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Pricing-Based Demand Response for a Smart Home With Various Types of Household Appliances Considering Customer Satisfaction

YI LIU[1,2], LIYE XIAO[1,2], GUODONG YAO[1,2], AND SIQI BU[3], (Senior Member, IEEE)

[1]Institute of Electrical Engineering, Chinese Academy of Sciences, Beijing 100190, China
[2]University of Chinese Academy of Sciences, Beijing 100049, China
[3]Hong Kong Polytechnic University, Hong Kong

Corresponding author: Guodong Yao (ygd2015@ mail.iee.ac.cn)

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ABSTRACT A home energy management system (HEMS) can potentially enable demand response (DR) applications for residential customers. This paper presents a detailed pricing-based DR for a smart home with various types of household appliances considering customer satisfaction. A wide variety of household appliances with different characteristics, together with energy storage units (ESUs) and distributed energy resources (DERs) can be flexibly incorporated in the proposed scheme. Besides, with a developed satisfaction model suitable for different types of household appliances, the proposed HEMS can provide multiple flexible solutions with different user satisfaction levels to occupants. In addition, other different DR strategies such as demand-limit-based DR and injection-limit-based DR can be easily adapted to the formulated scheme in this work. The numerical results reported in this paper demonstrate the effectiveness of the proposed scheme. The proposed scheme is generally applicable and valuable for any other kinds of the smart home.

INDEX TERMS Demand response (DR), distributed energy resource (DER), energy storage units (ESUs), home energy management system (HEMS), roof-mounted photovoltaic (PV), smart home, smart meter, smart grid.

LIST OF ABBREVIATIONS

t	Index of time periods.
i	Index of household appliances.
$\mathcal{T}$	Set of time periods.
$\mathcal{A}$	Set of household appliances, $\mathcal{A} = \mathcal{A}_{\text{in}} \cup \mathcal{A}_{\text{non}} \cup \mathcal{A}_{\text{ther}}$
$\mathcal{A}_{\text{in}}$	Set of interruptible household appliances.
$\mathcal{A}_{\text{non}}$	Set of non-interruptible appliances.
$\mathcal{A}_{\text{ther}}$	Set of thermostatically controlled appliances.
ϖ_1	The weight corresponds to J_1
ϖ_2	The weight corresponds to J_2.
λ_{buy}	Price of electricity purchased from the grid (cents/kWh).
λ_{sell}	Electricity price sold back to the grid (cents/kWh).
Δt	Length of time step (h).
ζ_i	Customer dissatisfaction associated with the appliance i.
ε_i	Coefficient representing the importance of appliances.
$T_{L,i}$	Time length of appliance i used from start to end.
L_i	Allowed the beginning time of the task for the appliance i.
U_i	Allowed the deadline of the task for the appliance i.
N_{T}	Number of all the time steps of a day.
$P_{\text{R},i}^{\text{APP}}$	Rated power of the appliance i.
E_i^{APP}	The required total energy of the task of the appliance i.
λ	Constant (1/3600000) for unit conversion.
c_{w}	Specific heat of water $(\text{J}/\text{kg}/°\text{C})$.
ρ_{wh}	Demand for hot water drawn (kg).
$T_{\text{c},i}$	The most comfortable temperature of the thermally controlled appliance i determined by the user.
T_{cold}	Temperature of inlet cold water (°C).
θ_i^{dn}	Minimum desired temperature (°C).

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θ_i^{up}	Maximum desired temperature (°C).
M	Mass of water in full storage (kg).
T_0	Initial water temperature in the water heater storage (°C).
η,γ	Coefficient denoting the thermal condition surrounding the air conditioner.
W_{out}	Outdoor temperature (°C).
η_{ESS}^{d}	Discharging efficiency of the ESUs.
η_{ESS}^{c}	Charging efficiency of the ESUs.
R_{ESS}^{d}	Maximum charging rate of the ESUs.
R_{ESS}^{c}	Maximum discharging rate of the ESUs.
S_{ESS}^{ini}	Initial state-of-energy of the ESUs (kWh).
S_{ESS}^{min}	Minimum allowed state-of-energy of the ESUs (kWh).
S_{ESS}^{max}	Maximum allowed state-of-energy of the ESUs (kWh).
P_{PV}	Forecasted power generation from PV system (kW).
N_1, N_2	Positive integer value.
P_{must}	Power of the non-controllable household appliances must run (kW).
J_1	Operation cost of HEMS (cents/kWh).
J_2	Objective function of the user's dissatisfaction level.
P_{buy}	Power when buying electricity from the grid (kW).
P_{sell}	Power when selling electricity back to the grid (kW).
F_i	Finishing time of the appliance$i$.
u_i^{APP}	Binary variable: 1 if the appliance is on, 0 else.
P_i^{APP}	Power consumption of the appliance i.
$T_{u,i}$	Temperature (air, water, etc.) determined by the schedule plan and directly perceived by the user for the appliance i (°C).
P_{ESS}^{use}	Power used to satisfy appliances from ESUs (kW).
P_{ESS}^{sell}	Power injected to grid from ESUs.
μ_{ESS}	Binary variable: 1 if ESUs is charging, 0 else.
P_{ESS}^{d}	Discharging power of the ESUs (kW).
P_{ESS}^{c}	Charging power of the ESUs (kW).
S_{ESS}	State-of-energy of the ESUs (kWh).
P_{PV}^{use}	Power use to satisfy household loads from PV (kW).
P_{PV}^{sell}	Power injected to grid from PV (kW).
μ_{grid}	Binary variable: 1 if grid supplying power, 0 else.

I. INTRODUCTION

A. MOTIVATION AND BACKGROUND

Smart grid is the vision for enhancing the efficiency of electricity utilization from the production to end-user points, together with effectively all generations and enabling consumer participation in demand response (DR) program [1], [2]. DR has been envisioned to deal with supply-limit events by selectively curtailing system loads, whereby regaining balance between power demand and supply. Through the two-way flow of information between suppliers and consumers, the grids can encourage users' participation in energy savings and cooperation through a DR mechanism [3]. Although the utilization of DR strategies can be considered mature for industrial customers, it is a relatively new concept for residential households responsible for approximate 40% of energy consumption in the world [4].

Smart meter and home energy management system (HEMS) has a leading role in managing DR activities in residential areas [5]. A HEMS is responsible for monitoring and controlling the operation of in-home appliances and providing load shifting and shedding according to a specified set of requirements [6]. Developing efficient DR model and efficient optimization algorithms for coordinating their operations are two critical problems in a HEMS in a smart home, which have received considerable attention recently.

