system efficiencies and generation coefficients, were assumed to be identical (Bahrami & Sheikhi, 2016; Sheikhi et al., 2015a; Wei et al., 2017), which is inconsistent with the engineering facts. To analyze the dynamic economic transactions and energy interactions between every two levels within a multi-level IES, this study applied the hierarchical MLMF Stackelberg game model to investigate the operation of a competitive three-level IES, which was composed of one electricity utility company (EUC), one natural gas utility company (GUC), multiple S.E. hubs with different system parameters, and multiple users. The simulation results can be used as a reference for energy scheduling by relevant stakeholders. The main contributions are as follows:

- The dynamic energy pricing scheme and energy interactions of a three-level IES, which is composed of the utility companies, S.E. hubs, and users, are studied by formulating a hierarchical MLMF Stackelberg game model.
- The analytical solution of the optimal operation of each market participant is derived and verified by an iterative decentralized algorithm.
- The established IES case implies that technical improvement is of great importance to S.E. hubs, particularly for those that already have certain technological advantages.

The remainder of this paper is organized as follows: Section 2 introduces the proposed energy system and the formulation of the problem. Section 3 proves the existence and uniqueness of the Stackelberg equilibrium (SE) of this Stackelberg game. Section 4 develops the iterative algorithm to achieve the SE. The results of the SE are presented and discussed in Section 5. Finally, Section 6 presents the conclusions of the study.

2. System model and problem formulation

2.1. System model

Due to the intensifying contradiction between human social development and conventional energy supply structure, the demand for the structural transformation of energy supply has increased globally. Multi-level IESs, which are commonly composed of utility companies, distributed energy stations, and users, are expected to replace the monopolistic mode of energy supply in the future energy retail market.

Fig. 1 depicts a three-level IES composed of one EUC, one GUC, I S.E. hubs, and K users. In this system, the energy demands of users comprise of electricity and heating, which are both provided by the S.E. hubs. All the S.E. hubs in the system share the same structure with one micro turbine and one furnace integrated into it, although the system efficiencies and generation coefficients are different. The micro turbine is used to produce electricity and heat from natural gas, while the furnace only produces heat. The electrical output of each S.E. hub is the sum of the electricity purchased from the EUC and the electrical output from the micro turbine; the thermal output of each S.E. hub is the sum

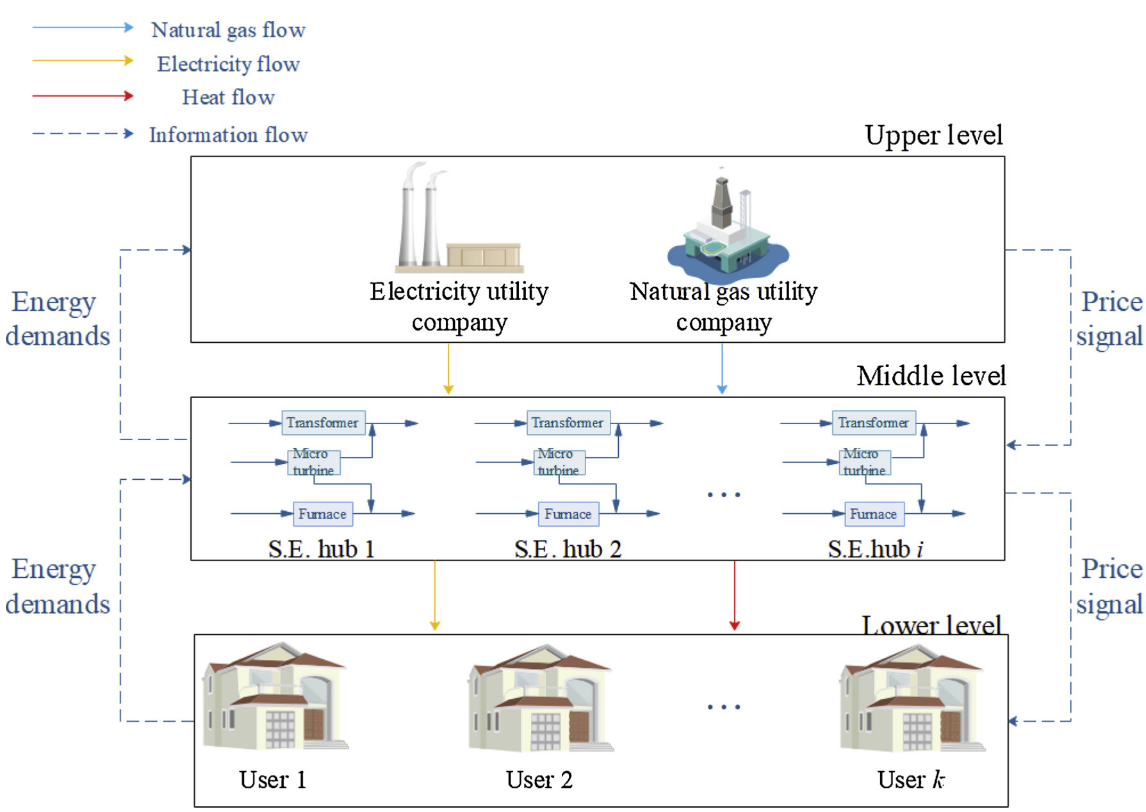


Fig. 1. Framework of the energy trading process in the IES.

of the thermal output of the micro turbine and the output of the furnace. The GUC is responsible for supplying natural gas to the micro turbine and furnace inside every S.E. hub. Smart metering enables the participants on different sides to interact by exchanging price and demand information; thus, the optimized operation of the IES can be ultimately achieved.

2.1.1. Utility

Utility companies adjust their energy outputs and energy prices as demands change; consequently, the energy supply to the IES and profits of the utility companies can be both guaranteed. The objective of the EUC is to maximize its profit, which is the difference between the revenue gained from selling electricity to the S.E. hubs and the cost of generating the corresponding amount of electricity. Thus, the optimization problem of the EUC can be written in the following form:

$$\begin{aligned}&\max F_{EUC} = \max\left[p_{e,EUC}P_{EUC} - C_e(P_{EUC})\right]\\&s.\ t.\ C_e(P_{EUC}) = \frac{a}{2}(P_{EUC})^2 + bP_{EUC} + c\\&P_{EUC} = \sum_{i\in I} P_{i,in}\end{aligned} \tag{1}$$

where $C_e(P_{EUC})$ is the generation cost of the EUC and is a polynomial function of P_{EUC} (Sheikhi et al., 2015a); a, b, and c are the generation coefficients of the EUC; $p_{e,EUC}$ is the price of electricity that the EUC sells to the S.E. hubs; P_{EUC} is the amount of electricity that the EUC produces and provides to the S.E. hubs; and $P_{i,in}$ is the electrical input of S.E. hub i.

For the natural gas utility company, the objective function and equality constraints are

$$\begin{aligned}&\max F_{GUC} = \max\left[p_g G_{GUC} - C_g(G_{GUC})\right]\\&s.\ t.\ C_g(G_{GUC}) = dG_{GUC} + e\\&G_{GUC} = \sum_{i\in I}(G_{i,in}^{MT} + G_{i,in}^{F})\end{aligned} \tag{2}$$

where $C_g(G_{GUC})$ is the generation cost of the GUC and is an increasing linear function of G_{GUC} (Sheikhi et al., 2015a); d and e are the generation coefficients of the GUC, they are positive coefficients of the polynomial function and are known by the natural gas utility company; p_g is the price of the gas that the GUC sells to S.E. hubs; G_{GUC} is the amount of gas that the GUC produces and provides to the S.E. hubs. $G_{i,in}^{MT}$ is the input of the micro turbine in S.E. hub i, and $G_{i,in}^{F}$ is the input of the furnace in S.E. hub i

2.1.2. Smart energy hub

Energy hub models, which are considered as interfaces between different energy infrastructures and demands, can be used to simplify the analysis of the system operation and energy interconnection within a complicated IES (Gholizadeh et al., 2019). From a systematic point of view, the energy hub is a structural unit that provides a basic input-output interface where different forms of energy can be generated, transformed, and stored (Sheikhi et al., 2015a). An energy hub is called a S.E. hub when it is equipped with smart grid technologies, such as an energy management system, to transmit or receive real-time data about the energy carriers' price values and load consumption to or from the utility companies via a two-way communication system (Sheikhi et al., 2015b, 2015c). In the IES of this study, all the S.E. hubs share the same structure as illustrated in Fig. 2.

