Transactive Energy Trading in Reconfigurable Multi-carrier Energy Systems

Yifei Wang, Zhiheng Huang, Zhenhao Li, Xi Wu, Loi Lei Lai, and Fangyuan Xu

***Abstract*—The penetration of multi-carrier energy systems in distribution system gains more and more concerns. In this paper, a bi-level transactive energy trading framework is proposed to improve the energy scheduling and operation efficiency for multi-carrier energy systems which are modeled as energy hubs (EHs). In the upper level, each EH in the distribution system not only makes energy scheduling decisions considering supplies and demands of local energy, but also trades energy with each other to further maximize their social welfare. The associated trading payment among EHs is made in a fair manner by applying Nash bargaining theory. We solve the bargaining problem by decomposing it into two subproblems: operation cost minimization problem and payment bargaining problem. Then, based on the trading decision, the nodal equivalent loads of EHs are sent to the distribution system operator (DSO) without publishing trading details. By applying the second-order cone programming (SOCP), DSO reconfigures the network to reduce the transmission loss of the system in the lower level. The network reconfiguration and the trading behavior of EHs interact and iterate until the convergence. Numerical studies on modified IEEE 33-bus distribution system demonstrate the effectiveness of the proposed framework.**

***Index Terms*—Multi-carrier energy system, energy hub (EH), transactive energy, distribution reconfiguration, Nash bargaining.**

I. Introduction

IN traditional power systems, power is generated centrally by large power plants and flown unidirectionally to load centers through transmission and distribution systems. With the increasing penetration of distributed energy resources (DERs) and multi-carrier energy systems (MESs), transactive energy market (TEM) emerges as a new power market which enables end-to-end energy trading and coordinated operation [1], [2]. Transactive energy (TE) applied to electricity production and consumption is constrained by operation characteristics and coordinated by market signals [3]-[5].

Multi-carrier energy systems supply different types of energy to customers such as electricity, nature gas, heat and cool. Different forms of energy are interconnected with each other via coupling infrastructures such as energy hub (EH). The cooperated scheduling and energy trading among EHs in TEM gain more and more concerns [6], [7].

TEM introduces new challenges for distribution system operators (DSOs) since the unconstrained TE trading between EHs connected with distribution system could change the status of power systems, increase power losses, and lead to congestion problems. Moreover, asset owners' privacy issues could make the stated tasks of DSO more difficult for determining the status of local DERs and coordinating their impacts on controllable loads. Furthermore, EHs, which are able to choose energy sources to supply load, bring more flexibility to the grid. These challenges increase the need for coordination between DSO and multiple participants such as EHs. The cooperated operation framework is devised in this paper in order to conceive an optimal TEM strategy in the hierarchical operation of distribution systems and multiple EHs.

The coordination of EHs in distribution system operations is mainly concerned with two issues. One is the optimal EH operation strategy and coordination and the other is the TE trading scheme and the TEM clearing process. In terms of the EH operation strategy and coordination, [8] modifies the traditional demand response (DR) program to integrate DR with EHs which can participate DR by switching the energy resources. Reference [9] presents an innovative method for modeling EHs based on the energy flow between its constituent elements. A mixed integer nonlinear programming model is presented for day-ahead 24-hour scheduling of an EH. Reference [10] considers the internal and external energy dependencies (EDs) and proposes a new model of EDs within a multig-eneration representation based on EHs. The carrier-based DR is introduced in the model. Reference [11] investigates the issues of day-ahead and real-time cooperative energy management for multi-energy systems. The objective is to maximize the day-ahead social welfare and smooth out the real-time load variations as well as renewable resource fluctuations. Optimal operation of multi-carrier energy system is proposed in [12] considering wind farm, electrical and thermal storage systems, electrical and thermal DR programs. The above references concern the optimal energy scheduling within one EH. The coordination among EHs and the cooperation between distribution system and EHs are

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less considered.

References [13]-[18] study the TE trading mechanism and clearing method among EHs. In [13], three quintessential schemes for organizing a cluster of EHs at demand side, i.e., individual, sharing market and aggregation, are studied in the distribution level. Reference [14] proposes a cooperative trading framework where a real-time rolling horizon energy management model is established based on cooperative game theory. Reference [15] formulates the real-time scheduling problem of EHs in a dynamic pricing market. The EH interaction is modeled as an exact potential game. In [16], energy systems are studied in the presence of wind farm, electrical and thermal storage. The electricity market and thermal energy market are established to clear the energy trading. A comprehensive optimal bidding strategy is proposed in [17] for an EH where stochastic optimization is introduced to handle the market uncertainties consisting of day-ahead market prices, real-time market prices, and wind generation. Reference [18] presents a bi-level game between so-called energy retailers and consumers with firm loads as formulated in a multi-carrier energy system. References [13]-[18] discuss the energy trading and clearing method in multi-carrier energy systems. However, different EHs locate at different positions in the distribution system. The distribution network topology and EH geographical locations affect the trading behaviors and energy delivery costs, which are often ignored in current works.

In this paper, a bi-level interaction framework is established to coordinate DSO and EH payoff functions in TEM for an optimal energy scheduling and clearing. We consider the trading among EHs, which is modeled by Nash bargaining problem for cooperating all EHs to achieve the maximum social welfare and fair payments. DSO reacts to the EH's corresponding TE trading signals to ensure the optimal distribution network operation (i. e., economy, security and line losses, etc.). In turn, EHs adjust their TE trading signals if the DSO mandates are violated, i. e., exceed a certain thresholds.The contributions of this paper are summarized:

1) A bi-level optimization framework is established to coordinate the EH TE trading with distribution network reconfiguration for optimal operation. The DSO and EH operations are optimized alternatively until a stable state is reached where the individual's decisions are no longer adjusted.

2) According to the wholesale market price at transmission level and optimal TE signals at EH level, the distribution network is reconfigured for optimal operation using the second-order cone programming (SOCP) with tightest convex relaxation.

3) At the EH trading level, an end-to-end trading is proposed among EHs and between EHs and the DSO using the Nash bargaining model. The impact of DSO operation and EH locations on their end-to-end trading and clearing is analyzed.

