

Trading Model Combining Electricity, Heating, and Cooling Under Multi-energy Demand Response

Fangdi Zeng, Zhaohong Bie, Shiyu Liu, Chao Yan, and Gengfeng Li

Abstract—The emerging multi-energy system has brought new challenges and opportunities to energy business worldwide. To address the issues in multi-energy trading, this paper proposes an electricity, heating, and cooling trading model for the interaction between the multi-energy service provider (MESP) and multi-energy consumer (MEC) by using bi-level programming. In the upper level, the model instructs the MESP to make decisions on the optimal energy purchasing scheme and energy economic dispatch. In the lower level, optimal consuming patterns of different energies with the given retail prices are modeled for the MEC. Specifically, a novel multi-energy demand response (DR) program that employs energy conversion devices is proposed. Numerical results show that MEC can reduce its consumption cost via the multi-energy DR. Meanwhile, MESP benefits greatly from the flexibilities of energy conversion. This research can provide theoretical support for the future development of multi-energy trading.

Index Terms—Demand response (DR), multi-energy consumer (MEC), multi-energy service provider (MESP), trading model.

I. INTRODUCTION

THE concept of the multi-energy system (MES)[1] has emerged in recent years, addressing multiple energy sectors including electricity, heating, and cooling. Its high flexibility [2], low carbon emission [3], [4], and high reliability [5] are gaining attention in society.

In an MES, the multi-energy service provider (MESP) purchases energy (e.g., natural gas (NG) and electricity) from wholesale markets and sells various energies (e.g., electricity, heating, and cooling) to multi-energy consumers (MECs), who are the energy end-users (e.g., hotels, hospitals, supermarkets) with electricity, heating, and cooling demands. MESP also dispatches various energies by operating a combined cooling, heating, and power (CCHP) system [6]. As

the seller, MESP is willing to offer a good price to earn more, while MEC prefers bidding at a lower price to save expenses. As main parties in MES, MESP and MEC have to deal with a conflict of economic interests between them. To cope with the aforementioned issue, a trading model that creates a tradeoff between the two entities is introduced. The trading model guarantees profits for MESP, who will invest in MES and participate in the trading, while MECs also benefit from the multi-energy trading.

The state-of-the-art research on trading models of the single-energy (e.g., electricity, heat, etc.) type has been conducted in the last decade. The electricity trading models in the retail market have been investigated and summarized in [7]. By now, retail pricing schemes in electricity power trading can be divided into two categories: dynamic (time-varying) and static (pre-determined). In particular, the static pricing scheme consists of stepwise pricing [8], critical peak pricing [9], and time-of-use [10], [11]. Among the dynamic pricing schemes, real-time pricing (RTP) is typically effective in encouraging consumers to participate in demand response (DR) [12], and has become a feasible scheme in practice with smart grid technologies. In [13], a project for future smart grids, in which end consumers can actively participate in a new real-time electricity market by responding to 5-minute real-time electricity prices, is introduced. Reference [14] presents an energy trading model based on dynamic retail price between plug-in electric vehicle (PEV) aggregators and PEV drivers, using mathematical programming with complementarity constraints (MPCC). On the other hand, [15] reviews the pricing schemes for district heating (DH) systems. In general, there are two representative DH pricing methods: the cost-plus pricing method [16], which is commonly applied in the regulated market, and the marginal-cost pricing method [17], which is applied in the deregulated market. However, those researchers discuss the trading model only in terms of the single-energy system. The conversion of different energies, which plays a crucial part in MES, has rarely been studied. Furthermore, DR regarding energy conversion at the end-user side has not been considered enough in existing research, which can be expanded to mutual alternatives and conversion of different energies.

Up to now, a variety of approaches have been proposed to model the decision-making in energy markets. Among them,

Manuscript received: July 14, 2018; accepted: August 28, 2019. Date of CrossCheck: August 28, 2019. Date of online publication: December 4, 2019.

This work was supported by National Key R&D Program of China (No. 2016YFB0901900).

This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>).

F. Zeng (corresponding author), Z. Bie, S. Liu, C. Yan, and G. Li are with the State Key Laboratory of Electrical Insulation and Power Equipment, Xi'an Jiaotong University, Xi'an, China (e-mail: zfangdi@gmail.com; zhbic@mail.xjtu.edu.cn; liushiyu982@gmail.com; yanchao19911224@stu.xjtu.edu.cn; gengfengli@xjtu.edu.cn).

DOI: 10.35833/MPCE.2018.000454



complementary models are quite appropriate for describing the interactions among market players [18]. The problem of setting day-ahead hourly price (DAHP) for the smart grid retailer is studied in [19] by using a bi-level model. In the upper level, the retailer determines DAHP, the operation details of storage unit, and energy contracts in the energy market. Whereas in the lower level, the customer decides its DR program, i.e., consuming pattern. In [20], a decision-making model for an energy hub by using bi-level stochastic programming is presented to seek to maximize its profits by selling electricity and heat. In [21], a distributed mechanism for energy trading among microgrids in a competitive market is proposed and studied via its hierarchical decision-making scheme as a multi-leader, multi-follower Stackelberg game. In addition, [22] discusses decision-making strategies for a residential CCHP system, including operation mode, energy pricing, and optimal dispatch. A cost-plus pricing method based on the characteristic of variable cost and cooling/heating/electricity demands is then used to calculate the energy price. As a result, the electricity price is constant, while the heating/cooling price is in multiple steps.

In this paper, an electricity, heating, and cooling trading model is proposed for the trading between MESP and MEC. The trading model in MES is quite different from that in the single-energy system, e.g., the electricity market in [19]. Firstly, MECs can convert energy by using conversion devices, e.g., air conditioners. Therefore, a multi-energy DR is made feasible by employing the mutual conversion of different energies. Secondly, MESP has greater flexibilities with energy purchasing and dispatch by employing energy conversion units. MESP will then obtain further benefits by exploiting these flexibilities. Thirdly, the supply and demand of electricity, heating, and cooling should be balanced simultaneously. Considering these differences, we believe the proposed trading model makes practical sense in MES. The contribution of this paper is summarized as follows:

1) We introduce a novel multi-energy DR program for the energy end-user, i.e., the MEC, which can employ conversion devices to adjust its consuming patterns in response to the prices of different energies.

2) A multi-energy trading model is introduced for the electricity, heating, and cooling trading between MESP and MEC. A bi-level model is proposed to consider the MESP's decisions in the upper level and the MEC's decisions in the lower level. The model is then reformulated into a single level.

3) The performance of the DR program is evaluated. Furthermore, risks arising from electricity price volatility in the wholesale market are analyzed for both MESP and MEC in the trading model.

The rest of the paper is organized as follows. The trading model is formulated in Section II. The solution procedure to transform the bi-level model into an equivalent single-level mixed integer linear programming (MILP) is then described in Section III. Section IV presents case studies and simulation results. Finally, conclusions are drawn in Section V.

