Resident-Centric Distributed Community Energy Management System

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***Abstract*—This study presents a resident-centric distributed community energy management system (CEMS). More specifically, the proposed resident-centric distributed CEMS allows residents to schedule their appliances autonomously, without the need to collaborate with the community and to consider whether their appliance scheduling is optimal from the perspective of the entire community. The central controller in the proposed CEMS will then determine a solution that is optimal for the entire community by dispatching the community's distributed energy sources according to the appliance scheduling of residents. In other words, the proposed distributed resident-centric CEMS allows residents to act autonomously while securing the collective goals of the community to a certain extent. In this paper, the collective goals of the community include participating in incentive-based demand response (IBDR) events at a specific time interval, and decreasing the total electricity cost of the community in response to time-varying electricity prices. The proposed distributed resident-centric CEMS is developed using the concept of distributed optimization and mixed-integer linear programming. Different types of public loads are incorporated into the proposed framework including stoppable and deferrable public loads. The simulation results show that the proposed framework dispatches power optimally.**

***Index Terms*—Community energy management system, demand response, home energy management system, mixed-integer linear programming.**

Nomenclature

Sets

A_d	Set of deferrable public load.
A_s	Set of stoppable public load.
$A_{u,c1}$	Set of interruptible household load.
$A_{u,c2}$	Set of uninterruptible household load.
$A_{u,c3}$	Set of time-varying household load.
$A_{u,uc}$	Set of uncontrollable household load.
A_{up}	Set of uncontrollable public load.

Parameters

E_{BESS}	Battery capacity.
L_{BESS}	Lifetime throughput of BESS system.
L_{PV}	Lifetime generated energy of PV system.
N	Total number of sampling intervals.
$P^{\max}$	Maximum contracted load for the community.
$\bar{P}_{base}$	Baseline load for the community.
$P^{\max}_{charge}$	Maximum BESS charging power.
$P^{max}_{discharge}$	Maximum BESS discharging power.
$\bar{P}_{u,base}$	Baseline load of the *u*-th household.
$P^{\max}_{u}$	Maximum contracted load for the *u*-th household.
$P^{\max}_{u,HVAC}$	Rated power of HVAC system.
P^{rated}_{p}	Rated power of public load.
$P^{rated}_{u,a}$	Rated power of household appliances.
P^{j}_{-n}	The power community purchased at the *j*-th sampling interval on previous *n*-th day.
P^{j}_{solar}	Maximum electrical power that the PV panels can generate from sunlight.
$P^{j}_{u,-n}$	The *u*-th household's load at the *j*-th sampling interval on previous *n*-th day.
Q_p	Number of sampling intervals public loads must operate.
$Q_{u,a}$	Number of sampling intervals interruptible appliances must operate.
R_u	Thermal resistance of HVAC system.
$SOC^{\min/max}$	Lower/ upper SOC limit of BESS.
$SOC^{threshold}$	SOC level of BESS at the end of the day.
T_s	Duration of each sampling interval.
U	Total number of households.
$V_{u,a}$	The number of times uninterruptible and time-varying appliances must work.
Y_{BESS}	Lifetime cost of BESS.
Y_{PV}	Lifetime cost of PV.
ε_u	System inertia of HVAC system.
$\Gamma_{u,a}$	Number of sampling intervals uninterruptible and time-varying appliances must run continuously.
$\eta_{u,cool}$	Cooling efficiency of HVAC system.
$\eta_{u,heat}$	Heating efficiency of HVAC system.
$\Theta^{\max/\min}_{in}$	Maximum/minimum indoor temperature.
Θ^{j}_{out}	Outdoor temperature.
λ^{j}	Community's decision on IBDR participation. 1 if the community participates in IBDR.
λ^{j}_{u}	Households' decision on IBDR participation. 1 if the *u*-th household participates in IBDR.
ρ^{j}_{b}	Price of electricity.
ρ^{j}_{f}	Incentive rate.

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$\sigma_{u,a}^{n}$	Load of time-varying appliances.
τ_p^s, τ_p^e	Operation interval of public loads.
τ_r^s, τ_r^e	Interval of IBDR event.
$\tau_{u,a}^s, \tau_{u,a}^e$	Operation interval of household appliances.
$\tau_{u,v}^s, \tau_{u,v}^e$	Operation interval of HVAC system.

Functions

B_1^j	Electricity cost for the community.
B_2^j	Incentive payoff for the community.
B_3^j	BESS degradation cost for the community.
B_4^j	PV degradation cost for the community.
$C_{u,1}^j$	Electricity cost for *u*-th household.
$C_{u,2}^j$	Incentive payoff for *u*-th household.
P_p^j	Power consumption of public loads.
P_u^j	Total household load of the *u*-th household.
$P_{u,a}^j$	Power consumption of household appliances.
SOC^j	SOC of BESS.
$\Theta_{u,in}^j$	Indoor temperature of the *u*-th household.
ρ_{BESS}	Degradation cost per kWh for BESS.
ρ_{PV}	Degradation cost per kWh for PV.

Variables

$I_{u,cool}^j$	Binary variable. 1 if HVAC is working in cooling mode.
$I_{u,heat}^j$	Binary variable. 1 if HVAC is working in heating mode.
P^j	Power purchased from power grid.
P_{BESS}^j	BESS power. Positive if charging; Negative if discharging.
$P_{BESS,pos}^j$	Absolute value of P_{BESS}^j when P_{BESS}^j is positive.
$P_{BESS,neg}^j$	Absolute value of P_{BESS}^j when P_{BESS}^j is negative.
P_{PV}^j	Electrical power generated from the PV panels.
$P_{u,cool}^j$	Power consumption of HVAC at cooling mode.
$P_{u,heat}^j$	Power consumption of HVAC at heating mode.
r_p^j	Binary variable. 1 if *p*-th public load is turned on.
$r_{u,a}^j$	Binary variable. 1 if *a*-th household appliance is turned on.
$\delta_{u,a}^j$	Binary variable. 1 if *a*-th household appliance is started.
μ_{BESS}^j	Binary variable. 1 if P_{BESS}^j is positive.

I. Introduction

TODAY, renewable energy sources (RES) are attracting a lot of attention due to the shortage of fossil energy and environmental concern [1]. For example, one in five residential households in Australia has a PV system [2]. To maximize the utilization of PV system, most residential solar customers are also interested in installing battery energy storage systems (BESS) [3]. At the other end of the network, utility companies have introduced demand response (DR) programs such as time-varying tariff and incentive-based DR (IBDR) to maintain a balance between electricity demand and supply [4], [5], [6]. Residential households can save electricity costs by shifting or reducing their electricity demand in response to time-varying tariff and/or IBDR. With PV systems and BESS in place, residential households can realize greater cost savings from leveraging these DR programs. In line with this trend, home energy management system (HEMS) have been widely introduced [7], [8], [9]. HEMS refers to a technological platform formed by a range of hardware and software for energy management in residential households [10], [11]. Numerous studies have formulated HEMS optimization schemes and demonstrated that these energy management approaches are effective in helping residential consumers to save electricity costs [12], [13], [14]. However, when a large number of HEMS operate independently, they might impose unnecessary peak loads to the community's transformers, which could pose a threat to the grid stability [15], [16], [17].

