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Day-Ahead Optimal Joint Scheduling Model of Electric and Natural Gas Appliances for Home Integrated Energy Management

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ABSTRACT Home energy management systems (HEMSs) enable residential customers to efficiently participate in demand response programs in order to obtain optimal benefits. Traditional HEMSs only manage household electric appliances to reduce the electricity consumption cost while the optimal scheduling of natural gas appliances has been overlooked. Due to the increasing popularity of natural gas appliances in modern smart homes, the electricity consumption of residential customers connected to the natural gas network is significantly affected by the use of natural gas appliances. To consider the interaction between electric and natural gas appliances in households, a day-ahead optimal joint scheduling model of electric and natural gas appliances for HEMS is proposed. Firstly, all household appliances are classified into several categories and the mathematical model of each appliance is presented. Then, a day-ahead optimal joint scheduling model of both electric and natural gas appliances for HEMS is formulated, in which the objective function is to minimize the household's energy cost and the dissatisfaction level caused by the shifting, reduction and replacement of loads in response to the time varying prices. Case studies using realistic data indicate that the proposed model can save the total energy costs up to 30% for customers whilst ensuring their satisfaction levels.

INDEX TERMS Home energy management system, natural gas, demand response, joint scheduling, dissatisfaction.

A. SUPERSCRIPTS

bch	Battery charging
bdch	Battery discharging
dw	Dishwasher
eac	Electric air conditioner
el	Electric light
es	Electric stove
ev	Electric vehicle
ewh	Electric water heater
gahs	Gas air heating system
gs	Gas stove
gwh	Gas water heater
ua	Uncontrollable appliance
s	Stove
wh	Water heater
wm	Washing machine

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B. INDEXES AND SETS

t	Index of timeslots
i	Index of appliances
k	Index of time periods
$\boldsymbol{K}$	Set of time periods

$\boldsymbol{T}$	Set of timeslots (scheduling cycle)
$\boldsymbol{T}_k$	Set of timeslots in time period k
$\boldsymbol{T}^i_{work}$	Operation time window of appliance i

C. PARAMETERS

C_p^{air}	The heat capacity of air
Cap^B	Battery capacity
$E^i_{electric}$	Electric energy demand of appliance i
E^i_{heat}	Heat energy demand of appliance i
M^{air}	The mass of air
P^i_{rated}	Rated power of appliance i
$P_t^{ini,i}$	Initial power of appliance i (without control actions)
$P^i_{\max}$	Maximum power of appliance i
$P^i_{\min}$	Minimum power of appliance i
$P^{bch}_{\max}$	Maximum charging power of battery
$P^{bdch}_{\max}$	Maximum discharging power of battery
R	The equivalent thermal resistance
SOC_{min}	Minimum state of charge
$SOC_{\max}$	Maximum state of charge
Δt	Time interval
δ^i	Operation durations of appliance i
η^i	Efficiency of appliance i
θ_t^{out}	Outdoor temperature at timeslot t
$\theta^{in}_{\min}$	Minimum indoor temperature
$\theta^{in}_{\max}$	Maximum indoor temperature
π^e	Electricity price
π^g	Natural gas price
π^B	Unit depreciation cost of a battery
$price^B$	The cost of a household battery
n^{bch}	Maximum charging number of batteries
S^i	Time shifting dissatisfaction function of appliance i
U^i	Preference parameters of appliance i
λ^{energy}	Coefficient of objective function 1
λ^{diss}	Coefficient of objective function 2

D. VARIABLES

P_t^i	Optimized power of appliance i at timeslot t
X_t^i	The on/off state of appliance i at timeslot t
θ_t^{in}	Indoor temperature at timeslot t
Q_t^H	Heating load supplied by air heating appliance at timeslot t
Q_t^C	Cooling load supplied by air cooling appliance at timeslot t
SOC_t	State of charge at timeslot t
P_t^{bch}	Charging power of battery at timeslot t
P_t^{bdch}	Discharging power of battery at timeslot t
X_t^{bch}	Charging state of battery at timeslot t
X_t^{bdch}	Discharging state of battery at timeslot t

I. INTRODUCTION

Demand response (DR) utilizes the demand side resources to help maintaining the reliability [1] and improving the flexibility [2] of power systems. DR is, indeed, considered as a promising means to facilitate the accommodation of renewable energy in addition to some other technologies such as wind and solar power forecasting with different time scales (e.g. ultra-short term [3], [4], short term [5], [6]). End-use customers participate in DR programs by changing their electricity consumption patterns in response to dynamic time varying electricity price or incentive signals [7]. For example, residential customers can shift their appliance usages from on-peak time to off-peak time to save electricity cost [8]. However, frequent active responses can make residential customers tired of tracking DR signals and their own electricity consumption, and this can surely affect the response deepness [9]. To address this issues, home energy management systems (HEMSs) can be used. A HEMS is defined as "*A technology system, comprised of both hardware and software that allows the user to monitor energy usage and production and to manually control and/or automate the use of energy within a household*" [10]. It performs optimal scheduling of each household appliance and distributed generator according to an objective function (e.g. the energy cost) predefined by customer or an aggregator and according to some external information (e.g. weather, electricity price, incentive signal, etc.) in order to help residential customers to efficiently manage their energy consumption [11].

HEMSs have been widely investigated in the literature. In [12] a multi-stage based HEMS for optimal scheduling of home energy resource in a high penetration of rooftop photovoltaic was proposed. In [13] a multi-objective mixed integer nonlinear programming model was proposed to optimize the energy use in a smart home, which considers a meaningful balance between energy saving and a comfortable lifestyle. Similarly, in [14] a novel residential energy management system was presented to improve the efficiency of energy consumption which considers both the minimum cost of energy and maximum user's comfort level. In recent years, an increasing number of studies incorporated the uncertainty of information such as renewable generations, weather conditions [15], and electricity prices into HEMS optimization models. For example, in [16] a stochastic model of a HEMS was proposed by considering the uncertainties of electric vehicles availability and renewable generations. In [17] an energy efficient scheduling algorithm was proposed to arrange the household appliances, which considers the uncertainties in household appliance operation time and intermittent renewable generation. In addition, studies on multi-household energy management are also receiving more and more attention. For example, in [18] an energy management system was proposed for coordinating the operation of a cluster of distributed household prosumers by considering the cooperative operations between multiply households, such as power sharing and storage energy balance.

Natural gas is playing an increasingly important role in the global energy structure. According to the statistical data from the International Energy Agency (IEA) [19], the natural gas will account for more than 24% of the energy structure and surpass oil to become the second largest energy source in the world in 2035. In fact, for households connected to the natural gas network, part of their electricity demands can be replaced by natural gas. For example, a natural gas stove can replace an electric stove to finish the cooking task. A traditional HEMS only optimizes the consumption of a single energy source (i.e. electricity), thus it cannot be applied into those households with multi-energy sources. To consider the interaction between electricity and natural gas in a multi-carrier energy home, it is essential to explore new optimal scheduling models.