II. TRADING MODEL FORMULATION

A. System Structure and Market Rules

The structure of an MES is shown in Fig. 1. The upper part shows the energy transmission from the physical layer, while the lower part shows the information exchange in MES. MESP operates the CCHP system and acts as an intermediary agent between the natural gas and electricity wholesale markets and MECs. Moreover, in this paper, the geographical scope of the trading model is restricted within a district. The decision of MESP inside the market environment contains three parts, i.e., energy purchasing scheme from wholesale markets, retail price setting, and energy dispatch of the CCHP system. Meanwhile, the decision of MEC is to determine its consuming pattern, i.e., the DR program, with respect to a given retail price.

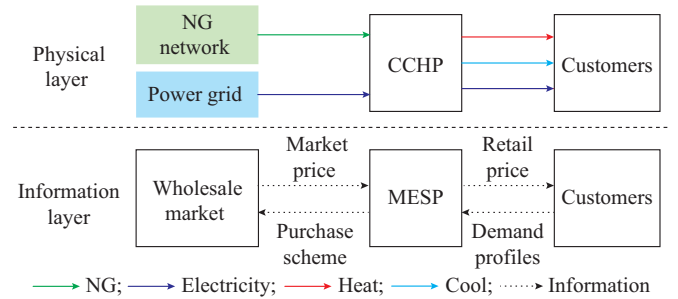


Fig. 1. Structure of an MES.

The optimal decisions made by MESP and MEC are based on the market environment such as market rules, price scheme, and scale of costumers, which is worthy of attention. In the current market environment, MESP owns a few market shares to influence the price in the wholesale market when it is within a district. Therefore, it purchases energy as a price-taker. Meanwhile, an MEC with a small capacity cannot purchase energy directly from the wholesale market. Furthermore, in the DH and cooling market, retail prices have been pre-determined in long-term contracts. Considering the benefit of DAHP for electricity in the current retail market [19],[23], the following market rules are proposed as the basis of the trading model in the current market environment:

1) In the wholesale market, MESP determines the purchasing scheme as a price-taker for the day ahead.

2) It is assumed that the NG price in the wholesale market varies per day and that the electricity price varies per hour [24].

3) Because the cooling and heating prices have been determined in the long-term contracts, they are supposed to be constant in the day-ahead decision-making process.

4) DAHP scheme for electricity retail is adopted. In DAHP, MESP decides the hourly electricity retail price for the next day and releases it to MEC in advance.

5) DAHP is restricted within a certain range to counteract strong market power of MESP.

In addition, it is assumed that MESP has enough knowledge of the customers' behaviors so that MESP can anticipate the reactions of the customers to its decisions on energy

price setting. Therefore, the interactions between MESP and MEC can be modeled as a one-leader, N -follower Stackelberg game. Specifically, MESP is the leader who sets DAHP, and MECs are the followers who adjust their consumption patterns in response to DAHP.

B. Decision Model of MEC: Optimal DR Program

As shown in Fig. 2, three types of energy demand are considered: heating demand associated with water heating, cooling demand in terms of air cooling, and electrical demand related to other electric appliances such as lights. For water heating, MEC could decide to purchase heating energy directly. Alternatively, MEC could use the electricity to generate heating energy indirectly with an electric water heater (EWH). In a similar way, MEC with an air cooling demand can purchase cooling energy directly, and alternatively, the cooling energy can be produced by an electric air conditioner (EAC). MEC is supposed to be a rational consumer who seeks to obtain high-comfort, low-cost energy consumption. Under the given heating, cooling, and electricity DAHPs, MEC will determine an optimal consumption pattern to meet their heating, cooling, and electricity demands. More precisely, MEC participates in the multi-energy DR by employing electricity to fulfil some of the heating and cooling demand using energy conversion devices.

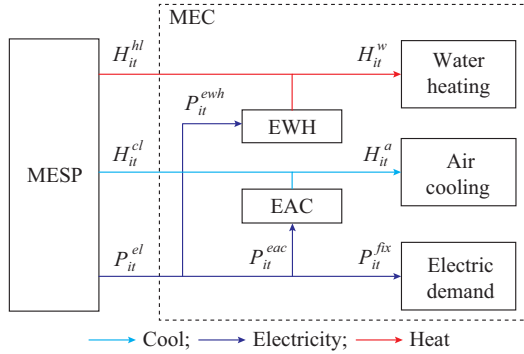


Fig. 2. The proposed MEC model.

In general, the control of water heating (or air cooling) aims to keep the water (or indoor) temperature at a desired level. According to the thermodynamic model in [22], the aim of the control is also to maintain the consumption of heating (or cooling) energy at a corresponding desired level (or reference level). In addition, a deviation from the reference level within a certain range is acceptable because humans are not sensitive enough to the water (or indoor) temperature. The unfitness functions are used to describe the effect of deviations and are formulated via piece-wise linear functions [25].

The MEC's decision could be modeled as:

$$\begin{cases} \min CO_i(X_i^{lp}) = \sum_{t=1}^T (u_{it}^w + u_{it}^a + \lambda^h H_{it}^{hl} + \lambda^c H_{it}^{cl} + \lambda_i^e P_{it}^{el}) \\ \text{s.t. } X_i^{lp} \in F_i^{lp} \\ X_i^{lp} = \{H_{it}^{cl}, H_{it}^{hl}, P_{it}^{el}, P_{it}^{ewh}, P_{it}^{eac}, u_{it}^w, u_{it}^a, d_{it}^w, d_{it}^a\} \end{cases} \quad (1)$$

where i is the index of MEC; t is the index of time periods; T is the number of time periods; $CO_i(\cdot)$ is the objective

function of MEC's decision model; X_i^{lp} is the set of decision variables associated with the decisions made by the i^{th} MEC; F_i^{lp} is the corresponding feasible region; P_{it}^{el} , H_{it}^{hl} , and H_{it}^{cl} are the electricity, heating, and cooling powers purchased by MEC, respectively; P_{it}^{ewh} and P_{it}^{eac} are the electricity powers of EWH and EAC, respectively; d_{it}^w and d_{it}^a are the deviations from the reference levels of water heating and air cooling demand, respectively; u_{it}^w and u_{it}^a are the unfitness functions related to deviations from water heating and air cooling demand, respectively; λ^h and λ^c are the retail prices for water heating and air cooling, respectively; and λ_i^e is the electricity retail price, i.e., DAHP.

In (1), the objective of MEC consists of two terms: the energy consumption unfitness and the energy purchasing cost. The feasible region F_i^{lp} is then formulated within the following constraints. For (2) to (11), the corresponding dual variables of the constraints are on the right side, following a colon.

1) Energy purchasing constraints

$$\begin{cases} H_{it}^{hl} \geq 0: \chi_{it}^{hl} \\ H_{it}^{cl} \geq 0: \chi_{it}^{cl} \end{cases} \quad (2)$$

Equation (2) imposes nonnegative constraints on the purchased heating and cooling energy. Note that the purchased electricity is guaranteed to be nonnegative in the following.

2) Power constraints of energy conversion devices

$$0 \leq P_{it}^{ewh} \leq P_{i,\max}^{ewh} \cdot \chi_{it}^{ewh} \cdot \bar{\chi}_{it}^{ewh} \quad (3)$$

$$0 \leq P_{it}^{eac} \leq P_{i,\max}^{eac} \cdot \chi_{it}^{eac} \cdot \bar{\chi}_{it}^{eac} \quad (4)$$

where $P_{i,\max}^{ewh}$ and $P_{i,\max}^{eac}$ are the maximum powers of EWH and EAC, respectively. Equations (3) and (4) represent the power ranges of EWH and EWC, respectively.