This gave rise to another energy management approach that performs energy management at the community level, i.e., by collectively considering multiple HEMS for energy management [18], [19]. Such energy management approach can be known as the community energy management system (CEMS). In a community, every household shares PV systems, BESS, and public loads. In addition to the HEMS in a community, a CEMS framework includes the public facilities in the community. CEMS can be implemented in a centralized or distributed manner. In a centralized CEMS, a global energy management system (GEMS) is responsible for controlling all the HEMS in the community, which also means that the GEMS can schedule the appliances of each residential household in the community [20]. Although centralized CEMS can bring about optimal energy management for the entire community, it also requires significant computational costs as there are too many different household appliances and public facilities to be scheduled under a single framework. In addition, it poses a great threat to the privacy of the residents as it requires detailed information of every residential household in the community.

In a distributed CEMS, each HEMS in the community operates independently but communicates with the GEMS and/or other HEMS in the community [21], [22]. Hence, distributed CEMS requires considerably less computational cost, since the computational burden is distributed among the HEMS within the community. Furthermore, there are no privacy concerns as only minimal information from HEMS are transferred to the GEMS [23]. Therefore, it is more appealing to implement CEMS in a distributed manner.

Numerous researchers have formulated distributed CEMS. For instance, [24] proposed a distributed CEMS that allows every HEMS in a community to iteratively adjust their appliance scheduling, but with a penalty term penalizing large changes in scheduling between consecutive iterations. In [25], a distributed CEMS was proposed to modify the aggregated load profiles in a community while minimizing resident payments without affecting their comfort nor compromising their privacy. In [26], a PL-Generalized Bender Algorithm was used to perform community energy management in a distributed manner to minimize the total power cost of a community while maximizing resident utilities and considering their privacy. To provide a distributed solution for CEMS, [27] formulated a load management problem as a constrained optimization problem. A distributed dynamic programming (DDP) algorithm was utilized to solve the load management problem. Game theory [28], multi-agent systems [29] and dual decomposition [30] were also utilized to develop distributed CEMS. For a community equipped with a shared energy storage system, a distributed CEMS was formulated in [31] to minimize the end-user costs and to maximize the self-sufficiency and self-consumption of the community. The distributed CEMS in [32] and [33] were formulated as a two-level hierarchical optimization framework.

Although there are some research works investigated distributed CEMS, these distributed CEMS require each HEMS in the community to take the collective goals of the community into account when scheduling their appliances. This is to ensure that their appliance scheduling is optimal from the perspective of the entire community. In some work, each HEMS is required to re-plan their appliance scheduling for several times until their appliance scheduling is optimal to the entire community. Such an approach is certainly good as it delivers a scheduling result that is optimal from the collective point of view. However, it also limits the residents' freedom of electricity consumption to certain extent, which is contrary to the idea of economic freedom. This paper proposes the resident-centric distributed CEMS as an alternative solution to this problem. More specifically, in the proposed CEMS, each HEMS can schedule their appliances autonomously according to their own interest, without having to collaborate with the community and to consider whether their appliance scheduling is optimal from the perspective of the entire community. The central controller, i.e., GEMS, in the proposed CEMS will then determine a solution that is optimal to the entire community by optimally dispatching the public distributed energy sources according to the appliance scheduling of HEMS. In other words, the proposed distributed resident-centric CEMS allows residents to act autonomously while securing the collective goals of the community to certain extent.

In this paper, the collective goals of the community include participating in incentive-based DR (IBDR) at a specific time interval, and decreasing total electricity cost of the community in response to the time-varying tariff. The reason of considering participation in IBDR as one of the collective goals of the community is that a community comprising up to dozens or hundreds of residential households is well-suited for participating in IBDR, through aggregating the residential households in the community. Engaging in IBDR can further increases the economic benefits of a community and these benefits can be distributed to the residential households who contributed to engage the community in IBDR. This further increases the benefits to the residential households.

The proposed distributed CEMS also takes community public loads into account. To realize a more realistic environment, the community public loads are categorized into three types in the proposed work: uncontrollable, stoppable and deferrable public loads. Note that, most existing distributed CEMS do not consider the community public loads. Not to mention the public load with different characteristics. The main contributions and technical novelties of this paper are summarized as follows:

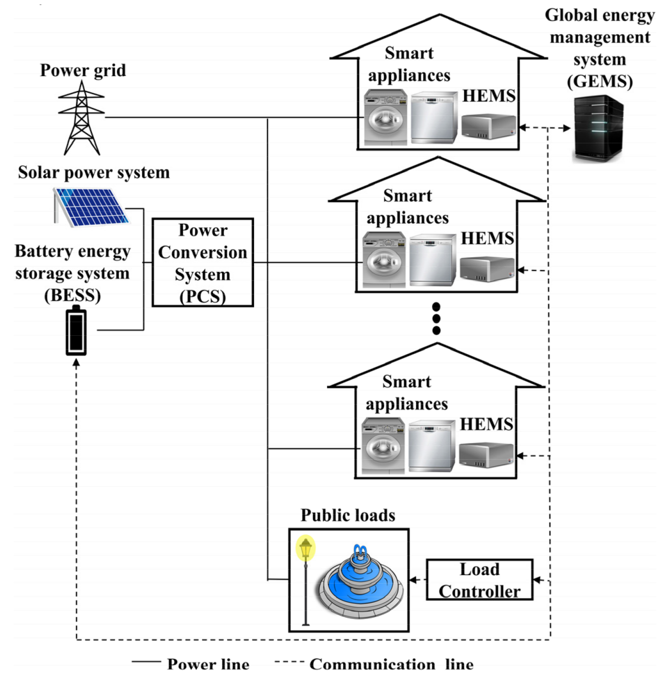

Fig. 1. Illustration of community energy management system.

1) A resident-centric distributed CEMS is proposed, which allows each residential household to manage their appliances autonomously using their HEMS, without the need to collaborate with the community and to share the load profiles of any individual appliances.
2) Delicate constraints and objective functions are designed in the proposed resident-centric distributed CEMS to engage community in IBDR events taking place at a specific time interval.
3) Different types of community public loads including the uncontrollable, stoppable and deferrable public loads are implemented in the proposed framework.
4) The proposed framework offers the possibility that each resident can choose to provide load curtailment at any time intervals within the IBDR event, rather than providing load curtailment throughout the entire IBDR event.

The rest of this paper is organized as follows. Section II presents the problem statement. The proposed distributed CEMS is presented in Section III. The computer simulations are presented in Section IV, and the conclusions are drawn in Section V.

II. Problem Statement

The primary intention of this paper is to present a resident-centric distributed CEMS, which allows each HEMS to schedule their appliances autonomously, without the need to collaborate with the community and to consider whether their appliance scheduling is optimal to the entire community. The GEMS in the proposed CEMS will then determine a solution that is optimal to the entire community by optimally dispatching the public distributed energy sources according to the appliance scheduling of HEMS. Fig. 1 depicts the CEMS that integrates the energy resources including the power grid, PV system, and BESS.

The GEMS manages all the loads in the community in a hierarchical way. The residential load of every household in the community is optimally managed by the HEMS. The optimal load scheduling results are sent from the HEMS to GEMS at every sampling interval. After receiving the optimization results of load scheduling from every household, the GEMS manages all the public energy resources and public load based on the collective HEMS optimization results. Time-varying tariff is used in the community. The community is required to engage in IBDR event as requested by the utility company.

The GEMS serves as the central controller for the CEMS. The HEMS communicates with the GEMS via a protected local area network (LAN) or an internet. The HEMS only communicates with the GEMS without sharing data with other HEMS. The appliances in every *u*-th household are scheduled by an individual HEMS. In addition to load scheduling, the HEMS also executes IBDR through load curtailment. The electricity of every household is supplied by the power grid, PV panels and BESS.