II. TE Framework with Multiple EHs

A. Proposed Framework for TE Trading

In Fig. 1, the proposed bi-level TE framework consists of two problems. The upper level is the Nash bargaining problem, which considers TE trading among EHs and optimizes the strategy of energy trading and payment among EHs. The lower level is the network reconfiguration problem. We decompose the Nash bargaining problem into two subproblems, i.e., EH operation cost minimization problem and payment bargaining problem. The EHs optimize their operation and trading without considering the network operation. The rationality of decomposition will be discussed in Section IV. By solving the Nash bargaining problem, the updated load information is sent to the lower level and reconfigures the network to minimize DSO cost. The network topology would change and affect the TE trading among EHs. Since each entity's decision would influence the strategies of other entities, an equilibrium state exists, where no entity can further optimize its own objective by unilaterally changing its decision. Once the equilibrium state is achieved, final trading decision will be determined and the final Nash equilibrium in payment among EHs can be achieved. Once the trading decisions are made, the lower level reconfigures the distribution network and minimizes the network operation cost. Different power distribution topologies impact the trading cost between EHs, thus their trading behaviors will be updated. Since the network reconfiguration is rarely considered in the gas pipeline system or heat pipeline system, the reconfiguration option is only for the electrical system.

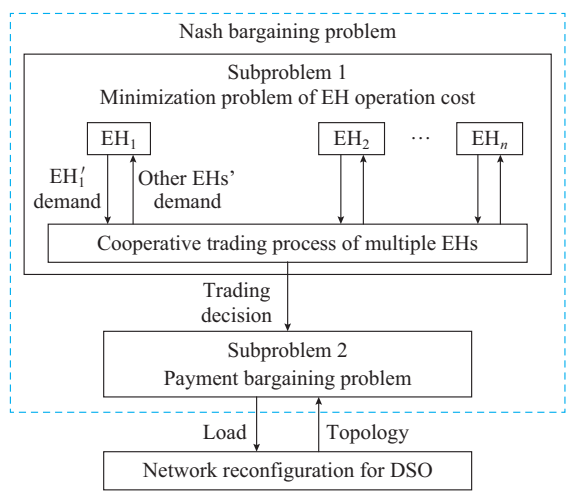

Fig. 1. Proposed framework for TE trading.

B. Modified EH Model

Figure 2 shows the modified topology of EH for the proposed multi-carrier energy system, which consists of combined heat and power (CHP), electricity storage (ES), electricity boiler (EB) and heat storage (HS). CHP converts gas into heat and electricity. ES stores the electricity produced by CHP or purchased from distribution system or other EHs, and discharges when electricity demand is large. EB utilizes the electricity purchased from distribution system or pro-

duced from ES or CHP to generate heat. HS stores the heat produced by EB and CHP, and releases when heat demand is large.

In Fig. 2, $m_1, m_2, ..., m_{15}$ are the internal energy flows in EH; $m^e_{pur,D}$ is the electricity brought from DSO; m^g_{in} and m^g_{out} are the gas input and output of EH, respectively; m^e_{in} and m^e_{out} are the electricity input and output of EH, respectively; m^h_{out} is the output of heat in EH; $m^e_{pur,ij}$ and $m^e_{sel,ij}$ are the purchase and sell of electricity among EHs, respectively; m^e_{Load} is the electricity load of EH; η_{CE} and η_{CG} are the efficiency of converting gas into electricity and heat in CHP, respectively; η_{SC} and η_{SD} are the efficiencies of charging and discharging in ES, respectively; η_{EB} is the efficiency of converting electricity into heat in EB; and η_{HC} and η_{HD} are the efficiencies of charging and discharging in HS, respectively.

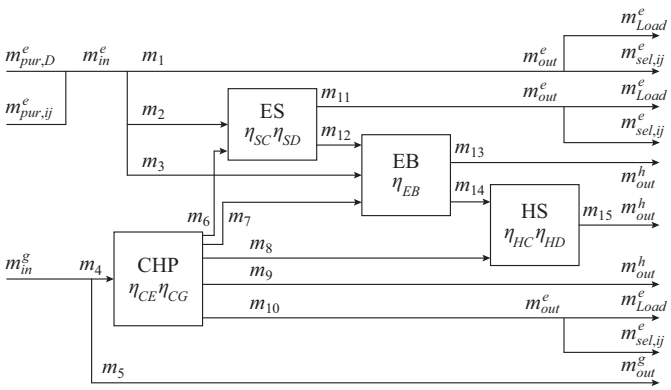

Fig. 2. Topology of EH for proposed multi-carrier energy system.

III. Trading Formulation of Multiple EHs

Consider a distribution network with M_{EH} individual EHs. These EHs locate at different nodes in the network, which is connected to the main power grid. Each EH can buy electricity from the main grid directly or exchange power with other EHs by making bilateral contracts. Consider an operation horizon of $NT = 24$ hours. In this paper, we focus on the energy trading and scheduling in the day-ahead market. We assume that the power supplies and loads are scheduled based on the daily prediction, and the mismatch part can be balanced in the real-time market. The objective for the trading of multiple EHs is to minimize the total operation cost of all EHs, while DSO is responsible for the transmission loss minimization of distribution system, to achieve the maximum social benefit. In this paper, we assume that all the EHs are managed by one operator. The joint optimization of all the EHs is in a centralized fashion.

A. Energy Scheduling Constraints in Each EH

1) Energy Purchased from Distribution System

EH i can purchase electricity from distribution system and gas from gas supplier, to meet local demand. $P^t_{pur,e,iD}$ and $P^t_{pur,g,iD}$ should satisfy the following constraints:

$$0 \le P^t_{pur,e,iD} \le P^{\max}_{pur,e,iD} \tag{1}$$

$$0 \le P^t_{pur,g,iD} \le P^{\max}_{pur,g,iD} \tag{2}$$

where $P^t_{pur,e,iD}$ and $P^t_{pur,g,iD}$ are the electricity purchased from distribution system by EH i at time slot t, and the gas purchased from distribution system by EH i at time slot t, respectively; and $P^{\max}_{pur,e,iD}$ and $P^{\max}_{pur,g,iD}$ are the maximum amounts of electricity and gas that EH i can purchase from distribution system and from gas supplier due to the physical capacity limit, respectively. Accordingly, the energy cost of EH i is expressed as:

$$C_e(P^t_{pur,e,iD}) = \sum_{t=1}^{NT} \sigma^t_{LMP} P^t_{pur,e,iD} \tag{3}$$

$$C_g(P^t_{pur,g,iD}) = \sum_{t=1}^{NT} \sigma^t_g P^t_{pur,g,iD} \tag{4}$$

where $C_e(P^t_{pur,e,iD})$ and $C_g(P^t_{pur,g,iD})$ are the energy costs of buying electricity and gas, respectively; and σ^t_{LMP} and σ^t_g are the electricity buying price and the gas buying price in time slot t, respectively.