3) Energy balance constraints

$$H_{it}^{hl} \eta_i^{hl} + P_{it}^{ewh} \cdot COP_i^{ewh} = H_{it}^w + d_{it}^w \cdot \alpha_{it} \quad (5)$$

$$H_{it}^{cl} \eta_i^{cl} + P_{it}^{eac} \cdot COP_i^{eac} = H_{it}^a + d_{it}^a \cdot \beta_{it} \quad (6)$$

$$P_{it}^{el} - P_{it}^{ewh} - P_{it}^{eac} = P_{it}^{fix} \cdot \gamma_{it} \quad (7)$$

where η_i^{hl} and η_i^{cl} are the transmission efficiencies of heating and cooling energy, respectively; COP_i^{ewh} and COP_i^{eac} are the coefficients of performance of EWH and EAC, respectively; H_{it}^w and H_{it}^a are the reference values of demands for water heating and air cooling, respectively; and P_{it}^{fix} is the reference value of the demand for electric appliances other than EWH and EAC.

Equations (5)-(7) represent the energy balances of heating, cooling, and electricity, respectively. More specifically, the right side of (5) represents the actual demand level, i.e., the reference minus the deviation, for water heating. While the left side of (5) is the sum of heating energies purchased from MESP and that generated by an EAC. Similarly, the actual cooling demand in (6) is supplied by the cooling energy purchased from MESP, plus that generated by an EAC. Equation (7) represents the nominated level of electricity demand, i.e., the demand for electric appliances other than EWH and EAC.

Although the relationship between electricity and heating/cooling of EWH and EAC in reality is not always linear,

i.e., EWH and EAC are variable-frequency devices [26], we use the linear model to simplify and help solve the problem as a bi-level problem solution, which will be introduced in Section III. Specifically, the heating power of EWH is expressed as the product of the electricity power and a coefficient in (5). An analogous reasoning applies to (6).

4) Constraints of the deviation

$$-d_{it}^{wm} \leq d_{it}^w \leq d_{it}^{wm}: \underline{\delta}_{it}, \bar{\delta}_{it} \quad (8)$$

$$-d_{it}^{am} \leq d_{it}^a \leq d_{it}^{am}: \underline{\theta}_{it}, \bar{\theta}_{it} \quad (9)$$

where d_{it}^{wm} and d_{it}^{am} are the maximum deviations from the reference levels of water heating and air cooling demand, respectively. The deviations from the reference levels of heating and cooling demands are bound within certain intervals by (8) and (9).

5) Constraints for unfitness functions

$$u_{it}^w \geq a_{itk}^w \cdot d_{it}^w + b_{itk}^w \cdot \rho_{itk}^w \quad (10)$$

$$u_{it}^a \geq a_{itk}^a \cdot d_{it}^a + b_{itk}^a \cdot \rho_{itk}^a \quad (11)$$

where a_{itk}^w and b_{itk}^w are the coefficients of piece-wise functions for water heating uncomfartableness; and a_{itk}^a and b_{itk}^a are the coefficients of piece-wise functions for air cooling uncomfartableness.

Equations (10) and (11) are the piece-wise linearized formulations of unfitness functions corresponding to d_{it}^w and d_{it}^a , respectively.

Given the energy price parameters, optimal DR program of MEC is the energy purchasing scheme corresponding to the optimal solutions of problem (1), as formulated in (12).

$$\begin{aligned} \{H_{it}^{hl}, H_{it}^{cl}, P_{it}^{el}\} &= DR(\lambda^h, \lambda^c, \lambda_e^e) = \\ \{H_{it}^{hl}, H_{it}^{cl}, P_{it}^{el} | X_{it}^{lp} = \arg \min_{X_{it}^{lp} \in F_{it}^{lp}} CO_{it}(X_{it}^{lp})\} \end{aligned} \quad (12)$$

C. Decision Model of MESP

As shown in Fig. 3, MESP operates a CCHP system consisting of energy conversion and storage devices such as gas turbine (GT), heat exchanger (HE), absorption chiller (AC), electric chiller (EC), and thermal storage tank (TST). MESP purchases NG and electricity from wholesale markets and sells electricity, heating, and cooling to MECs. Furthermore, MESP dispatches energy conversion and storage devices in the CCHP system.

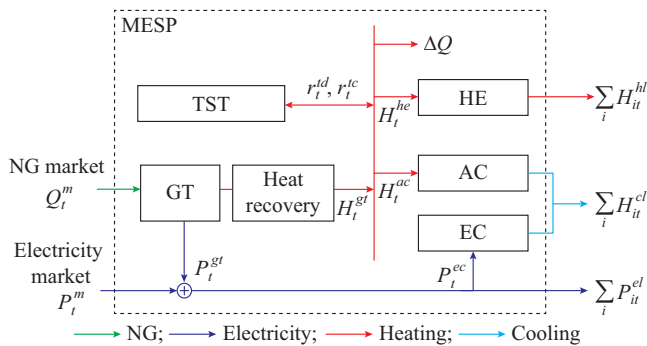


Fig. 3. The proposed MESP model.

The MESP's decision could be modeled as:

$$\begin{cases} \max PO(X^u) = \sum_{t=1}^T \sum_{i=1}^{NC} (\lambda^h H_{it}^{hl} + \lambda^c H_{it}^{cl} + \lambda_e^e P_{it}^{el}) - \\ \sum_{t=1}^T (\lambda^{gm} Q_t^m + \lambda_t^{em} P_t^m) \\ \text{s.t. } X^u \in F^u \\ X^u = \{\lambda_t^e, Q_t^m, P_t^m, H_t^{gt}, P_t^{gt}, H_t^{ac}, P_t^{ec}, r_t^{td}, r_t^{tc}, S_t^{th}\} \\ \{H_{it}^{hl}, H_{it}^{cl}, P_{it}^{el}\} = DR(\lambda^h, \lambda^c, \lambda_e^e) \end{cases} \quad (13)$$

where NC is the number of MECs; $PO(\cdot)$ is the objective function of MESP's decision model; X^u is the variable related to the decisions made by MESP; $\{H_{it}^{hl}, H_{it}^{cl}, P_{it}^{el}\}$ are the variables related to the decisions made by the MEC, i.e., the optimal DR under energy price; λ^{gm} and λ_t^{em} are the prices of NG and electricity in wholesale markets, respectively; Q_t^m and P_t^m are NG and electricity purchased from wholesale markets, respectively; H_t^{gt} , H_t^{ac} , and H_t^{he} are the heating power of GT, AC, and HE, respectively; P_t^{gt} and P_t^{ec} are the electricity powers of GT and EC, respectively; r_t^{td} and r_t^{tc} are the charging and discharging power of TST, respectively; S_t^{th} is the state of charge (SOC) of TST; and F^u is the constraint of the MESP's decisions.