There are various types of household appliances that pro-vide several pros and cons in terms of effective HEMS-based operating strategy. Home appliances can be classified into controllable appliances and non-controllable appliances according to the controllability [7]. According to the operational characteristics, controllable home appliances are divided into three types: (1) non-interruptible appliances (NIA), such as dishwasher (DW), rice cooker (RC), washing machine (WM), etc.; (2) interruptible appliances (IA), such as electric vehicle (EV), pool pump (PP), etc.; (3) thermostatically controlled appliances (TCA), such as water heater (WH), air conditioner (AC), etc.; The NIA are required to follow predefined steps of operation, and the operation has to be run to completion once it starts. Unlike the NIA, the IA is allowed to operate at any time within a user's defined time interval, and it can be shut down during operation. However, the operation of the TCA depends on the thermal inertia of the water or the air inside the house.

In recent years, distributed energy resources (DERs) such as roof-mounted photovoltaic (PV) and small wind turbine, have become another import energy source of the smart home. Although distributed generation poses significant challenges to HEMS operation due to the randomness power output, it presents more demand flexibility to end users. Energy storage units (ESUs) can be applied to deal with such challenges. The ESUs can not only store the surplus energy produced by distributed generations but also provide an opportunity to make a profit from electricity trade with the grid, by buying and storing electricity at a low electricity rate and sells it back to the grid at a desired high electricity rate.

To capture the benefits of the above-demonstrated aspects as well as to cover the customers' desired comfort preferences and lifestyles, an effective HEMS structure is strongly required.

B. RELATED WORKS

Considerable previous publications on designing HEMS for scheduling target appliances, such as WM, DW, and tumble dryer, have been reported [5], [6]. A control strategy of freezer and refrigerator cycles is proposed in [7] to reduce the peak load. Several studies in the literature propose HEMS with priced-based DR programs for minimizing the total electricity payment, by shifting the consumption to the periods of relatively low electricity prices. Authors of [8] present a HEMS framework for automatically and optimally operating appliances in a household while considering the tradeoff between minimum electricity bill and maximum consumer's utility.

In [9], a DR program based on "user-expected price" for a smart household aiming at lowering the total electricity cost by charging and discharging the ESUs at off-peak and peak price periods, respectively. Also, with an introduction of EV in residential markets, EV load can be performed within a home for peak clipping in certain periods when it is at home. A collaborative evaluation of dynamic-pricing and peak power limiting-based DR strategies with a bi-directional utilization possibility for EV and ESUs is investigated in [1].

In recent years, multiple researchers have done some work to tackle PV integration issues in household operation with DR program. Authors of [10] apply a HEMS based on neural networks with experimental results for a household, including PV and ESUs. However, this study does not consider the impacts of varying prices as well as other types of DR strategies.

Depending on load types and requirements of DR programs available in different regions, different algorithms and models can be applied [5], [11]–[13]. Several thermal loads such as ACs and WHs that have an essential role in customer satisfaction are neglected in most of the above studies. In [13], issues of optimal appliance scheduling to minimize the electricity bill is studied. However, such programming will cause a wait time for operation of each appliance.

As surveyed in this paper, most of the mentioned papers fail in addressing the customers' desired comfort preferences and lifestyles. In [14] and [15], the users' satisfaction in the DR programs is considered. However, the model cannot be used to measure the satisfaction on the thematically controlled appliances, and only a single optimum solution can be provided to occupants by using the method.

C. CONTRIBUTIONS

This paper presented a detailed pricing-based demand response model for a smart home with various types of household appliances, considering customer satisfaction. In the scheme, a wide variety of household appliances are divided into different kinds of devices according to their characteristics. Then a multi-objective optimization problem is built with the user satisfaction level being considered. Furthermore, a PV-based DER, EV, ESUs, and all types of both thermostatically and non-thermostatically controllable appliances are taken fully into consideration in the proposed scheme.

To the best of the author's knowledge, this is the first study in the literature combining all aforementioned operational possibilities in a single MILP-based HEMS framework. A wide variety of household appliances with different characteristics, together with energy storage units (ESUs) and distributed energy resources (DERs) can be flexibly incorporated in the proposed scheme. Besides, with a developed satisfaction model suitable for to different types of household appliances, the proposed HEMS can provide multiple flexible solutions with different user satisfaction levels to occupants.

Table 1 shows the taxonomy of methodologies for designing DR-Based HEMS.

TABLE 1. Taxonomy of the model used for designing DR-based HEMS.

	ESUs	DER	Customer preference	Wide variety of appliances	Flexible solutions
[1],[5],[8],[9, 16]	Y	Y	N	N	N
[2],[7]	N	N	N	N	N
[17],[10]	Y	N	N	Y	N
[18],[13]	N	N	Y	N	N
[6]	Y	Y	N	Y	N
[14],[15]	N	N	Y	N	N
Proposed	Y	Y	Y	Y	Y

Y/N denotes that the subject is /is not considered.

D. ORGANIZATION

The following paper is organized as follows. Section II provides the methodology employed in this paper. Section III presents the case study. Discussions and conclusions are provided in Section IV and V, respectively.

II. METHODOLOGY

The block diagram of the designed HEMS is presented in Fig. 1. As shown in Fig. 1, the HEMS regulates the operation of smart household considering price-based, and other signals from the power company owned a smart meter, the forecasted output from distributed generations, etc., together with load priority and comfortable level set by the customer. The schematic diagram of the optimization problem is shown in Fig. 2.

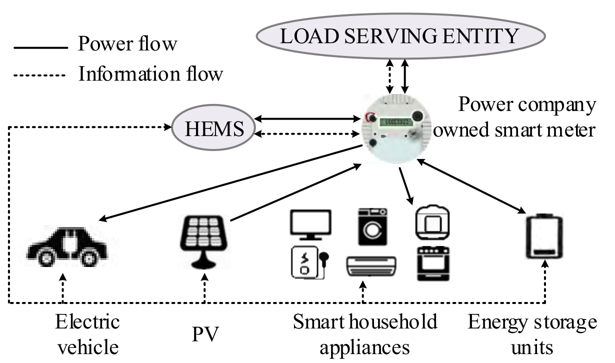

FIGURE 1. Block diagram of the designed HEMS.