2) Local Power Demand

DR in each EH is considered. Power loads in each EH are divided into two categories: elastic loads and inelastic loads. DR can control the elastic loads such as washing machine, electrical vehicle, and heating, ventilation and air conditioning (HVAC), to reduce or shift the elastic power demand to other time. However, the inelastic loads such as lighting, cooking and refrigerator, can not be shifted to other time easily. For simplicity, we only consider the reducible load in DR. As the elastic power consumption is scheduled by DR, which may lead to discomfort of users in EH, the discomfort cost of each EH is considered. Let $L^t_{e,el,i}$ and $L^t_{e,0,i}$ denote the loads after and before implementing DR, respectively, subjecting to the following constraints:

$$L^{\min}_{e,el,i} \le L^t_{e,el,i} \le L^{\max}_{e,el,i} \tag{5}$$

$$C_{dr}(L^t_{e,el,i}) = \sum_{t=1}^{NT} \alpha (L^t_{e,el,i} - L^t_{e,0,i})^2 \tag{6}$$

where $C_{dr}(L^t_{e,el,i})$ is the cost of DR; and $L^{\min}_{e,el,i}$ and $L^{\max}_{e,el,i}$ are the minimum and maximum loads after scheduling, respectively, to ensure the actual power consumption meet the necessity of life. In (6), $(L^t_{e,el,i} - L^t_{e,0,i})^2$ is used to measure the deviation between the actual power consumption and the preferred power consumption. The coefficient α indicates the sensitivity of each EH towards the load deviation.

3) Operation Constraints

Constraints (7)-(38) represent the operation constraints of the proposed modified EH. Constraints (7) - (22) are the equality relationship among the variables of EH shown in Fig. 2. Since each branch in the proposed EH is given the energy flow direction, the input energy and the energy flow variables are positive in (23) and (24). Constraints (25) and (26) limit the input of CHP and EB. Constraints (27) and (28) limit the input, output and the operation mode of HS. HS is not allowed to store and release heat at the same time. Constraints (29) and (30) limit the capacity of HS. Constraints (31) and (32) limit the input, output and the operation mode of ES. Constraints (33) and (34) limit the capacity of ES. ES is not allowed to store and release electricity at the same time. Constraints (35)-(38) are the operation constraints of CHP that the output of electricity and heat are within a certain range [19].

$$m_{1,i}^t + m_{2,i}^t + m_{11,i}^t = m_{out,e,i}^t \tag{7}$$

$$m_{out,e,i}^t = L_{e,el,i}^t + \sum_j P_{sel,e,ij}^t \tag{8}$$

$$L_{e,el,i}^t = L_{e,0,i}^t - L_{e,dr,i}^t \tag{9}$$

$$m_{out,e,i}^t = L_{h,i}^t \tag{10}$$

$$m_{out,g,i}^t = L_{g,i}^t \tag{11}$$

$$m_{5,i}^t = m_{out,g,i}^t \tag{12}$$

$$m_{9,i}^t + m_{13,i}^t + m_{15,i}^t = m_{out,h,i}^t \tag{13}$$

$$m_{1,i}^t + m_{2,i}^t + m_{3,i}^t = m_{in,e,i}^t \tag{14}$$

$$m_{4,i}^t + m_{5,i}^t = m_{in,g,i}^t \tag{15}$$

$$\eta_{HC}(m_{8,i}^t + m_{14,i}^t) - \eta_{HD} m_{15,i}^t = \Delta E_{hs,i}^t \tag{16}$$

$$\eta_{SC}(m_{2,i}^t + m_{6,i}^t) - \eta_{SD} m_{11,i}^t = \Delta E_{es,i}^t \tag{17}$$

$$\eta_{CE} m_{4,i}^t - m_{6,i}^t - m_{7,i}^t - m_{10,i}^t = 0 \tag{18}$$

$$\eta_{CG} m_{4,i}^t - m_{8,i}^t - m_{9,i}^t = 0 \tag{19}$$

$$\eta_{EB}(m_{3,i}^t + m_{7,i}^t + m_{12,i}^t) - m_{13,i}^t - m_{14,i}^t = 0 \tag{20}$$

$$m_{in,e,i}^t = P_{pur,e,iD}^t + \sum_{j \neq i, j \in M} P_{pur,e,ij}^t \tag{21}$$

$$m_{in,g,i}^t = P_{pur,g,iD}^t \tag{22}$$

$$m_{in,e,i}^t, m_{in,g,i}^t \geq 0 \quad \forall i, \forall t \tag{23}$$

$$m_{1,i}^t, m_{2,i}^t, \ldots, m_{15,i}^t \geq 0 \quad \forall i, \forall t \tag{24}$$

$$m_{4,i}^t \leq CHP_i^{\max} \quad \forall i, \forall t \tag{25}$$

$$m_{3,i}^t + m_{7,i}^t + m_{12,i}^t \leq EB_i^{\max} \tag{26}$$

$$m_{8,i}^t + m_{14,i}^t \leq S_{hs,i}^t E_{ch,h,i}^{\max} \quad \forall i, \forall t \tag{27}$$

$$m_{15,i}^t \leq (1 - S_{hs,i}^t) E_{dis,h,i}^{\max} \quad \forall i, \forall t \tag{28}$$

$$0 \leq E_{hs,i}^t \leq E_{hs,i}^{\max} \tag{29}$$

$$E_{hs,i}^t = \begin{cases} E_{hs,i}^0 & t = 0 \\ E_{hs,i}^{t-1} + \Delta E_{hs,i}^{t-1} & \text{otherwise} \end{cases} \tag{30}$$

$$m_{2,i}^t + m_{6,i}^t \leq S_{es,i}^t E_{ch,e,i}^{\max} \quad \forall i, \forall t \tag{31}$$

$$m_{11,i}^t + m_{12,i}^t \leq (1 - S_{es,i}^t) E_{dis,e,i}^{\max} \quad \forall i, \forall t \tag{32}$$

$$0 \leq E_{es,i}^t \leq E_{es,i}^{\max} \tag{33}$$

$$E_{es,i}^t = \begin{cases} E_{es,i}^0 & t = 0 \\ E_{es,i}^{t-1} + \Delta E_{es,i}^{t-1} & \text{otherwise} \end{cases} \tag{34}$$