The day-ahead pricing is assumed to be utilized. The IBDR request, incentive rate, and the time interval in which the IBDR event takes place are sent by the utility company to the GEMS, HEMS and the community residents via internet. A web-based platform is provided for the residents of every household to provide their willingness and time intervals of participating in the IBDR event. Notably, every household can freely choose to participate in IBDR at any time intervals within the IBDR event. The GEMS will retrieve the decisions on the IBDR participation for every household from the web-based platform. Then, the GEMS will send the decision on the IBDR participation from every individual household to the corresponding HEMS for residential energy management optimization. Through this process, GEMS is able to automatically set up the HEMS of every household based on residents' decision on the IBDR participation to save residents' effort of setting up their HEMS for IBDR.

The HEMS determines the optimal load scheduling autonomously, without collaborating with the community and considering whether their appliance scheduling is optimal from the perspective of the entire community. According to the scheduling results obtained from the HEMS of every household, the GEMS then determines a solution that is optimal to the entire community by optimally dispatching the power from the power grid, BESS and PV panels and scheduling the public loads.

III. Two-Level Optimization Framework in CEMS

The proposed resident-centric distributed CEMS is formulated as a two-level hierarchical optimization framework that comprises two optimization schemes including the local optimization scheme (Level 1) installed in the HEMS of every individual household, and the global optimization scheme (Level 2) installed in the GEMS.

In Level 1, the HEMS optimization scheme is conducted independently to determine the optimal load scheduling in every household. The HEMS optimization is designed to minimize the electricity cost of every individual household without having to consider whether their appliance scheduling is optimal to the entire community. In Level 2, the GEMS optimally dispatch the power from the grid, PV panels, BESS and determines the optimal scheduling of public loads of the entire community. The optimization conducted in GEMS is based on the energy management optimization results from all HEMSs.

A. HEMS Optimization Model: Level 1

Assume that there are *U* households in the community. A HEMS is installed in every household for load scheduling of residential appliances. The HEMS aims to minimize the electricity cost for every corresponding household. The entire scheduling horizon considered by the HEMS of every household is one day, i.e., 24 hours. The scheduling horizon is divided into *N* sampling intervals with T_s hours, $N = (24 \times 60)/T_s$.

The household appliances in every household are classified as uncontrollable and controllable appliances. Uncontrollable appliances such as refrigerators, lighting, and personal computers, cannot be scheduled by HEMS and therefore follow a fixed consumption pattern throughout the entire scheduling horizon. In contrast, controllable appliances can be scheduled by HEMS and can be categorized into interruptible, uninterruptible, time-varying appliances, and HVAC system. Interruptible appliances can be interrupted anytime, e.g., water pump, humidifier, fans, etc. Uninterruptible appliances, once started, must operate continuously for a period of time to complete their task properly, e.g., rice cooker, boiler, oven, etc. Similar to an uninterruptible appliance, a time-varying appliance such as washing machine and dish washer cannot be interrupted until it has completed its task, except that its power consumption varies with its operating modes. The set of uncontrollable, interruptible, uninterruptible and time-varying appliances in the *u*-th household are denoted as $A_{u,uc}$, $A_{u,c1}$, $A_{u,c2}$ and $A_{u,c3}$ respectively, where $u = 1, 2, \ldots, U$.

To allow the *u*-th HEMS to schedule the *a*-th controllable appliance in the *u*-th household, a binary variable $r_{u,a}^{j} \in \{0, 1\}$ is introduced such that $r_{u,a}^{j} = 1$ indicates the *a*-th controllable appliance in the *u*-th household is turned on at the *j*-th sampling interval and $r_{u,a}^{j} = 0$ indicates the opposite, $j = 0, \ldots, N - 1$, $\forall a \in (A_{u,c1} \cup A_{u,c2} \cup A_{u,c3})$, $u = 1, 2, \ldots U$. Every *a*-th controllable appliance in the *u*-th household is preassigned an operation interval starting from $\tau_{u,a}^{s}$ to $\tau_{u,a}^{e}$ where $\tau_{u,a}^{s} < \tau_{u,a}^{e}$, $\tau_{u,a}^{s}, \tau_{u,a}^{e} \in [0, N - 1]$. Every *a*-th controllable appliance in the *u*-th household is only allowed to operate within its respective operation interval $[\tau_{u,a}^{s}, \tau_{u,a}^{e}]$. Hence, the following constraint is set:

$$r_{u,a}^{j} = \begin{cases} \beta, \beta \in \{0, 1\}, j \in \left[\tau_{u,a}^{s}, \tau_{u,a}^{e}\right], \\ \quad 0, \quad \text{otherwise}; \end{cases} \forall a \in A_{u,c1} \cup A_{u,c2} \cup A_{u,c3}. \tag{1}$$

While the interruptible appliances in the *u*-th household can be interrupted at any time, they should operate at least for a certain number of sampling intervals every day to provide their designated functions. Assuming that every a-th appliance in the u-th household belonging to the set of interruptible appliances $A_{u,c1}$ should operate at least $Q_{u,a}$ sampling intervals every day, then the following constraint is set:

$$\sum_{j=\tau^s_{u,a}}^{\tau^e_{u,a}} r^j_{u,a} \geq Q_{u,a}, \forall a \in A_{u,c1}, u = 1, 2, \ldots, U. \tag{2}$$

Different from the interruptible appliances, the uninterruptible and time-vary appliances will not be stopped before they complete their functions. Assume that the a-th uninterruptible or time-varying appliance in the u-th household operates $V_{u,a}$ times a day and operates for $\Gamma_{u,a}$ consecutive sampling intervals each time, where $(V_{u,a}\Gamma_{u,a}) \leq (\tau^e_{u,a} - \tau^s_{u,a} + 1)$, $\forall a \in (A_{u,c2} \cup A_{u,c3})$, $u = 1 \ldots U$. An auxiliary binary variable $\delta^j_{u,a} \in \{0, 1\}$ is introduced for the following optimization using linear programming such that $\delta^j_{u,a} = 1$ indicates the a-th appliance in the u-th household starts operating at the j-th sampling interval and $\delta^j_{u,a} = 0$ indicates the appliance is not scheduled to start at the j-th sampling interval. Once the a-th appliance is started at the j-th sampling interval, assume that it must operate continually for $\Gamma_{u,a}$ sampling intervals. The HEMS optimally selects the optimal starting time interval from the interval $[\tau^s_{u,a}, \tau^e_{u,a} - \Gamma_{u,a} + 1]$ for the a-th uninterruptible or time-varying appliance to work $V_{u,a}$ times. Therefore,

$$\sum_{j=\tau^s_{u,a}}^{\tau^e_{u,a}-\Gamma_{u,a}+1} \delta^j_{u,a} = V_{u,a}, \forall a \in (A_{u,c2} \cup A_{u,c3}), u = 1 \ \ldots \ U. \tag{3}$$

If $\delta^j_{u,a} = 1$ then $r^j_{u,a}, r^{j+1}_{u,a}, \ldots, r^{j+\Gamma_{u,a}}_{u,a} = 1$. It leads to the constraint:

$$r^{j+n}_{u,a} \geq \delta^j_{u,a}, n = 0, \ldots, (\Gamma_{u,a} - 1), \forall a \in (A_{u,c2} \cup A_{u,c3}). \tag{4}$$

