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A HIERARCHICAL FRAMEWORK FOR ENERGY SCHEDULING AND TRADING OF A DISTRIBUTED ENERGY SYSTEM BASED ON BI-LEVEL OPTIMIZATION

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ABSTRACT

Distributed energy systems (DESs) exhibit potential to promote the energy market reform worldwide. In this study, a bi-level optimization model is proposed to analyze the operation of a DES that purchases high-voltage electricity and natural gas from utility companies, and supplies low-voltage electricity and heat to multiple users. To simplify the resolution process, the bi-level optimization is transformed into a single-level mixed integer linear programming model using the Karush-Kuhn-Tucker approach and Big M method. The results indicate that (i) the time-sensitive energy prices offered by the DES could smoothen the load profiles of users; and (ii) the tiered pricing scheme set up by the utility companies could maximize the utility of the ESS integrated into the DES, but the capacity of the ESS should be accurately designed to fit the corresponding pricing scheme.

Keywords: bi-level optimization, distributed energy system, Karush-Kuhn-Tucker condition, demand response, tiered pricing

NONMENCLATURE

symbols	
F	objective function value ($)
U	utility ($)
S	Shapley value
P	electrical power (kWh)
Q	thermal power (kWh)
G	calorific value of natural gas (kWh)
p	energy price ($/kWh)
η	efficiency (%)
SOC	state-of-charge (%)
N	nominal capacity (kWh)
A	Area (m^2)
R	solar radiation (kWh/m^2)
T	temperature(℃)

1. INTRODUCTION

With the depletion of fossil energy and aggravation of the environmental crisis, the contradiction between the human social development and conventional energy supply structure has been increasingly evident; thus, the demand for the structural transformation of energy supply has increased worldwide. Distributed energy systems (DESs), which are commonly built close to end users, are expected to become the main force in the future energy retail market. As most DESs are privately operated, their energy scheduling and trading of DESs have become crucial in guaranteeing their economic benefits, although the operation optimization is a complex and challenging task.

Several studies have focused on the operation of DESs, which could be divided into two categories: off-grid DESs and on-grid DESs. Off-grid DESs, which are also known as standalone or autonomous systems, is separated from the grid-network and are responsible for fulfilling demands at all times [1,2]. Compared with the off-grid DES, the connection with the utility grid requires the DES to be designed and operated in a more energy-efficient way to compete with the existing energy supply system [3,4,5]. With the rapid development of information technology, it has been possible for different types of market participants, including but not limited to utility companies, DES, and end users, to exchange multi-energy price and demand information to maximize their personal interests in a real time energy market. For example, Li et al. [6] studied the design and management

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of a DES incorporating renewable energy generation and heterogeneous end-users; a hierarchical framework for the energy demand side management through peer-to-peer exchange of energy information in a real-time market was proposed. Lu et al. [7] designed a transaction mechanism among heterogeneous retailers and consumers in a regional energy market.

Because the conventional utility companies are the existing and necessary participants in the energy markets, the operation performance of a DES directly decides whether it can take on its corresponding responsibilities and reach the expectations during the energy market reform as a specific market participant. This study investigated a three-level IES composed of one electricity utility company (EUC) and one gas utility company (GUC) (upper level), one DES (middle level), and I users (lower level). The energy demands of users consist of electricity demand and heating demand, which are both directly provided by the DES. The interactions between the utility companies, DES, and users were formulated as a bi-level optimization model, and solved as a mixed integer linear programming (MILP) problem by applying the Karush-Kuhn-Tucker (KKT) approach and Big M method. Besides, the impacts of tiered pricing on the performance of the DES were investigated as well.

2. SYSTEM MODEL

2.1 Distributed energy system side (upper level)

The DES in this study comprises a transformer, ESS, micro turbine, furnace, and PV panels. (Figure 1).