$$m_{6,i}^t + m_{7,i}^t + m_{10,i}^t = \sum_k \mu_{k,i}^t v_{k,i} \tag{35}$$

$$m_{8,i}^t + m_{9,i}^t = \sum_k \mu_{k,i}^t \omega_{k,i} \tag{36}$$

$$0 \leq \mu_{k,i}^t \leq 1 \quad \forall k, \forall i, \forall t \tag{37}$$

$$\sum_k \mu_{k,i}^t = 1 \quad \forall k, \forall i, \forall t \tag{38}$$

where $m_{1,i}^t, m_{2,i}^t, \ldots, m_{15,i}^t$ are the internal energy flows in EH; $m_{in,g,i}^t$ and $m_{in,e,i}^t$ are the inputs of gas and electricity in EH, respectively; $m_{out,g,i}^t$, $m_{out,e,i}^t$, $m_{out,h,i}^t$ are the outputs of gas, electricity and heat in EH, respectively; $P_{pur,e,ij}^t$ and $P_{sel,e,ij}^t$ are the trading amount of electricity that EH i buys from EH j and the trading amount of electricity that EH i sells to EH j, respectively; $L_{e,dr,i}^t$ is the shedding load in DR; $L_{h,i}^t$ and $L_{g,i}^t$ are the heat load and gas load of EH, respectively; $\Delta E_{hs,i}^t$ and $\Delta E_{es,i}^t$ are the energy changes of HS and ES, respectively; $CHP_i^{\max}$ and $EB_i^{\max}$ are the maximum inputs of CHP and EB, respectively; $S_{hs,i}^t$ is the state of HS; $E_{ch,h,i}^{\max}$ and $E_{dis,h,i}^{\max}$ are the maximum charging and discharging of HS, respectively; $E_{hs,i}^t$ and $E_{hs,i}^{\max}$ are the HS and maximum HS, respectively; $E_{es,i}^t$ and $E_{es,i}^{\max}$ are the ES and maximum ES, respectively; $S_{es,i}^t$ is the state of ES; $E_{ch,e,i}^{\max}$ and $E_{dis,e,i}^{\max}$ are the maximum charging and discharging of ES, respectively; $v_{k,i}$ and $\omega_{k,i}$ are the boundary points of the operation region; and $\mu_{k,i}^t$ is used to guarantee the solution in the certain range.

B. Energy Trading Constraints in Each EH

EHs at different locations have different internal characteristics and local loads. By trading energy with each other, all the EHs reschedule their power supplies and demands, and can achieve mutual benefit. To reach a state of Pareto optimality, Nash bargaining method [20] is applied to the proposed TE model.

Each EH bargains with other EHs and makes the trading decision. For market clearing, the energy trading amount and payment should satisfy the following constraints:

$$P_{pur,e,ij}^t P_{sel,e,ji}^t \geq 0 \tag{39}$$

$$P_{pur,e,ij}^t = P_{sel,e,ji}^t \tag{40}$$

$$\varphi_{ij} = -\varphi_{ji} \tag{41}$$

where φ_{ij} is the corresponding trading payment, $\forall i, j \in M$, $i \neq j$. Here, $P_{pur,e,ij}^t$ and $P_{sel,e,ij}^t$ are non-negative. If EH i purchases energy from EH j in time slot t, $P_{pur,e,ij}^t > 0$, $P_{sel,e,ij}^t > 0$ and EH i makes payment to EH j, i.e., $\varphi_{ij} > 0$. Otherwise, if EH i sells energy to EH j in time slot t, $P_{sel,e,ji}^t > 0$, $P_{pur,e,ji}^t > 0$ and EH i receives payment from EH j, i.e., $\varphi_{ij} < 0$.

Since each EH is an individual player, it only focuses on its own performance and benefit in the energy trading process. Each EH should make the payment to other EHs if there exists energy trading, which also leads to an extra cost:

$$C_{tr}(\varphi_i) = \sum_{j \neq i} \varphi_{ij} \quad \forall i, j \tag{42}$$

We assume that the EHs locate at different nodes in the network, and the loss of energy exchange is considered. We use a quadratic relationship with transferred power to estimate the cost of the loss of power exchange:

$$C_{del}(P_{pur,e,ij}^t) = \sum_{t=1}^{NT} \beta R_{ij}^t \left(P_{pur,e,ij}^t\right)^2 \tag{43}$$

where R_{ij}^t is the equivalent distance between EHs i and j at time slot t; $C_{del}(\cdot)$ is the line resistance between the two EH nodes; and β is to indicate the relationship between the exchange cost and the transferred power.

C. Nash Bargaining Based Energy Trading

The operation cost for EH i consists of four parts, i.e., the cost of buying electricity from the main grid, the cost of purchasing gas from gas suppliers, the cost of users' discomfort and the cost of the loss of power transfer, which is written

as:

$$C_{0,i}(P^t_{pur,e,iD}, P^t_{pur,g,iD}, L^t_{e,el,i}, P^t_{pur,e,ij}) = C_e(P^t_{pur,e,iD}) + C_g(P^t_{pur,g,iD}) + C_{dr}(L^t_{e,el,i}) + C_{del}(P^t_{pur,e,ij}) \quad (44)$$

where $C_{0,i}(P^t_{pur,e,iD}, P^t_{pur,g,iD}, L^t_{e,el,i}, P^t_{pur,e,ij})$ is the operation cost. EH i will only trade energy with other EHs if its total cost can be reduced through the trading. Thus, we have the following constraint:

$$C_{0,i}(P^t_{pur,e,iD}, P^t_{pur,g,iD}, L^t_{e,el,i}, P^t_{pur,e,ij}) + C_{tr}(\varphi_i) \le C_{non,i} \quad (45)$$

where $C_{non,i}$ is the disagreement point in the bargaining theory, which means the boundary of non-cooperative situation. It denotes the optimal value to minimize (44), which indicates that EH i can achieve the minimum cost without energy trading with other EHs. At this time, $C_{del}(P^t_{pur,e,ij}) = 0$. The left-hand side of the inequality in (45) is the total cost of EH i, including the operation cost and the trading payment, which should be smaller than $C_{non,i}$ in the energy trading.