In this IES, the S.E. hubs play intermediate roles between the utility companies and users because they purchase electricity and gas from the EUC and GUC, respectively, and then produce and sell electricity and heat to the users. We assume that the objective function of S.E. hub i is to maximize its profit; thus, the optimization problem of S.E. hub i holds the following structure:

$$\begin{aligned}&\max F_i = \max\left[P_{i,out}p_{e,SEH} + Q_{i,out}p_h - P_{i,in}p_{e,EUC}\right.\\&\qquad\left. - (G_{i,in}^{MT} + G_{i,in}^{F})(p_g + cc_i)\right]\\&s.\ t.\ \sum_{i\in I} P_{i,out} = \sum_{k\in Z} P_k\\&\sum_{i\in I} Q_{i,out} = \sum_{k\in Z} Q_k\end{aligned} \tag{3}$$

where $P_{i,out}$ and $Q_{i,out}$ are the electrical and thermal output of S.E. hub i, respectively; $p_{e,SEH}$ and p_h are the prices of the electricity and heat, respectively, that users receive from the S.E. hubs; cc_i is the generation coefficient of S.E. hub i; and P_k and Q_k are the electricity and heat demands of user k, respectively.

In S.E. hub i, the input and output energy carriers are related to each other according to the following expressions:

$$P_{i,out} = \eta_T P_{i,in} + \eta_{i,MT}^{e} G_{i,in}^{MT} \tag{4}$$

$$Q_{i,out} = \eta_{i,MT}^{g} G_{i,in}^{MT} + \eta_i^{F} G_{i,in}^{F} \tag{5}$$

2.1.3. User

Users trade with the S.E. hubs for energy. When the S.E. hubs announce the selling price, users who are aware of the information will adjust their energy consumption load according to the price. In this study, it is assumed that only electricity and heat demands exist for users, and no technologies are installed in buildings. Both the electricity and heat demands of users are met by the S.E. hubs. The adjustment strategies of user k are closely related to his /her optimization objective, which has the following expression:

$$\max F_k = \max(U^k - p^{e,SEH}P^k - p^h Q^k) \tag{6}$$

where U_k denotes the satisfaction gain of user k as a function of his/her consumed energy P_k and Q_k (Wei et al., 2017). Residential customers may have different responses to the same price. The different responses of different customers to various electricity and heat prices scenarios can be modeled analytically by adopting the concept of utility function from microeconomics (Sheikhi et al., 2015a). In this study, the utility function is measured in monetary unit, and the expression of U_k is as follows:

$$U^k = \left[-\frac{1}{2}\alpha_{p,k}(P^k)^2 + \beta_{p,k}P^k\right] + \left[-\frac{1}{2}\alpha_{q,k}(Q^k)^2 + \beta_{q,k}Q^k\right] \tag{7}$$

where $\alpha_{p,k}$ and $\beta_{p,k}$ are the electricity preference coefficients, which reflect the demand preference of user k in regard to electricity; $\alpha_{q,k}$ and $\beta_{q,k}$ are the heat preference coefficients, which reflect the demand preference of user k in regard to heat. A user with a relatively high $\beta_{p,k}$ and $\beta_{q,k}$ prefers to consume more P_k and Q_k to improve his/her satisfaction level.

2.2. Problem formulation

In Stackelberg games, once followers observe the strategy of the leader, they decide how best to react. Leaders realize that each follower

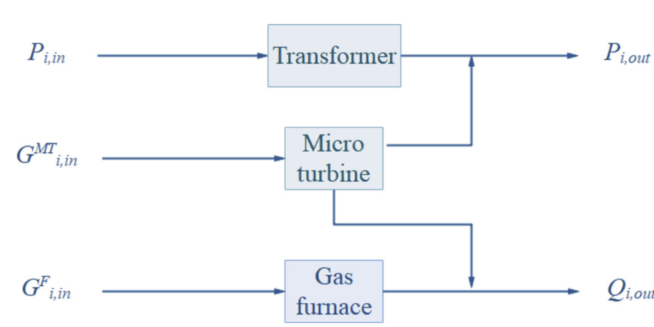


Fig. 2. Schematic diagram of the smart energy hub in the IES.

chooses his/her best response according to the strategies of leaders. Therefore, leaders optimize their utility functions and anticipate the expected response from their followers. The presented system model has a three-level structure; consequently, the hierarchical Stackelberg game, which is a specific multi-loop Stackelberg game, is suitable for formulating the problem. In the upper loop of the Stackelberg game model, the EUC and GUC act as leaders, and the S.E. hubs act as followers; in the lower loop, the S.E. hubs act as leaders, and the users act as followers. For this hierarchical Stackelberg game, a set of strategies constitute the SE if and only if the following constraints can be satisfied:

$$S_{EUC}^{*} = \arg\max_{S_{EUC}} F_{EUC}(S_{EUC}, S_{GUC}^{*}, \mathbf{S}_i^{*}, \mathbf{S}_k^{*}) \tag{8}$$

$$S_{GUC}^{*} = \arg\max_{S_{GUC}} F_{GUC}(S_{EUC}^{*}, S_{GUC}, \mathbf{S}_i^{*}, \mathbf{S}_k^{*}) \tag{9}$$

$$S_i^{*} = \arg\max_{S_i} F_i(S_{EUC}^{*}, S_{GUC}^{*}, S_i, \mathbf{S}_{-i}^{*}, \mathbf{S}_k^{*}) \tag{10}$$

$$S_k^{*} = \arg\max_{S_k} F_k(S_{EUC}^{*}, S_{GUC}^{*}, \mathbf{S}_i^{*}, S_k, \mathbf{S}_{-k}^{*}) \tag{11}$$

where $\boldsymbol{S}_{-i}$ denotes the strategies of all S.E. hubs except S.E. hub i; $\boldsymbol{S}_{-k}$ denotes the strategies of all users except user k, and S_{EUC}^{*}, S_{GUC}^{*}, S_i^{*}, and S_k^{*} represent the optimal operation strategies of the EUC, GUC, S.E. hub i, and user k in the SE, respectively. Eqs. (8)–(11) signify that, when all players are at an SE, no user can increase his/her utility by choosing a different strategy other than S_k^{*}, and no S.E. hub can improve its profit by deviating to other strategies other than S_i^{*}; in addition, the EUC and GUC cannot further increase their profit by choosing strategies other than S_{EUC}^{*} and S_{GUC}^{*} (Yu & Hong, 2017).

3. Existence and uniqueness of the Stackelberg equilibrium

In this hierarchical Stackelberg game wherein participants exist in three levels, the premise of the existence and uniqueness of the SE is that each layer of the game has and only has one Nash equilibrium (NE). The NE ensures that when all participants adopt the equilibrium strategy, participants cannot increase their own profits by changing their own strategy alone. In other words, the equilibrium strategy is one that maximizes the utility or profit of each rational participant in the market environment. If analytical solutions could be achieved at the side of each participant, then the optimal strategies of the Stackelberg game can be obtained. In this section, we will derive the analytical solution of each participant's operation strategies and prove the existence and uniqueness of the SE thereby. Notably, this model is based on the assumption of a perfectly competitive energy market. The process of proving the SE and obtaining the analytical solutions of the Stackelberg game model is illustrated in Fig. 3.