If $\delta^j_{u,a} = 1$followed by $\delta^{(j+h)}_{u,a} = 1$ according to (3), the time difference h needs to be large enough so that $h > \Gamma_{u,a}$ in order to satisfy (4). To prevent from selecting the time intervals to start operating not separated enough, an additional constraint is given as follows for the uninterruptible or time-vary appliances.

$$\sum_{j=\tau^s_{u,a}}^{\tau^e_{u,a}} r^j_{u,a} = V_{u,a}\Gamma_{u,a}, \forall a \in (A_{u,c2} \cup A_{u,c3}), u = 1 \ \ldots \ U. \tag{5}$$

Both the interruptible and uninterruptible appliances in the u-th household consume a fixed power. Let the rated power of a-th interruptible and uninterruptible appliances be $P^{rated}_{u,a}$, $\forall a \in (A_{u,c1} \cup A_{u,c2})$. The power consumption of the a-th interruptible and uninterruptible appliances at any j-th sampling interval is calculated as:

$$P^j_{u,a} = \begin{cases} r^j_{u,a} P^{rated}_{u,a}, j \in \left[\tau^s_{u,a}, \tau^e_{u,a}\right], \\ 0, \quad \text{otherwise}; \end{cases} \quad \forall a \in (A_{u,c1} \cup A_{u,c2}). \tag{6}$$

The power consumption of time-varying appliances varies with operating modes. Denote $\sigma^n_{u,a}$ as the load of the a-th time varying appliance at the n-th sampling interval, $\forall a \in A_{u,c3}$. The power consumption corresponding to the situation that the a-th time varying appliance is selected by HEMS to operate at the j-th sampling interval is calculated as:

$$P^{j+n}_{u,a} = \begin{cases} r^{j+n}_{u,a}\sigma^n_{u,a}, n = 0, \ldots, (\Gamma_{u,a} - 1); \\ 0, \ \text{otherwise}; \end{cases} \quad \forall a \in A_{u,c3}, u = 1, \ldots, U. \tag{7}$$

Assume that every u-th household is equipped with an electric HVAC system and the HVAC system operates in every household within the preassigned interval $[\tau^s_{u,v}, \tau^e_{u,v}]$. The HVAC system is only allowed to work in one mode, i.e., either cooling, heating or idle at each sampling interval. To realize this statement, the following constraint is set:

$$I^j_{u,cool} + I^j_{u,heat} \leq 1, \tag{8}$$

where $I^j_{u,cool}, I^j_{u,heat} \in \{0, 1\}$ are the binary variables such that $I^j_{u,cool} = 1$ or $I^j_{u,heat} = 1$ indicates that the HVAC system of the u-th household is working in the cooling or heating modes at the j-th sampling interval. Note that the HVAC only operates within the operation interval $[\tau^s_{u,v}, \tau^e_{u,v}]$. Hence, the following constraint is set:

$$I^j_{u,cool} + I^j_{u,heat} = \begin{cases} \beta, \beta \in \{0, 1\}, j \in \left[\tau^s_{u,v}, \tau^e_{u,v}\right]; \\ 0, \quad \text{otherwise}. \end{cases} \tag{9}$$

Denote $P^j_{u,cool} \geq 0$ and $P^j_{u,heat} \geq 0$ as the power consumption of the HVAC system at cooling and heating modes, respectively. The variable $P^j_{u,cool} = 0$ or $P^j_{u,heat} = 0$ if $I^j_{u,cool} = 0$ or $I^j_{u,heat} = 0$. Thus,

$$P^j_{u,cool} \leq I^j_{u,cool} P^{\max}_{u,HVAC}, \tag{10}$$

$$P^j_{u,heat} \leq I^j_{u,heat} P^{\max}_{u,HVAC}. \tag{11}$$

where $P^{\max}_{u,HVAC}$ is the HVAC system's rated power.

The u-th household's indoor temperature $\Theta^j_{u,in}$ at the j-th sampling interval is characterized as follows [34], [35]:

$$\Theta^j_{u,in} = \varepsilon_u \Theta^{j-1}_{u,in} + (1 - \varepsilon_u) \Big(\Theta^{j-1}_{out} - \eta_{u,cool} R_u P^{j-1}_{u,cool} T_s + \eta_{u,heat} R_u P^{j-1}_{u,heat} T_s\Big). \tag{12}$$

Note that, $\eta_{u,cool} R_u P^j_{u,cool} T_s = 0$ or $\eta_{u,heat} R_u P^j_{u,heat} T_s = 0$ if $I^j_{u,cool} = 0$ or $I^j_{u,heat} = 0$, due to the constraint in (8)–(11). Every u-th household has individually different HVAC environment and facility, leading to different system inertia ε_u, thermal resistance R_u, cooling efficiency $\eta_{u,cool}$ and heating efficiency $\eta_{u,heat}$ of HVAC system.

To prevent causing thermal discomfort to the residents, the indoor temperature $\Theta^j_{u,in}$ is constrained by an upper and lower bound $\Theta^{\max}_u$ and $\Theta^{\min}_u$, respectively. Thus,

$$\Theta^{\min}_u \leq \Theta^j_{u,in} \leq \Theta^{\max}_u, j \in [\tau^s_{u,v}, \tau^e_{u,v}]. \tag{13}$$

Without loss of generality, assume that the power consumption of the *a*-th uncontrollable loads, i.e., $P_{u,a}^j\ \forall a \in A_{u,uc}$, are predictable. In other words, every uncontrollable appliance is assumed to follow a fixed load profile in the real-time optimization. The total load of very *u*-th household at any *j*-th sampling interval is calculated as:

$$P_u^j = \sum_{a \in A_{u,c1} \cup A_{u,c2} \cup A_{u,c3}} P_{u,a}^j + P_{u,cool}^j + P_{u,heat}^j. \tag{14}$$

The community can participate in the IBDR by accumulating every household's individual load curtailment and the curtailment of public loads through CEMS. Every household in the community can decide whether to participate in the collective IBDR. Let $[\tau_r^s, \tau_r^e]$ be the interval of the collective IBDR sent in advance from the utility company or curtail service provider. Members of community households can go to the website made for the community energy management to indicate their choice of participation and preferred intervals of load curtailment. Assume that the IBDR is designed to request the participants to curtail their loads to the level less than their baseline loads.

Let $\lambda_u^j \in \{0,1\}$ be every *u*-th household's IBDR participation decision such that $\lambda_u^j = 1$ if the *u*-th household chooses to participate the IBDR at the *j*-th sampling interval, and $\lambda_u^j = 0$ otherwise, $\forall j \in [\tau_r^s, \tau_r^e]$. If $\lambda_u^j = 1$, it means that the household is willing to maintain their electric load P_u^j calculated as in (14) less than their baseline load $\bar{P}_{u,base}$. The baseline load $\bar{P}_{u,base}$ is defined as the average load during the interval of IBDR of previous M days, i.e.,

$$\bar{P}_{u,base} = \frac{1}{M}\frac{1}{\tau_r^e - \tau_r^s}\sum_{n=1}^{M}\sum_{j=\tau_r^s}^{\tau_r^e} P_{u,-n}^j \tag{15}$$

where $P_{u,-n}^j$ is the *u*-th household's load at the *j*-th sampling interval on previous *n*-th day. Note that $P_{u,-n}^j$ is recorded in the HEMS. If $\lambda_u^j = 0$ or outside of the interval of IBDR, P_u^j can only be constrained by a looser upper limit, the maximum contracted power $P_u^{\max}$. The load curtailment can be achieved by adjusting the upper limit of the household power consumption in the HEMS. Then, P_u^j in (14) is constrained as:

$$P_u^j < \begin{cases} \bar{P}_{u,base}, & \text{if } \lambda_u^j = 1 \text{ and } j \in [\tau_r^s, \tau_r^e]; \\ P_u^{\max}, & \text{otherwise.} \end{cases} \tag{16}$$