Let $M' \in M$ denote the EHs that participate in the energy trading. For EH $j \in M \setminus M'$, it can not benefit from the energy trading and thus not participate in the trading. Therefore, we formulate the proposed energy trading problem based on Nash bargaining as:

$$\begin{cases} \max \prod_{i \in M'} [\, C_{non,i} - (C_{o,i}(P^t_{pur,e,iD}, P^t_{pur,g,iD}, L^t_{e,el,i}, P^t_{pur,e,ij}) + C_{tr}(\varphi_i))\,] \\ \text{s.t. } (1), (2), (5), (7)\text{-}(41), (45) \end{cases} \quad (46)$$

D. Distribution System Reconfiguration

The reconfiguration model of distribution system is based on the SOCP shown as:

$$\min \sum_{t=1}^{NT} \sum_{i=1}^{NB} \eta^t_{LMP}(P^t_{inj,i} - PL^t_i) \quad (47)$$

s.t.

$$\omega_l = \gamma_{mn} + \gamma_{nm} \quad \forall l \in L \quad (48)$$

$$\sum_{n \in N(m)} \gamma_{mn} \le 1 \quad \forall m \in N \backslash N_s \quad (49)$$

$$\begin{cases} \gamma_{mn} \in \{0,1\} \\ 0 \le \omega_l \le 1 \quad \forall l \in L \end{cases} \quad (50)$$

$$p_{mn} = \sqrt{2}\, G_l u^l_m - G_l J_l - B_l K_l \quad \forall l \in L \quad (51)$$

$$q_{mn} = -\sqrt{2}\,(B_l + \frac{B^{sh}_l}{2}) u^l_m + B_l J_l - G_l K_l \quad l \in L \quad (52)$$

$$J_l^2 + K_l^2 \le 2 u^l_m u^l_n \quad \forall l \in L \quad (53)$$

$$0 \le u^l_m \le \frac{V^2_{m,\max}}{\sqrt{2}} \omega_l \quad \forall m \in N \quad (54)$$

$$0 \le u_m - u^l_m \le \frac{V^2_{m,\max}}{\sqrt{2}} (1 - \omega_l) \quad \forall m \in N \quad (55)$$

$$\sqrt{2}\, A_L u^l_m - \sqrt{2}\, B_L u^l_n - 2C_L J_l + 2D_L K_l \le I^2_{l,\max} \quad \forall l \in L \quad (56)$$

$$0 \le J_l \le V_{m,\max} V_{n,\max} \quad \forall l \in L \quad (57)$$

$$-V_{m,\max} V_{n,\max} \le K_l \le V_{m,\max} V_{n,\max} \quad \forall l \in L \quad (58)$$

$$\frac{V^2_{m,\min}}{\sqrt{2}} \le u_m \le \frac{V^2_{m,\max}}{\sqrt{2}} \quad \forall m \in N \quad (59)$$

$$\sum_l (\omega_l + \hat{\omega}_l - 2H_l) \le N_{switch} \quad \forall l \in L \quad (60)$$

$$H_l - \omega_l \le 0 \quad \forall l \in L \quad (61)$$

$$H_l - \hat{\omega}_l \le 0 \quad \forall l \in L \quad (62)$$

$$\omega_l + \hat{\omega}_l - H_l \le 1 \quad \forall l \in L \quad (63)$$

$$H_l \ge 0 \quad \forall l \in L \quad (64)$$

where NB is the number of bus; η^t_{LMP} is the locational marginal price in slot t; $P^t_{inj,i}$ and PL^t_i are the injection power and load at node i, respectively; $\hat{\omega}_l$, γ_{mn} and γ_{nm} are the binary variables, γ_{mn} is equal to 1 if bus n is the parent of bus m, and 0 otherwise; p_{mn} and q_{mn} are the active and reactive power flows from bus m to bus n, respectively; G_l and B_l are the series conductance and susceptance of a line between buses m and n, respectively; B^{sh}_l is the shunt susceptance of a line between buses m and n; $V_{m,\max}$ and $V_{m,\min}$ are the maximum and minimum voltages of bus m, respectively; $I_{l,\max}$ is the maximum current; H_l is an auxiliary variable; N_{switch} is the maximum switching times; L is the branch set; N_s is the set of substation nodes; N is the set of all the nodes; and $N \backslash N_s$ is the set of remaining nodes except sustation nodes..

The objective of network reconfiguration is to minimize DSO cost, which is measured by the transmission loss in the network. $P^t_{inj,i}$ is zero at the non-substation node. For non-EH nodes, PL^t_i is constant. For EH nodes, PL^t_i is determined by TE trading decisions among EH nodes.

Constraints (48)-(50) limit the tree structure of the distribution network. By defining auxiliary variables $u^l_m = V_i^2/\sqrt{2}$, $J_l = V_i V_j \cos\theta_{ij}$, $K_l = V_i V_j \sin\theta_{ij}$, branch active and reactive power flow constraints are linearized in (51) and (52), respectively. Constraint (53) represents the conic relaxation relationship of the auxiliary variables J_l, K_l and u^l_m, u^l_n. Constraints (54) and (55) link the network configuration variable ω_l to the auxiliary voltage variable u^l_m. By defining $A_L = G_l^2 + \left(B_l + B^{sh}_l/2\right)^2$, $B_L = G_l^2 + B_l{}^2$, $C_L = G_l^2 + B_l\left(B_l + B^{sh}_l/2\right)$ and $D_L = G_l B^{sh}_l/2$, constraint (56) limits the line capacity. Constraints (57)-(59) give the lower and upper bounds for the auxiliary variables J_l, K_l and u_m. The change of switch status between every two adjacent scheduling time should be within a certain number of times in (60)-(64).

IV. Nash Bargaining Problem Decomposition

In this section, to reduce computational complexity, we decompose the bargaining problem (46) into two subproblems P1 and P2. Subproblem P1 solves the operation cost minimization problem to determine the power schedule and trading decision of EHs. Subproblem P2 solves the payment bargaining problem to share the benefits from the cooperation in a fair manner. According to [21], [22], P1 and P2 are both convex.

The problem decomposition is based on the following proposition. If the whole system gets cost reduction or extra benefit, the EHs participating in energy trading can get bene-

fit by making proper payment. These EHs prefer to make cooperation to minimize their operation cost. As to the EHs in $M \setminus M'$, their operation cost keeps the same as $C_{non,i}$. Only the EHs in M' contribute to the cost reduction of the whole system. Thus, we can conclude a proposition that the optimal solution of total benefit of the whole system maximization problem (46) also minimizes the operation cost of the EHs in M'. Based on the above proposition, the bargaining problem (46) can be decomposed into P1 and P2 as follows.

A. P1: Minimization Problem of Operation Cost

$$\begin{cases} \min C_{0,i}(P^t_{pur,e,iD}, P^t_{pur,g,iD}, L^t_{e,el,i}, P^t_{pur,e,ij}) \\ \text{s.t. } (1),(2),(5),(7)\text{-}(38) \end{cases} \tag{65}$$

We assume that all the EHs in the network are operated by one manager so that the power schedule of all the EHs are in a centralized manner. By solving P1, trading decision of each EH can be determined. Note that some EHs may not participate in the energy trading, since participating in the trading can not reduce their operation cost. They do not participate in payment bargaining. For the EHs participating in energy trading, they will continue to participate in payment bargaining in P2.