There are few studies trying to address the issues related to the operation of HEMS in a multi-carrier energy home. In [20] the authors explored the multi-energy management of a home where a combined heat and power (CHP) system is installed, the aim of the optimization model is to minimize the cost of electricity and natural gas. In [21] an energy management system was proposed for integrated building and microgrid systems. Some key modeling aspects are considered as constraints such as heat transfer, thermal dynamics of sustainable residential buildings and load scheduling potentials of household appliances. Similarly, in [22] a multi-agent based energy management system was proposed for an integrated energy system. In [23] the integration of electricity and natural gas networks were studied based on a reinforcement learning algorithm but the thermal load is simply modeled without considering specific appliance characteristics. In [24] an optimization-based formulation for optimal operation of residential energy hub and management of household demands was presented. In [25] a smart home energy management model was presented for joint scheduling of electrical and thermal appliances. However, the interactions between different appliances are not considered.

In summary, even though there are many studies on HEMSs, only a limited number of them make preliminary efforts to carry out the optimal household multi-energy management. Some limitations can be found for these works.

1) Most works use CHP to model the interaction between the natural gas and the electricity. The proposed model in the existing literature maybe cannot work for those households without CHP. Considering the fact that there are very few households that use CHP in China, new models that can meet the realistic requirements in China need to be proposed.

2) It is common for Chinese households to have appliances doing the same task while being operated by different energy sources (e.g. electric stoves and natural gas stoves). These appliances can be substituted for each other. However, to the best of authors' knowledge, there is no existing work considering the interactions between appliances supplied by different energy sources. In other words, researches on the optimal multi-energy management at the household appliance level are urgently needed.

3) In fact, both the operation time shifting and the power consumption reduction can lead to the dissatisfaction of customers. However, in most of the previous literature, customers' dissatisfactions caused by the re-scheduling of appliance operation have been overlooked or incompletely considered (i.e. only considering the dissatisfactions caused by the time shifting or the power reduction) [26]. Moreover, the dissatisfaction caused by the operation time shifting is usually considered to be correlated with the deviation between the initial and shifted operation time [27], which cannot accurately reflect the lifestyles and habits of residential customers in practice. For example, an office worker living alone may prefer to use the washing machine before or after work. Considering such a case that the HEMS shifts the operation time of the washing machine to a period when he is not at home such as 30 minutes later after leaving his house. Such a scheduling can be considered to have only a little impact on the customer if the existing methods are used to describe the dissatisfaction, because the deviation between the initial time and the shifted time is small. However, such a scheduling will actually cause significant inconvenience to the customer in practice.

To address the above issues, a novel HEMS considering the interaction between electric and natural gas appliances is proposed in this paper. The novel contributions of the paper can be summarized as follows.

1) A novel appliance classification method is proposed in this paper, which considers the replacement between the appliances with the same function but supplied by different energy sources (i.e. electricity and natural gas).

2) A novel day-ahead optimal joint scheduling model of both electrical and natural gas appliances for HEMS is proposed. Particularly, natural gas wall hanging furnace, a very popular natural gas appliance in modern households, is considered and modeled, which can not only heat the house (i.e. equivalent to an electric air conditioner) but also provide hot water (i.e. equivalent to an electric water heater), thus providing more flexibility for home integrated energy management.

3) A complete and realistic dissatisfaction characterization model is proposed to describe customers' dissatisfaction caused by the re-scheduling of loads in response to time varying electricity price. The proposed model not only considers the dissatisfaction caused by the operation time shifting and power consumption reduction of appliances, but also considers customers' preferences for different types of energy when optimizing the cooperation of electric appliances and natural gas appliances.

The rest of the paper is organized as follows. The mathematical formulations of the HEMS model are presented in Section II. The numerical studies and discussions are presented in Section III. Section IV highlights the conclusions of this paper.

II. MODELING OF THE PROPOSED HEMS

A. APPLIANCE CLASSIFICATION

In this paper, home appliances are classified into the following categories according to the appliance types and their functions.

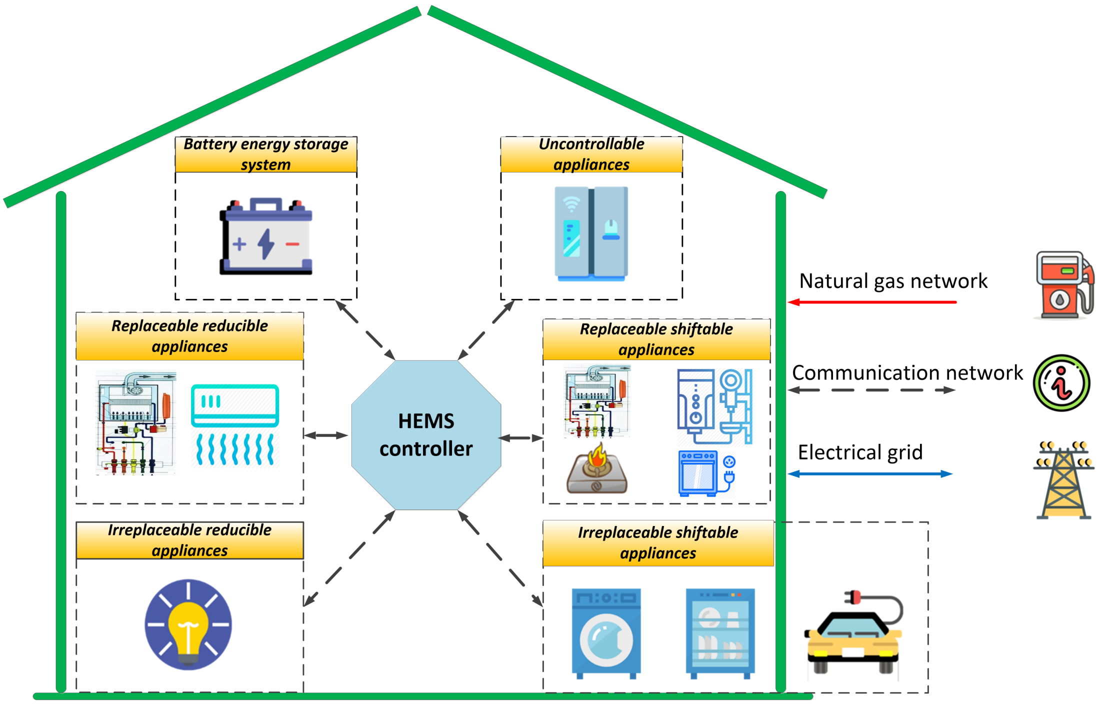

FIGURE 1. Schematic diagram of the smart household.

1) Uncontrollable appliances: this type of appliances are uncontrolled and have to be preserved without intervention. A typical example is the refrigerator.

2) Shiftable appliances: all appliances whose operation time can be shifted across the day, whilst achieving the required energy use within a single day. These appliances can be further divided into two sub-categories: i) replaceable; ii) irreplaceable.

i) Replaceable shiftable appliances: all shiftable appliances that can be replaced by natural gas appliances with the same function. For example, cooking appliances such as electric stoves can be replaced by natural gas stoves.

ii) Irreplaceable shiftable appliances: all shiftable appliances which cannot be replaced by natural gas appliance. For example, the washing machine cannot be replaced by any natural gas appliance.