3.1. User side

The market is perfectly competitive; consequently, the market prices will not be influenced by any individual behavior as each participant has an infinitesimal influence on the market. Thus, each S.E. hub will charge users with the same unit price when SE is achieved (Wei et al., 2017). Therefore, the objective function of the user can be formulated as follows:

$$F_k = \left[-\frac{1}{2}\alpha_{p,k}(P^k)^2 + \beta_{p,k}P^k\right] - p^{e,SEH}P^k + \left[-\frac{1}{2}\alpha_{q,k}(Q^k)^2 + \beta_{q,k}Q^k\right] - p^h Q^k \tag{12}$$

As can be observed, the objective function of the users is strictly concave and continuous differentiable. To obtain the optimal response of user k with the aim to maximize his/her welfare, the first-order derivatives of the objective with respect to the electrical and thermal demands are assumed to be equal to zero as follows:

$$\begin{cases} -\alpha_{p,k}P^k + \beta_{p,k} - p^{e,SEH} = 0 \\ -\alpha_{q,k}Q^k + \beta_{q,k} - p^h = 0 \end{cases} \tag{13}$$

Thus, the optimal demand response of user k can be calculated according to Eq. (13) as

$$\begin{cases} P^k = \dfrac{\beta_{p,k}}{\alpha_{p,k}} - \dfrac{1}{\alpha_{p,k}}p^{e,SEH} \\ Q^k = \dfrac{\beta_{q,k}}{\alpha_{q,k}} - \dfrac{1}{\alpha_{q,k}}p^h \end{cases} \tag{14}$$

3.2. Utility side

By determining the first-order derivative of Eq. (1), the optimal electricity price offered by EUC can be calculated as

$$p_{e,EUC} = \frac{\partial c_e}{\partial P_{EUC}} = aP_{EUC} + b \tag{15}$$

Similarly, the solution to the optimization problem in Eq. (2) is

$$p_g = \frac{\partial c_g}{\partial G_{GUC}} = d \tag{16}$$

3.3. Smart energy hub side

All the S.E. hubs in this game selfishly pursue their own profits with strategies different from each other. However, if the NE in this non-cooperative game between the S.E. hubs exists, and if this is a perfect competition market, the electricity price and heat price announced by each S.E. hubs would reach the same value at the NE (Wei et al., 2017). To achieve the optimal strategy of S.E. hub i, the equation of the constrained optimization problem defined in Eq. (3) needs to be solved first. Here, the Lagrange's function is used to convert the constrained optimization problem into a non-constrained one. The Lagrange's function of the optimization problem can be formulated as follows:

$$L(F^i) = P^{i,out}p^{e,SEH} + Q^{i,out}p^h - P^{i,in}(a\sum_{i\in I}P_{i,in} + b) - (G_{i,in}^{MT} + G_{i,in}^{F})(d + cc_i) + \mu^{i,1}\left(\sum_{i\in I}P^{i,out} - \sum_{k\in Z}P^k\right) + \mu^{i,2}\left(\sum_{i\in I}Q^{i,out} - \sum_{k\in Z}Q^k\right) \tag{17}$$

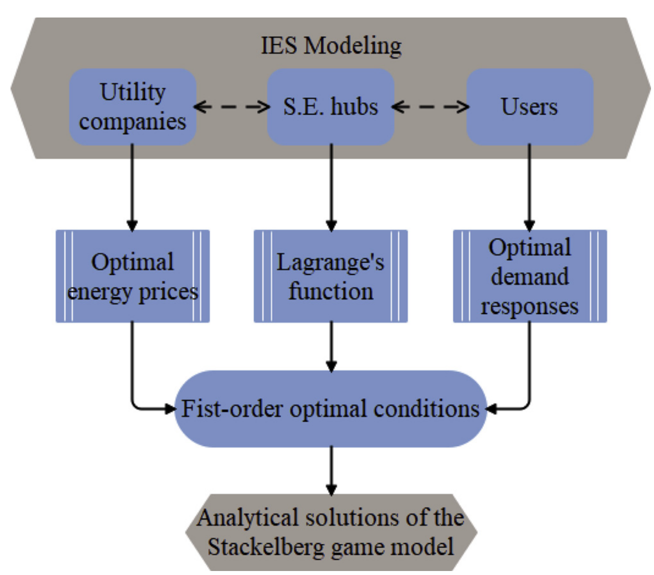


Fig. 3. Schematic diagram of the process to prove the Stackelberg equilibrium.

where $\mu_{i,1}$ and $\mu_{i,2}$ are the Lagrange's multipliers.

By substituting Eqs. (4) and (5) into Eq. (17), the first-order optimal condition gives

$$\frac{\partial F^i}{\partial p^{e,SEH}} = \eta_T P^{i,in} + \eta_{i,MT}^e G_{i,in}^{MT} + \sum_{k\in Z} \frac{\mu^{i,1}}{\alpha_{p,k}} = \eta_T P^{i,in} + \eta_{i,MT}^e G_{i,in}^{MT} + A\mu^{i,1} = 0 \quad (18)$$

$$\frac{\partial F^i}{\partial p^h} = \eta_{i,MT}^g G_{i,in}^{MT} + \eta_i^F G_{i,in}^F + \sum_{k\in Z} \frac{\mu^{i,2}}{\alpha_{q,k}} = \eta_{i,MT}^g G_{i,in}^{MT} + \eta_i^F G_{i,in}^F + B\mu^{i,2} = 0 \quad (19)$$

$$\frac{\partial F^i}{\partial \mu^{i,1}} = \sum_{i\in I} (\eta_F P^{i,in} + \eta_{i,MT}^e G_{i,in}^{MT}) - \sum_{k\in Z} \left(\frac{\beta_{p,k}}{\alpha_{p,k}} - \frac{1}{\alpha_{p,k}} p^{e,SEH}\right) = \sum_{i\in I} (\eta_F P^{i,in} + \eta_{i,MT}^e G_{i,in}^{MT}) - D + Ap^{e,SEH} = 0 \quad (20)$$

$$\frac{\partial F^i}{\partial \mu^{i,2}} = \sum_{i\in I} (\eta_{i,MT}^g G_{i,in}^{MT} + \eta_i^F G_{i,in}^F) - \sum_{k\in Z} \left(\frac{\beta_{q,k}}{\alpha_{q,k}} - \frac{1}{\alpha_{q,k}} p^h\right) = \sum_{i\in I} (\eta_{i,MT}^g G_{i,in}^{MT} + \eta_i^F G_{i,in}^F) - E + Bp^h = 0 \quad (21)$$

$$\frac{\partial F_i}{\partial P_{i,in}} = p_{e,SEH}\eta_T - 2aP_{i,in} - \left(a \sum_{j\in I, j\neq i} P_{j,in} + b\right) + \mu_{i,1}\eta_T = p_{e,SEH}\eta_T - aP_{i,in} - a\sum_{i\in I} P_{i,in} - b + \mu_{i,1}\eta_T = 0 \quad (22)$$

$$\frac{\partial F_i}{\partial G_{i,in}^{MT}} = p_{e,SEH}\eta_{i,MT}^e + p_h\eta_{i,MT}^g - d - cc_i + \mu_{i,1}\eta_{i,MT}^e + \mu_{i,2}\eta_{i,MT}^g = 0 \quad (23)$$

$$\frac{\partial F_i}{\partial G_{i,in}^F} = p_h\eta_i^F - d - cc_i + \mu_{i,2}\eta_i^F = 0 \quad (24)$$

According to Eqs. (18)–(21), the expressions of electricity price, heat price, and Lagrange multipliers can be expressed as

$$\mu^{i,1} = -\frac{\eta_T}{A} P^{i,in} - \frac{\eta_{i,MT}^e}{A} G_{i,in}^{MT} \quad (25)$$

$$\mu^{i,2} = -\frac{\eta_{i,MT}^g}{B} G_{i,in}^{MT} - \frac{\eta_i^F}{B} G_{i,in}^F \quad (26)$$

$$p^{e,SEH} = \frac{D - \sum_{i\in I} (\eta_T P^{i,in} + \eta_{i,MT}^e G_{i,in}^{MT})}{A} \quad (27)$$

$$p^h = \frac{E - \sum_{i\in I} (\eta_{i,MT}^g G_{i,in}^{MT} + \eta_i^F G_{i,in}^F)}{B} \quad (28)$$

where $A = \sum_{k\in K} \frac{1}{\alpha_{p,k}}$, $B = \sum_{k\in K} \frac{1}{\alpha_{q,k}}$, $D = \sum_{k\in K} \frac{\beta_{p,k}}{\alpha_{p,k}}$, and $E = \sum_{k\in K} \frac{\beta_{q,k}}{\alpha_{q,k}}$.

The relationships between energy prices and S.E. hub energy inputs can be obtained from Eqs. (22)–(24) and expressed as

$$p_{e,SEH} + \mu_{i,1} = H_i(d + cc_i) = \frac{a(P_{i,in} + \sum_{i\in I} P_{i,in}) + b}{\eta_T} \quad (29)$$

$$p_h + \mu_{i,2} = \frac{d + cc_i}{\eta_i^F} \quad (30)$$

where $H_i = \frac{\eta_i^F - \eta_{i,MT}^g}{\eta_{i,MT}^e \eta_i^F}$

Eq. (29) defines the quantitative relation between the electrical input of S.E. hub i and the total electrical input of all the S.E. hubs. Note that Eq. (29) applies to each S.E. hub. Thus, by adding together Eq. (29) for each S.E. hub, we can obtain the electrical inputs of all the S.E. hubs as follows:

$$\sum_{i\in I} P_{i,in} = \frac{\eta_T G - bI}{a(I+1)} \quad (31)$$

where $G = \sum_{i\in I} H_i(d + cc_i)$.