1) DAHP constraints: it is assumed that the MESP and MECs have reached certain agreements that the DAHP should be limited to within an admissible set [19], as shown in (14) and (15).

$$\lambda_{t, \min}^e \leq \lambda_t^e \leq \lambda_{t, \max}^e \quad (14)$$

$$\sum_{t=1}^T \lambda_t^e / T \leq \lambda_{avg}^e \quad (15)$$

where $\lambda_{t, \min}^e$, $\lambda_{t, \max}^e$, and λ_{avg}^e are the minimum, maximum, and average of DAHP, respectively.

Constraint (14) restricts DAHP within the interval, and constraint (15) represents an upper bound on the average of DAHP.

2) Energy storage devices: the thermal tanks are operated as energy storage devices [27].

$$0 \leq r_t^{tc} \leq r_{\max}^{tc} \quad (16)$$

$$0 \leq r_t^{td} \leq r_{\max}^{td} \quad (17)$$

$$\begin{cases} S_{\min}^{th} \leq S_t^{th} \leq S_{\max}^{th} \\ 2 \leq t \leq T \end{cases} \quad (18)$$

$$S_{t+1}^{th} = (1 - \sigma_{th}) S_t^{th} + \eta^{tc} r_t^{tc} - r_t^{td} / \eta^{td} \quad (19)$$

$$\begin{cases} S_t^{th} = S_0^{th} \\ t = \{1, T+1\} \end{cases} \quad (20)$$

where $r_{\max}^{tc}$ and $r_{\max}^{td}$ are the maximum charging and discharging power of TST, respectively; $S_{\min}^{th}$ and $S_{\max}^{th}$ are the minimum and maximum SOC of TST, respectively; σ_{th} is the energy loss rate of TST; η^{tc} and η^{td} are the charging and discharging efficiencies of TST, respectively; and S_0^{th} is the initial SOC of TST.

Equations (16)-(18) define the bounds of charging rates, discharging rates, and SOC, respectively. Equation (19) represents the SOC dynamics. Equation (20) represents the initial and final conditions of the thermal tanks.

3) Energy conversion devices: the GT, EC, and AC are op-

erated as energy conversion devices in the CCHP system [28].

$$H_t^{gt} = P_t^{gt} (1 - \eta_e^{gt} - \eta_{loss}^{gt}) \eta^{hr} / \eta_e^{gt} \quad (21)$$

$$P_{\min}^{gt} \leq P_t^{gt} \leq P_{\max}^{gt} \quad (22)$$

$$H_{\min}^{ac} \leq H_t^{ac} \leq H_{\max}^{ac} \quad (23)$$

$$P_{\min}^{ec} \leq P_t^{ec} \leq P_{\max}^{ec} \quad (24)$$

where η_e^{gt} and η_{loss}^{gt} are the electricity efficiency and heat loss rate of GT, respectively; η^{hr} is the heat recovery efficiency; $P_{\min}^{gt}$ and $P_{\max}^{gt}$ are the minimum and maximum power of GT, respectively; $H_{\min}^{ac}$ and $H_{\max}^{ac}$ are the minimum and maximum power of AC, respectively; and $P_{\min}^{ec}$ and $P_{\max}^{ec}$ are the minimum and maximum power of EC, respectively.

Equation (21) represents the output heat of the GT through a heat recovery unit. The power outputs of the GT, AC, and EC are limited by (22)-(24).

4) Energy balance:

$$P_t^m + P_t^{gt} - P_t^{ec} = \sum_{i=1}^{NC} P_{i,t}^{el} \quad (25)$$

$$H_t^{gt} - H_t^{ac} + r_t^{td} - r_t^{tc} \geq \sum_{i=1}^{NC} H_{i,t}^{hl} / \eta^{he} \quad (26)$$

$$P_t^{ec} \cdot COP_{ec} + H_t^{ac} \cdot COP_{ac} = \sum_{i=1}^{NC} H_{i,t}^{cl} \quad (27)$$

$$Q_t^m = P_t^{gt} / \eta_e^{gt} \quad (28)$$

where η^{he} is the efficiency of HE; and COP_{ac} and COP_{ec} are the coefficients of performance of AC and EC, respectively.

The energy balances of electricity, heating, cooling, and gas are represented by (25)-(28). Among these four mathematical expressions, the inequality in (26) indicates that excess heat can be released into the air directly.

III. SOLUTION

The Stackelberg game model is a bi-level structure which cannot be solved directly. As a workaround to the problem, the method in [19] is used to transform the bi-level model into an equivalent single-level MILP model. To be specific, the transformation is as follows:

1) The lower-level problem, i.e., the customer's decision, is replaced by its corresponding Karush-Kuhn-Tucker (KKT) conditions. The replacement is reasonable because the lower-level model is convex, specifically and linear [29]. The bi-level problem is then transformed into a complementary model.

2) The KKT conditions are further transformed into mixed integer linear constraints by exploiting the disjunctive nature of the complementary slackness conditions [30].

3) The bilinear terms in the objective function (13) are replaced using the strong duality theorem [31].

Finally, the equivalent single-level MILP is formulated as follows:

$$X_i^{ld} = \{\chi_{it}^{hl}, \chi_{it}^{cl}, \underline{\chi}_{it}^{ewh}, \bar{\chi}_{it}^{ewh}, \underline{\chi}_{it}^{eac}, \bar{\chi}_{it}^{eac}, \dots, \alpha_{it}, \beta_{it}, \gamma_{it}, \underline{\delta}_{it}, \bar{\delta}_{it}, \underline{\theta}_{it}, \bar{\theta}_{it}, \rho_{itk}^w, \rho_{itk}^a\} \quad (29)$$

$$X_i^{lz} = \{\underline{z}_{it}^{hl}, \underline{z}_{it}^{cl}, \underline{z}_{it}^{ewh}, \bar{z}_{it}^{ewh}, \underline{z}_{it}^{eac}, \bar{z}_{it}^{eac}, \dots, \underline{z}_{it}^w, \bar{z}_{it}^w, \underline{z}_{it}^a, \bar{z}_{it}^a, \underline{z}_{itk}^{tw}, \bar{z}_{itk}^{tw}\} \quad (30)$$

$$\left\{ \begin{array}{l} \max \sum_{i=1}^{NC} \sum_{t=1}^T [-H_{it}^w \alpha_{it} - H_{it}^a \beta_{it} - P_{it}^{fix} \gamma_{it} - \bar{\chi}_{it}^{ewh} P_{i,\max}^{ewh} - \bar{\chi}_{it}^{eac} P_{i,\max}^{eac} + \\ (\underline{\delta}_{it} - \bar{\delta}_{it}) d_{it}^w + (\underline{\theta}_{it} - \bar{\theta}_{it}) d_{it}^a - u_{it}^w - u_{it}^a] - \\ \sum_{i=1}^{NC} \sum_{t=1}^T \sum_{k=1}^K (\rho_{itk}^w b_{itk}^w + \rho_{itk}^a b_{itk}^a) - \sum_{t=1}^T (\lambda_g^m Q_t^m + \lambda_{e,t}^m P_t^m) \\ \text{s.t. } X^u \in F^u \\ \{X_i^{lp}, X_i^{ld}, X_i^{lz}\} \in NCC_i \cap LCC_i \end{array} \right. \quad (31)$$

where X_i^{ld} is the dual variable of lower-level problems, i.e., the MEC's decision models; X_i^{lz} is the binary variable introduced to linearize the complementary slackness conditions; LCC_i represents the linearization formulations of the complementary slackness conditions in 2); and NCC_i represents the remaining linear constraints of the lower level's KKT conditions in 1).