3) Reducible appliances: all appliances whose power consumption can be controlled. Similarly, these appliances also can be divided into replaceable and irreplaceable appliances.

i) Replaceable reducible appliances: all reducible appliances which can be replaced by natural gas appliance. For example, an electric air conditioner can be replaced by a natural gas wall hanging furnace.

ii) Irreplaceable reducible appliances: all reducible appliances which cannot be replaced by natural gas appliance.

4) Energy storage system: a household energy storage system usually has two operation modes: Grid-to-Household (G2H) and Household-to-Grid (H2G). The energy stored in an energy storage system not only can supply the household demand, but also can be injected into the electrical grid. Typically, an energy storage system stores energy during low-tariff periods (i.e. G2H mode) and sells it to the grid during high-tariff periods to allow a cost reduction for the customer (i.e. H2G mode).

It should be noted that the above classification is performed according to the realistic situation. Actually, it is common for a household in China to have appliances doing the same task while being operated by different energy sources. For example, a Chinese household usually has both an electric stove and a natural gas stove. There are several factors contributing to this phenomenon. One of the factors is that Chinese people have different cooking demands. For example, it is more convenient to make a soup by electric stoves. However, it is better to stir fry with natural gas stoves.

B. OVERVIEW OF THE PROPOSED HEMS

A modern smart household is selected for analysis in this paper. The schematic diagram of the smart household is presented in Fig. 1. The household has the following different types of appliances: 1) Uncontrollable appliances: a refrigerator, a TV, a personal computer, critical electric lights; 2) Irreplaceable shiftable appliances: a washing machine, an electric vehicle and a dishwasher; 3) Irreplaceable reducible appliances: non-necessary electric lights; 4) Replaceable shiftable appliances: an electric water heater, a natural gas water heater contained in a natural gas wall hanging furnace, an electric stove and a natural gas stove; 5) Replaceable shiftable appliances: an electric air conditioner and a natural gas air heater contained in the natural gas furnace. 6) Energy storage system: a household battery is contained in the household.

The overview of the proposed day-ahead scheduling model can be illustrated as follows. The HEMS controller first receives the external information such as the forecasted electricity price and outdoor temperature data for the upcoming 24 h period, as well as the customer settings information such as the valid operation time windows of shiftable appliances, operation durations and preference for different appliances [28]. Subsequently, the HEMS aims to find the best scheduling of all appliances across a finite time horizon of a single day to minimize the daily energy cost whilst achieving maximum satisfaction level [29].

C. APPLIANCES MODELING

1) MODEL OF UNCONTROLLABLE APPLIANCES

For uncontrollable appliances, neither the operation time nor the power can be controlled. Therefore, the daily power consumption of all uncontrollable appliances are aggregated and modeled as a lumped load, which can be predicted from historical load profiles.

2) MODEL OF IRREPLACEABLE SHIFTABLE APPLIANCES

The models of irreplaceable shiftable appliances are presented in Eqs. (1)-(4). In Eq.(1), P_t^i is the optimized power of appliance i at timeslot t. X_t^i is a binary variable representing the state of appliance i at timeslot t, which is 1 if the appliance is on and is 0 if the appliance is off. P_{rated}^i is the rated power of appliance i. Eq. (1) shows that the optimized power consumption of each irreplaceable shiftable appliance at each timeslot is equal to its rated power if the appliance is on. Eq. (2) ensures the appliance to operate within a valid operation time window, where $\boldsymbol{T}_{work}^i$ is the pre-defined valid operation time window of appliance i. In Eq.(3), Δt is the time interval. $E_{electric}^i$ is the electric energy demand of appliance i. Eq. (3) ensures that the consumption of appliance i within a day should achieve the required electric energy demand $E_{electric}^i$. Eq. (4) is used to guarantee that the appliance operates continuously during a operation cycle without any interruption, where δ^i is the operation duration of appliance i.

$$P_t^i = X_t^i P_{rated}^i, \quad \forall i \in \{ev, wm, dw\}, \ \forall t \in \boldsymbol{T} \tag{1}$$

$$X_t^i = \begin{cases} 0, & \forall i \in \{ev, wm, dw\}, \ \forall t \notin \boldsymbol{T}_{work}^i \\ 0 \ or \ 1, & \forall i \in \{ev, wm, dw\}, \ \forall t \in \boldsymbol{T}_{work}^i \end{cases} \tag{2}$$

$$\sum_{t \in \boldsymbol{T}} P_t^i \Delta t = E_{electric}^i, \quad \forall i \in \{ev, wm, dw\} \tag{3}$$

$$\sum_{t=t}^{t=t+\delta^i-1} X_t^i = \delta^i, \quad \forall i \in \{ev, wm, dw\}, \ \exists t \in \boldsymbol{T} \tag{4}$$

3) MODEL OF REPLACEABLE SHIFTABLE APPLIANCES

There are two kinds of replaceable shiftable appliances in the studied household, i.e. stoves and water heaters. Eqs. (5)-(10) present the models of the stoves. Stoves are used for cooking during each time period $k \in \boldsymbol{K}, \boldsymbol{K} = \{morning, noon, night\}$ in a day. There are two different stoves in the studied household: an electric stove and a natural gas stove. The customers can choose one of them to finish the cooking task during each period. The operation time of stoves can be shifted during each time period. Eqs. (5) and (6) describe the optimized power consumption of the electric stove and the natural gas stove, respectively, where P_{rated}^{es} and P_{rated}^{gs} represent the rated power of the electric stove and the natural gas stove, respectively. $\boldsymbol{T}_k$ is the set of timeslots during each time period k. $X_{k,t}^s$ is a binary variable showing the operation state of stoves at timeslot t during each time period k. X_k^{es} and X_k^{gs} are also binary variables indicating whether the appliance is chosen for cooking or not. Eq. (7) ensures the stove to operate within a pre-defined valid time window. Eq. (8) ensures that only one stove can be used during the same time period. This constraint is important since it avoids an unrealistic situation that the cooking task transfers from one stove to another stove. Eq. (9) is used to guarantee that the total heat energy generated by electric stoves and natural gas stoves can meet the customer's heating energy demand $E_{k,heat}^s$, where η^{es} and η^{gs} are the energy conversion efficiency of the electric stove and the natural gas stove. Eq. (10) guarantees the continuity of operation process for stoves during each time period, where δ_k^s is the operation duration of the stove during each time period k.

$$P_{k,t}^{es} = X_{k,t}^s X_k^{es} P_{rated}^{es}, \quad \forall t \in \boldsymbol{T}_k, \ \forall k \in \boldsymbol{K} \tag{5}$$

$$P_{k,t}^{gs} = X_{k,t}^s X_k^{gs} P_{rated}^{gs}, \quad \forall t \in \boldsymbol{T}_k, \ \forall k \in \boldsymbol{K} \tag{6}$$

$$X_{k,t}^s = \begin{cases} 0, & \forall t \notin \boldsymbol{T}_{k,work}^s, \ \forall k \in \boldsymbol{K} \\ 0 \ or \ 1, & \forall t \in \boldsymbol{T}_{k,work}^s, \ \forall k \in \boldsymbol{K} \end{cases} \tag{7}$$

$$X_k^{es} + X_k^{gs} = 1, \quad \forall k \in \boldsymbol{K} \tag{8}$$

$$\sum_{t \in \boldsymbol{T}_k} X_{k,t}^s \left(X_k^{es} P_{rated}^{es} \eta^{es} + X_k^{gs} P_{rated}^{gs} \eta^{gs} \right) \Delta t = E_{k,heat}^s, \quad \forall k \in \boldsymbol{K} \tag{9}$$

$$\sum_{t=t}^{t=t+\delta_k^s-1} X_{k,t}^s = \delta_k^s, \quad \exists t \in \boldsymbol{T}_k, \ \forall k \in \boldsymbol{K} \tag{10}$$