Firstly, 24h day-ahead hourly electricity load and PV output are forecasted based on historical data and weather forecast information. Next, the optimization problem of DR is formulated based on the input data of predicted PV output and electricity load, electricity price from the Load Serving Entity (LSE), initial state-of-energy (SOE) of ESUs, together with the user desired input by the house-owner. The rest of

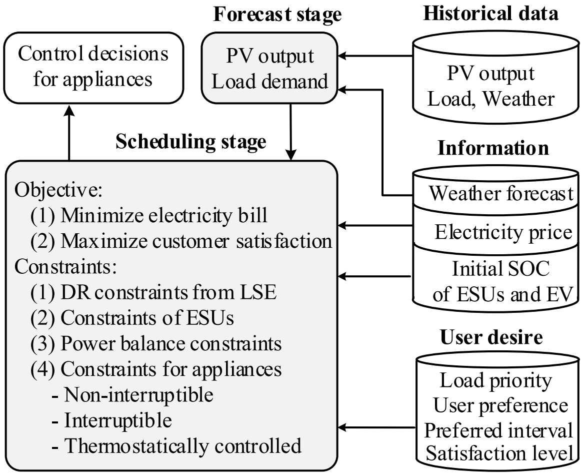

FIGURE 2. The multi-objective optimization problem for HEMS.

this section describes the proposed MILP-based model in details.

A. MULTI-OBJECTIVE FUNCTION

The multi-objective problem demonstrated in Fig. 2 is presented as a single objective function by using weights attached to the two different objective functions, as shown in Equation (1):

$$\min\ \varpi_1 J_1 + \varpi_2 J_2 \quad \varpi_1 + \varpi_2 = 1,\ \varpi_1,\ \varpi_2 \in [0, 1] \tag{1}$$

The expression of Equation (1) provides an opportunity for the customers to decide the combinations that better fit their interests and meet their requirements, by adjusting ω_1 and $\omega_2 \cdot \varpi_2$. σ_2 can reflect the desired user satisfaction level. The higher ϖ_2 is, the greater the need there is for satisfaction. J_1 and J_2 in Equation (1) are expressed as (2) and (3), respectively.

$$J_1 = \sum_{t\in \mathrm{T}} \left[\lambda_{\mathrm{buy}} \cdot P_{\mathrm{buy}}(t) \cdot \Delta t - \lambda_{\mathrm{sell}} \cdot P_{\mathrm{sell}}(t) \cdot \Delta t\right] \tag{2}$$

$$J_2 = \sum_{i\in A} \zeta_i \tag{3}$$

The model of J_2 which is expressed by a summation of weighted comfort of all appliances will be depicted later.

B. CONSTRAINTS OF HOUSEHOLD APPLIANCES

The limitations for household appliances scheduling are about operation limits and user comfort demand for different types of controllable appliances. The limitations for the controllable household appliances are presented as follows:

1) NON-INTERRUPTIBLE APPLIANCES

The NIAs are required to follow predefined steps of operation, and the operation has to be run to completion once it starts. The power consumption of the non-interruptible appliance i is considered to be constant, and the duration of the task lasts for as long as $T_{L,i}$. Assuming $[L_i, U_i] \in \mathrm{T}$ is the preferred time interval in which the NIAs i is expected to be used. It denotes that the household i should be started later than L_i, and should be finished earlier than U_i. It can be easily obtained that $F_i \in \left[L_i + T_{L,i},\ U_i\right]$. Note that $U_i - L_i$ should be no less than $T_{L,i}$. An illustrative example of the non-interruptible appliance with $T_{L,i} = 4$h is shown in Fig. 3.

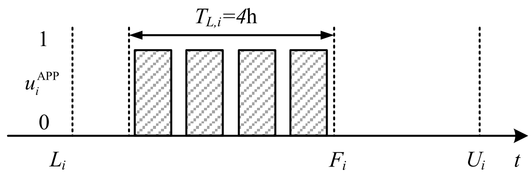

FIGURE 3. An illustrative example of non-interruptible appliances.

Given the above, the limits for the non-interruptible appliance throughout the scheduling horizon should satisfy (4) and (5). Limit of (6) which has been used in the unit commitment optimization problem [19] for ensuring the minimum on-line time of generations has been employed here to satisfy the non-interruptibility of the appliances.

$$u_i^{\mathrm{APP}}(t) = 0 \quad \forall t \in [1, L_i) \cup (U_i,\ N_{\mathrm{T}}],\ \forall i \in A_{\mathrm{non}} \tag{4}$$

$$P_i^{\mathrm{APP}}(t) = u_i^{\mathrm{APP}}(t) \cdot P_{\mathrm{R},i}^{\mathrm{APP}} \quad \forall t \in [L_i, U_i],\ \forall i \in A_{\mathrm{non}} \tag{5}$$

$$\sum_{t=j}^{j+T_{L,i}-1} u_i^{\mathrm{APP}}(t) \geq T_{L,i} \cdot \left(u_i^{\mathrm{APP}}(j) - u_i^{\mathrm{APP}}(j-1)\right) \quad \forall j \in \left(L_i,\ U_i - T_{L,i} + 1\right],\ \forall i \in A_{\mathrm{non}} \tag{6}$$

To reflect the satisfaction of customers in the scheduling programs, a weighted L_1 regularization term [20] which is commonly used in automatic model selection is employed to model the customer dissatisfaction on the NIA, as expressed in Equation (7):

$$\zeta_i = \sum_{t=L_i}^{U_i} (1 + \varepsilon_i \cdot t) \cdot u_i^{\mathrm{APP}}(t) \quad \forall i \in A_{\mathrm{non}} \tag{7}$$

Note that $\mathcal{E}_i$ in Equation (7) is positive constants. Considering Equation (6) ensures the duration of the task lasting for as long as $T_{L,i}$, minimizing ζ_i means that the time slots are enforced to be as small as possible. In this case, the task of the NIA can be completed as earlier as possible, which is favorable to the customer.

2) INTERRUPTIBLE APPLIANCES

As the NIAs, the IA is considered to work between Li and Ui. Unlike the NIAs, the IAs, such as EVs (In this paper, we treat EV as a charging load, that is, we do not consider the situation that the EV feed the energy back to the power grid) and PPs, can change the power in a range $\left[0, P_{\mathrm{R},i}^{\mathrm{APP}}\right]$ continuously. But they should be provided with the required energy during the whole operation cycle. An illustrative example of the interruptible appliance with the required energy of $3h \cdot P_{\mathrm{R},i}^{APP}$ is shown in Fig. 4.