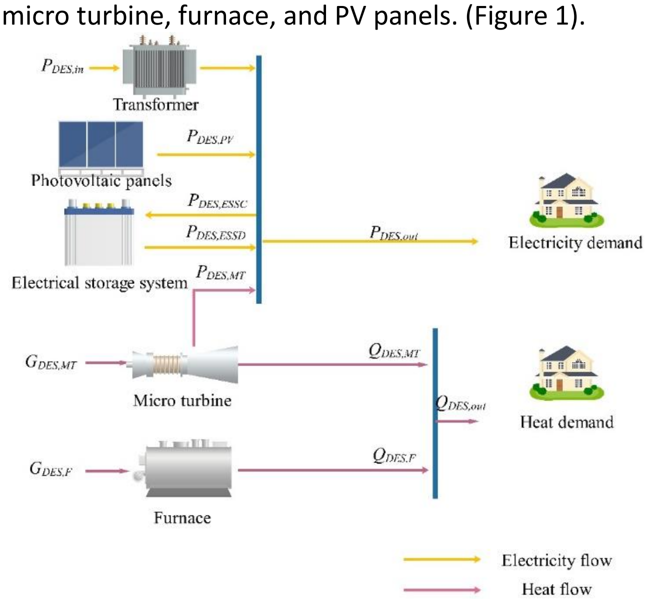


Fig 1 Schematic of the DES

Because most of the DESs in the market are privately owned and operated, the primary operation goal of a DES could be considered as the economic benefit; thus, the objective function of the DES can be written as

$$\max F = \max \sum_{t=1}^{24} \left[\begin{array}{l} P^t_{DES,out} p^t_e + Q^t_{DES,out} p^t_q \\ -P^t_{DES} p_E - \left(G^t_{DES,MT} + G^t_{DES,F} \right) p_G \end{array} \right] \tag{1}$$

where $P^t_{DES,out}$ and $Q^t_{DES,out}$ are respectively the electrical output and thermal output of the DES, p^t_e and p^t_q are respectively the real-time prices of electricity and heat offered by the DES, P^t_{DES} is the electricity DES purchased from the EUC, $G^t_{DES,MT}$ and $G^t_{DES,F}$ are respectively the natural gas DES purchased from the GUC for the micro turbine and furnace, and p_E and p_G are respectively the prices of electricity and natural gas that the DES purchased from the utility companies.

The electric power balance and thermal power balance of the energy system are expressed as

$$P^t_{DES,in}\eta_T + P^t_{DES,PV} + P^t_{DES,ESSD} + P^t_{DES,MT} - P^t_{DES,ESSC} = P^t_{DES,out} = \sum_k P^t_{k,d} \tag{2}$$

$$Q^t_{DES,MT} + Q^t_{DES,F} = Q^t_{DES,out} = \sum_k Q^t_{k,d} \tag{3}$$

where $P^t_{DES,PV}$ is the output of the PV, $P^t_{DES,ESSD}$ and $P^t_{DES,ESSC}$ are respectively the power charged and discharged by the ESS, $P^t_{DES,MT}$ is the electrical output of the micro turbine, $Q^t_{DES,MT}$ and $Q^t_{DES,F}$ are respectively the thermal outputs of the micro turbine and furnace, $P^t_{k,d}$ and $Q^t_{k,d}$ are respectively the electrical and thermal demands of user k during the time interval t, and η_T is the efficiency of the transformer.

The state-of-charge (SOC) of the ESS in adjacent time intervals should always satisfy the following relationship [8].

$$SOC^t{}_{DES,ESS} = SOC^{t-1}{}_{DES,ESS} + \frac{P^t_{DES,ESSC}\Delta t \eta_{ESSC}}{N_{DES,ESS}} - \frac{P^t_{DES,ESSD}\Delta t}{\eta_{ESSD} N_{DES,ESS}} \tag{4}$$

where $N_{DES,ESS}$ is the nominal capacity, η_{ESSC} is the corresponding charge efficiency, and η_{ESSD} is the discharge efficiency of the ESS. All the efficiencies are assumed to be constant, and the self-discharge rate of the ESS is not considered in this study.