Similar to stoves, there are two different water heaters in the studied household: an electric water heater and a natural gas water heater (contained in the natural gas wall hanging furnace). Their models are respectively shown in Eqs. (11)-(16), where η^{ewh} and η^{gwh} are the energy conversion efficiency of the electric water heater and the natural gas water heater, respectively.

$$P_t^{ewh} = X_t^{wh} X_k^{ewh} P_{rated}^{ewh}, \quad \forall t \in \boldsymbol{T}_k, \ \forall k \in \boldsymbol{K} \tag{11}$$

$$P_t^{gwh} = X_t^{wh} X_k^{gwh} P_{rated}^{gwh}, \quad \forall t \in \boldsymbol{T}_k, \ \forall k \in \boldsymbol{K} \tag{12}$$

$$X_{k,t}^{wh} = \begin{cases} 0, & \forall t \notin \boldsymbol{T}_{work}^{wh}, \ \forall k \in \boldsymbol{K} \\ 0 \ or \ 1, & \forall t \in \boldsymbol{T}_{work}^{wh}, \ \forall k \in \boldsymbol{K} \end{cases} \tag{13}$$

$$\sum_{t \in \boldsymbol{T}_k} X_t^{wh} (X_k^{ewh} P_{rated}^{ewh} \eta^{ewh} + X_k^{gwh} P_{rated}^{gwh} \eta^{gwh}) = E_{k,heat}^{wh}, \quad \forall k \in \boldsymbol{K} \tag{14}$$

$$X_k^{ewh} + X_k^{gwh} = 1, \quad \forall k \in \boldsymbol{K} \tag{15}$$

$$\sum_{t=t}^{t=t+\delta_k^{wh}-1} X_{k,t}^{wh} = \delta_k^{wh}, \quad \exists t \in \boldsymbol{T}_k, \ \forall k \in \boldsymbol{K} \tag{16}$$

4) MODEL OF IRREPLACEABLE REDUCIBLE APPLIANCES

The non-necessary electric lights in the studied household are considered to be a kind of irreplaceable reducible appliance, whose models are presented in Eqs. (17) and (18). P^i_{rated} is the rated power consumption of all non-necessary lights before implementing the control actions. The power of non-necessary lights can be modified to 0 in order to reduce the cost of purchasing electricity but this will result in dissatisfaction of customers.

$$P^i_t = X^i_t P^i_{rated}, \quad \forall i \in \{el\}, \ \forall t \in \boldsymbol{T} \tag{17}$$

$$X^i_t = \begin{cases} 0, & \forall i \in \{el\}, \ \forall t \notin \boldsymbol{T}^i_{work} \\ 0 \ or \ 1, & \forall i \in \{el\}, \ \forall t \in \boldsymbol{T}^i_{work} \end{cases} \tag{18}$$

5) MODEL OF REPLACEABLE REDUCIBLE APPLIANCES

Air heating appliances are typical examples of replaceable reducible appliances. There are two air heating appliances: an electric air conditioner and an natural gas air heating system (contained in the natural gas wall hanging furnace). The model of air heating appliances is shown in Eqs. (19)-(23). Eq. (19) is a linearized model of the thermal inertia of buildings [16], where θ^{in}_t and θ^{out}_t are the indoor and outdoor temperature at timeslot t. C^{air}_p is the heat capacity of air, M^{air} is the mass of air, R is the equivalent thermal resistance. Different from previous HEMSs which only use the electric air conditioner to supply the heating energy demand Q^H_t at each timeslot t, the HEMS proposed in this paper can control and optimize the power consumption of both electric air conditioners and natural gas air heating systems to meet the required heating load which is shown in Eq. (20), where P^{eac}_t and P^{gahs}_t are the power consumption of the electric air conditioner and the natural gas air heating system, respectively. η^{eac} and η^{gahs} are the energy conversion efficiency of the electric air conditioner and the natural gas air heating system, respectively. Eq. (21) limits the indoor temperature within a certain range, where $\theta^{in}_{\min}$ and $\theta^{in}_{\max}$ are the minimum and maximum indoor temperature pre-defined by customers. Eqs. (22) and (23) present the power consumption limitation of the electric air conditioner and the gas air heating system.

$$\theta^{in}_{t+1} = (1 - \frac{1}{M^{air}C^{air}_p R})\theta^{in}_t + \frac{1}{M^{air}C^{air}_p R}\theta^{out}_t + \frac{Q^H_t}{M^{air}C^{air}_p}, \quad \forall t \in \boldsymbol{T} \tag{19}$$

$$Q^H_t = (P^{eac}_t \eta^{eac} + P^{gahs}_t \eta^{gahs})\Delta t, \quad \forall t \in \boldsymbol{T} \tag{20}$$

$$\theta^{in}_{\min} \le \theta^{in}_t \le \theta^{in}_{\max}, \quad \forall t \in \boldsymbol{T} \tag{21}$$

$$P^{eac}_{\min} \le P^{eac}_t \le P^{eac}_{\max}, \quad \forall t \in \boldsymbol{T} \tag{22}$$

$$P^{gahs}_{\min} \le P^{gahs}_t \le p^{gahs}_{\max}, \quad \forall t \in \boldsymbol{T} \tag{23}$$

It should be noted the above model can only be applied in winter since the air cooling load in summer can be only supplied by the electric air conditioner. The models of air cooing appliances in summer are shown in Eqs. (24) - (27), where Q^C_t is the cooling energy demand.

$$\theta^{in}_{t+1} = (1 - \frac{1}{M^{air}C^{air}_p R})\theta^{in}_t + \frac{1}{M^{air}C^{air}_p R}\theta^{out}_t + \frac{Q^C_t}{M^{air}C^{air}_p} \quad \forall t \in \boldsymbol{T} \tag{24}$$

$$Q^C_t = P^{eac}_t \eta^{eac} \Delta t, \quad \forall t \in \boldsymbol{T} \tag{25}$$

$$\theta^{in}_{min} \le \theta^{in}_t \le \theta^{in}_{\max}, \quad \forall t \in \boldsymbol{T} \tag{26}$$

$$P^{eac}_{\min} \le P^{eac}_t \le P^{eac}_{\max}, \quad \forall t \in \boldsymbol{T} \tag{27}$$

6) MODEL OF THE BATTERY

Eqs. (28)-(32) give the model of household batteries. Eq. (28) describes the variations of the state of charge (SOC) of the battery [30], where X^{bch}_t and X^{bch}_t are binary variables showing the charging/discharging state of the battery at timeslot t, where P^{bch}_t and P^{bdch}_t are the Charging power of battery at timeslot t and the Discharging power of battery at timeslot t. where η^{bch} and η^{bdch} are the battery efficiency of charging and battery efficiency of discharging. Where Cap^B is the Battery capacity. Eq. (29) guarantees that a household battery cannot be charged and discharged at the same time. Inequality (30) limits the depth of discharge and guarantees that the battery is not overcharged. The maximum charging and discharging power are limited in Eqs. (31) and (32).