Given the above, the limits for the interruptible appliance i throughout the scheduling horizon should satisfy the

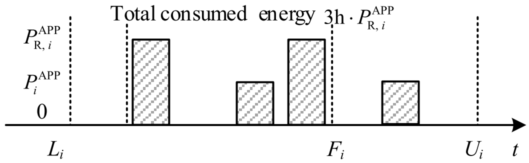

FIGURE 4. An illustrative example of interruptible appliances.

constraints of (8)-(11). Equation (11) is used for measuring the dissatisfaction on the interruptible appliance.

$$P_i^{APP}(t) = 0 \quad \forall t \in [1, L_i) \cup (U_i, N_T], \ \forall i \in A_{in} \tag{8}$$

$$\sum_{t=L_i}^{U_i} P_i^{APP}(t) \cdot \Delta t \geq E_i^{APP} \quad \forall i \in A_{in}, \ \forall t \in T \tag{9}$$

$$0 \leq P_i^{APP}(t) \leq P_{R,i}^{APP} \quad \forall t \in T, \ \forall i \in A_{in} \tag{10}$$

$$\zeta_i = \sum_{t=L_i}^{U_i} (1 + \varepsilon_i \cdot t) \cdot u_i^{APP}(t) \quad \forall i \in A_{in} \tag{11}$$

3) THERMOSTATICALLY CONTROLLED APPLIANCES

Typical TCAs including AC, WH, and FR, etc., in which the temperature can be adjusted by the amount of electrical energy consumed. In this study, WH and AC, which are the most critical TCAs in a smart home, are modeled in detail. The model of WH can be expressed as constraints (12)-(16). Constraints in (12) ensure the power of WH change in a permitted range. Constraint (13) and (14) state that the WH should satisfy the users' demand at each step. Constraint (15) ensures that the heat storage at each time step must not exceed the maximum limit of the water storage. Limitation (16) presents the boundaries of the temperature range.

$$0 \leq P_i^{APP}(t) \leq P_{R,i}^{APP} \quad \forall t \in T, \ \forall i \in WH \tag{12}$$

$$\sum_{k=1}^{t} P_i^{APP}(k) \cdot \Delta t \geq \sum_{k=1}^{t} \rho_{wh}(t) \quad \forall t \in T, \ \forall i \in WH \tag{13}$$

$$\rho_{wh}(t) = \lambda \cdot m(t) \cdot c_w \cdot \left(T_{u,i}(t) - T_{cold}\right) \quad \forall t \in T, \ \forall i \in WH \tag{14}$$

$$\sum_{k=1}^{t} P_i^{APP}(k) \cdot \Delta t \leq \lambda \cdot M \cdot c_w \cdot \left(\theta_i^{up} - T_0\right) + \sum_{k=1}^{t} \rho_{wh}(k) \quad \forall t \in T, \ \forall i \in WH \tag{15}$$

$$\theta_i^{dn} \leq T_{u,i}(t) \leq \theta_i^{up} \quad \forall t \in T, \ \forall i \in WH \tag{16}$$

The constraints for the AC are presented as (17)-(19). Constraint (17) is imposed on the power of AC to specify its possible operating range. Constraint of (18) presents the relation between the indoor temperature and the energy consumption of AC. Constraint (19) gives the limits of the desired room temperature.

$$0 \leq P_i^{APP}(t) \leq P_{R,i}^{APP} \quad \forall t \in T, \ \forall i \in AC \tag{17}$$

$$T_{u,i}(t) = T_{u,i}(t-1) + \eta \left[W_{out}(t) - T_{u,i}(t-1)\right] + \gamma \cdot P_i^{APP}(t) \cdot \Delta t \quad \forall t > 1, t \in T, \ \forall i \in AC \tag{18}$$

$$\theta_i^{dn} \leq T_{u,i}(t) \leq \theta_i^{up} \quad \forall t \in T, \ \forall i \in AC \tag{19}$$

The following linear piecewise function shown in Fig. 5 is applied to measure the user's satisfaction for the TCA. It can be seen that deviation from $T_{c,i}$ will incur a penalty to the objective function.

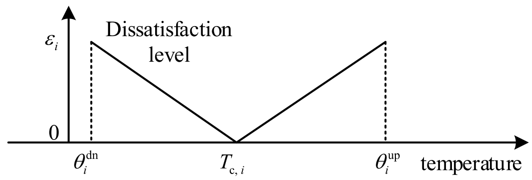

FIGURE 5. Dissatisfaction function for thermostatically controlled appliances.

By adding some variables and constraints in (20), the dissatisfaction function is shown in Fig. 5 can be modeled in MILP problem as Equation (21) and (22).

$$\begin{aligned} & w_{1,i} \leq z_{1,i}, \quad w_{2,i} \leq z_{1,i} + z_{2,i}, \ w_{3,i} \leq z_{2,i} \\ & w_{1,i} + w_{2,i} + w_{3,i} = 1, \quad w_{k,i} \geq 0 (k = 1, 2, 3) \\ & z_{1,i} + z_{2,i} = 1, \ z_{k,i} = 0 \text{ or } 1 (k = 1, 2) \end{aligned} \tag{20}$$

$$T_{u,i}(t) = \theta_i^{dn} \cdot w_{1,i} + T_{c,i} \cdot w_{2,i} + \theta_i^{up} \cdot w_{3,i} \quad \forall i \in A_{ther} \tag{21}$$

$$\zeta_i = w_{1,i} \cdot \varepsilon_i + w_{3,i} \cdot \varepsilon_i \quad \forall i \in A_{ther} \tag{22}$$

In summary, the above framework is very general, and it is suitable for most of TCA.

C. CONSTRAINTS OF ENERGY STORAGE SYSTEM

The constraints that model the operation of the ESUs are given as (23)-(28).

$$P_{ESS}^{used}(t) + P_{ESS}^{sold}(t) = \eta_{ESS}^{d} \cdot P_{ESS}^{d}(t) \quad \forall t \in T \tag{23}$$

$$0 \leq P_{ESS}^{c}(t) \leq R_{ESS}^{c} \cdot \mu_{ESS}(t) \quad \forall t \in T \tag{24}$$

$$0 \leq P_{ESS}^{d}(t) \leq R_{ESS}^{d} \cdot (1 - \mu_{ESS}(t)) \quad \forall t \in T \tag{25}$$

$$S_{ESS}(t) = S_{ESS}(t-1) + \eta_{ESS}^{c} \cdot P_{ESS}^{c} \cdot \Delta t - \eta_{ESS}^{d} \cdot P_{ESS}^{d} \cdot \Delta t \quad \forall t > 1, \ \forall t \in T \tag{26}$$

$$S_{ESS}(t) = S_{ESS}^{ini}(t), \quad \text{if } t = 1 \tag{27}$$

$$S_{ESS}^{max}(t) \leq S_{ESS}(t) \leq S_{ESS}^{max}(t) \quad \forall t \in T \tag{28}$$

Equation (23) enforces the power provided by the ESUs discharge can be injected back to the grid or used to cover a portion of the house demands. Constraint (24) and (25) present the limits on the charging/discharging power of the ESUs. Constraint (26) and (27) describe the relationship between the current SOE and the SOE at the previous time interval. Constraint (28) prevents the deep discharge or full charge of the ESUs.