According to , the power output of a PV panel array at time t with an area of $A_{DES,PV}$ is given by

$$P^t_{DES,PV} = R^t \eta^t_{PV} A_{DES,PV} \tag{5}$$

$$\eta_{PV}^{t} = \eta_r \left[1 - N_T \left(T_c^t - T_r \right) \right] \tag{6}$$

$$T_c^t = T_a^t + \left(\frac{NOCT - 20}{800} \right) R^t \tag{7}$$

where R^t denotes the solar radiation on a unit area of a panel, η_{PV}^t the electrical efficiency of the panel, T_C^t the cell temperature, η_r the reference electrical efficiency of the panel, N_T the PV panel efficiency temperature coefficient, T_r the reference temperature, and $NOCT$ is the nominal cell operating temperature.

The micro turbine output and furnace output could be expressed as

$$Q_{DES,F}^t = \eta_F G_{DES,F}^t \tag{8}$$

$$Q_{DES,MT}^t = \eta_{MT}^g G_{DES,MT}^t \tag{9}$$

$$P_{DES,MT}^t = \eta_{MT}^e G_{DES,MT}^t \tag{10}$$

where $G_{DES,F}^t$ and $G_{DES,MT}^t$ are respectively the gas input of the furnace and micro turbine, η_F is the efficiency of the furnace, and η_{MT}^g and η_{MT}^e are respectively the thermal and electrical efficiencies of the micro turbine.

To maintain a normal operation, the minimum and maximum operation limit of each device in the DES are as follows:

$$SOC_{ESS,\min} \le SOC_{DES,EES}^t \le SOC_{ESS,\max} \tag{11}$$

$$G_{MT,\min} \le G_{DES,MT}^t \le G_{MT,\max} \tag{12}$$

$$G_{F,\min} \le G_{DES,F}^t \le G_{F,\max} \tag{13}$$

$$x_{DES,EESC}^t P_{DES,EESC,\min} \le P_{DES,EESC}^t \le x_{DES,EESC}^t P_{DES,EESC,\max} \tag{14}$$

$$x_{DES,EESD}^t P_{DES,EESD,\min} \le P_{DES,EESD}^t \le x_{DES,EESD}^t P_{DES,EESD,\max} \tag{15}$$

To ensure that the ESS can only charge or discharge simultaneously, the following constraint holds.

$$x_{DES,ESSC}^t + x_{DES,ESSD}^t \le 1 \tag{16}$$

where $x_{DES,EESC}^t$ and $x_{DES,EESD}^t$ are binary values.

2.2 User side (lower level)

The objective of user k could be expressed as its welfare, which is the surplus of user k retained between its utility and the payment to the DES. The formulation of the objective function is

$$\max f_k = \max \sum_{t=1}^{24} (U_{k,e}^t + U_{k,q}^t - P_k^t p_e^t - Q_k^t p_q^t) \tag{17}$$

where $U_{k,e}^t$ and $U_{k,q}^t$ are the satisfaction gained from consuming the electricity and heat, respectively, which can be expressed as

$$U_{k,e}^t = -\frac{\alpha_{k,e}^t}{2} \left(P_k^t \right)^2 + \beta_{k,e}^t P_k^t \tag{18}$$

$$U_{k,q}^t = -\frac{\alpha_{k,q}^t}{2} \left(Q_k^t \right)^2 + \beta_{k,q}^t Q_k^t \tag{19}$$

here $\alpha_{k,e}^t$, $\alpha_{k,q}^t$, $\beta_{k,e}^t$, and $\beta_{k,q}^t$ are the preference constants of the quadratic utility function.

In this study, the energy demands of users are assumed to be adjustable, but the permitted adjustment amounts are within a certain range. It is assumed that the energy demands of user k during the time interval t should not exceed $(1 + a)$ times P_k^t or Q_k^t, which are the energy demands of users when the DES is not applied; meanwhile, the minimal energy demands should be larger than $(1 - a)$ times P_k^t or Q_k^t. Thus, the lower and upper limits of the energy demands of user k could be expressed as

$$\left(1-a\right) P_{k,d}^t \le P_k^t \le \left(1+a\right) P_{k,d}^t \tag{20}$$

$$\left(1-a\right) Q_{k,d}^t \le Q_k^t \le \left(1+a\right) Q_{k,d}^t \tag{21}$$

where a is a constant value. The technical characteristics of key components in the energy system are listed in Table 1.