B. P2: Payment Bargaining Problem

$$\begin{cases} \max \prod_{i \in M'} (\xi^* - C_{tr}(\varphi_i)) \\ \text{s.t. } (39)\text{-}(41),(45) \end{cases} \tag{66}$$

where $\xi^* \triangleq C_{non,i} - C_{0,i}(P^{t*}_{pur,e,iD}, P^{t*}_{pur,g,iD}, L^{t*}_{e,el,i}, P^{t*}_{pur,e,ij})$ is the operation cost reduction of EH i based on the optimal solution of P1. By solving P2, each EH $i \in M'$ can achieve benefits fairly.

The trading decisions of EHs are then sent to DSO level, and DSO reconfigures the network to minimize its own cost. The topology will be updated and may affect the trading decisions of EHs. The final trading decisions will be determined until the topology does not change any more.

The proposed trading process is described as:

1) Initialize parameters including the network topology, EH operation characteristics, locational marginal price (LMP) of DSO, gas price and system load. Then, the problem (47), (65) and (66) are formed.

2) Solve P1 (65) to achieve $P^t_{pur,e,iD}$, $P^t_{pur,g,iD}$, $L^t_{e,el,i}$ and $P^t_{pur,e,ij}$ of EHs. Then, these TE trading decisions are sent to P2 (66) for payment bargaining. The payment $C_{tr}(\varphi_i)$ of each EH is achieved.

3) The trading decisions of EHs are then sent to DSO level for distribution reconfiguration. The updated topology has an impact on the cost of loss of energy exchange (43), which would change EH trading behaviors. The bi-level iterative process will end when the topology is no longer altered. Then, the final TE trading decision and the final payment among EHs are achieved.

V. Case Studies

As shown in Fig. 3, a modified IEEE 33-bus distribution system with five tie-lines is utilized to prove the effectiveness of the proposed model and algorithm [23], [24]. EH1, EH2 and EH3 are located at nodes 9, 11 and 29, respectively. The dashed lines in Fig. 3 represent the tie-line. The hourly LMP in PJM market is shown in Fig. 4.

Here, we consider two cases: Case 1 is to demonstrate the merit of trading among EHs without distribution network reconfiguration; and Case 2 focuses on the impact of distribution reconfiguration. All simulations are conducted on a Windows 10 64-bit personal computer with Intel Core i5-6500 3.2 GHz CPU and 8 GB of RAM using MATLAB 2016b with Yalmip and Gurobi.

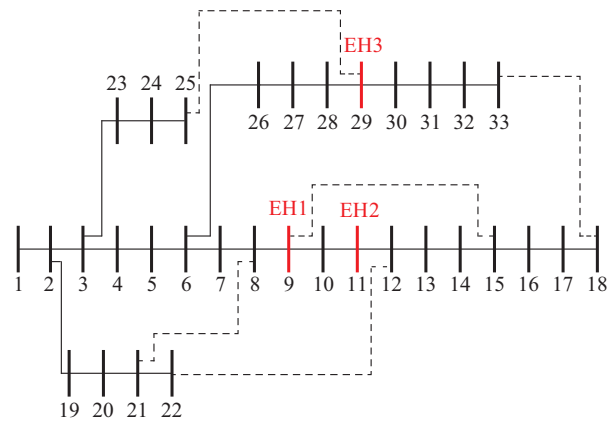

Fig. 3. Modified IEEE 33-bus distribution system.

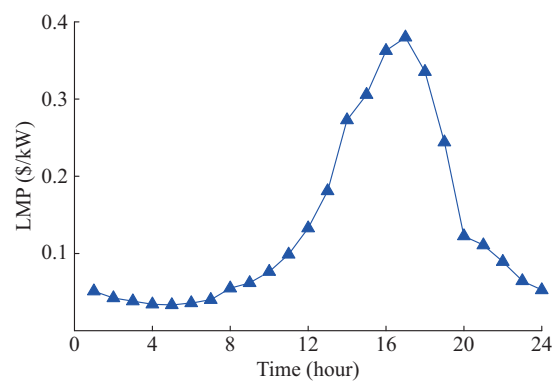

Fig. 4. Hourly LMP in PJM market.

A. Case 1: TE Trading Without Network Reconfiguration

In Case 1, two scenarios are discussed as follows.

1) Scenario 1: EHs only buy electricity from DSO and gas from gas supplier, but they do not trade with each other.

2) Scenario 2: energy trading is considered. EHs not only buy electricity and gas, but also trade electricity with each other.

In Scenario 1, when no energy trading among EHs is considered, each EH supplies its electricity load by DSO, CHP and ES, and makes independent decision, which leads to the highest total cost of $1152.11.

Considering energy trading between EHs in Scenario 2, the total cost of EHs is reduced up to 9.28% from $901.33 to $817.65. As shown in Fig. 5, EH3 has large load and buys less electricity in the time slot when LMP is high. Meanwhile, EH1 and EH2 buy more electricity before the peak time of LMP and then EH1 and EH2 trade with EH3.

In Fig. 6, we can notice that EHs do not trade with each other when the LMP is low. With the increase of LMP, EHs trade more. When LMP is highest, EH3 buys the largest amount of electricity from EH1 and EH2.

Since the EHs participate in energy trading, the energy is utilized much efficiently and EHs can have better decision on energy management. As a result, they will benefit from energy trading. Compared with Scenario 1, EH1, EH2 and EH3 have the benefit of \$26.59, \$26.59 and \$30.5, respectively when EHs trade with each other in Scenario 2. The detailed comparison of Scenario 1 and Scenario 2 is shown in Table I.

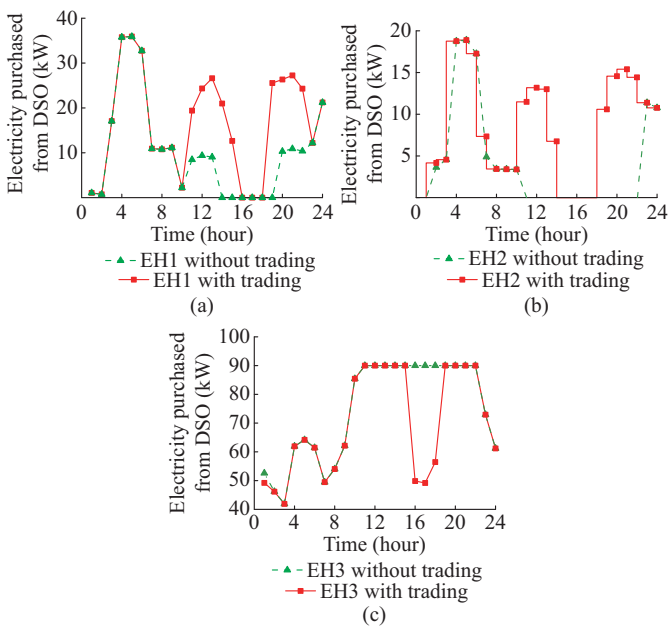

Fig. 5. Electricity purchased from DSO by EHs. (a) EH1. (b) EH2. (c) EH3.