Let the electricity price and the IBDR incentive price at the *j*-th sampling interval be ρ_b^j and ρ_f^j , respectively. The electricity cost $C_{u,1}^j$ and incentive payoff $C_{u,2}^j$ for the *u*-th household is calculated as follows:

$$C_{u,1}^j = \rho_b^j P_u^j T_s, \forall j \in [0, N-1]; \tag{17}$$

$$C_{u,2}^j = \lambda_u^j \rho_f^j (\bar{P}_{u,base} - P_u^j) T_s, \forall j \in [\tau_r^s, \tau_r^e]; \tag{18}$$

With the electricity cost $C_{u,1}^j$ defined in (17) and the incentive payoff $C_{u,2}^j$ defined in (18), the objective function of the HEMS optimal scheduling model is formulated as:

The optimization in (19) shown at the bottom of this page, is conducted at every current *k*-th sampling interval, $k = 0 \ldots (N\text{-}1)$. The optimization horizon is from the current sampling interval to the end of day, i.e., from $j = k$ to (*N*-1). It is obvious that the scheduling optimization in (19) aims to minimize the electricity costs and maximize the IBDR incentive payoffs.

B. GEMS Optimization Model: Level 2

As opposed to the local optimization model that is installed in the HEMS of each *u*-th household in the community, the global energy management system, i.e., GEMS, for the entire community is installed in the central controller. The operation statuses $r_{u,a}^j$ and auxiliary variables $\delta_{u,a}^j$ of the *a*-th appliances, along with the operation statuses $I_{u,cool}^j, I_{u,heat}^j$ and power consumption $P_{u,cool}^j, P_{u,heat}^j$ of HVAC system, of the *u*-th household are optimized by the HEMS. The total load P_u^j in every *u*-th household is calculated as in (14) based on the optimized $r_{u,a}^j$, $\delta_{u,a}^j$, $I_{u,cool}^j$, $I_{u,heat}^j$, $P_{u,cool}^j$ and $P_{u,heat}^j$. The calculated P_u^j in every *u*-th household is sent to the GEMS through HEMS at every *j*-th sampling interval. The optimization for appliance scheduling conducted in HEMS can be considered as the level-1 optimization. The level-2 optimization for community energy management is conducted in GEMS. The local optimization

$$\begin{cases} \min\limits_{\substack{r_{u,a}^j, j=k,\ldots,N-1, a \in A_{u,c1}\cup A_{u,c2}\cup A_{u,c3};\\ \delta_{u,a}^j, j=k,\ldots,N-1, a\in A_{u,c2}\cup A_{u,c3};\\ I_{u,cool}^j, I_{u,heat}^j, P_{u,cool}^j, P_{u,heat}^j,\\ j=k,\ldots,N-1}} \sum_{j=k}^{N-1} C_{u,1}^j - \sum_{j=\tau_r^s}^{\tau_r^e} C_{u,2}^j, & \text{If } k < \tau_r^s \\ \min\limits_{\substack{r_{u,a}^j, j=k,\ldots,N-1, a \in A_{u,c1}\cup A_{u,c2}\cup A_{u,c3};\\ \delta_{u,a}^j, j=k,\ldots,N-1, a\in A_{u,c2}\cup A_{u,c3};\\ I_{u,cool}^j, I_{u,heat}^j, P_{u,cool}^j, P_{u,heat}^j,\\ j=k,\ldots,N-1}} \sum_{j=k}^{N-1} C_{u,1}^j - \sum_{j=k}^{\tau_r^e} C_{u,2}^j, & \text{If } \tau_r^s \le k \le \tau_r^e \\ \min\limits_{\substack{r_{u,a}^j, j=k,\ldots,N-1, a \in A_{u,c1}\cup A_{u,c2}\cup A_{u,c3};\\ \delta_{u,a}^j, j=k,\ldots,N-1, a\in A_{u,c2}\cup A_{u,c3};\\ I_{u,cool}^j, I_{u,heat}^j, P_{u,cool}^j, P_{u,heat}^j,\\ j=k,\ldots,N-1}} \sum_{j=k}^{N-1} C_{u,1}^j, & \text{If } k > \tau_r^e \end{cases}$$

$$\text{subject to (1)–(18).} \tag{19}$$

models HEMS at every households and the global optimization model GEMS are executed sequentially at every sampling interval. The GEMS optimizes the power dispatch from the grid, PV panels, and BESS while optimizing the scheduling of community public loads. The optimal energy management conducted at GEMS is based on the optimized energy management results P_u^j by HEMS in every *u*-th household at every *j*-th sampling interval.

The community public loads are classified as uncontrollable and controllable ones. Assume that the controllable public loads consist of stoppable loads such as part of lighting in public space, fountains, sprinklers, etc., and deferrable loads such as water pumps, sewer pumps, ventilation fans, etc. The sets of uncontrollable, stoppable and deferrable public loads are denoted as A_{up}, A_s, and A_d, respectively.

Both stoppable and deferrable public loads are similar to the residential interruptible appliances that can be turned off or on any time within their operation intervals. To enable the GEMS to schedule the controllable public loads in the community, a binary variable $r_p^j \in \{0, 1\}$ is introduced to denote the operating status of *p*-th controllable public load at the *j*-th sampling interval. The variable $r_p^j = 1$ indicates the *p*-th controllable public load is turned on at the *j*-th sampling interval and $r_p^j = 0$ indicates the opposite, $j = 0 \ldots N$-1, $\forall p \in (A_s \cup A_p)$. Every *p*-th controllable public load is preassigned an operation interval denoted as τ_p^s and τ_p^e where $\tau_p^s < \tau_p^e$, $\tau_p^s, \tau_p^e \in [0, N-1]$. The controllable public load only operates during its assigned operation interval $[\tau_p^s, \tau_p^e]$, i.e.,

$$r_p^j = \begin{cases} \beta, \beta \in \{0,1\}, j \in \left[\tau_p^s, \tau_p^e\right] \\ 0, j \in [0, N-1] \setminus \left[\tau_p^s, \tau_p^e\right] \end{cases}, \forall p \in (A_s \cup A_d). \quad (20)$$

Every *p*-th controllable public load is constrained to operate for at least Q_p sampling intervals to provide designated services. Recall that $[\tau_r^s, \tau_r^e]$ is the interval of the collective IBDR. The stoppable public loads are turned off within the interval $[\tau_r^s, \tau_r^e]$. Therefore,

$$r_p^j = 0, \forall j \in ([\tau_p^s, \tau_p^e] \cap [\tau_r^s, \tau_r^e]), \forall p \in A_s. \quad (21)$$

Although r_p^j for stoppable public loads are set to be 0 as $j \in ([\tau_p^s, \tau_p^e] \cap [\tau_r^s, \tau_r^e])$, the interval for being on will be increased to compensate for the interval being off. If the number of sampling intervals for the set $([\tau_p^s, \tau_p^e] \cap [\tau_r^s, \tau_r^e])$is Q_r, i.e., $Q_r = |[\tau_p^s, \tau_p^e] \cap [\tau_r^s, \tau_r^e]|$, then the constraint in (21) is modified as

$$\sum_{j=0}^{N-1} r_p^j \geq (Q_p - Q_r), \forall p \in A_s. \quad (22)$$

As for the deferrable public loads, they are not forced to turned off during the interval of the collective IBDR. The GEMS will determine whether they should be turned off based on cost optimization. Note that the designated services need to be maintained despite of being turned off or deferred for IBDR. Therefore, the constraint is imposed on the deferrable pubic loads as following:

$$\sum_{j=\tau_p^s}^{\tau_p^e} r_p^j \geq Q_p, \forall p \in A_d. \quad (23)$$

For ease of analysis, assume that every controllable public load in the community consumes a fixed power. Denote the power consumption of the *p*-th public load at the *j*-th sampling interval as P_p^j, then

$$P_p^j = \begin{cases} r_p^j P_p^{rated}, j \in \left[\tau_p^s, \tau_p^e\right], \\ 0, \quad \text{otherwise}; \end{cases} \forall p \in (A_s \cup A_d). \quad (24)$$

where P_p^{rated} is the rated power of the *p*-th public load.