Table 1 Technical characteristics of key components

Parameter	Value (Unit)
p_E	0.06 \$/kWh
p_G	0.02 \$/kWh
T_r	25 ℃
η_T	0.9
η_{ESSC}	0.85
η_{ESSD}	0.85
$N_{DES,ESS}$	200 kWh
$A_{DES,PV}$	2560 m^2
η_r	15.5%
N_T	3.7×10^{-3} /℃
$NOCT$	43 ℃
η_F	0.9
η_{MT}^g	0.5
η_{MT}^e	0.4
$SOC_{ESS,min}$	0.2
$SOC_{ESS,max}$	1
$G_{MT,min}$	0 kW
$G_{MT,max}$	500 kW
$G_{F,min}$	0 kW
$G_{F,max}$	500 kW
$P_{DES,ESSC,min}$	0 kW
$P_{DES,ESSC,max}$	40 kW
$P_{DES,ESSD,min}$	0 kW

$P_{DES,ESSD,max}$	40 kW
a	0.2

3. METHODOLOGY

Because the lower level optimization in this study is a convex problem with continuous variables, the KKT conditions of the lower level optimization of this model can be expressed as

$$L\left(f_k\right)=\sum_{t=1}^{24}(U_{k,e}^t+U_{k,q}^t-P_k^t p_e^t-Q_k^t p_q^t)$$
$$+\sum_{t=1}^{24}\varphi_{k,e}^t\left[P_k^t-\left(1+a\right)P_{k,d}^t\right]+\sum_{t=1}^{24}\sigma_{k,e}^t\left[-P_k^t+\left(1-a\right)P_{k,d}^t\right]$$
$$+\sum_{t=1}^{24}\varphi_{k,q}^t\left[Q_k^t-\left(1+a\right)Q_{k,d}^t\right]+\sum_{t=1}^{24}\sigma_{k,q}^t\left[-Q_k^t+\left(1-a\right)Q_{k,d}^t\right] \tag{22}$$

$$\frac{\partial L\left(f_k\right)}{\partial P_k^t}=-\alpha_{k,e}^t P_k^t+\beta_{k,e}^t-p_e^t+\varphi_{k,e}^t-\sigma_{k,e}^t=0 \tag{23}$$

$$\frac{\partial L\left(f_k\right)}{\partial Q_k^t}=-\alpha_{k,q}^t Q_k^t+\beta_{k,q}^t-p_q^t+\varphi_{k,q}^t-\sigma_{k,q}^t=0 \tag{24}$$

$$0\le\varphi_{k,e}^t\perp -P_k^t+\left(1+a\right)P_{k,d}^t\ge 0 \tag{25}$$

$$0\le\varphi_{k,q}^t\perp -Q_k^t+\left(1+a\right)Q_{k,d}^t\ge 0 \tag{26}$$

$$0\le\sigma_{k,e}^t\perp P_k^t+\left(a-1\right)P_{k,d}^t\ge 0 \tag{27}$$

$$0\le\sigma_{k,q}^t\perp Q_k^t+\left(a-1\right)Q_{k,d}^t\ge 0 \tag{28}$$

Thus, the bi-level optimization problem is transformed into a single level MINLP problem, but still time-consuming to solve. To simplify the solving process, we transform the MINLP problem into an MILP problem by adding a very large number M to Eqs. (25-28) as follows:

$$0\le\varphi_{k,e}^t\le\xi_{k,e}^t M \tag{29}$$

$$0\le -P_k^t+\left(1+a\right)P_{k,d}^t\le\left(1-\xi_{k,e}^t\right)M \tag{30}$$

$$0\le\varphi_{k,q}^t\le\xi_{k,q}^t M \tag{31}$$

$$0\le -Q_k^t+\left(1+a\right)Q_{k,d}^t\le\left(1-\xi_{k,q}^t\right)M \tag{32}$$

$$0\le\sigma_{k,e}^t\le\zeta_{k,e}^t M \tag{33}$$

$$0\le P_k^t+\left(a-1\right)P_{k,d}^t\le\left(1-\zeta_{k,e}^t\right)M \tag{34}$$

$$0\le\sigma_{k,q}^t\le\zeta_{k,q}^t M \tag{35}$$

$$0\le Q_k^t+\left(a-1\right)Q_{k,d}^t\le\left(1-\zeta_{k,q}^t\right)M \tag{36}$$

where $\xi_{k,e}^t$, $\xi_{k,q}^t$, $\zeta_{k,e}^t$, and $\zeta_{k,q}^t$ are binary values.