η_T is same for all the DESs; consequently, the following equation holds.

$$\sum_{i\in I} \eta_T P_{i,in} = \eta_T \sum_{i\in I} P_{i,in} = \frac{\eta_T(\eta_T G - bI)}{a(I+1)} \quad (32)$$

By substituting Eq. (31) into Eq. (29), $\eta_T P_{i,in}$ can be expressed as

$$\eta_T P_{i,in} = \eta_T \left[\frac{\eta_T H_i(d + cc_i) - b}{a} - \frac{\eta_T G - bI}{a(I+1)}\right] \quad (33)$$

Based on Eqs. (29), (32) and (33), the expression of $\sum_{i\epsilon I} \eta_{i,MT}^e G_{i,in}^{MT}$ can be obtained as follows:

$$\sum_{i\in I} \eta_{i,MT}^e G_{i,in}^{MT} = \frac{aID - aAG - \eta_T(\eta_T G - bI)}{a(I+1)} \quad (34)$$

Thus, the expression of $\eta_{i,MT}^g G_{i,in}^{MT}$ can be derived as

$$\eta_{i,MT}^g G_{i,in}^{MT} = \left\{ \begin{array}{l} D - \frac{\eta_T(\eta_T G - bI)}{a(I+1)} - \frac{aID - aAG - \eta_T(\eta_T G - bI)}{a(I+1)} \\ - \eta_T \left[\frac{\eta_T H_i(d + cc_i) - b}{a} - \frac{\eta_T G - bI}{a(I+1)}\right] - AH_i(d + cc_i) \end{array} \right\} \cdot \frac{\eta_{i,MT}^g}{\eta_{i,MT}^e} \quad (35)$$

To simplify the expression, $\sum_{i\in I} \eta_{i,MT}^g G_{i,in}^{MT}$ is substituted by J as follows:

$$\sum_{i\in I} \eta_{i,MT}^g G_{i,in}^{MT} = \sum_{i\in I} \left\{ \begin{array}{l} D - \frac{\eta_T(\eta_T G - bI)}{a(I+1)} - \frac{aID - aAG - \eta_T(\eta_T G - bI)}{a(I+1)} \\ - \eta_T \left[\frac{\eta_T H_i(d + cc_i) - b}{a} - \frac{\eta_T G - bI}{a(I+1)}\right] - AH_i(d + cc_i) \end{array} \right\} \cdot \frac{\eta_{i,MT}^g}{\eta_{i,MT}^e} = J \quad (36)$$

Thus, the expression of $\sum_{i\epsilon I} \eta_i^F G_{i,in}^F$ can be derived as the following according to Eqs. (26), (28), and (30):

$$\sum_{i\in I} \eta_i^F G_{i,in}^F = \frac{EI - BM - (I+1)J}{I+1} \quad (37)$$

where $M = \sum_{i\in I} \frac{d + cc_i}{\eta_i^F}$.

By substituting Eq. (32), Eq. (34), and Eqs. (36) and (37) into Eqs. (27) and (28), the electricity and heat prices in the market can be obtained as

$$p_{e,SEH} = \frac{D + AG}{A(I+1)} \quad (38)$$

$$p_h = \frac{E + BM}{B(I+1)} \quad (39)$$

The relationship of the total S.E. hubs output and energy prices can be derived as

$$\sum_{i\in I} \eta_T P_{i,in} + \sum_{i\in I} \eta_{i,MT}^e G_{i,in}^{MT} = \sum_{i\in I} P_{i,out} = A(p_{e,SEH} I - G) \quad (40)$$

$$\sum_{i\in I} \eta_{i,MT}^g G_{i,in}^{MT} + \sum_{i\in I} \eta_i^F G_{i,in}^F = \sum_{i\in I} Q_{i,out} = B(p_h I - M) \quad (41)$$

Thus far, the closed-form expressions for the optimal strategies of each participant are all obtained. As can be seen, one unique optimal strategy exists for each participant; therefore, the SE of this Stackelberg game can be reached.

4. Algorithm

To verify the correctness of the analytical solutions derived in Section 3, a decentralized algorithm (Bahrami & Sheikhi, 2016; Bahrami et al., 2017, 2018) is developed to determine the energy prices in the market. In this algorithm, the EUC is responsible for determining $p_{e,EUC}$, while the S.E. hubs are responsible for determining $p_{e,SEH}$ and p_h within each iteration; p_g has been confirmed to be a constant value; thus, it is considered as a value of d in accordance with Eq. (16) in the procedure of iteration. The following constraints must hold between the EUC and S.E. hubs in each iteration:

$$P_{EUC} = \sum_{i \in I} P_{i,in} = \frac{\sum_{i \in I} P_{i,out} - \sum_{i \in I} \eta^{e}_{i,MT} G^{MT}_{i,in}}{\eta_T} \tag{42}$$

By substituting Eqs. (42), (40), and (34) into Eq. (15), $p_{e,EUC}$ and $p_{e,SEH}$ prove to have the following relationship:

$$p_{e,EUC} = \frac{Aa(I+1)(p_{e,SEH} I - G) - aID + aAG + \eta_T(\eta_T G - bI)}{(I+1)\eta_T} + b \tag{43}$$

Thus, $p_{e,SEH}$ can be determined once $p_{e,EUC}$ is determined. Meanwhile, the electrical outputs of the S.E. hubs, which also have a linear correlation with $p_{e,SEH}$, must meet the electrical demands of all users. Similarly, the thermal outputs of the S.E. hubs must be equal to the heat demands of all the users. As p_g is a constant value that has no correlation with p_h, the S.E. hubs independently determine p_h. Imagine that there is a virtual organization that determines the energy prices on behalf of all the S.E. hubs. In each iteration, the EUC initially determines $p_{e,EUC}$; subsequently, the virtual organization determines $p_{e,SEH}$ and p_h according to the energy prices announced by the utility companies; all the participants in the market adjust their operation strategies according to the announced electricity prices. If the total energy demand of all users exceeds the total energy output of all the S.E. hubs, the EUC and virtual organization increase the energy prices; if the total energy output exceeds the energy demands, the EUC and virtual organization decrease the energy prices. This process is repeated until the total energy demands equal the total energy outputs, and $p_{e,EUC}$, $p_{e,SEH}$ and p_h would finally reach the SE of the Stackelberg game. The detailed process of the algorithm is shown below:

Algorithm

1: Set n=0.
2: Randomly initialize $p^n_{e,EUC}$
3: Randomly initialize p^n_h.
4: **While** (the termination conditions are not met) **do**
5: Solve $p^n_{e,SEH}$ using Eq. (43).
6: Solve $\sum_{i \in I} P^n_{i,out}$ and $\sum_{i \in I} Q^n_{i,out}$ using Eq. (40-41).
7: **for** (User k=1,2,…,K) **do**
8: Solve P^n_k and Q^n_k using Eq. (14).
9: **end for**
10: Calculate $p^{n+1}_{e,EUC}$ and p^{n+1}_h using Eq. (40-41).
11: **if** ($|p^{n+1}_{e,EUC} - p^n_{e,EUC}| < \theta$ and $|p^{n+1}_h - p^n_h| < \theta$)
12: break
13: **else**
14: Update prices and go to 4
15: **end if**
16: n=n+1
17: **end while**
18: $p_{e,EUC}, p_{e,SEH}, p_h$ at SE are obtained

The $p^{n+1}_{e,EUC}$ and p^{n+1}_h values within each iteration are derived by the following equations (Wei et al., 2017):

$$p^{n+1}_{e,EUC} = p^n_{e,EUC} + \frac{(\sum_{k \in Z} P^n_k - \sum_{i \in I} P^n_{i,out})}{\varphi_e + \sigma_e n} \tag{40}$$

$$p^{n+1}_h = p^n_h + \frac{(\sum_{k \in Z} Q^n_k - \sum_{i \in I} Q^n_{i,out})}{\varphi_h + \sigma_h n} \tag{41}$$

where n is the iteration number; θ is a threshold value to examine if the SE has been achieved; φ_e and σ_e are constant values to adjust the convergence speed of the electricity price offered by EUC; φ_h and σ_h are constant values to adjust the convergence speed of the heat price

Table 1
Parameters setting (Sheikhi et al., 2015a; Wei et al., 2017).