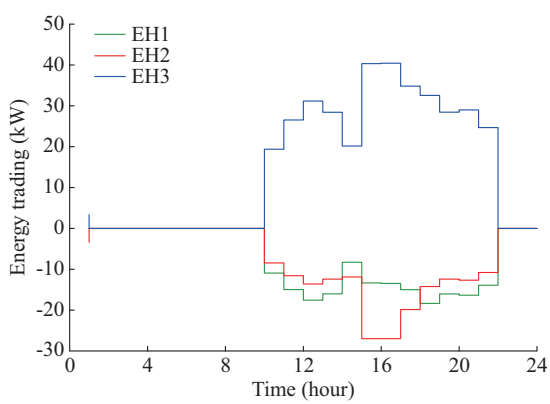

Fig. 6. Energy trading among EHs.

TABLE I
COST AND PAYMENT

EH	Cost without trading (\$)	Cost with trading (\$)	Payment with trading (\$)	Cost + payment with trading (\$)
1	180.98	214.98	−60.59	154.39
2	136.19	162.40	−52.80	109.60
3	584.16	440.27	113.39	553.66
Total	901.33	817.65	0	817.65

The energy in ES is shown in Fig. 7. Since EHs have ES, EHs will be able to make good use of energy, make better electricity management and save their cost caused by the increase of LMP. EHs tend to store electricity when LMP is low and discharge when LMP is high, in order to decrease their cost and maximize their own benefit.

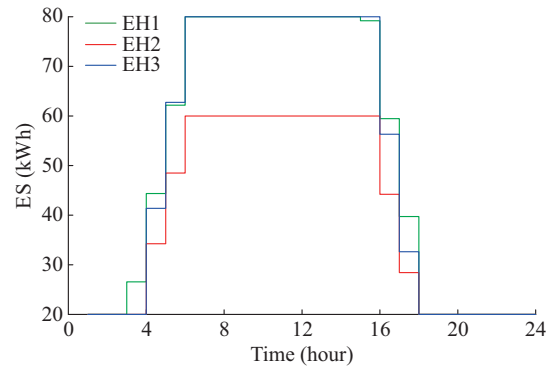

Fig. 7. Energy in ES.

HS is greatly different from ES. The HS has relationship with ① the LMP and the transforming cost of CHP; ② the operation area of CHP and the heat load. The energy in HS, gas input of CHP, heat load of EHs and heat production of EB are shown in Figs. 8-11, respectively. Note that the heat load is mainly supplied by CHP. If CHP cannot provide enough heat, EB will transform electricity into heat since the cost of transforming electricity into heat is higher than cogeneration by CHP. CHP provides electricity and heat at the same time.

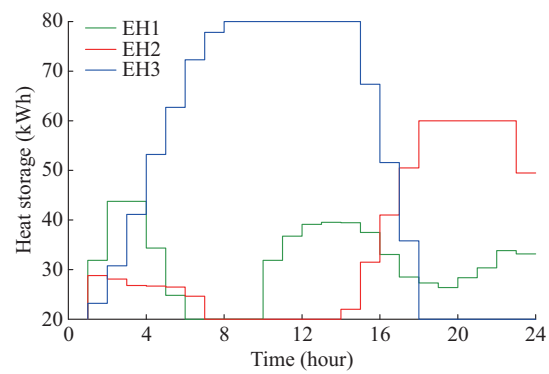

Fig. 8. Energy in HS.

Here, natural gas price is set to 28 \$/MWh and the efficiencies of transforming gas into electricity and heat are 35% and 45%, respectively, which indicates that it costs \$0.08 to produce 1 kWh electricity and \$0.062 to produce 1 kWh heat. When LMP is higher than \$0.08, EHs tend to produce more electricity by CHP instead of buying from DSO.

EH1 and EH2 have small electricity and heat load. Their heat loads are supplied by CHP mostly and HS partly. Hence their gas inputs of CHP have the same tendency with their heat load.

EH3 has large electricity and heat load, hence the CHP runs in a maximum way and its gas input of CHP maintains maximum all the time. The heat energy is stored when the

heat load is small from hour 2 to hour 8, and released when the heat load is small from hour 15 to hour 18. The EB of EH3 produces heat from hour 8 to hour 24 since the CHP cannot provide enough heat. Note that EB is a backup heat resource since the cost of producing 1 kWh heat by EB is higher than the cost of producing 1 kWh heat by CHP from hour 8 to hour 15.

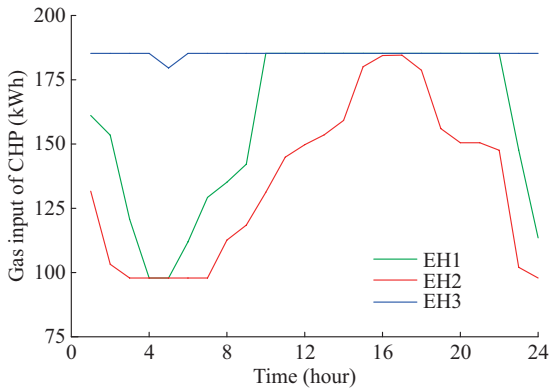

Fig. 9. Gas input of CHP.

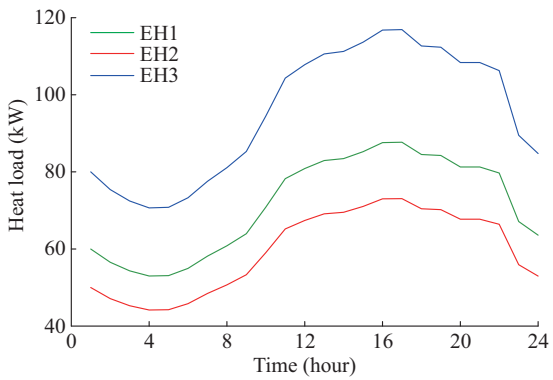

Fig. 10. Heat load of EHs.