$$SOC_t = SOC_{t-1} + X^{bch}_t \frac{P^{bch}_t \eta^{bch} \Delta t}{Cap^B} - X^{bdch}_t \frac{P^{bdch}_t \Delta t}{\eta^{bdch} Cap^B}, \quad \forall t \in \boldsymbol{T} \tag{28}$$

$$X^{bch}_t + X^{bdch}_t = 1, \quad \forall t \in \boldsymbol{T} \tag{29}$$

$$SOC_{\min} \le SOC_t \le SOC_{\max}, \quad \forall t \in \boldsymbol{T} \tag{30}$$

$$0 \le P^{bch}_t \eta^{bch} \le P^{bch}_{\max}, \quad \forall t \in \boldsymbol{T} \tag{31}$$

$$0 \le \frac{P^{bdch}_t}{\eta^{bdch}} \le P^{bdch}_{\max}, \quad \forall t \in \boldsymbol{T} \tag{32}$$

D. OBJECTIVE FUNCTIONS

The objective functions of the proposed HEMS contain two parts:

1) MINIMIZATION OF COST

The first objective function is to minimize the total energy costs subject to aforementioned constraints, which is formulated in Eq. (33). Total energy costs include three parts: electricity purchasing costs, natural gas purchasing costs and depreciation costs of the household battery. Eq. (34) indicates that the electricity costs are equal to the electricity fee consumed by all electric appliances minus the revenue from selling electricity back to the grid. Eq. (35) gives the model for calculating the natural gas purchasing costs. The costs of battery depreciation due to be operated in discharging modes are shown in Eqs. (36) and (37) [31]. π^B is the depreciation cost of battery for unit discharging power. $price^B$ denotes the cost of the battery. n^{bdch} and Cap^B are the maximum discharging times and the capacity of the battery.

$$\min \text{cost}^{\text{energy}} = \text{cost}^{\text{e}} + \text{cost}^{\text{g}} + \text{cost}^{\text{B}} \tag{33}$$

$$\begin{aligned}\text{cost}^{\text{e}} = \pi_t^e \sum_{t\in \boldsymbol{T}} (&X_t^{bch}P_t^{bch} - X_t^{bdch}P_t^{bdch} + P_t^{ua} \\ &+ P_t^{ev} + P_t^{wm} + P_t^{dw} + P_t^{el} + P_t^{ewh} \\ &+ P_t^{es} + P_t^{eac})\Delta t \end{aligned}\tag{34}$$

$$\text{cost}^{\text{g}} = \pi_t^g \sum_{t\in \boldsymbol{T}} \left(P_t^{gwh} + P_t^{gs} + P_t^{gah}\right)\Delta t \tag{35}$$

$$\text{cost}^{B} = \pi^B \sum_{t\in \boldsymbol{T}} X_t^{bdch}P_t^{bdch}\Delta t \tag{36}$$

$$\pi^B = \frac{price^B}{n^{bdch}Cap^B} \tag{37}$$

2) MINIMIZATION OF DISSATISFACTION

The second objective function is to minimize the dissatisfaction level caused by the re-scheduling of appliances, as shown in Eq. (38). A complete and realistic dissatisfaction characterization model is proposed to describe the dissatisfaction level caused by the shifting, reduction and replacement of loads in response to the time varying electricity prices.

$$\min f^{diss} = f_{shift}^{diss} + f_{reduce}^{diss} + f_{replace}^{diss} \tag{38}$$

Eq. (39) presents the model for calculating the dissatisfaction level resulting from shifting the operation time of the appliance. S_t^i is a score evaluating the dissatisfaction level caused by operating shiftable appliance i at timeslot t, which is determined by customers according to their living arrangement in the next day. S_t^i ranges from 0 to 5. A larger value of S_t^i means a higher dissatisfaction level. X_t^i is a binary variable representing the state of appliance i at timeslot t.

$$f_{shift}^{diss} = \sum_{i\in\{ev,wm,dw,wh,s\}} \sum_{t\in \boldsymbol{T}} X_t^i S_t^i \tag{39}$$

Eq. (40) introduces the model for calculating the customers' dissatisfaction resulting from reducing the power of the appliance, where $P_t^{ini,el}$, $P_t^{ini,eac}$, $P_{\text{t}}^{ini,gahs}$ are the initial power consumption of reducible appliances before implementing the HEMS and P_t^{el}, P_t^{eac}, P_t^{gahs} are the optimized power consumption of reducible appliances after implementing the proposed HEMS. Larger value of power reduction means a higher dissatisfaction level for users.

$$\begin{aligned} f_{reduce}^{diss} = &\sum_{t\in \boldsymbol{T}} (P_t^{ini,el} - P_t^{el})\Delta t \\ &+ \sum_{t\in \boldsymbol{T}} \left(\left(P_t^{ini,eac} + P_t^{ini,gahs}\frac{\eta^{gahs}}{\eta^{eac}}\right)\right. \\ &\left. - \left(P_t^{eac} + P_t^{gahs}\frac{\eta^{gahs}}{\eta^{eac}}\right)\right)\Delta t \end{aligned}\tag{40}$$

In the previous HEMS models, one kind of load demand can only be supplied by one kind of energy, but for the proposed HEMS, one kind of load demand can be supplied provided by different energy sources. In order to consider customers' preferences for different types of energy when optimizing the cooperation of electric appliances and natural gas appliances, a novel model for calculating the dissatisfaction level caused by the alternative use of different kind of appliances is proposed as shown in Eq. (41), where U denotes the customers' preference parameters. A lower value of U means a higher preference level. The specific values of U for different appliances are determined by customers. The deeper the user's preference for the appliance i, the smaller the U^i, the smaller the P^iU^i, that is to say, the less dissatisfied the user will be if HEMS choosing the appliance i to meet users' demand.

$$\begin{aligned} f_{replace}^{diss} = &\sum_{t\in \boldsymbol{T}} (P_t^{ewh}U^{ewh} + P_t^{es}U^{es} + P_t^{eac}U^{eac})\Delta t \\ &+ \sum_{t\in \boldsymbol{T}} (P_t^{gwh}U^{gwh} + P_t^{gs}U^{gs} + P_t^{gahs}U^{gahs})\Delta t \end{aligned}\tag{41}$$

E. OPTIMIZATION MODEL OF THE PROPOSED HEMS

The decision variables are the on/off state of shiftable appliances, power consumption of reducible appliances, the charging and discharging power of the battery.

It is noted that the two objective functions given in Eqs. (33) and (38) show different quantitative units. In order to eliminate the impacts of quantitative units on the optimization results, the two objective functions are normalized to their maximum values. The maximum value of the first objective function is the total energy costs without implementing the HEMS. The maximum value of the second objective function occurs when all appliances are re-scheduled to the most unsatisfactory situation, i.e. all shiftable appliances are shifted to the most unsatisfactory time, the power of all reducible appliances are reduced to zero and all selected replaceable appliance are disliked by customers. The optimization problem can be reformulated as a single-objective optimization shown in Eq. (42).

$$\begin{aligned} \min \text{f} = &\lambda^{energy}\frac{\text{cost}^{energy}}{\text{cost}_{\max}^{energy}} \\ &+ \frac{\lambda^{diss}}{3}\left(\frac{f_{shift}^{diss}}{f_{shift,\max}^{diss}} + \frac{f_{reduce}^{diss}}{f_{reduce,\max}^{diss}} + \frac{f_{replace}^{diss}}{f_{replace,\max}^{diss}}\right) \\ &\textit{Subject to } \text{Eqs. (1)} - (32) \end{aligned}\tag{42}$$

The above model can be efficiently solved by the existing commercial solvers.