Item	Value
α_p, α_q	0.5 ($/MWh)
β_p	19 ($/MWh^2)
β_q	23 ($/MWh^2)
$\eta^e_{i,MT}$	0.45
$\eta^g_{i,MT}$	0.4
η^F_i	0.95
η_T	0.9
φ_e	0.05 (MWh/$)
φ_q	0.05 (MWh/$)
a	6 ($/MWh^2)
b	3 ($/MWh)
c	5 ($)
d	6 ($/MWh)
e	0.3 ($)
cc_i	4 ($/MWh)
θ	10^{-8} ($/MWh)
σ_e	10 (MWh/$)
σ_q	10 (MWh/$)

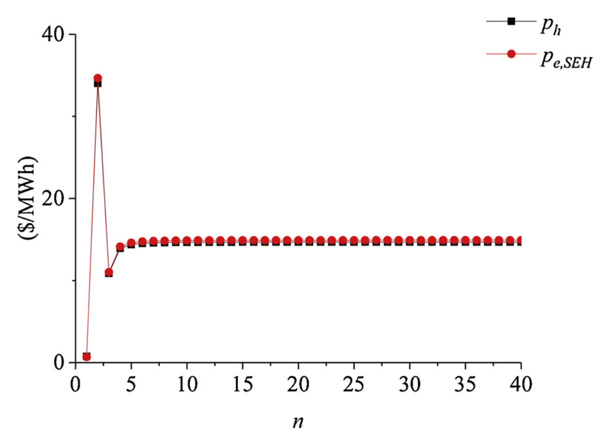


Fig. 4. Convergence procedure of energy prices.

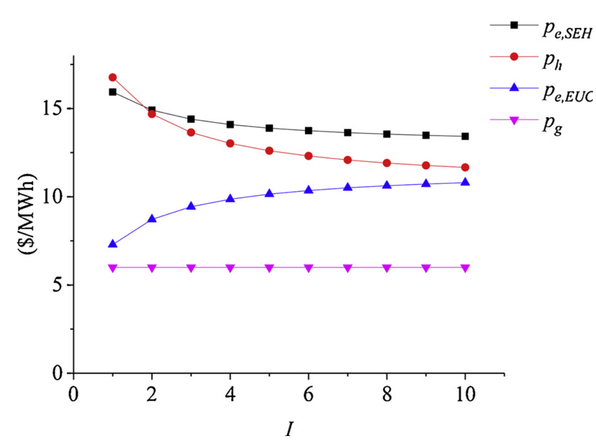


Fig. 5. Impact of the number of S.E. hubs on the energy prices.

offered by the S.E. hubs.

5. Results and discussion

The SE of the Stackelberg game is obtained with the relevant parameter values listed in Table 1. In this study, either electricity or heat is measured in MWh, and the unit of energy price is $/MWh for $p_{e,SEH}$, p_h, $p_{e,EUC}$, and p_g.

Fig. 4 shows the convergence procedure of $p_{e,SEH}$ and p_h when I equals 2 and K equals 4 using the decentralized algorithm introduced in Section 4. Noticeably, $p_{e,SEH}$ and p_h converge rapidly in less than ten iterations, and the results coincide well with the analytical solutions derived from Section 3.2.

5.1. Impacts of the number of participants

In this section, the impacts of the number of S.E. hubs and users on a series of system performances, which include the profits of energy providers, utilities of energy users, and energy prices derived from the market information between providers and users, are investigated.

5.1.1. On energy prices

It can be seen from Fig. 5 that $p_{e,SEH}$ and p_h decrease with the increase in the number of S.E. hubs, while $p_{e,EUC}$ increases with the increase in the number of S.E. hubs. This is because the increase in the number of S.E. hubs brings more competition into the market, thus lowering the energy prices received by the users. With more S.E. hubs, the electricity demand on the side of the EUC is increased; subsequently, $p_{e,EUC}$ is increased. The first-order derivative of $c_g(P_{GUC})$ is p_g, which is a constant value. Thus, the price of natural gas does not change with the number of S.E. hubs. Note that the number of users does not affect the energy prices in this model.

5.1.2. On users

Besides the energy prices, the energy demand and welfare of each user are impacted by the number of S.E. hubs rather than by the number of users. As the number of S.E. hubs increases, competition brings down the energy price in the market. Therefore, the energy demand of each user increases accordingly, and their welfares also increase with the number of S.E. hubs. As the number of S.E. hubs increases, the welfare of each user gradually approaches the maximum value. As illustrated in Fig. 6, more S.E. hubs are welcome from the viewpoint of users. When the number of S.E. hubs is small, an increment in the participation of S.E. hubs could increase the welfare of users significantly; when the number of S.E. hubs is already at a relatively high level, the effect of increasing the number on the improvement of the welfare of the user would be less noticeable.

5.1.3. On S.E. hubs

Fig. 7 illustrates the impacts of the number of S.E. hubs and the number of users on the operation strategies and profits of the S.E. hubs. It can be seen from Fig. 7 that the increase in the number of S.E. hubs decreases the energy inputs and profit of each S.E. hub, indicating that each S.E. hub strives to crowd out other S.E. hubs as much as possible. With a fixed S.E. hub number, the increase in the number of users directly increases the total energy demands, and subsequently, the profit of each S.E. hub increases. Notably, $P_{i,in}$ remains the same regardless of the number of users. In other words, the amount of electricity from the EUC is only determined by the S.E. hubs, and has no correlation with the users.

Fig. 8 depicts the composition of the total energy outputs when the number of S.E. hubs increases from 1 to 10 (K is fixed at 4). As shown in the figure, both the total electricity and heating demands increase with the increase in the number of S.E. hubs. In regard to electricity, the EUC provides more electricity as I increases, although the electricity output of the micro turbine increases comparatively rapidly. In regard to heating, the outputs of the micro turbine and furnace basically increase at the same pace as I increases.

Different from the relatively low impact of the number of S.E. hubs on energy demands, the total energy demand has a linear relationship with the number of users (Fig. 9). The amount of electricity purchased from the EUC has no correlation with the number of users; consequently, the increased electrical demand owing to the increase in users can only be met by using micro turbines. Thus, the electricity from the EUC only reaches a very small percentage and remains at the same level when meeting the increasing power demands of all users as K increases. Meanwhile, the ratio of the heat produced by the micro turbine output to the heat produced by the furnace basically remains the same.

5.2. Impacts of the parameters

In the previous discussion, we assumed that the parameters of all the S.E. hubs are identical; however, obviously, this assumption does not agree with the facts. In this section, $\eta_{i,MT}^{e}$, $\eta_{i,MT}^{g}$, η_i^F, and cc_i of each S.E. hub are changed within a certain range to illustrate their impacts on the energy interaction of the entire energy market. The influences on other S.E. hubs owing to the change of the parameters of one S.E. hub are investigated as well.

5.2.1. Efficiency of the micro turbine ($\eta_{i,MT}^{e}$ and $\eta_{i,MT}^{g}$)

The impacts of $\eta_{i,MT}^{e}$ and $\eta_{i,MT}^{g}$ on the energy prices and profits of S.E. hubs are illustrated in Fig. 10: the range of $\eta_{i,MT}^{e}$ and $\eta_{i,MT}^{g}$ are (0.4, 0.5) and (0.36, 0.46), respectively. It can be observed from Fig. 10(a) that the increase in the electrical efficiency of the micro turbine in either S.E. hub lowers $p_{e,SEH}$, but has no relationship with p_h. Similarly, the thermal efficiency of the micro turbine in either S.E. hub is negatively correlated with $p_{e,SEH}$, but not correlated with p_h (Fig. 10(c)). According

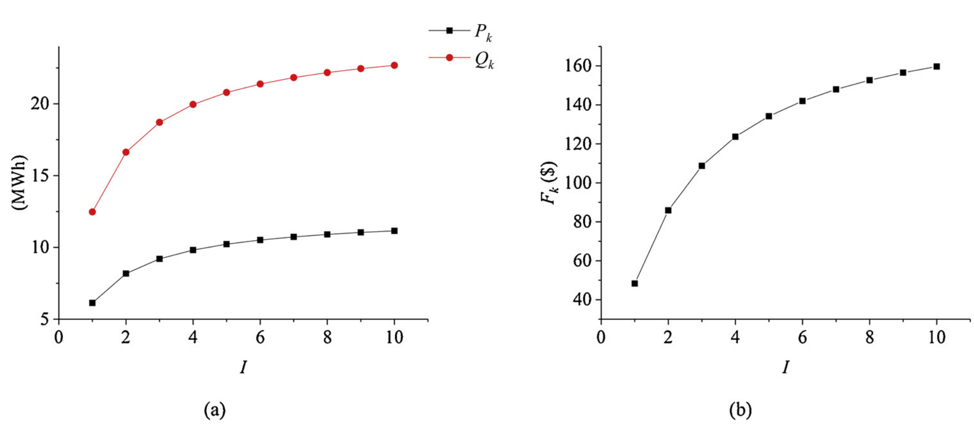


Fig. 6. Impact of the number of S.E. hubs on users: (a) energy demands; (b) welfares.