The equivalent single-level MILP (29)-(31) are further coded in GAMS and solved using CPLEX 12.4.

IV. CASE STUDY

A tested energy market with an MESP and multiple MECs is investigated in the case study. The CCHP system operated by MESP consists of a micro-GT, an EC, an AC, an HE, and a TST, as shown in Fig. 3. The parameters are listed in Table I [28].

TABLE I
PARAMETERS OF MESP

Parameter	Value	Parameter	Value
η_e^{gt}	0.3	$P_{\min}^{gt}$	500 kW
η_{loss}^{gt}	0.2	$P_{\max}^{gt}$	2000 kW
η^{hr}	0.75	$H_{\min}^{ac}$	0
η^{he}	0.9	$H_{\max}^{ac}$	1000 kW
COP_{ac}	1.2	$P_{\min}^{ec}$	0
COP_{ec}	4	$P_{\max}^{ec}$	1000 kW
η^{tc}	0.9	$S_{\min}^{th}$	0
η^{td}	0.9	$S_{\max}^{th}$	2000 kW
σ_{th}	0.1	S_0^{th}	1000 kW
$r_{\max}^{tc}$	1000 kW	$r_{\max}^{td}$	1000 kW

The buildings such as restaurants, hospitals, and hotels, in Ellington, Houston, USA, are considered as MECs, and the hourly load data are obtained from [32]. The rest of the parameters of MECs are set as shown in Table II and Table III.

A daily simulation is conducted to investigate the effects of the behaviors of MESP and MECs. The total demands of the MECs for electricity, heating, and cooling are plotted in Fig. 4. The electricity price in the wholesale market and the DAHP bounds are plotted in Fig. 5. The prices of NG, heating, and cooling are set at 0.0106 \$/kWh, 0.0155 \$/kWh, and 0.0076 \$/kWh, respectively.

The benchmark case with the parameter settings described

in the previous paragraphs is solved firstly. Other cases are then set up by changing the parameters for EWH and EAC capacities.

TABLE II
PARAMETERS OF MECs

Parameter	Value
COP_i^{ewh}	0.95
COP_i^{eac}	3.30
η_i^{hl}	0.85
η_i^{cl}	0.85

TABLE III
CAPACITIES OF EWH AND EAC

Consumer	$P_{i,max}^{ewh}$ (kW)	$P_{i,max}^{eac}$ (kW)
1	15	6
2	45	150
3	450	45
4	20	150
5	3	30
6	15	10
7	10	30
8	20	30
9	5	3
10	45	240
11	35	15
12	1	3
13	0	25

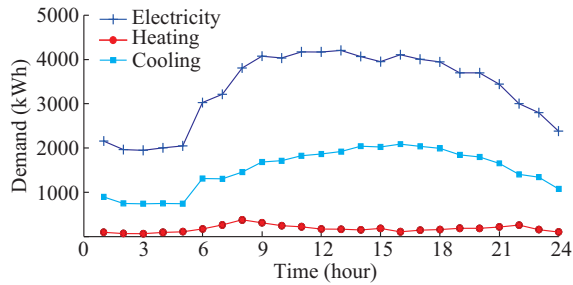


Fig. 4. Total demand.

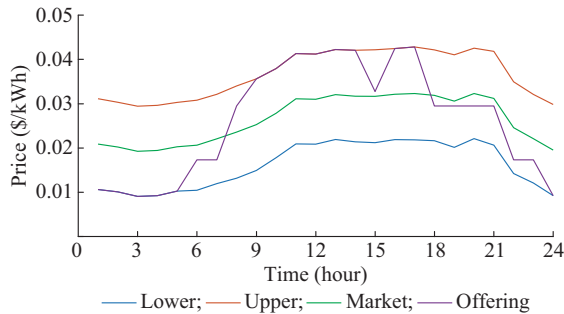


Fig. 5. Electricity price.

The daily results of the benchmark case are shown in Figs. 6-9. DAHP is plotted in Fig. 5. NG and electricity purchasing strategies from wholesale markets are shown in Fig.

6. The energy dispatch of TST is plotted in Fig. 7. The electric and heat power balance in CCHP system is shown in Fig. 8, indicating electric power dispatch and heat power dispatch. The consumption patterns of MEC for water heating and air cooling are shown in Fig. 9.

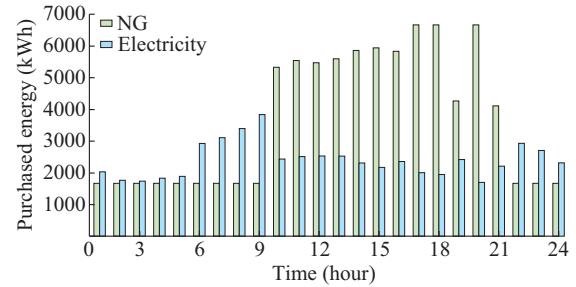


Fig. 6. Energy from wholesale markets.

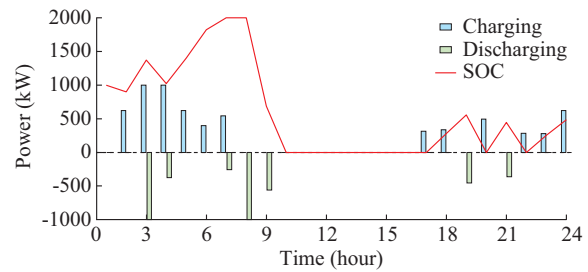


Fig. 7. Dispatch of TST.

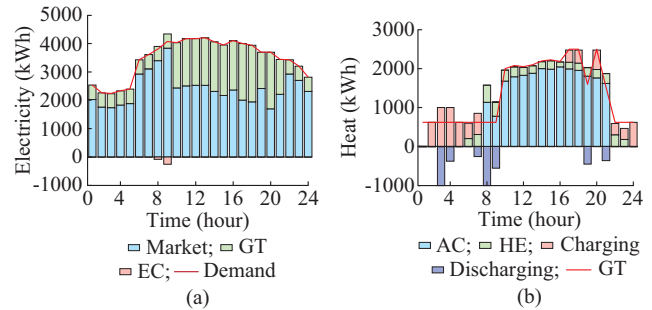


Fig. 8. Energy balance in CCHP system for MESP. (a) Electric power balance. (b) Heat power balance.

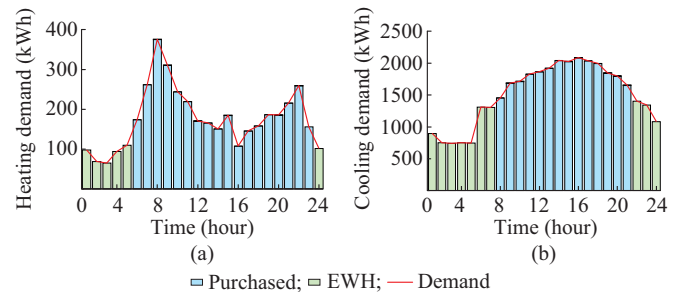


Fig. 9. Consumption patterns of MEC. (a) Water heating (b) Air cooling.