By adding $\xi_{k,e}^t$, $\xi_{k,q}^t$, $\zeta_{k,e}^t$, $\zeta_{k,q}^t$, and M, the multiplication of variables in the inequality constraints can be removed, but there still exit multiplication terms in the objective function. By substituting Eqs. (23-24) into Eq. (1), the objective of the upper level optimization can be written as

$$F=\sum_{t=1}^{24}\begin{bmatrix}\sum_k p_e^t P_k^t+\sum_k p_q^t Q_k^t-P_{DES}^t p_E- \\ \left(G_{DES,MT}^t+G_{DES,F}^t\right)p_G\end{bmatrix}$$
$$=\sum_{t=1}^{24}\begin{bmatrix}\sum_k\left(-\alpha_{k,e}^t P_k^t+\beta_{k,e}^t+\varphi_{k,e}^t-\sigma_{k,e}^t\right)P_k^t \\ +\sum_k\left(-\alpha_{k,q}^t Q_k^t+\beta_{k,q}^t-p_q^t+\varphi_{k,q}^t-\sigma_{k,q}^t\right)Q_k^t \\ -P_{DES}^t p_E-\left(G_{DES,MT}^t+G_{DES,F}^t\right)p_G\end{bmatrix} \tag{37}$$

By transforming Eqs. (25-28) and substituting them into Eq. (37), the multiplications terms in the objective function can be expressed as

$$\sum_{t=1}^{24}\left(\sum_k\varphi_{k,e}^t P_k^t\right)=\left(1+a\right)\sum_k\left(\sum_{t=1}^{24}\varphi_{k,e}^t P_{k,d}^t\right) \tag{38}$$

$$\sum_{t=1}^{24}\left(\sum_k\sigma_{k,e}^t P_k^t\right)=\left(1-a\right)\sum_k\left(\sum_{t=1}^{24}\sigma_{k,e}^t P_{k,d}^t\right) \tag{39}$$

$$\sum_{t=1}^{24}\left(\sum_k\varphi_{k,q}^t Q_k^t\right)=\left(1+a\right)\sum_k\left(\sum_{t=1}^{24}\varphi_{k,q}^t Q_{k,d}^t\right) \tag{40}$$

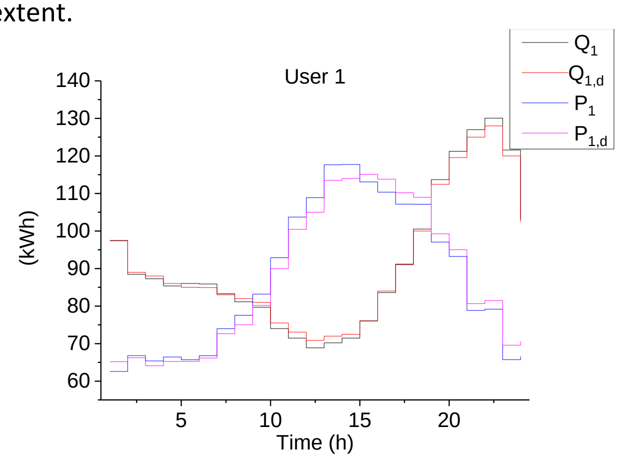
$$\sum_{t=1}^{24}\left(\sum_k\sigma_{k,q}^t Q_k^t\right)=\left(1-a\right)\sum_k\left(\sum_{t=1}^{24}\sigma_{k,q}^t Q_{k,d}^t\right) \tag{41}$$

Consequently, the bi-level optimization problem has been transformed into an MILP problem, and can be solved by most commercial optimizers. This study utilized the ILOG's CPLEX optimization solver to solve the MILP model, which is formulated in MATLAB.