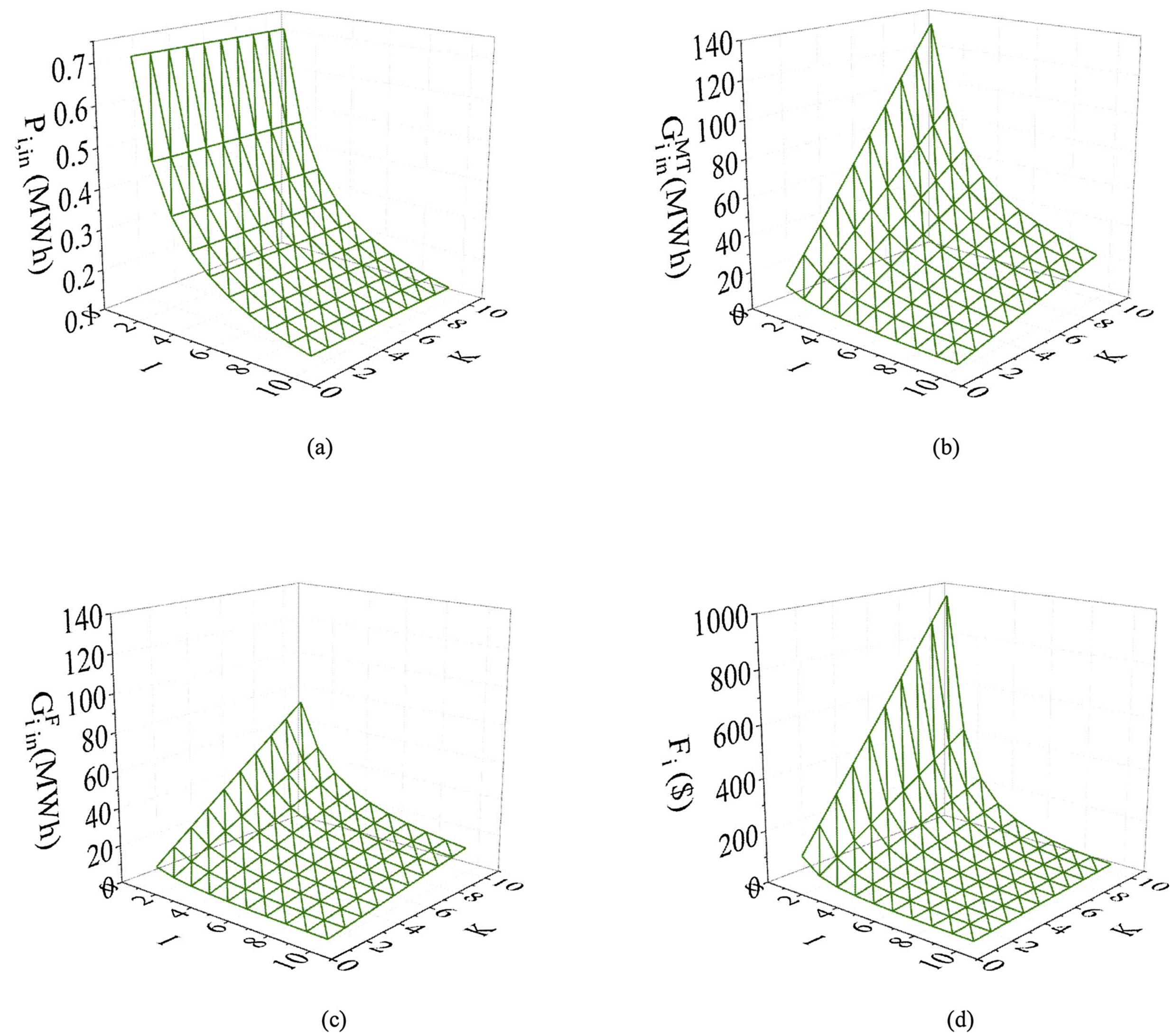


Fig. 7. Impact of the number of S.E. hubs and users on the operation strategies and profits of the S.E. hubs: (a) electricity purchased from the EUC; (b) natural gas supplied to micro turbine; (c) natural gas supplied to furnace; (d) profit of the S.E. hub.

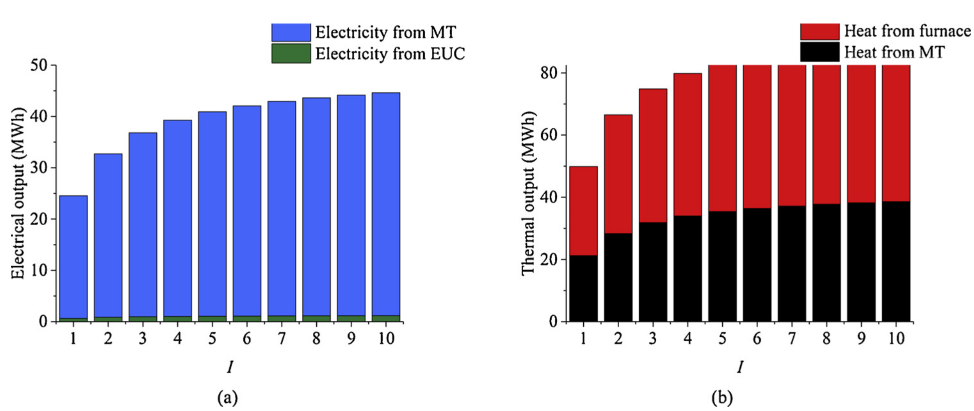


Fig. 8. Composition of the total energy outputs of the S.E. hubs when the number of S.E. hubs changes (K is fixed at 4): (a) electrical output; (b) thermal output.

to Fig. 10(b) and Fig. 10(d), the increase in the efficiency of the micro turbine in either S.E. hub could not only increase its own profit, but also decreases the profit of the other S.E. hubs. The detailed analysis can be found in Fig. 11.

The vertical axis in Fig. 11 is the ratio of the increased profit of S.E. hub i ($i \in \mathbb{I}$) to the decreased profit of S.E. hub j ($j \in \mathbb{I},\ j \neq i$) when $\eta_{i,MT}^{e}$ (Fig. 10(a)) or $\eta_{i,MT}^{g}$ (Fig. 10(b)) increases by 0.01. Here, the ratio is expressed as $\Delta F_i/\Delta F_j$. The horizontal axis is the $\eta_{i,MT}^{e}$ or $\eta_{i,MT}^{g}$ of S.E. hub i. As can be observed in Fig. 10, when $\eta_{i,MT}^{e}$ and $\eta_{i,MT}^{g}$are fixed, the lower $\eta_{j,MT}^{e}$ and $\eta_{j,MT}^{g}$ means the higher $\Delta F_i/\Delta F_j$. Another trend can be seen from Fig. 10 is that $\Delta F_i/\Delta F_j$ increases with the increase in $\eta_{i,MT}^{e}$ and $\eta_{i,MT}^{g}$, and the increase rate is negatively related to $\eta_{j,MT}^{e}$ and $\eta_{j,MT}^{g}$. This result indicates that the impacts of technical improvement is not only related

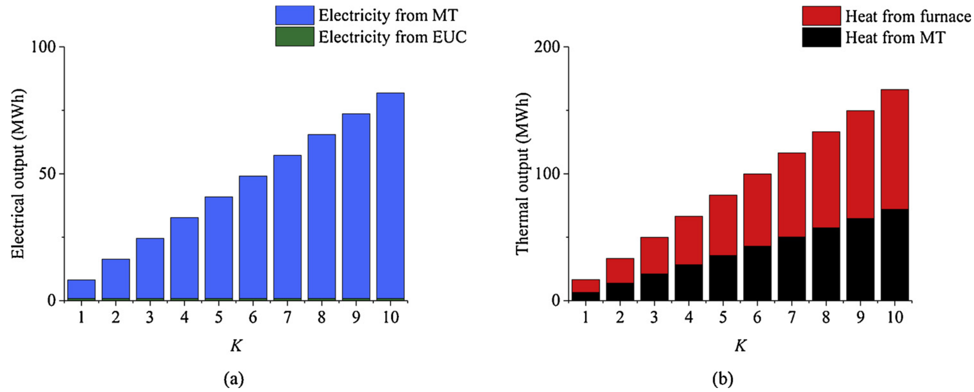


Fig. 9. Composition of total energy outputs of the S.E. hubs when the number of users increases (I is fixed at 2): (a) electrical output; (b) thermal output.