D. PV MODELLING

Equation (29) enforces the fact that the actual generated power from PV can be injected back to the grid or used by the household appliances.

$$P_{\mathrm{PV}}^{\mathrm{use}}(t) + P_{\mathrm{PV}}^{\mathrm{sell}}(t) = P_{\mathrm{PV}}(t) \quad \forall t \in \mathrm{T} \tag{29}$$

E. POWER BALANCE CONSTRAINT

Equation (30) states that energy consumption needs within the household are either satisfied by the grid or by the combined procurement of energy by the ESUs and the PV.

$$P_{\mathrm{buy}}(t)+P_{\mathrm{PV}}^{\mathrm{use}}(t)+P_{\mathrm{ESS}}^{\mathrm{use}}(t)=P_{\mathrm{ESS}}^{\mathrm{c}}(t)+\sum_{i\in \mathrm{A}} P_i^{\mathrm{APP}}(t) \quad \forall t \in \mathrm{T} \tag{30}$$

F. TOTAL POWER INJECTED TO THE GRID

The total amount of power injected to the grid can be expressed by Equation (31):

$$P_{\mathrm{sell}}(t) = P_{\mathrm{PV}}^{\mathrm{sell}}(t) + P_{\mathrm{ESS}}^{\mathrm{sell}}(t) \quad \forall t \in \mathrm{T} \tag{31}$$

G. GPOWER TRANSACTION RESTRICTIONS

Constraints (32) and (33) implement the logic of power exchange, ensuring that the drawing power from the grid and injecting power to the grid can't happen simultaneously.

$$P_{\mathrm{buy}}(t) \leq N_1 \cdot \mu_{\mathrm{gid}}(t) \quad \forall t \in \mathrm{T} \tag{32}$$

$$P_{\mathrm{sell}}(t) \leq N_2 \cdot \left(1 - \mu_{\mathrm{gid}}(t)\right) \quad \forall t \in \mathrm{T} \tag{33}$$

TABLE 2. User's desired comfort preferences.

Type	Appliances	Preferred temperature (℃)	Duration (Hour)	Preferred interval $[L_i, U_i]$	Rated power (kW)	Required energy (kWh)	Coefficient resenting importance
NA	WM	-	2	[8, 23]	1.8	-	0.1
	DW1	-	1	[13,16]	1.2	-	0.2
	DW2	-	1	[17,23]	1.2	-	0.3
IA	PP	-	-	[2, 15]	0.8	1.6	0.1
	EV1	-	-	[6,24]	2.2	6.5	0.2
	EV2	-	-	[11,23]	1.7	5.0	0.3
TA	AC	27	-	-	2.0	-	1
	WH	50	-	-	3.0	-	2

III. CASE STUDY

A. DESCRIPTION OF DESIGNED TEST SYSTEM

A single house with various types of household appliances connected to HEMS is taken as a test system. Before the HEMS operation, customers are asked to fill up a table like Table 2, which contains the residents' desired comfort preferences and lifestyles. The parameters in the WH model and AC model are given in Table 3 and Table 4, respectively. The parameters of ESUs in the test system is presented in Table 5. The hourly electricity price and forecasted PV output is shown in Fig. 6 and Fig. 7, respectively. Fig. 8 shows the outdoor temperature over a day. The water demand and must-run power are given in Fig. 9 and Fig.10, respectively.

TABLE 3. Parameters in the water heater model.

λ(kWh/J)	c_w(J/kg/℃)	T_{cold}(℃)	θ_i^{up}(℃)	θ_i^{dn}(℃)	M(kg)	T_0(℃)	$T_{c,i}$(℃)	$\theta_i^{\max}$(℃)
1/3600000	4.2×10³	30	68	45	140	49	55	75

TABLE 4. Parameters in the air conditioner model.

η	γ	θ_i^{dn}(℃)	θ_i^{up}(℃)	$T_{c,i}$(℃)	$T_{u,i}(0)$
0.90	-0.0095	23	29	26	23

TABLE 5. Parameters of ESUs.

$R_{\mathrm{ESS}}^{\mathrm{c}}$ (kW)	$R_{\mathrm{ESS}}^{\mathrm{d}}$ (kW)	$\eta_{\mathrm{ESS}}^{\mathrm{d}}$	$\eta_{\mathrm{ESS}}^{\mathrm{c}}$	S_{ESS} (kWh)	$S_{\mathrm{ESS}}^{\mathrm{ini}}$ (kWh)	$S_{\mathrm{ESS}}^{\min}$ (kWh)	$S_{\mathrm{ESS}}^{\max}$ (kWh)
1.8	1.8	0.95	0.95	8	2.8	0.8	7.2

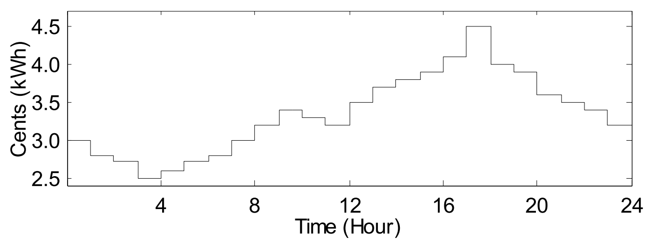

FIGURE 6. Time-varying price information received from the utility.

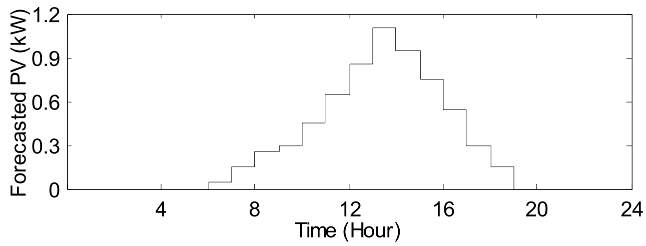

FIGURE 7. Forecasted hourly PV output.