III. CASE STUDY

A case study is performed to verify the effectiveness of the proposed model. The program is developed using MATLAB R2015a. The optimization solver is Gurobi 8.1.0 [32].

A. SIMULATION SETTINGS

The day-ahead optimal scheduling of electric and natural gas appliance on a typical day in winter is investigated in this paper. A household in the U.S. is selected to perform the simulation [33]. The parameters of each appliance in the household are given in Table 1. It is assumed that there

TABLE 1. The parameters of household appliances.

Appliance type	Appliance	Power (kWh)	Start time	Operation durations (h)	Efficiency η^i	T^i_{work}
Irreplaceable shiftable appliances	Electric vehicle	3.500	18:00	3	-	[18:00, 6:00^{+1}]
	Washing machine	0.800	19:00	1	-	[7:00, 6:00^{+1}]
	Dishwasher	0.400	19:00	1	-	[19:00, 21:00]
Replaceable shiftable appliances	Electric water heater / Natural gas water heater	0.000 / 3.150 0.000 / 3.150	7:00 19:00	1 1	0.95/0.95	[7:00, 8:00] [18:00, 20:00]
	Electric stove / Natural gas stove	0.625 / 0.000 1.250 / 0.000 1.250 / 0.000	7:00 11:00 17:00	1 1 1	0.8/0.4	[7:00, 8:00] [10:00, 12:00] [17:00, 18:00]
Irreplaceable reducible appliances	Electric lights	0.500	17:00	5	-	-
Replaceable reducible appliances	Electric air conditioner / Natural gas air heating system	-	7:00	24	2.5/0.8	-

TABLE 2. The parameters of the household battery.

Capacity	SOC_{max}	SOC_{min}	$P_{max}^{bch/bdch}$	$\eta^{bch/bdch}$	π^B
5kWh	0.95	0.1	1kW	0.95	0.005$/kWh

TABLE 3. Different DR programs.

DR program	on-peak 7:00-11:00, 17:00-20:00	mid-peak 11:00-17:00	off-peak 20:00-7:00
Fixed tariff		0.094 $ /kWh	
TOU	0.132 $ /kWh	0.094 $ /kWh	0.065 $ /kWh
RTP	[0.081, 0.078, 0.076, 0.076, 0.077, 0.079, 0.087, 0.099, 0.115, 0.114, 0.104, 0.094, 0.087, 0.086, 0.088, 0.093, 0.101, 0.127, 0.125, 0.117, 0.094, 0.088, 0.087, 0.084] $ /kWh		

is a battery with the capacity of 5kWh in the household. The initial SOC of the battery is set to be 0.8. The detailed parameters of the battery are presented in Table 2.

Three different electricity tariffs are considered, including fixed tariff, time-of-use (TOU) tariff [34] and real-time pricing (RTP) tariff, as presented in Table 3. In fact, the RTP price varies day by day. Therefore, a day-ahead electricity price forecasting should be performed in the day-ahead optimal scheduling. However, electricity price forecasting is out of the scope of this paper. More details on electricity price forecasting can be found in [35]. The price of natural gas is set to be 0.034 $/kWh. The scheduling cycle is from 7:00 to 6:00 in the next day.

B. SIMULATION RESULTS

When there is no DR, customers tend to use their appliances in a way to have the highest comfort level. Fig. 2 shows the household energy consumption of electric appliances and natural gas appliances without DR program (i.e. fixed tariff). If a TOU program is implemented, customers have motivations to change their electricity consumption patterns to save the cost. The proposed HEMS can help customers to efficiently participate in the DR program by re-scheduling the appliance usages. Fig.3 shows the household energy consumption after implementing the proposed HEMS under the TOU program.

1) SCHEDULING OF IRREPLACEABLE SHIFTABLE APPLIANCES

It can be seen from Fig. 2 (a) that the charging time of the electric vehicle is during the on-peak time period if the proposed HEMS is not employed. According to Fig. 3(a), by employing the proposed HEMS and considering a TOU program, the start time of electric vehicle charging is shifted from 18:00 (i.e. on-peak time) to 20:00 (i.e. off-peak time)

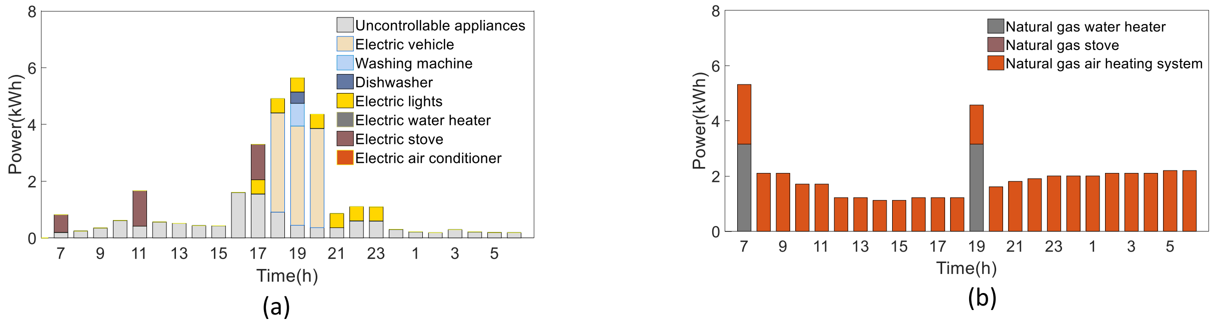

FIGURE 2. The household energy consumption of electric and natural gas appliances without the proposed HEMS under the fixed tariff program. (a) Electric appliances. (b) Natural gas appliances.

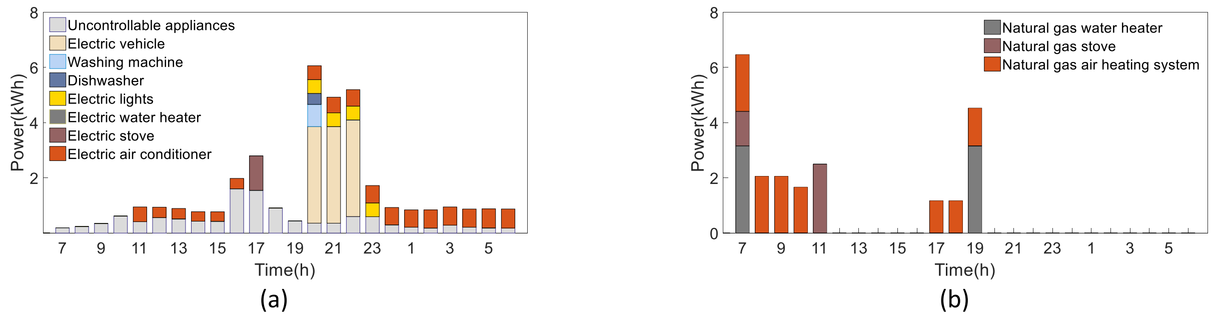

FIGURE 3. The household energy consumption of electric and natural gas appliances after implementing the proposed HEMS under the TOU program. (a) Electric appliances. (b) Natural gas appliances.

in order to reduce the electricity cost. Similar to the electric vehicle, the operation time of the washing machine and the dishwasher are shifted from 19:00 (i.e. on-peak time) to 20:00 (i.e. off-peak time).