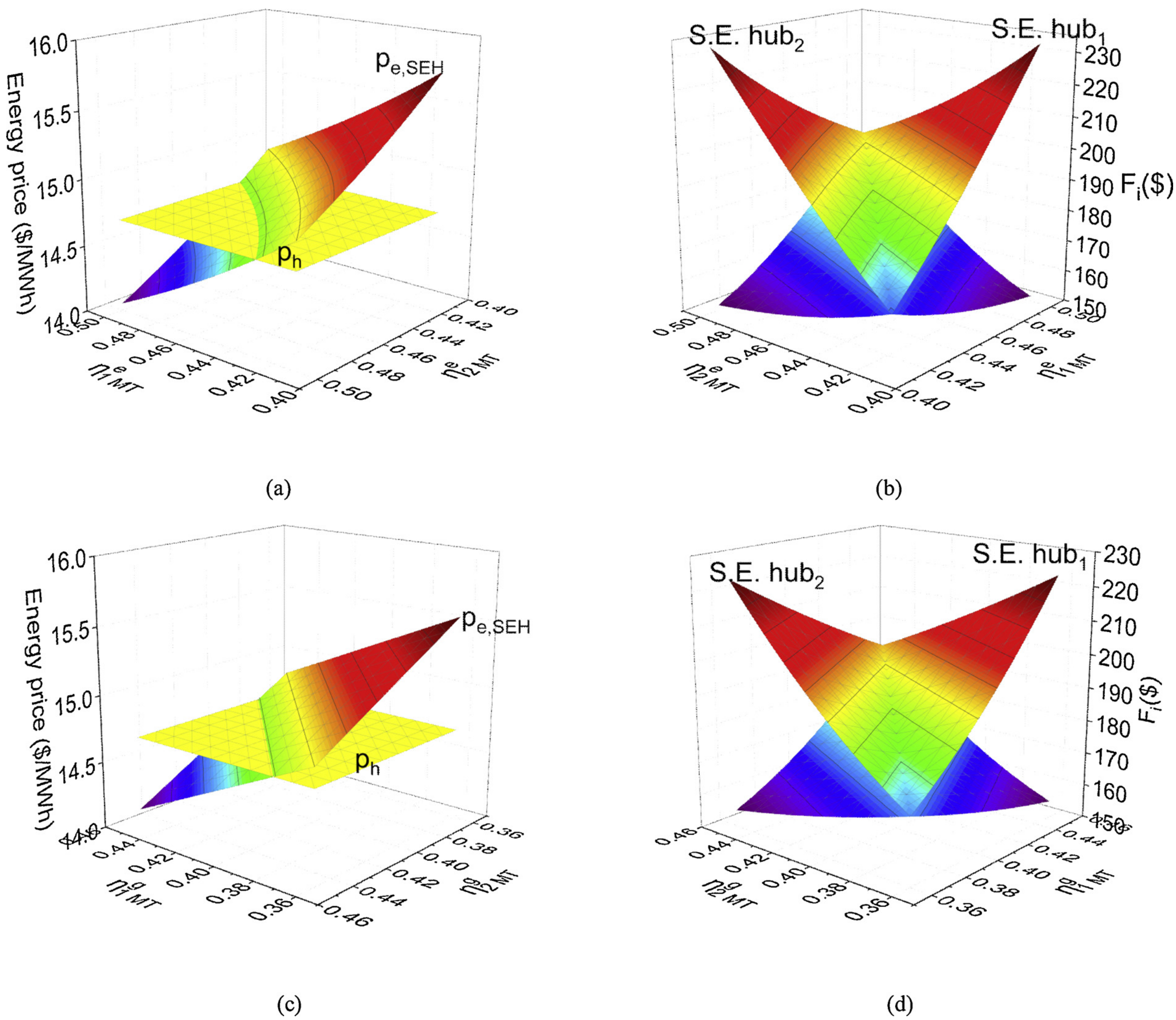


Fig. 10. Impact of the efficiencies of the micro turbines: (a) impacts of $\eta^{e}_{i,MT}$ on the energy prices; (b) impacts of $\eta^{e}_{i,MT}$ on the profits of S.E. hubs; (c) impacts of $\eta^{g}_{i,MT}$ on the energy prices; (d) impacts of $\eta^{g}_{i,MT}$ on the profits of the S.E. hubs.

to how much of the technology is improved, but also in what technological level each market participant is. In other words, the S.E. hubs already equipped with higher efficiency devices occupy an advantageous position.

5.2.2. *Efficiency of the furnace* (η_i^F)

The impacts of η_i^F on the energy prices and profits of the S.E. hubs are illustrated in Fig. 12. As can be observed from Fig. 12(a), the increase in η_i^F not only lowers the heat price, but also raises the electricity price offered by the S.E. hubs. Similar to $\eta^{e}_{i,MT}$ and $\eta^{g}_{i,MT}$, the improvement of $\eta_i^F (i \in \mathbb{I})$ simultaneously increases $F_i (i \in \mathbb{I})$ and decreases $F_j (j \in \mathbb{I},\ j \neq i)$. This result, together with the conclusion from Section 5.2.1, reflects the importance of technological advancement in the market competition between different S.E. hubs.

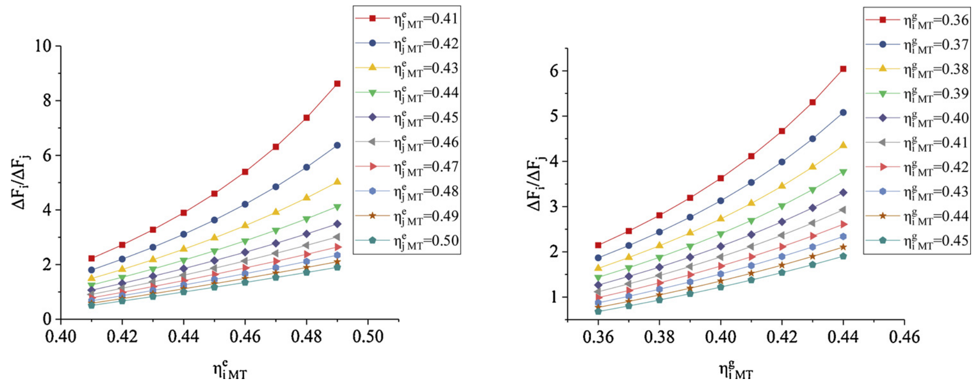
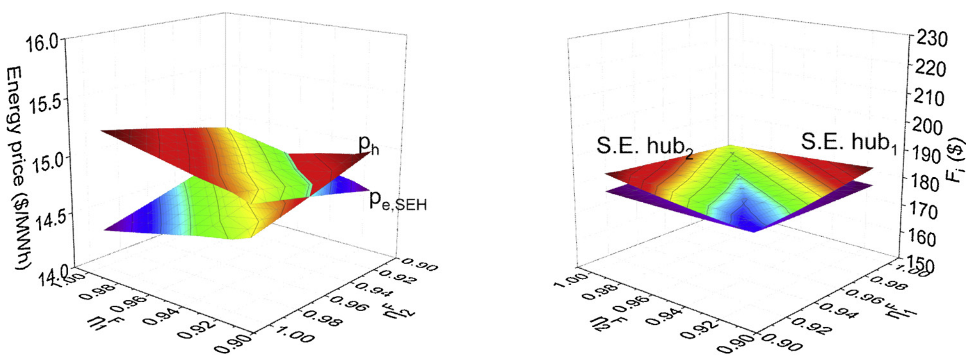


Fig. 11. Ratio of the increased profit of S.E. hub i to the decreased profit of S.E. hub j: (a) when $\eta^{e}_{i,MT}$ increase by 0.01; (b) when $\eta^{g}_{i,MT}$ increase by 0.01.



(a) (b)

Fig. 12. Impact of η_i^F (a) on the energy prices; (b) on the profits of the S.E. hubs.