From the results plotted in the figures, some interesting facts are observed as follows.

1) According to Fig. 6, MESP purchases more NG and less electricity during the high-electricity-price time (10:00-18:00), because MESP can use the cheaper NG to generate costlier electricity to supply any extra electricity demand.

2) According to Fig. 8, the GT operates at a high level during 10:00-20:00. There are two reasons to explain this inference. Firstly, it is necessary to generate more heat to supply the demand of high-level cooling. Secondly, MESP can buy less high-price electricity from the wholesale market, while the GT generates more electricity.

3) According to Fig. 9, MECs are inclined to purchase and use electricity to meet the demands for water heating and air cooling using EWH and EAC during the low-electricity-price period (00:00-5:00).

The effect of the DR capacity of MEC is further analyzed. The DR program is achieved by using electricity to generate heating and cooling energy using energy conversion devices, i.e., EWH and EAC. This means that the capacity of the energy conversion devices can be regarded to be the DR capacity. In other words, MECs with larger capacities of EWH and EAC have a larger DR capacity. For example, an MEC can scarcely adjust its consumption pattern if it has no such energy conversion devices, i.e., its capacity is zero. To investigate the impact of the capacities of EWH and EAC, we change the corresponding parameters in Table IV according to the percentages of those in the benchmark case, while other parameters remain unchanged. For example, the case with 100% capacity would refer to the benchmark case, and the case with 0% capacity would correspond to the case without EWH and EAC.

TABLE IV
ANNUAL ACCOUNTS OF MESP AND MEC

Party	Account	Value (\$)
MESP	NG cost	706346
	Electricity cost	357000
	Total cost	1063346
	Revenue	1853379
	Profit	790033
MEC	Electricity cost	1143468
	Heating cost	269163
	Cooling cost	440749
	Total cost	1853381

Figure 10 shows the results with different EWH and EAC capacities. In Fig. 10, the benchmark case is set as the baseline with the value “1”, while the values for other cases are the ratios relative to the benchmark case. From Fig. 10, it is obvious that the EWH and EAC capacities have an influence on both MESP and MEC.

For MEC, the increase in the EWH and EAC capacities result in a slight increase in the electricity purchasing cost, but with relatively large decrease in heating and cooling purchasing costs, and the overall decrease in the total cost. It is obvious that MECs are willing to purchase cheaper electricity for heating and cooling demands during the low-electricity-price period if they have larger EWHs and EACs.

As for MESP, the total cost varies slightly, because the increment of NG cost offsets the decrement of the electricity cost as the capacities of EWH and EAC increase. However, the MESP’s revenue (i.e., the total cost for MECs) decreases

by a large amount, and its profit goes down.

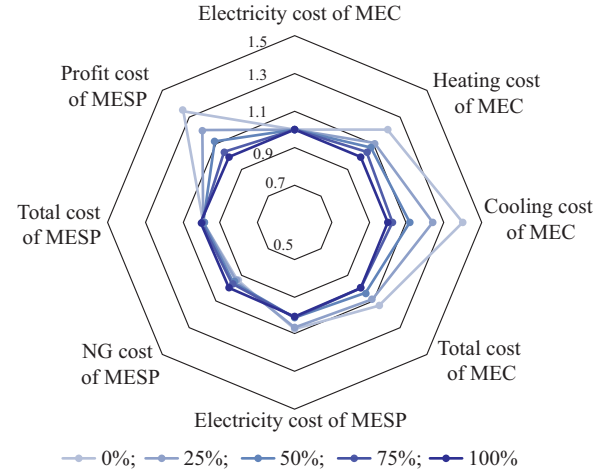


Fig. 10. Impact of capacities of EWH and EAC.

Based on the results, it is not difficult to draw the conclusion that the proposed DR program can help reduce the energy consumption cost of MEC considerably, which means that the proposed trading model will be attractive to MECs.

The annual operation is simulated to evaluate the performance of the trading model in the yearly horizon. The electricity and NG prices in wholesale markets are derived from the data of locational marginal price of the Pennsylvania-New-Jersey-Maryland (PJM) Interconnection [33] in 2017 and Henry Hub Natural Gas Spot Prices [34] in 2017, respectively, as plotted in Fig. 11. The time series of the simulation results are plotted in Fig. 12. The annual accounts of MESP and MEC are then summarized in Table IV.

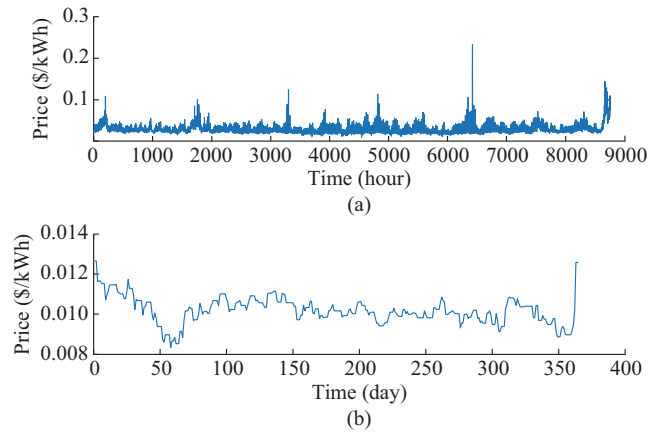


Fig. 11. Electricity and NG prices in wholesale markets. (a) Electricity price in wholesale market. (b) NG price in wholesale market.

The risks for MESP and MEC that result from electricity price volatility in the wholesale market are further analyzed. In this regard, we analyze three items, including daily electricity purchase cost (DEPC) of MEC, DEPC of MESP, and daily profit (DP) of MESP. Table V summarizes the three items and the daily average electricity price (DAEP) in the wholesale market. Figure 13 shows the histograms displaying the distributions. In addition, the scatter plots in Fig. 14

show the relationship of DAEP in the wholesale market to these three items. Furthermore, Fig. 15 plots the ratios of MESP's daily purchased electricity (DPE) to daily purchased NG (DPNG) with the ratios of DAEP to NG price (NGP).

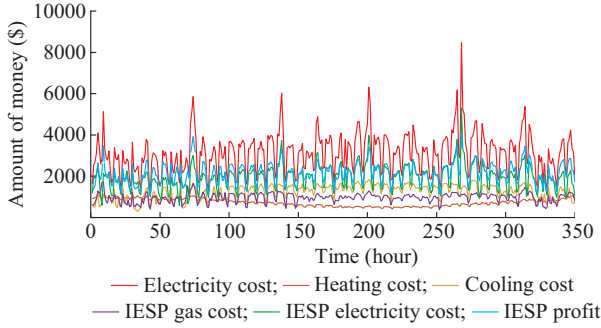


Fig. 12. Time series of annual simulation results.