2) SCHEDULING OF REPLACEABLE SHIFTABLE APPLIANCES

Theoretically, the operation time of replaceable shiftable appliances can be shifted. However, it can be found by comparing Fig. (2) and Fig.(3) that the proposed HEMS does not shift the operation time of water heaters and stoves. The reasons can be illustrated as follows: the operation time of each shiftable appliance is limited within valid time windows. For example, the operation time of the stove is limited to 7:00-8:00 and 18:00-19:00. Both electricity and natural gas prices remain unchanged during these valid time windows. In other words, shifting the operation time of water heaters and stoves cannot reduce the total energy cost but result in the increase of the customer's dissatisfaction level, thus the proposed HEMS does not shift the operation time of these two appliances. The water heating load is still supplied by the natural gas water heater after re-scheduling since the natural gas price is lower than the electricity price during the operation time of the water heater. The proposed HEMS uses the natural gas stove to replace the electric stove to supply the cooking related heating load at 7:00 and 11:00 due to the lower price of natural gas, while still uses the electric stove at 17:00. This is because that the battery discharges at 17:00 and the electricity consumed by the electric stove is supplied by the battery without purchasing extra electricity from the grid at 17:00. The scheduling of the battery will be analyzed in the following section.

3) SCHEDULING OF IRREPLACEABLE REDUCIBLE APPLIANCES

It can be observed by comparing Fig.2 (a) and Fig. 3(a) that the proposed HEMS curtails a part of the load during the on-peak time period (i.e. 17:00-19:00) by turning off the non-necessary electric lights. However, the electricity cost saving is lower than the dissatisfaction cost due to the power consumption reduction of electric lights during off-peak time, thus the electric lights remain on during 22:00-23:00.

4) SCHEDULING OF REPLACEABLE REDUCIBLE APPLIANCES

It can be found from Fig.2 that the air heating load is entirely supplied by the natural gas air heating system before implementing the HEMS. It can be observed from Fig.3 that the air heating load is supplied by the natural gas air heating system during the on-peak time and supplied by the electric air conditioner during the remaining time after implementing the proposed HEMS. This is because that the efficiency of the electric air conditioner is higher than that of the natural gas air heating system. Thus, even if the natural gas price is lower than the electricity price during the mid-peak and off-peak time, the proposed HEMS still uses the electric air conditioner to replace the natural gas air heating system to supply the air heating load. Meanwhile, the air heating load

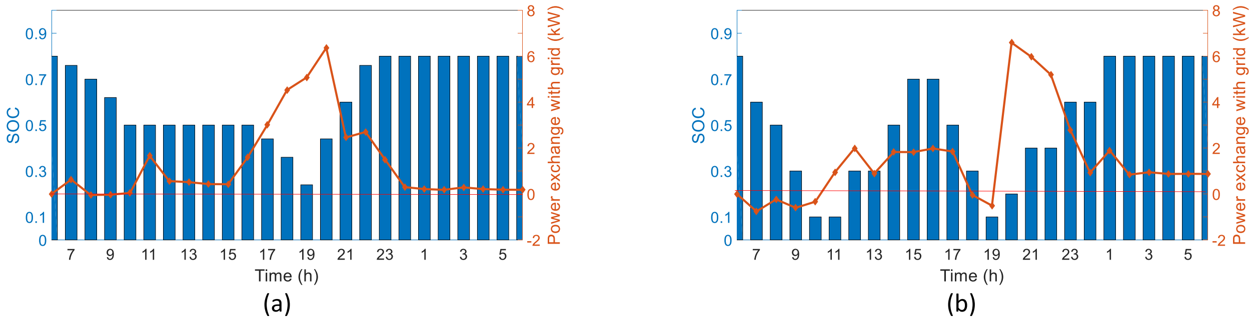

FIGURE 4. The SOC of the battery and the power exchange with the grid. (a). Initial performance without the proposed HEMS under fixed tariff. (b). Optimized performance after implementing the proposed HEMS under the TOU program.

TABLE 4. Comparisons of energy costs under different DR programs.

Case		G2H cost ($)	H2G income ($)	Natural gas cost ($)	Total cost ($)	Cost saving ratio (%)
Fixed tariff	Without HEMS	3.110	-0.007	1.636	4.738	18.05
	With HEMS	3.540	0.000	0.344	3.883	
TOU	Without HEMS	3.192	-0.010	1.636	4.817	30.41
	With HEMS	2.939	-0.327	0.739	3.352	
RTP	Without HEMS	3.535	-0.008	1.636	5.163	30.70
	With HEMS	3.091	-0.250	0.737	3.578	

is reduced from 14.97 million J to 12.51 million J in order to reduce the energy costs.

5) SCHEDULING OF THE BATTERY

Fig. 4 shows the operation of the battery and the power exchange with the grid. It can be observed from Fig. 4 that the operation of the battery is significantly affected by the electricity price. The battery charges during the off-peak and mid-peak time due to the lower electricity price during these periods. It discharges during the on-peak time, not only to supply the demand but also to inject the power back to the grid.

6) COMPARISON OF TOTAL ENERGY COST UNDER DIFFERENT CASES

Fig.5 and Table 4 show the comparisons of energy costs under different cases. It should be noted that the total energy cost in Table 4 and Fig.5 refers to the energy bill excluding the depreciation costs of the battery for one day. The proposed HEMS can significantly reduce the total energy cost from 18.05% up to 30.70%. TOU is the most economic DR program for the customer after implementing the proposed HEMS.

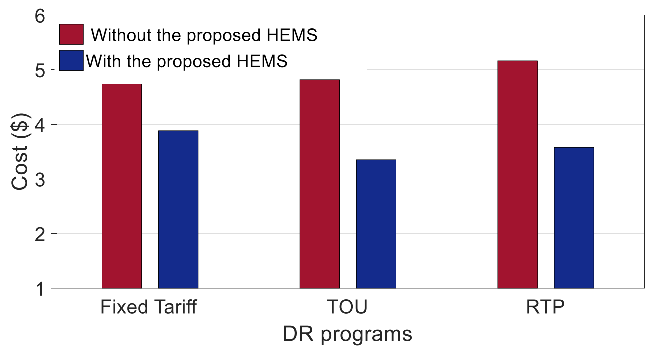

FIGURE 5. Comparisons of household energy costs under different cases.

C. DISCUSSIONS

1) IMPACT OF THE PROPOSED HEMS ON CUSTOMERS' DISSATISFACTION

To analyze the impact of the proposed HEMS on customers' dissatisfaction level and verify the effectiveness of the proposed dissatisfaction characterization model, the proposed dissatisfaction characterization model is compared with the traditional dissatisfaction model (i.e. the model describes customers' dissatisfaction level according to the deviation between the initial time and the shifted time) in this section. Taking the electric vehicle as an example, dissatisfaction

TABLE 5. Dissatisfaction levels of a customer on electric vehicle charging in each time period.