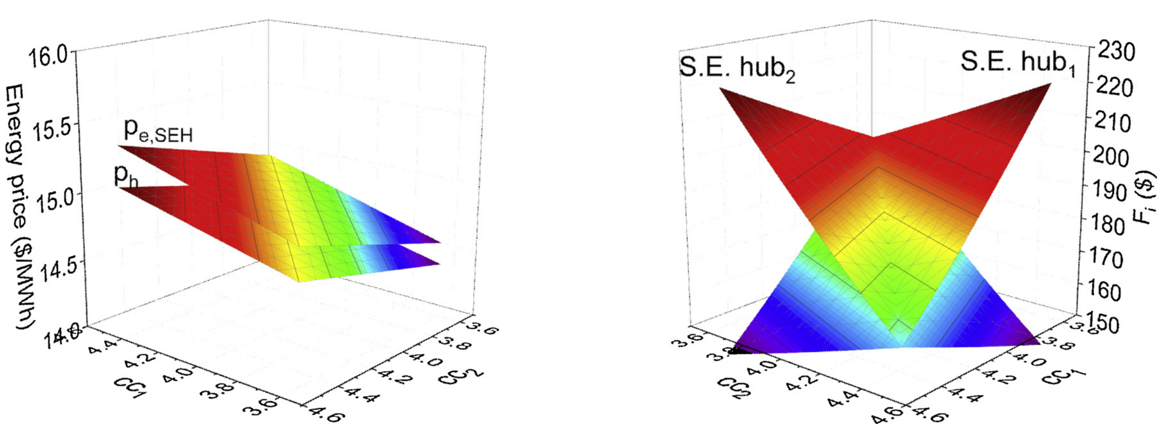


Fig. 13. Impact of cc_i (a) on the energy prices; (b) on the profits of the S.E. hubs.

5.2.3. Generation coefficients of the S.E. hubs (cc_i)

In this section, we change the generation coefficient (cc_i) of one S.E. hub, and investigate its impacts on other S.E. hubs. The results are illustrated in Fig. 13.

According to Fig. 13(a), the increase in cc_i increases the electricity price and heat price to the same extent. As illustrated in Fig. 13(b), the increase in cc_i lowers the profit of S.E. hub i, while the profits of other S.E. hubs increase accordingly. On the contrary, the decrease in cc_i increases the profit of S.E. hub i and decreases the profit of the other S.E. hubs simultaneously. According to the previously obtained conclusion, that each S.E. hub strives to crowd out other S.E. hubs as much as possible, decreasing cc_i and increasing system efficiencies would be effective methods for S.E. hubs to win the market competition.

5.2.4. Preference coefficients of the users ($\alpha_{p,k}$, $\alpha_{q,k}$, $\beta_{p,k}$, and $\beta_{q,k}$)

The impacts of preference coefficients on the users are investigated in this section. As can be observed in Fig. 14, the increases in $\alpha_{p,k}$ and $\alpha_{q,k}$ only decrease the welfare of user k ($k \in \mathbb{K}$), while the welfares of the other users, which are defined as user m ($m \neq k$, $m \in \mathbb{K}$), are not influenced. However, $\beta_{p,k}$ and $\beta_{q,k}$ impact the welfare of each user simultaneously: the increases in $\beta_{p,k}$ and $\beta_{q,k}$ not only increase the user's welfare, but also decreases the welfares of the other users.

6. Conclusion

In this study, we develop a hierarchical Stackelberg game approach for obtaining the SE in a three-level IES with S.E. hubs built in. The energy interactions between the utility companies, S.E. hubs, and users,

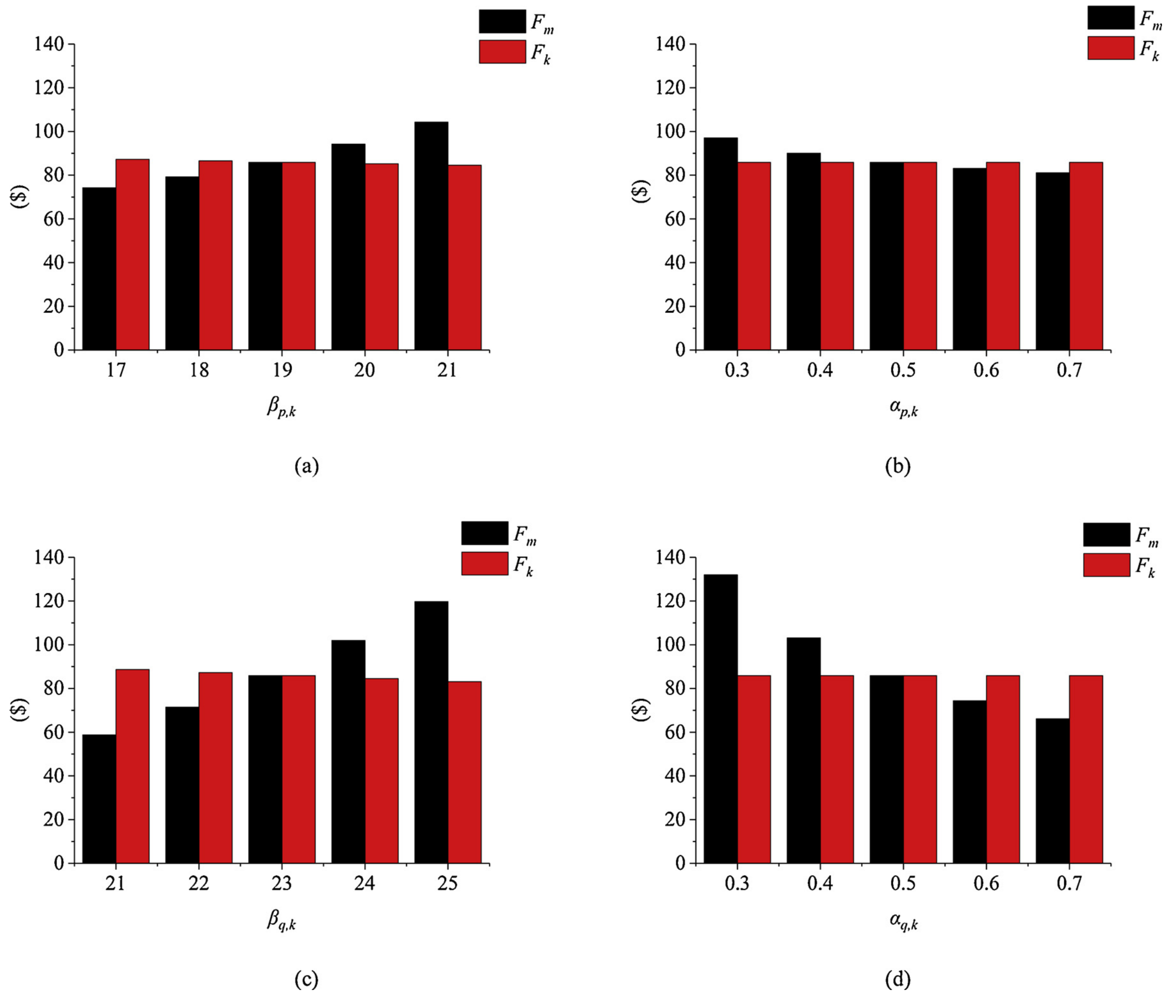


Fig. 14. Cross impacts between users when the preference coefficient changes: (a) $\beta_{p,k}$; (b) $\alpha_{p,k}$; (c) $\beta_{q,k}$; (d) $\alpha_{q,k}$.

particularly the impacts of the numbers and parameters of participants on these energy interactions, are investigated. The primary conclusions are as follows:

- In a perfectly competitive three-level IES, the increase in the number of S.E. hubs would decrease the energy prices they provide due to the increased competition, and subsequently, the user energy demands and welfares increase. This result signifies that more energy providers in the middle level are welcome from the perspective of users. From the perspective of the S.E. hubs, more users bring more profit, whereas more S.E. hubs bring more competition. Therefore, each S.E. hub strives to attract more users and crowd out other S.E. hubs as much as possible.
- The increase in the system efficiency in one S.E. hub not only improves its own profit, but also lowers the profits of other competitors. Thus, technological advancement plays an important role for S.E. hubs in winning the energy market competition. According to the simulation results, the relative differences in system efficiencies determine the competitiveness of each S.E. hub in the energy market; if the technology levels of all S.E. hubs are increased by the same extent, the S.E. hubs whose technological levels are lower would be at a disadvantage.

In future work, cooling demands would be assigned to the users to clearly illustrate the market response to their multiple energy demands. In addition, the technical constraints related to the physical relationships between different market participants will be considered in future work.

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