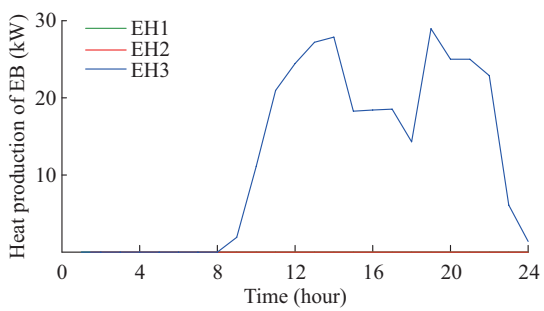

Fig. 11. Heat production of EB.

In conclusion, CHP cogenerates electricity and heat at the same time. CHP supplies heat as much as possible for heat load. When LMP goes up, CHP produces more electricity and more heat. If the heat is surplus, it will be stored and if the heat is insufficient, HS will release heat and EB acts as backup heat resource. With CHP, EH can make better energy management. EHs can save their money effectively through changing the distribution of electricity and heat resources according to the fluctuation of LMP.

Considering the DR, the EHs can make wiser decision for load management. We assume that the DR is curtailable load, instead of shiftable load. With the increase of LMP, EHs decide to cut more load to reduce their cost even though the cost of discomfort is considered. Note that the cost of discomfort of EH is the bonus for the users to change their load behavior. With DR, the EHs save money for buying electricity when the LMP is high and the users also benefit from changing their behavior. The DR of EHs is shown in Fig. 12.

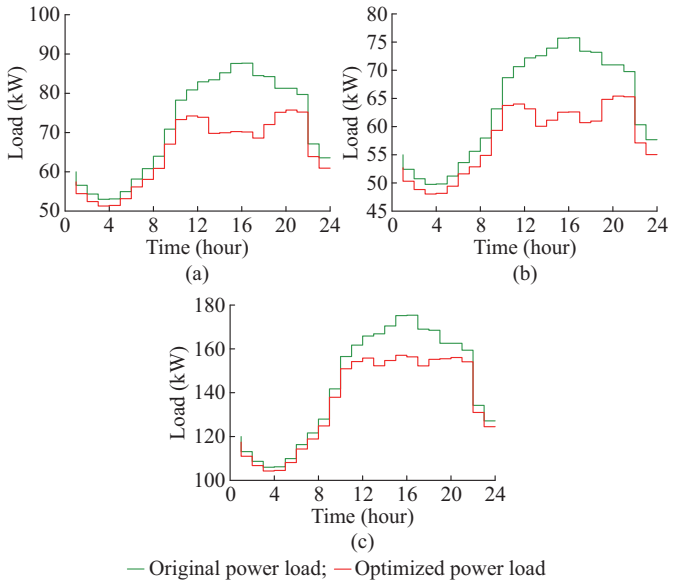

Fig. 12. DR of EHs. (a) EH1. (b) EH2. (c) EH3.

B. Case 2: TE Trading with Network Reconfiguration

Distribution network reconfiguration can optimize the hourly power flow, which may lead to less cost of DSO in distribution system. As shown in Fig. 13, the cost of DSO can be reduced with reconfiguration, especially when the LMP is high. The cost of DSO is evaluated by the network loss multiplied by LMPs, which means that the DSO pays for the distribution network loss.

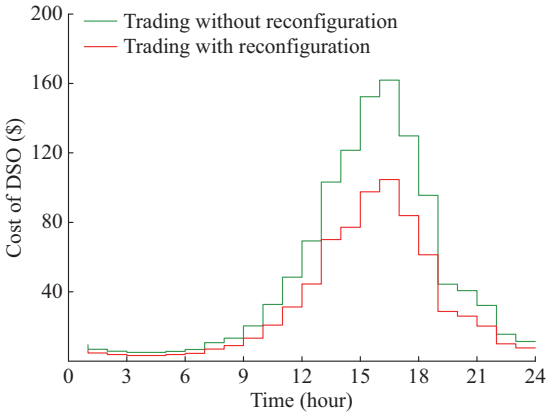

Fig. 13. Cost of DSO with and without reconfiguration.

Two scenarios are considered: no trading and trading among EHs. Each scenario can be further divided into two situations: with and without reconfiguration. The results are

shown in Table II. When reconfiguration is considered, the trading among EHs can reduce the cost of DSO up to 11.8% from \$842.17 to \$742.56. When EHs trade with each other, reconfiguration can reduce the cost of DSO up to 35.3% from \$1147.79 to \$742.56. Thus, we can draw a conclusion that the social cost, including the cost of DSO and EHs, can be reduced effectively in the proposed model.

TABLE II
COST OF DSO

Scenario	Cost of DSO (\$)
No trading without reconfiguration	1152.11
No trading with reconfiguration	842.17
Trading without reconfiguration	1147.79
Trading with reconfiguration	742.56

Note that trading among EHs will change the power flow in distribution network, which will increase or relieve the congestion of lines. Meanwhile, the reconfiguration will optimize the power flow but not always reduce the loss of network. This problem has strong relationship with network topology and the location of EHs.

C. Analysis of Convergence

Due to the complexity of the problem, it is not trivial to prove the convergence of bi-level framework. However, the convergence trend can be divided into the following cases.

Case 1: as long as the deviation between two iterations is less than the tolerance ε, the proposed bi-level framework can be considered as the convergence.

Case 2: if the last result is the same as the result which has been obtained in the iterations before, there is a cycle of solution. It is available to choose one solution of the cycle as the optimal solution. The criteria can be the minimum of network cost or the minimum of total cost of EHs.

The solution space of reconfiguration in distribution system is definite, hence the final solution can be obtained in Case 1 or Case 2. In general, for a distribution system, electricity trading among EHs has relatively small effect on the load distribution for the whole network. The proposed framework will usually converge within 3-5 iterations.

For one iteration, the network reconfiguration and trading decisions in 24 hours are calculated. The computation time is about 100 s. Typically, it takes about 3-5 times to get the convergence. Thus, the total computation time is about 300-500 s in most situations.

In general, the computation time is within the acceptable range for day-ahead or intra-day operation. Moreover, a general solver is applied to solve the proposed approach; however, the calculation efficiency can be further improved by devising algorithms that are particularly developed for this kind of problem. For instance, the total CPU time would be greatly reduced if parallel computation is adopted.

VI. CONCLUSION

This paper devises a TE trading model based on the bi-level bargaining using Nash bargaining theory. With the proposed transactive energy framework, EHs can reduce their operation cost and make more profits through trading with each other, on the premise of network security. The proposed model can also coordinate DSO and EHs in both system operation and market trading, reduce the network power losses and enhance the EH total economic benefits effectively. In our future work, we will focus on the effect of distribution locational marginal pricing (DLMP) on the transactive energy trading.

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