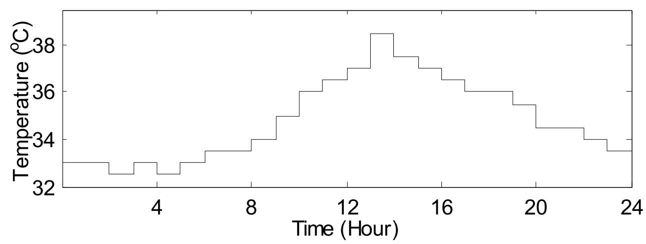

FIGURE 8. Outdoor temperature over a day.

B. RESULTS

To demonstrate and compare, the following cases are considered in the simulation.

(1) Case 0: $\varpi_2 = 0$, which means that the objective is to minimize the total daily cost without considering the customer comfort. This case is taken as a base case in the study.

(2) Case 1: $\varpi_2 = 0.5$, this case is used to compare with Case 0, to investigate the effects on electricity bill purchased by changing of user desired satisfaction level.

(3) Case 2: $\varpi_2 = 1$, in this case, the primary objective is to pursue user comfort. This case is used to compare with

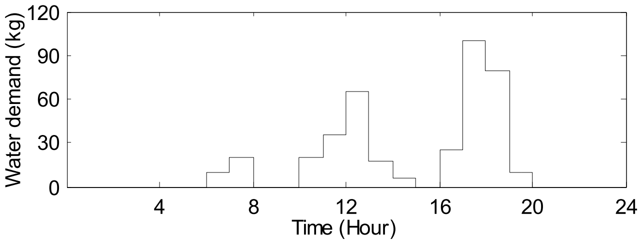

FIGURE 9. Water demand over a day.

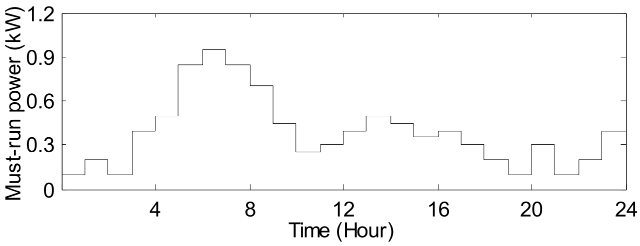

FIGURE 10. Must-run power over a day.

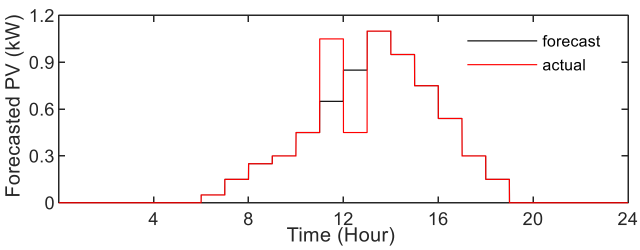

FIGURE 11. Forecasted PV output with a forecasting error。.

Case 0 and Case 1, aiming to study the operational costs further as affected by user-desired satisfaction level.

(4) Case 3: $\varpi_2 = 0.5$, in this case, the important factor of WH is changed from 2 to 4.5. This case is applied to study the scheduling results as affected by the pre-defined importance factor of the appliances.

(5) Case 4: $\varpi_2 = 0$, and $\varpi_2 = 0$ is replaced by a time-depended parameter. This case is to demonstrate how other different DR strategies (e.g., demand-limit-based DR) can be easily adapted to the formulated scheme.

(6) Case 5: $\varpi_2 = 0.5$, and the predicted PV output depicted in Fig. 7 is accompanied with a forecasting error, as seen in Fig. 11. The forecasting error is assumed as a zero-mean normally distributed random variables. The standard deviation is considered as a percentage (20% in this work) of the expected PV output. This case is used to compare with Case 1 and study how the forecasting error will affect the energy cost and customer convenience.

The proposed MILP model is tested in GAMS [21] v.23.7 using the CPLEX solver, and the simulation results are presented in the following.

1) WITHOUT CONSIDERING CUSTOMER COMFORT (CASE 0)

The operational cost for case 0 is 113.83 cents. The hourly energy injected to or sold back to the grid is presented in Fig. 12. The hourly energy change of ESUs is given in Fig. 13. The scheduling power of appliances and the expected temperatures of WH and AC are shown in Fig. 14, and Fig. 15, respectively.

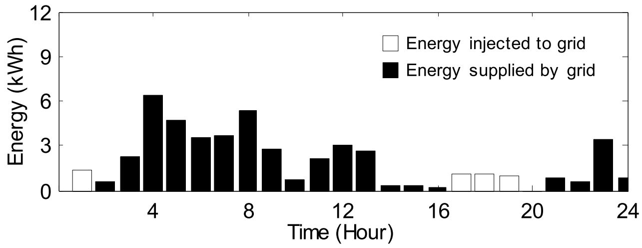

FIGURE 12. Hourly energy buying from or selling back to the grid for Case 0.

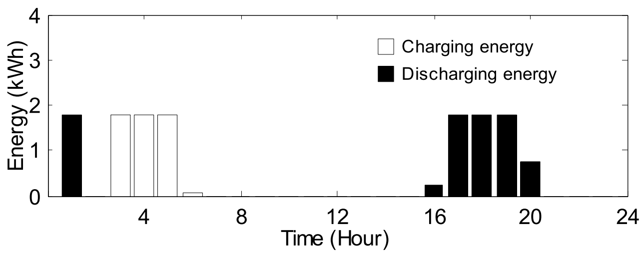

FIGURE 13. Hourly energy change of ESUs over a day for Case 0.

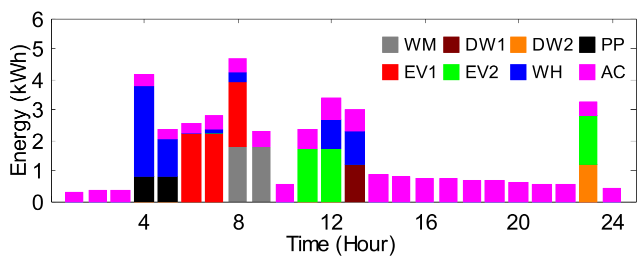

FIGURE 14. Scheduling of household appliances for Case 0.