Without loss of generality, assume that the power consumption of the *p*-th uncontrollable public load, i.e., $P_p^j \; \forall p \in A_{up}$, is predictable. In other words, every uncontrollable public load is assumed to follow a fixed profile in the following real-time optimization.

The power of BESS denoted as P_{BESS}^j can also be dispatched by the GEMS. Positive P_{BESS}^j indicates the BESS is charging from the grid and negative P_{BESS}^j indicates that the BESS is discharging to the grid. Note that P_{BESS}^j is constrained by the battery management system with a lower and upper bounds $P_{discharge}^{\max}$ and $P_{charge}^{\max}$ respectively, i.e.,

$$P_{discharge}^{\max} \leq P_{BESS}^j \leq P_{charge}^{\max}, \quad (25)$$

where $P_{discharge}^{\max}$ and $P_{charge}^{\max}$ are positive and negative, respectively.

Given that E_{BESS} is the rated capacity of the BESS, the state-of-charge (SOC) of the BESS at the *j*-th sampling interval is calculated as:

$$SOC^j = SOC^{j-1} + \frac{P_{BESS}^j T_s}{E_{BESS}}. \quad (26)$$

To prevent the BESS from overcharging or over discharging, the SOC of the BESS at every *j*-th sampling interval is constrained by an upper and lower bound $SOC^{\max}$ and $SOC^{\min}$, respectively. Thus,

$$SOC^{\min} \leq SOC^j \leq SOC^{\max}. \quad (27)$$

To guarantee enough BESS energy for the energy management in CEMS next day, the SOC of the BESS at the end of the day is constrained to be no lower than a threshold, $SOC^{threshold}$, i.e.,

$$SOC^{N-1} \geq SOC^{threshold}. \quad (28)$$

The power generated from the PV panels is denoted as P_{PV}^j, which can also be dispatched by the GEMS. Assuming that P_{solar}^j is the maximum electrical power that the PV panels can generate from sunlight at the *j*-th sampling interval, then

$$0 \leq P_{PV}^j \leq P_{solar}^j. \quad (29)$$

Denote P^j as the power purchased from the grid for the whole community at every *j*-th sampling interval. The power P^j is balanced with the aggregated loads from all households in the community, the community public loads, the power from the BESS and the PV panels. Then,

$$P^j = \sum_{p\in A_s\cup A_d\cup A_{up}} P_p^j + \sum_{u=1}^{U} P_u^j + P_{BESS}^j - P_{PV}^j. \quad (30)$$

Note that P_u^j in (30) is calculated by HEMS in every *u*-th household according to the optimization in (19). Due to the existence of the P_u^j, the power balance constraint in (30) allows the GEMS to schedule the public loads and dispatch the power from the power grid, PV panels and BESS according to the household load of every *u*-th household during the level-2 power dispatch optimization.

Let $\lambda^j \in \{0,1\}$ be the decision whether the community participates in the IBDR at the *j*-th sampling interval, $\forall j \in [\tau_r^s, \tau_r^e]$. Set $\lambda^j = 1$ if the community chooses to participate in the IBDR and agrees to curtail community's purchased power P^j to the level less than the baseline load $\bar{P}_{base}$, and $\lambda^j = 0$ otherwise. The baseline load $\bar{P}_{base}$ for the community is calculated as the average load during the interval of IBDR of previous M days, i.e.,

$$\bar{P}_{base} = \frac{1}{M}\frac{1}{\tau_r^e - \tau_r^s}\sum_{n=1}^{M}\sum_{j=\tau_r^s}^{\tau_r^e} P_{-n}^j \quad (31)$$

where P_{-n}^j is the power community purchased at the *j*-th sampling interval on previous *n*-th day. The GEMS adjusts the upper limit of the power from the grid in response to the IBDR. If $P^{\max}$ is the maximum contracted load of the community, then P^j is constrained as:

$$P^j < \begin{cases} \bar{P}_{base}, \text{ if } \lambda^j = 1 \text{ and } j \in [\tau_r^s, \tau_r^e]; \\ P^{\max}, \quad \text{otherwise.} \end{cases} \quad (32)$$

Recall that the electricity price and the IBDR incentive price at the *j*-th sampling interval are ρ_b^j and ρ_f^j, respectively. The electricity cost B_1^j and incentive payoff B_2^j for the community is calculated as follows:

$$B_1^j = \rho_b^j P^j T_s, \forall j \in [0, N-1]; \quad (33)$$

$$B_2^j = \lambda^j \rho_f^j (\bar{P}_{base} - P^j) T_s, \forall j \in [\tau_r^s, \tau_r^e]. \quad (34)$$

In addition to the electricity cost and IBDR incentive, the degradation costs of BESS and PV panels are also taken into consideration for the optimization. Denote Y_{BESS} and Y_{PV} as the total cost of BESS and PV panels over their lifetime, respectively, including the initial investment, installation and annual maintenance costs. The degradation cost per kWh for BESS and PV panels, denoted as ρ_{BESS} and ρ_{PV}, respectively, are approximated as [36], [37], [38]:

$$\rho_{BESS} = \frac{Y_{BESS}}{L_{BESS}}, \quad (35)$$

$$\rho_{PV} = \frac{Y_{PV}}{L_{PV}}, \quad (36)$$

where L_{BESS} and L_{PV} is the lifetime throughput of BESS and lifetime generated energy of PV system, respectively. Note that L_{BESS} is approximated as the lifetime charged and discharged power, i.e., the total amount of charged and discharged energy in the lifetime of BESS. Similarly, L_{PV} is the total amount of generated solar energy in the lifetime of PV system. Recall that P_{BESS}^j is positive if BESS is charging and negative if BESS is discharging. The BESS degradation cost at the *j*-th sampling interval, denoted as B_3^j, is expressed as:

$$B_3^j = \rho_{BESS} \left| P_{BESS}^j \right| T_s. \quad (37)$$

Similarly, the PV system degradation cost at the *j*-th sampling interval, denoted as B_4^j, is expressed as:

$$B_4^j = \rho_{PV} P_{PV}^j T_s. \quad (38)$$

The GEMS minimizes the electricity costs, degradation costs of BESS and PV system, and maximizes incentive payoffs by optimizing the power purchases from the grid, the charging or discharging power from the BESS, and scheduling of all the public loads. The optimization in GEMS is to be achieved by using MILP with the objective function defined in terms of $B_i^j, i = 1\ldots 4$. However, B_3^j defined in (37) cannot be directly utilized in the objective function for MILP because it is not linear. To get around this difficulty, two auxiliary optimization variables $P_{BESS,pos}^j \geq 0$ and $P_{BESS,neg}^j \geq 0$ are utilized to represent $|P_{BESS}^j|$ when P_{BESS}^j is positive or negative, respectively. Apparently, $P_{BESS,pos}^j$ and $P_{BESS,neg}^j$ cannot be positive at the same *j*-th sampling interval. An auxiliary binary optimization variable $\mu_{BESS}^j \in \{0,1\}$ is defined where $\mu_{BESS}^j = 1$ indicates $P_{BESS}^j \geq 0$ and $P_{BESS,pos}^j = |P_{BESS}^j|$ but $P_{BESS,neg}^j = 0$, $\mu_{BESS}^j = 0$ indicates $P_{BESS}^j < 0$ and $P_{BESS,neg}^j = |P_{BESS}^j|$ but $P_{BESS,pos}^j = 0$. According to the auxiliary optimization variables, the following two constraints are formulated:

$$P_{BESS,pos}^j \leq \mu_{BESS}^j P_{charge}^{\max}, \quad (39)$$

$$P_{BESS,neg}^j \leq -(1 - \mu_{BESS}^j) P_{discharge}^{\max}. \quad (40)$$

Recall that $P_{discharge}^{\max} < 0$ is a maximum discharging power for BESS. The power of BESS P_{BESS}^j can be represented as

$$P_{BESS}^j = P_{BESS,pos}^j - P_{BESS,neg}^j. \quad (41)$$

The power balance constraint in (30) is reformulated as:

$$P^j = \sum_{p\in A_s\cup A_d\cup A_{up}} P_p^j + \sum_{u=1}^{U} P_u^j + P_{BESS,pos}^j - P_{BESS,neg}^j - P_{PV}^j. \quad (42)$$

Note that P_{BESS}^j defined in (41) can be either positive or negative and $|P_{BESS}^j| = P_{BESS,pos}^j + P_{BESS,neg}^j$. Therefore, the BESS degradation cost B_3^j in (37) can be replaced with:

$$B_3^j = \rho_{BESS}(P_{BESS,pos}^j + P_{BESS,neg}^j) T_s. \quad (43)$$

With the costs B_1^j, B_2^j, B_3^j, and B_4^j defined in (33), (34), (43), and (38), respectively, the objective function for the optimization conducted in the GEMS is defined as following:

Referring to (29), the real-time optimization in (44) shown at the bottom of next page, uses the forecast of the maximum power

P^j_{solar} that the PV system can generate from sunlight. There have been various approaches for solar energy forecast such as in [39], [40]. To be more focused on the proposed hierarchical optimization for CEMS, the solar energy forecast approaches are not introduced in the paper although they are equally important. A profile for the forecast of P^j_{solar} is utilized for the simulation in next section. The hierarchical optimization sequence of CEMS that consists of both HEMS and GEMS is shown in the flow chart of Fig. 2.

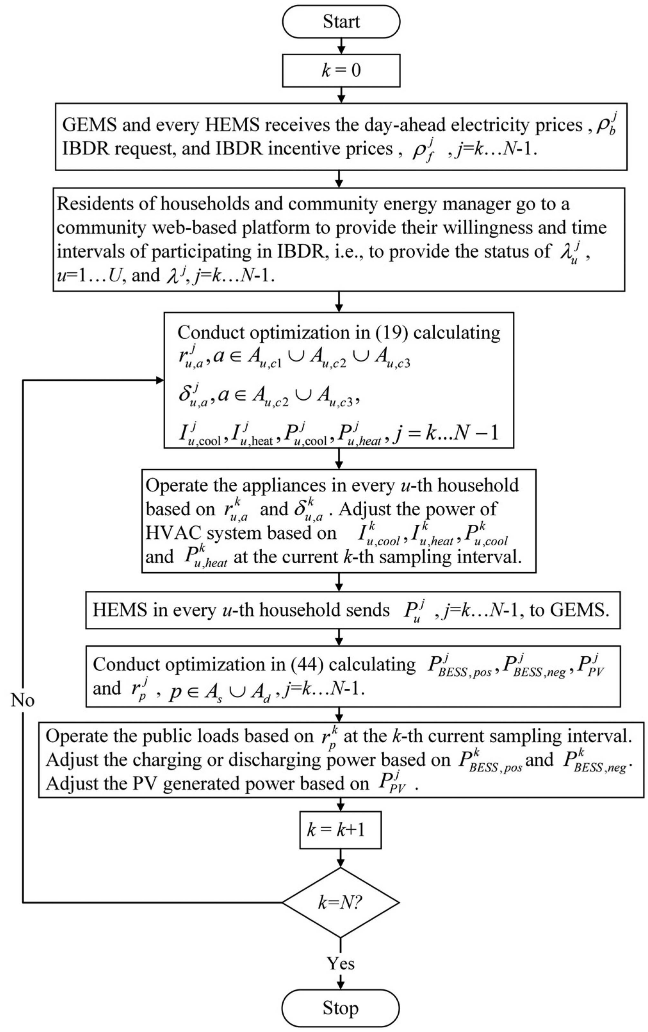

Fig. 2. Hierarchical optimization sequence of CEMS.

IV. Simulation

Simulations are conducted to verify the proposed distributed CEMS. The length of each sampling interval is set as $T_s = 15\text{minutes}$. Therefore, there are 96 sampling intervals throughout the day, i.e., calculated by $N = (24 \times 60)/T_s = 96$. There are 50 households in the community, i.e., $U = 50$.

A. Simulation Settings for Households

The number of appliances in residential homes ranges from 15 to 18. More specifically, each household has two uncontrollable, 7–13 interruptible, 2–5 uninterruptible and 0–3 time-varying appliances. To realize the stochasticity of uncontrollable household appliance, the load profiles of uncontrollable household appliances in every household are randomly configured. The controllable appliances in each residential household are formed by the appliances presented in Table I. Specifically, different combinations of the controllable appliances in Table I are randomly assigned to every household. To increase the diversity of consumption in residential households, the allowed operating interval and minimum operating duration for each appliance is configured to vary from household to household, as shown in Table I. The interruptible and uninterruptible appliances consume fixed power while the power consumption of time-varying appliance varies with operating cycles. To create realistic scenarios, the sampling intervals at which each household chosen to participate in the collective IBDR are randomly configured. The maximum contracted load for every household is set as $P_u^{\max} = 10\text{kW}$. The baseline load $\bar{P}_{u,base}$ for every *u*-th household ranges between 1.1 and 6.4 kW. The parameters for the HVAC in every household are assumed to be same for ease of analysis. The operation interval $[\tau^s_{u,v}, \tau^e_{u,v}]$ of the HVAC system is set as $[0, 67]$, the system inertia is set as $\varepsilon_u = 0.82$, the thermal resistance is set as $R_u = 7^{\text{o}}\ \text{C/kW}$, the cooling and heating efficiency for the HVAC are set as $\eta_{cool}, \eta_{heat} = 2.5$ and the rated power of the HVAC is set as $P^{\max}_{u,HVAC} = 3.5$ kW. The minimum and maximum indoor temperatures are set as $\Theta_u^{\min} = 24^{\text{o}}\ C$ and $\Theta_u^{\max} = 26^{\text{o}}\ C$, respectively. The initial indoor and outdoor temperatures are set as 26° C.