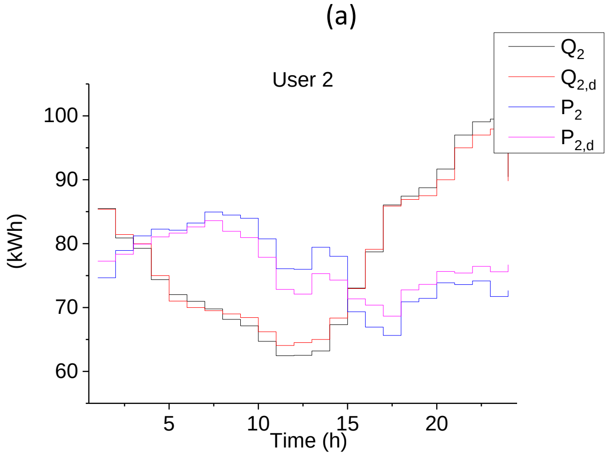
4. RESULTS AND DISCUSSION

In this study, the weather information and energy demands (P_k^t or Q_k^t) of four actual buildings in Xi'an in a typical November day are utilized, and $\alpha_{k,e}^t$ and $\alpha_{k,q}^t$ are assumed to be constant values equal to 0.003 and 0.001, respectively. Given the condition that the electricity price received by the users is 0.08$/kWh and the heating price is 0.04$/kWh, $\beta_{k,e}^t$ and $\beta_{k,q}^t$ could be derived based on $\alpha_{k,e}^{t}$, $\alpha_{k,q}^{t}$, P_k^t , and Q_k^t. p_E and p_G are constant values.

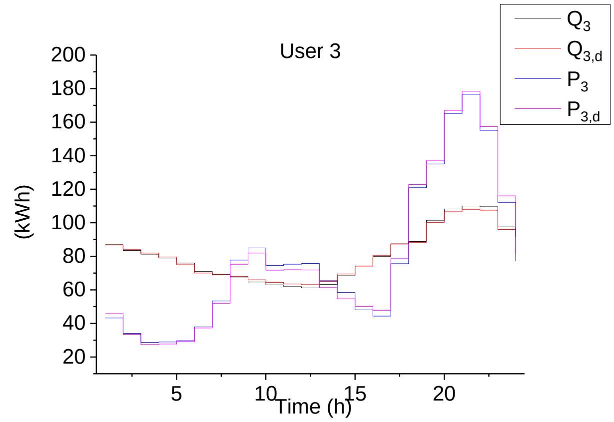
Figure 2 shows the energy demands of the four users in two scenarios: (i) with DES; and (ii) without DES. It can be observed from Figure 2 that compared with the scenarios without the DES, the electrical demands of all the four users in the first 12 h are increased with the addition of the DES, while those in the next 12 h are decreased. Meanwhile, the thermal demands in the first 12 h are increased, while those in the next 12 h are increased. This can be attributed to the real time energy prices announced by the DES. As illustrated in Figure 3, the electrical prices announced by the DES in the first 12 h are generally higher than those in the next 12 h; thus, users aware of the electricity prices tend to consume more electricity in the first 12 h, so that the electrical profile changes subsequently. The same analysis can be applied to the change in thermal demands. This result indicates that the time-sensitive energy prices could smoothen the energy demands of users to a certain extent.



(a)



(b)



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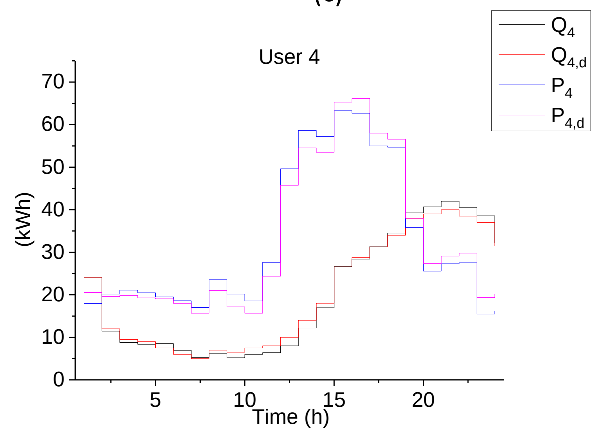

(d)

Fig 2 Energy demands of the four users with and without the DES: (a) user 1, (b) user 2, (c) user 3 and, (d) user 4.