Time	1:00	2:00	3:00	4:00	5:00	6:00	7:00-17:00	18:00	19:00	20:00	21:00	22:00	23:00	24:00
S_t^{ev}	1	1	1	3	4	5	--[a]	0	0	0	1	5	5	1

a: It is assumed that the electric vehicle cannot be charged at home during 7:00-17:00. Thus, there is no dissatisfaction level during this period.

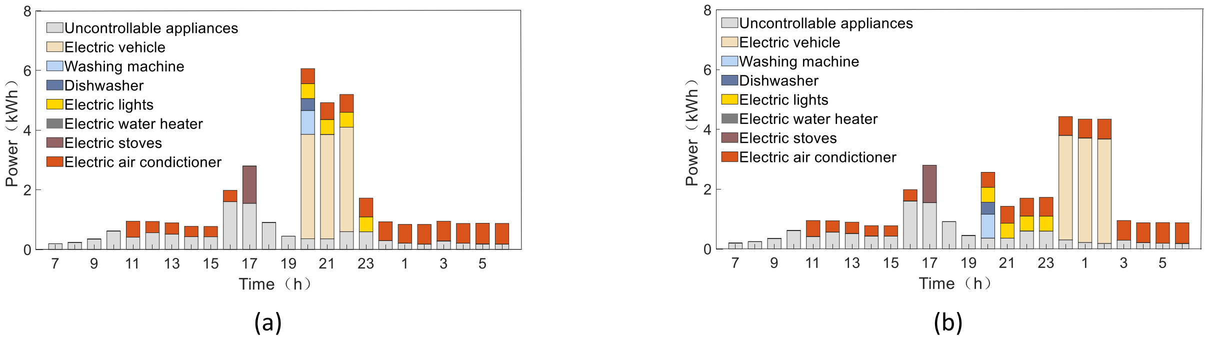

FIGURE 6. Comparison of scheduling schemes obtained by different dissatisfaction characterization models. (a). Obtained by the traditional dissatisfaction model. (b). Obtained by the proposed dissatisfaction characterization model.

levels of a customer on electric vehicle charging in each time period are given in Table 5, where a larger value of S_t^{ev} means a higher dissatisfaction level. S_t^{ev} is equal to 0 during 18:00-20:00 since the initial electric vehicle charging time period (i.e. the baseline condition without DR) is during 18:00-20:00.

Fig. 6 presents the comparison of scheduling schemes obtained by different dissatisfaction characterization models. It can be observed from Fig.6 that both of two scheduling schemes delay the electric vehicle charging time after 20:00 to save energy costs because the off-peak time period begins from 20:00. Both of two scheduling schemes show the same energy cost. The difference is that, in the first scheduling scheme, the electric vehicle charging time is shifted to a time period that is close to the initial operation time period. By contrast, the scheduling scheme obtained by the proposed model shifts the operation time of electric vehicle charging to 24:00-2:00^{+1}. However, it can be seen from Table 5 that the customer is not willing to charge the electric vehicle during 22:00-23:00 in this case. The traditional dissatisfaction model simply takes the deviation between the initial and shifted operation time as the metric to describe the customer's dissatisfaction level but doesn't consider customer's actual requirements, which may lead to significant inconvenience to customer's life. The proposed dissatisfaction model calculates the dissatisfaction level according to the customer's actual requirement, which can produce more reasonable scheduling results.

2) IMPACT OF NATURAL GAS PRICE

In order to analyze the impacts of natural gas prices and battery capacities on the effectiveness of the proposed model, different natural gas prices and different capacities of the battery are individually investigated. Fig. 7 presents the expected household daily energy costs for different natural gas prices. Both the energy costs before and after implementing the HEMS increase with the increase of the natural gas price. However, the growth of the cost before implementing the HEMS is greater than that of the cost after implementing the HEMS. Moreover, the deviation is getting larger and larger with the increase of natural gas prices, which means the higher the natural gas price, the more obvious the advantage of using the HEMS. In addition, when the natural gas price reaches a certain level, the increase of natural gas price cannot lead to the increase of the household daily energy cost, because all natural gas appliances have been replaced by electric appliances, and the natural gas price no longer affect the household daily energy cost.

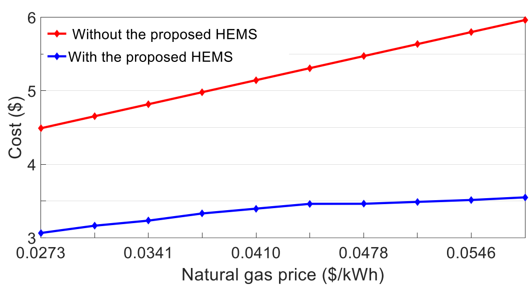

FIGURE 7. The impact of the natural gas price on the household daily energy cost.

3) IMPACT OF BATTERY CAPACITY

Fig. 8 shows the impact of the battery capacity on the household daily energy cost. It can be observed that introducing a

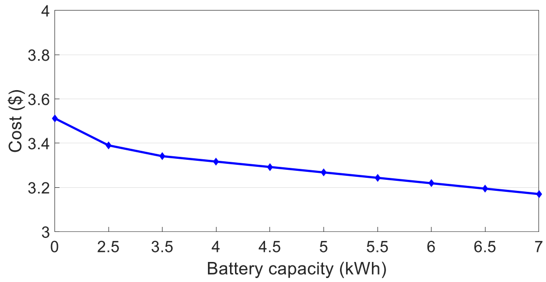

FIGURE 8. **The impact of battery capacity on the household daily energy cost.**

household battery can significantly reduce the daily energy cost. In addition, the daily energy cost decreases with the increase of the battery capacity because the battery with larger capacity can provide more electricity to supply the household demand without purchasing extra electricity from the grid.

IV. CONCLUSION

A novel model for day-ahead optimal joint scheduling of electric and natural gas appliances was proposed in this paper, which considered the interactions between the electric and natural gas appliances. In addition, a complete and realistic dissatisfaction characterization model was proposed to describe the dissatisfaction level caused by the shifting, reduction and replacement of loads in response to the time varying electricity prices. Simulation results indicated that the proposed model can significantly reduce the costs of customer's energy consumption up to 30% whilst guaranteeing the customer's satisfaction level by considering the technical limits of electric and natural gas appliances and the household battery. Due to the impacts of various influence factors, residential electricity consumption patterns vary for different days and different customers [36]. Thus, the results obtained in this paper are case-sensitive and different results may be obtained for different datasets. It is noted that distributed renewable generations are playing important roles in the distribution network. Particularly, more and more households are installing distributed photovoltaic systems [37]. Therefore, distributed renewable generations will be considered in the optimal scheduling model in future works. In addition, this paper only considers price-based DR programs [38], [39] such as TOU [40]. Actually as another important DR program, incentive-based DR program [41] is gradually applied into the residential sector [42]. The optimal scheduling of appliance under incentive-based DR programs will be incorporated into the HEMS in the future.

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