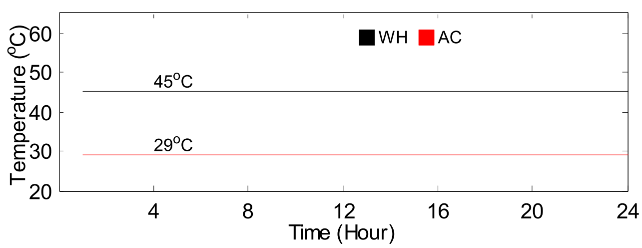

FIGURE 15. Expected air temperatures and water temperature for Case 0.

As can be seen, the proposed scheme tries to achieve lowest electricity bill by charging ESUs and buying electricity from the grid in low-price periods, together with discharging ESUs and selling electricity back to grid in high-price periods, while keeping the appliances working in the lowest level of pre-defined comfort.

2) EFFECT OF THE DESIRED SATISFACTION LEVEL (CASE 1 AND CASE 2)

The electricity bill for Case 1, which is used to investigate the impacts of the customer's desired satisfaction is 133.49 cents.

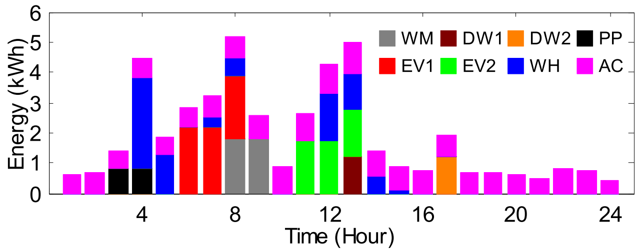

FIGURE 16. Scheduling power of appliances for Case1.

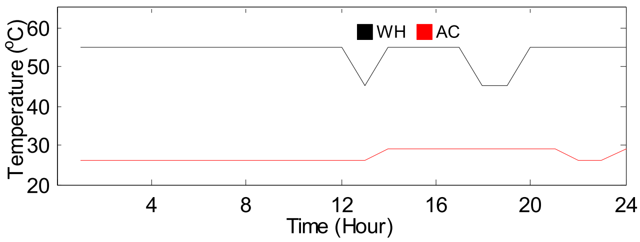

FIGURE 17. Expected hourly air temperature and water temperature for Case 1.

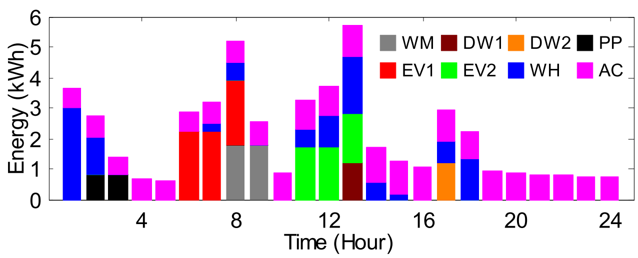

FIGURE 18. Scheduling power of appliances for Case2.

The obtained relative scheduling power for the appliances and expected temperatures of AC and WH are given in Fig. 16, and Fig. 17, respectively. As can be seen, the results change significantly compared with the base case, which is demonstrated before. Although the user needs to pay 39.91 cents more, some appliances such as PP and EV2 have been shifted to an earlier time. Besides, air temperature and water temperate reach the pre-defined most-desired value in more hours compared with Case 0.

However, the cost result for Case 2 reaches as high as 173.40 cents. But in this case, the users' comfort is maximized as the pre-defined most desired preferences and lifestyles, as presented in Fig. 18, and Fig. 19, respectively.

The electricity bills for more different satisfaction levels are calculated and shown in Fig. 20. It indicates that daily payments of the user increase with the growth of the desired satisfactions. This indicates that the proposed HEMS scheme can provide multiple flexible solutions with different user satisfaction levels to occupants.

3) EFFECT OF THE IMPORTANT FACTOR OF APPLIANCES (CASE 3)

Within the same desired satisfaction level, it is possible to assign an importance factor $\mathcal{E}_i$ to each appliance before

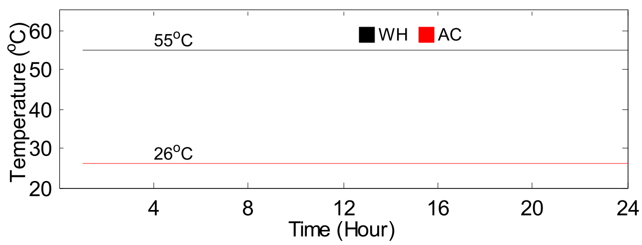

FIGURE 19. Expected hourly air temperature and water temperature for Case 2.

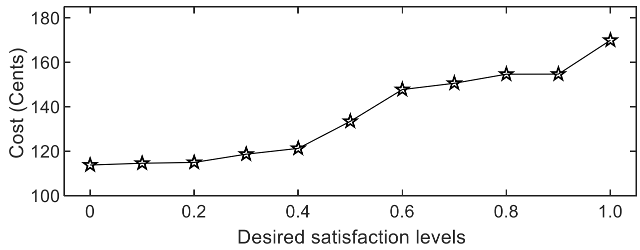

FIGURE 20. Daily electricity bills as affected by the desired satisfaction levels.

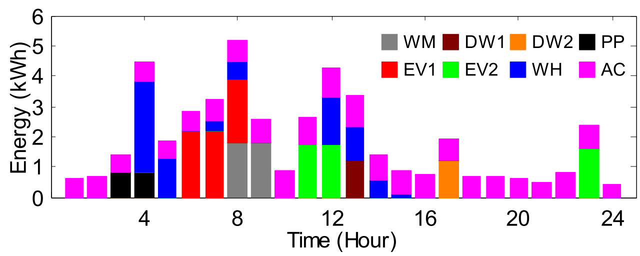

FIGURE 21. Scheduling power of appliances for Case 3.

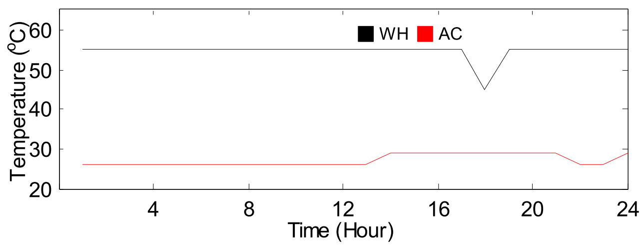

FIGURE 22. Expected hourly air temperature and water temperature for Case 3.

scheduling them. That is, the user can schedule an appliance with higher priority by assigning a larger factor to it. To validate its effectiveness, simulation for Case 3 in which the important factor for WH is different from that of Case 2 is carried out, and the results are presented in Fig. 21 and Fig. 22, respectively. The cost result for Case 3 is 139.83 cents, which causes an increase of 6.34 cents. However, the hours during which the water temperature deviates from predefined most-comfort value have reduced, while just resulting in an operation time shifting for EV2. Therefore, adjusting $\mathcal{E}_i$ of the specified appliance will cause certain impacts on the operation cost and the scheduling of other appliances.