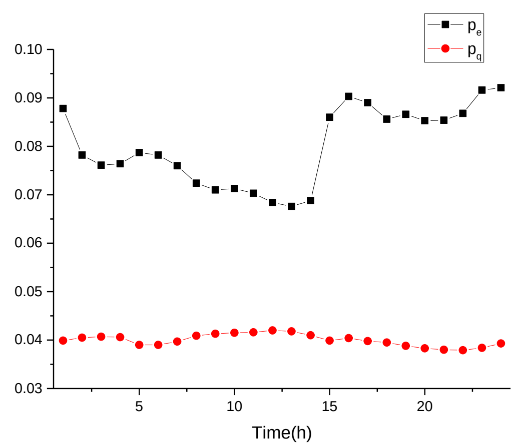

Fig 3 Electricity and heat prices announced by the DES in a typical day

According to the electrical demands of the four users in this study, a day is divided into three periods: period 1 (off-peak time) is from 23:00 to 6:00, period 2 is from 7:00 to 14:00, and period 3 (peak time) is from

15:00 to 22:00. To regulate the electrical demand, the EUC could use the tiered pricing to adjust the energy outputs of the DES and energy demands of users. To achieve this goal, the electrical price offered by the EUC during period 1 should be decreased to simulate the electricity consumption, and the electrical price in period 3 should be increased to decrease the electrical demands. In this study, it is assumed that the electrical prices during the three periods have the following relationships in the tiered pricing scheme:

$$p_{E,1} = p_E - \sigma \tag{42}$$

$$p_{E,1} = p_E \tag{43}$$

$$p_{E,1} = p_E + \sigma \tag{44}$$

where p_E is equal to 0.06$/kWh. The profit of the DES with different σ are illustrated in Figure 4.

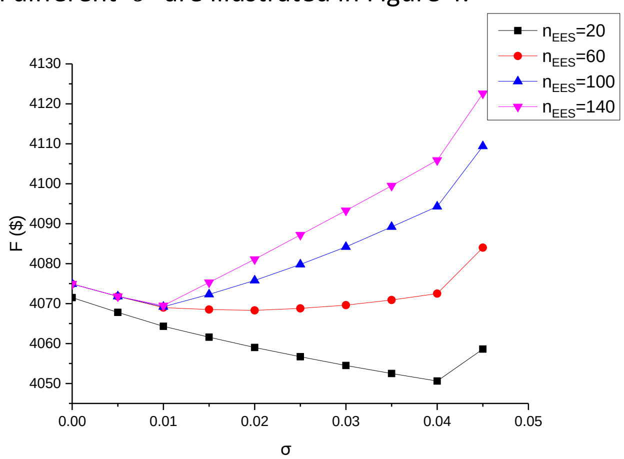

Fig 4 Profit of the DES under different energy prices with different capacities of ESS

As shown in Figure 4, an increase in σ first decreases the profit of the DES. However, as σ keeps continues to increase, the profit of the DES encounters a turning point and begins to increase after that. This is because DES mainly purchases electricity from the EUC during period 3 (as shown in Figure 3), which is the peak time. Thus, the increase in electricity price during period 3 would not only lower the profit of the DES, but also impact the operations of all components in the DES to reduce the loss. When σ becomes large enough, the change in operation may lead to an increase in the profit of the DES. Because more ESS means more flexibility in operation strategies, the DES with more ESS could adjust the operations of all components within a larger range to gain more profit under the tiered pricing scheme, and this influence becomes larger as σ increases.

5. CONCLUSION

In this study, we proposed a bi-level optimization model to investigate the operations of a DES in a hierarchical IES composed of utility companies, DES and users. The results indicate that the time-sensitive energy prices offered by the DES could smoothen the load profiles of users within a certain range. Although an appropriate application of tiered pricing could maximize the utility of the ESS, the capacity of the ESS should be accurately designed to fit the corresponding pricing scheme; otherwise, the benefit of the DES may not be improved and may even be dragged down. In future work, the operation strategies of multiple DESs would be investigated.

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