TABLE V
STATISTICS FOR DEPC OF MEC, DEPC OF MESP AND DP OF MESP

Item	DEPC of MEC	DEPC of MESP	DP of MESP	DAEP
Min	1277.00	564.00	1067.00	0.020
Max	9678.00	5300.00	5631.00	0.095
Mean	3133.00	1935.00	2164.00	0.030
Std	1088.00	636.00	585.00	0.008
Std/mean	0.35	0.33	0.27	0.270

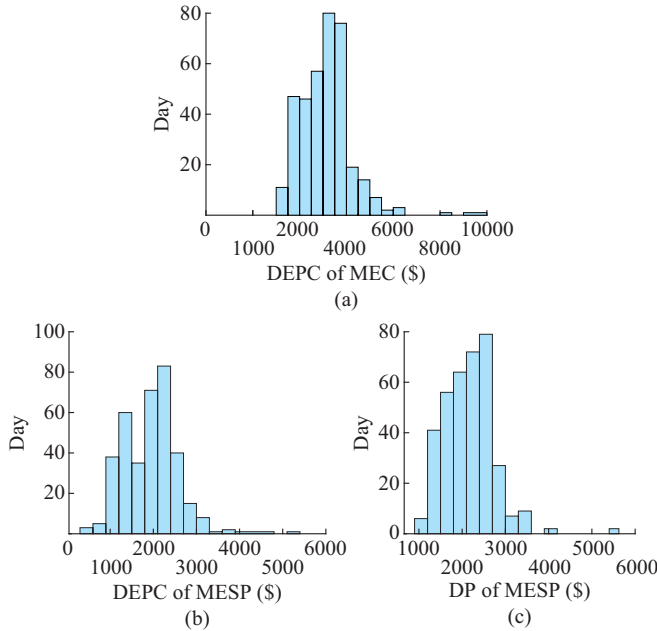


Fig. 13. Histograms of MEC's DEPC, MESP's DEPC and MESP's DP.

The following results can be determined from the given tables and figures.

1) In Fig. 14, there appears to be a positive correlation between DEPC and DAEP of MEC, indicating that the volatility of electricity prices in the wholesale market will influence the MEC's cost. In other words, MEC faces a cost volatility risk resulting from the electricity price volatility in the wholesale market with the dynamic pricing scheme, i. e., DAHP.

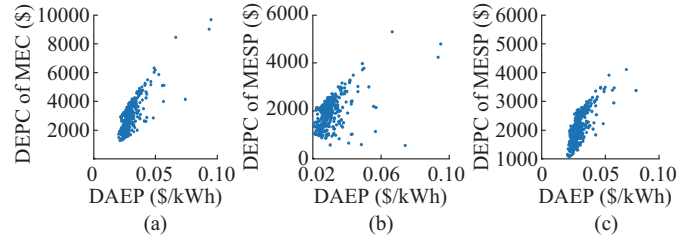


Fig. 14. Scatter plots of DEPC of MEC, DEPC of MESP, and DP of MESP relative to DAEP in wholesale market and corresponding correlation coefficients (CC).

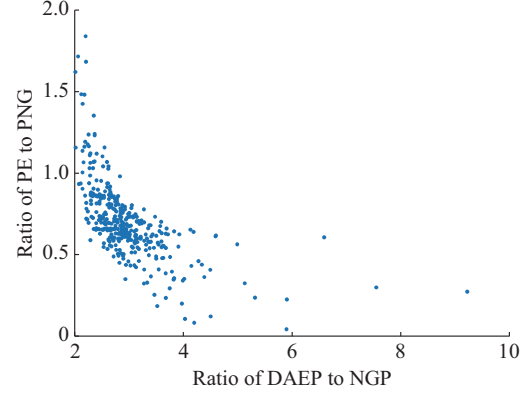


Fig. 15. Scatter plots of the ratios of DPE to DPNG corresponding to the ratios of DAEP to NGP.

2) In Table V, the coefficient of variations, i.e., the standard deviation (Std) divided by the mean value, of the three items are approximately close to that of DAEP. This result suggests that the volatility risks facing MESP and MECs are roughly equal to the degree of the volatility of DAEP in the wholesale market.

3) In Fig. 15, there appears to be a negative correlation between the ratio of DPE to DPNG and the ratio of DAEP to NGP, indicating that MESP will purchase more NG and less electricity from the wholesale market on days when the electricity price is more expensive but NG is relatively cheaper. Thus, the energy conversion from NG to electricity can help the MESP reduce its total purchase cost and further hedge against the volatility risk of electricity price.

V. CONCLUSION

In this paper, a multi-energy trading model is presented for the electricity, heating, and cooling trading between MESP and MEC. In this model, a multi-energy DR program for MEC is proposed, in which MEC can use electricity to meet some of the heating and cooling demands using energy conversion devices. The interaction between MESP and MEC is then modeled using bi-level programming. The bi-level model is further reformulated into a single level using KKT conditions. Case studies are conducted with two simulations in daily and yearly time horizons. The simulation results show that both MESP and MEC are exposed to the risks of electricity price volatility in the wholesale market with DAHP. However, MESP can hedge against the electricity price volatility risk by purchasing NG to generate electricity. On the other hand, the DR program can reduce the total

energy cost of MEC with DAHP.

In practice, MESP and MEC make decisions under an uncertain environment. The uncertain factors include the prices of NG and electricity in wholesale markets and the electricity, cooling, and heating demands of MEC. Future work would focus on the decision-making while considering these uncertainties.