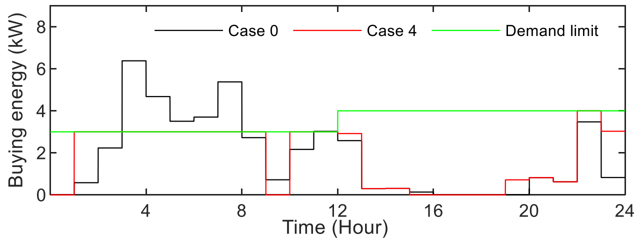

FIGURE 23. Energy demand comparison of Case 0 and Case 4.

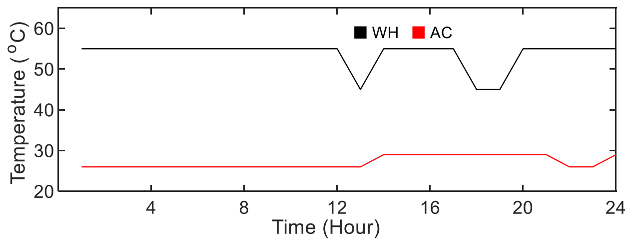

FIGURE 24. Expected hourly air temperature and water temperature for Case 5.

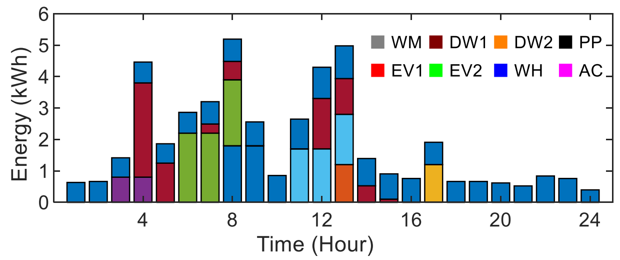

FIGURE 25. Scheduling power of appliances for Case 5.

4) CONSIDERING DEMAND LIMIT RULED BY LSE (CASE 4)

In the simulation above in this work, N_1 and N_2 in Equation (31), (32) and (33) is considered as infinite positive constants. However, by replacing them by time-dependent parameters, other DR strategies can be considered as demonstrated before. In this paper, it is assumed that a restriction is posed by the aggregator or LSE for the end-user electrification in the corresponding control area. The operation cost for this case is 116.86 cents, higher than 113.83 cents for Case 0. The optimization result for the final SOE of ESUs for Case 4 is 0.8 kWh, which is the same as that in Case 0. The hourly limitation of load demand in Case 4, as well as the hourly energy supplied by the grid in Case 0 and Case 4, are shown in Fig. 23. As can be seen in the result of Case 4, the peak demands over the limit in Case 1 are shifted successfully to other periods.

5) EFFECT OF THE FORECASTING ERRORS (CASE 5)

The electricity bill for Case 5 is 131.77 cents, which is lower than the bill for Case 1, 133.49 cents. The expected hourly air temperature, water temperature, and scheduling power of appliances for Case 5 are depicted in Fig. 24 and Fig. 25, respectively. As can be seen, the scheduling power for the appliances change significantly compared with the base 1 (depicted in Fig. 16 and Fig 17). However, the expected hourly air temperature and water temperature do not change much when the forecasting error is taken into consideration. From the study of Case 5, it can be concluded that the forecasting error associated with the uncertain output of rooftop PVs will affect the operation cost of HEMS and customer convenience.

IV. CONCLUSION

In this paper, a novel household load scheduling framework for pricing-based home energy management is proposed. The framework aims to minimize the energy expense while taking occupants' desired comfort preferences and lifestyles into full consideration. In addition to the ESUs and DERs, a wide variety of household appliances with different characteristics are modeled in the proposed framework, which makes it easy for practice. Besides, the proposed HEMS can provide multiple flexible solutions with different user satisfaction levels to occupants. Furthermore, the proposed scheme is generally applicable and valuable for any other kinds of smart home energy management, considering different DR strategies such as demand-limit-based DR and injection-limit-based DR.

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YI LIU received the B.S. degree in electrical engineering from Tianjin University, Tianjin, China, in 2008, and the Ph.D. degree in electrical theory and new technology from the Institute of Electrical Engineering, Chinese Academy of Sciences, China, in 2015.

He is currently with the Institute of Electrical Engineering, Chinese Academy of Sciences. His research interests include power system economics and stability, wind energy, energy storage, and HVDC technology.

LIYE XIAO received the Ph.D. degree in electrical theory and new technology from the Institute of Electrical Engineering, Chinese Academy of Sciences, China, in 1995.

He is currently a Professor with the Institute of Electrical Engineering, Chinese Academy of Sciences. His research interests include the applications of superconductivity, the fault-current limiters, and HVDC technology.

GUODONG YAO received the B.S. degree in mechanical engineering from the University of Science and Technology Beijing, Beijing, China, in 2013, and the master's degree in mechanical engineering and automation from Beihang University, Beijing, in 2015.

His research interests include smart home and energy management systems.

SIQI BU (S'11–M'12–SM'17) received the Ph.D. degree in electric power and energy research cluster from The Queen's University of Belfast, Belfast, U.K., in 2012, where he continued his Postdoctoral research work before entering the industry. Subsequently, he joined National Grid U.K., as a Senior Power System Engineer, and then, became an experienced U.K. National Transmission System Planner and Operator. He is an Assistant Professor with The Hong Kong Polytechnic University, Kowloon, Hong Kong, and also a Chartered Engineer with the U.K. Royal Engineering Council, London, U.K. His research interests include power system stability analysis and operation control, including wind power generation, PEV, HVDC, FACTS, ESS, and VSG.

He has received various prizes for excellent performances and outstanding contributions in operational and commissioning projects during the employment with National Grid U.K. He is also a recipient of the Outstanding Reviewer Awards from the IEEE Transactions on Sustainable Energy, the IEEE Transactions on Power Systems, *Renewable Energy*, and the *International Journal of Electrical Power and Energy Systems*. He is an Associate Editor of IEEE Access, a Guest Editor of *IET Renewable Power Generation*, and an Editor of the *Protection and Control of Modern Power Systems*.