REFERENCES

- [1] P. Mancarella, "MES (multi-energy systems): an overview of concepts and evaluation models," *Energy*, vol. 65, no. 1, pp. 1-17, Feb. 2014.
- [2] M. Yan, N. Zhang, X. Ai *et al.*, "Robust two-stage regional-district scheduling of multi-carrier energy systems with a large penetration of wind power," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 3, pp. 1227-1239, Aug. 2018.
- [3] Y. Cheng, N. Zhang, Y. Wang *et al.*, "Modeling carbon emission flow in multiple energy systems," *IEEE Transactions on Smart Grid*, vol. 10, no. 4, pp. 3562-3574, Jul. 2019.
- [4] J. Yang, N. Zhang, Y. Cheng *et al.*, "Modeling the operation mechanism of combined P2G and gas-fired plant with CO₂ recycling," *IEEE Transactions on Smart Grid*, vol. 10, no. 1, pp. 1111-1121, Jun. 2018.
- [5] M. Yan, Y. He, S. Mohammad *et al.*, "Coordinated regional-district operation of integrated energy systems for resilience enhancement in natural disasters," *IEEE Transactions on Smart Grid*, vol. 10 no. 5, pp. 4881-4892, Sep. 2018.
- [6] H. Cho, P. J. Mago, R. Luck *et al.*, "Evaluation of CCHP systems performance based on operational cost, primary energy consumption, and carbon dioxide emission by utilizing an optimal operation scheme," *Applied Energy*, vol. 86, no. 12, pp. 2540-2549, Dec. 2009.
- [7] S. Braithwait, D. Hansen, and M. O'Sheasy, "Retail electricity pricing and rate design in evolving markets," Jun., 2007. [Online]. Available: https://www.smartgrid.gov/document/retail_electricity_pricing_and_rate_design_evolution_markets
- [8] C. Li, S. Tang, Y. Cao *et al.*, "A new stepwise power tariff model and its application for residential consumers in regulated electricity markets," *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 300-308, Feb. 2013.
- [9] K. Herter, "Residential implementation of critical-peak pricing of electricity," *Energy Policy*, vol. 35, no. 4, pp. 2121-2130, Apr. 2007.
- [10] E. Celebi and J. D. Fuller, "Time-of-use pricing in electricity markets under different market structures," *IEEE Transactions on Power Systems*, vol. 27, no. 3, pp. 1170-1181, Aug. 2012.
- [11] R. S. Ferreira, L. A. Barroso, L. P. Rochinha *et al.*, "Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: a stochastic optimization approach," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 2285-2295, Dec. 2013.
- [12] L. Jia and L. Tong, "Dynamic pricing and distributed energy management for demand response," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 1128-1136, Mar. 2016.
- [13] Y. Ding, S. Pineda, P. Nyeng *et al.*, "Real-time market concept architecture for EcoGrid EU-A prototype for European smart grids," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 2006-2016, Dec. 2013.
- [14] I. Momber, S. Wogrin, and T. G. S. Roman, "Retail pricing: a bilevel program for PEV aggregator decisions using indirect load control," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 464-473, Jan. 2016.
- [15] H. Li, Q. Sun, Q. Zhang *et al.*, "A review of the pricing mechanisms for district heating systems," *Renewable and Sustainable Energy Reviews*, vol. 42, no. 1, pp. 56-65, Feb. 2015.
- [16] D. Poputoaia and S. Bouzarovski, "Regulating district heating in Romania: legislative challenges and energy efficiency barriers," *Energy Policy*, vol. 38, no. 7, pp. 3820-3829, Jul. 2010.
- [17] Q. Sun, H. Li, G. Wallin *et al.*, "Marginal costs for district heating," *Energy Procedia*, vol. 104, pp. 323-328, Dec. 2016.
- [18] S. A. Gabriel, A. J. Conejo, J. D. Fuller *et al.*, *Complementarity Modeling in Energy Markets*. New York: Springer, 2012.
- [19] W. Wei, F. Liu, and S. Mei, "Energy pricing and dispatch for smart grid retailers under demand response and market price uncertainty," *IEEE Transactions on Smart Grid*, vol. 6, no. 3, pp. 1364-1374, May 2015.
- [20] A. Najafi, H. Falaghi, J. Contreras *et al.*, "A stochastic bilevel model for the energy hub manager problem," *IEEE Transactions on Smart Grid*, vol. 8, no. 5, pp. 2394-2404, Sep. 2017.
- [21] J. Lee, J. Guo, J. K. Choi *et al.*, "Distributed energy trading in microgrids: a game-theoretic model and its equilibrium analysis," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 6, pp. 3524-3533, Jun. 2015.
- [22] W. Gu, S. Lu, Z. Wu *et al.*, "Residential CCHP microgrid with load aggregator: operation mode, pricing strategy, and optimal dispatch," *Applied Energy*, vol. 205, pp. 173-186, Nov. 2017.
- [23] S. Borenstein, "The long-run efficiency of real-time electricity pricing," *The Energy Journal*, vol. 26, no. 3, pp. 93-116, Jul. 2005.
- [24] P. Jirutitijaroen, S. Kim, O. Kittithreerapornchai *et al.*, "An optimization model for natural gas supply portfolios of a power generation company," *Applied Energy*, vol. 107, pp. 1-9, Jul. 2013.
- [25] P. Samadi, A. Mohsenian-Rad, R. Schober *et al.*, "Optimal real-time pricing algorithm based on utility maximization for smart grid," in *Proceedings of 2010 1st IEEE International Conference on Smart Grid Communications*, Gaithersburg, USA, Oct. 2010, pp. 415-420.
- [26] M. Song, C. Gao, H. Yan *et al.*, "Thermal battery modeling of inverter air conditioning for demand response," *IEEE Transactions on Smart Grid*, vol. 9, no. 6, pp. 5522-5534, Nov. 2018.
- [27] W. Gu, Y. Tang, S. Peng *et al.*, "Optimal configuration and analysis of combined cooling, heating, and power microgrid with thermal storage tank under uncertainty," *Journal of Renewable and Sustainable Energy*, vol. 7, no. 1, Jan. 2015.
- [28] W. Gu, Z. Wang, Z. Wu *et al.*, "An online optimal dispatch schedule for CCHP microgrids based on model predictive control," *IEEE Transactions on Smart Grid*, vol. 8 no. 5, pp. 2332-2342, Sep. 2017.
- [29] M. S. Bazaraa, H. D. Sherali, and C. M. Shetty, *Nonlinear Programming: Theory and Algorithms*, 3rd ed. Manhattan: John Wiley & Sons, Inc., 2013, pp. 163-236.
- [30] J. Fortuny-Amat and B. McCarl, "A representation and economic interpretation of a two-level programming problem," *Journal of the Operational Research Society*, vol. 32, no. 9, pp. 783-792, Sep. 1981.
- [31] D. G. Luenberger and Y. Ye, *Linear and Nonlinear Programming*, 3rd ed. New York: Springer, 2010, pp. 469-505.
- [32] "Energy information and data," Apr., 2018. [Online]. Available: <https://openai.org/datasets/files/961/pub/>
- [33] PJM, "PJM daily day-ahead LMP," Apr., 2018. [Online]. Available: <http://www.pjm.com/markets-and-operations/energy/dayahead/lmpda.aspx>
- [34] Energy Information Administration, "Natural gas spot and future prices (NYMEX)," Apr., 2018. [Online]. Available: https://www.eia.gov/dnav/ng/ng_pri_fut_s1_d.htm.

Fangdi Zeng received the B.S. degree from Xi'an Jiaotong University, Xi'an, China, in 2016. He is currently pursuing the Master's degree at Xi'an Jiaotong University, Xi'an, China. His research interests include power system optimization and energy market.

Zhaohong Bie received the B.S. and M.S. degrees from the Electric Power Department of Shandong University, Jinan, China, in 1992 and 1994, respectively, and the Ph.D. degree from Xi'an Jiaotong University, Xi'an, China, in 1998. Currently, she is a Professor in Xi'an Jiaotong University. Her main research interests are power system planning and reliability evaluation, integration of the renewable energy as well as Energy Internet.

Shiyu Liu received the B.S.E.E. degree from Hohai University, Nanjing, China, in 2014, and the M.S. degree from Xi'an Jiaotong University, Xi'an, China, in 2017. She is currently pursuing Ph.D. degree at Xi'an Jiaotong University, Xi'an, China. Her research interests include power system optimization and renewable energy integration.

Chao Yan received the B.S. degree from Xi'an Jiaotong University, Xi'an, China, in 2014. He is currently working toward the Ph.D. degree at Xi'an Jiaotong University. His major research interest includes power system reliability evaluation.

Gengfeng Li received the Ph.D. degree in electrical engineering from Xi'an Jiaotong University, Xi'an, China, in 2014. He is currently an associate professor of School of Electrical Engineering in Xi'an Jiaotong University. His research interests include power system reliability evaluation and integration of renewable energy.