$$\begin{cases} \min\limits_{\substack{P^j, P^j_{BESS,pos}, P^j_{BESS,neg}, \\ P^j_{PV}, \mu^j_{BESS}, j=k,\ldots,N-1; \\ r^j_p, j=k,\ldots,N-1, \forall p \in A_s \cup A_d}} \sum_{j=k}^{N-1} (B_1^j + B_3^j + B_4^j) - \sum_{j=\tau_r^s}^{\tau_r^e} B_2^j, & \text{if } k < \tau_r^s \\ \min\limits_{\substack{P^j, P^j_{BESS,pos}, P^j_{BESS,neg}, \\ P^j_{PV}, \mu^j_{BESS}, j=k,\ldots,N-1; \\ r^j_p, j=k,\ldots,N-1, \forall p \in A_s \cup A_d}} \sum_{j=k}^{N-1} (B_1^j + B_3^j + B_4^j) - \sum_{j=k}^{\tau_r^e} B_2^j, & \text{if } \tau_r^e \le k \le \tau_r^e \\ \min\limits_{\substack{P^j, P^j_{BESS,pos}, P^j_{BESS,neg}, \\ P^j_{PV}, \mu^j_{BESS}, j=k,\ldots,N-1; \\ r^j_p, j=k,\ldots,N-1, \forall p \in A_s \cup A_d}} \sum_{j=k}^{N-1} B_1^j + B_3^j + B_4^j, & \text{if } k > \tau_r^e \end{cases}$$

$$\text{s.t. } (20)\text{–}(29), (31)\text{–}(36), (38)\text{–}(43). \qquad (44)$$

TABLE I
CONTROLLABLE HOUSEHOLD APPLIANCES

APP	PC (kW)	MOD (sampling interval)	AOI	
			Start (time)	End (time)
Int #1	1	12–49	0000–0745	0500–1230
Int #2	1.6	7–16	0845–1330	1400–1730
Int #3	1	8–24	1600–2200	2100–2345
Int #4	0.4	96	0000	2345
Int #5	0.4	1–15	0645–1915	1130–2245
Int #6	0.3	7–24	0830–1300	1245–1645
Int #7	0.3	4–24	1500–2100	2000–2345
Int #8	0.6	1–4	0400–1000	0600–1200
Int #9	0.6	1–4	0730–1400	1100–1630
Int #10	0.6	1–3	1500–2100	1615–2330
Int #11	0.4	3–16	0900–1330	1200–1730
Int #12	0.8	10–28	1500–2000	2100–2345
Int #13	0.5	1–36	0000–2000	0600–2345
Int #14	0.8	1–20	0630–2100	0800–2330
Int #15	1.2	1–36	0000–2130	0730–2345
Uni #1	0.7	3–3	0730–1215	1100–1445
Uni #2	0.7	3–3	1500–1845	1730–2115
Uni #3	1.4	2–9	0000–1730	0930–2345
Uni #4	0.9	3–7	0730–2000	1100–2345
Uni #5	0.4	2–8	0500–1730	0730–2000
Tv #1	0.4,0.5,0.6	4	0615–1900	0845–2200
Tv #2	0.3,0.4,0.5	4	0615–1900	0845–2200
Tv #3	0.6,0.7,0.8	4	0615–1715	0845–2000

APP = Appliance, PC = Power Consumption, MOD = Minimum Operating Duration, Int = Interruptible, Uni = Uninterruptible, Tv = Time-varying, AOI=Allowed Operating Interval.

TABLE II
CONTROLLABLE PUBLIC LOADS

Public Load	AOI	PC (kW)	MOD (Sampling Interval)
StopPL #1	0700–1230	5	22
StopPL #2	0000–2345	7.5	96
StopPL #3	1000–2000	10	40
DefPL #1	0845–1115	6	6
DefPL #2	1115–1445	7	7

AOI = Allowed Operating Interval, PC = Power Consumption, StopPL = Stoppable Public Load, DefPL = Deferable Public Load, MOD = Minimum Operating Duration.

B. Simulation Settings for Community

The parameters for the controllable public loads are presented in Table II. The load profiles of the uncontrollable public loads are randomly configured to create realistic scenarios. Other important parameters used in the simulation are presented in Table III. The proposed CEMS optimization consists of the HEMS and GEMS optimization problems. In the simulation, the HEMS and GEMS problem are solved using the GNU programming kit (GLPK). All the simulations are made using C programming on a workstation equipped with AMD Ryzen 9 3900XT CPU @ 3.80 GHz.

C. Simulation Results

Four cases are simulated as illustrated in Table IV. The electricity cost, BESS cost, PV cost, incentive payoff and total

TABLE III
IMPORTANT PARAMETER SETTINGS

Parameters	Values	Parameters	Values
τ_r^s, τ_r^e	43,60	Initial SOC	0.3
$P^{\max}$	500 kW	$SOC^{\min}, SOC^{\max}$	0.2,1
$\bar{P}_{base}$	400 kW	$SOC^{threshold}$	0.3
λ^j	1 over the entire IBDR interval	E_{BESS}	150 kWh
ρ_f^j	10 Taiwan Dollar (TWD) over the entire IBDR interval	$P_{discharge}^{\max}, P_{charge}^{\max}$	-105 kW, 105 kW
Y_{BESS}	160000 TWD	L_{BESS}	150000 kWh
Y_{PV}	3750000 TWD	L_{PV}	1875000 kWh

cost for the community in each case is presented in Table IV as well. The total cost for the community is calculated as the sum of the electricity cost, BESS cost and PV cost minus the incentive payoff. The community can participate in IBDR over the entire IBDR interval $[\tau_r^s, \tau_r^e]$, or not participate in IBDR at all. If the community participates in IBDR, then every u-th household can choose to participate in IBDR at any j-th sampling interval within the IBDR interval by correspondingly configuring the parameter λ_u^j in (16). If the community does not participate in IBDR, then every u-th household does not participate in IBDR at all. If the community does not participate in IBDR, the incentive payoff cost function is omitted from the objective function of the GEMS optimization (44), resulting in zero incentive payoff to the community. Therefore, the community receives zero incentive payoff in Cases 2 and 4. This results in a lower total cost in Case 1 than in Case 2, and a lower total cost in Case 3 than in Case 4.

The PV generated power P_{PV}^j in the power balance constraint (30) of the GEMS optimization problem allows the solar energy to be taken into consideration. This allows the community total cost to be further reduced when greater abundance of solar energy is available, resulting in a lower total cost in Case 1 than that in Case 3, and a lower total cost in Case 2 than that in Case 4. As shown in (38), the PV degradation cost is calculated based on the PV generated power P_{PV}^j. Therefore, the PV degradation cost in Cases 1 and 2 are identical as they consider the same weather, i.e., sunny day. For the similar reason, the PV degradation costs in Cases 3 and 4 are identical. The BESS degradation costs in Cases 2–4 are identical, indicating that the BESS is used to the same extent in these cases.

Fig. 3 presents the load scheduling results produced by the HEMS of household #1 in Cases 1 and 3. Fig. 4 presents the load scheduling results produced by the HEMS of household #3 in Cases 1 and 3. The gray areas in Figs. 3 and 4 indicate the intervals when the household 1 or 3 opts to participate in IBDR. The red line indicates the upper limit of the household power consumption. The load scheduling results produced by the HEMS of household #1 in Cases 1 and 3 are identical, although they consider different weather. This is because the PV power variable P_{PV}^j is integrated into the GEMS optimization problem in (44) instead of the HEMS optimization problem in (19) to

TABLE IV
SIMULATION RESULTS

Cases	Weather	IBDR engagement	EC (TWD)	BC (TWD)	PVC (TWD)	IP (TWD)	TC(TWD)
Case 1	Sunny day	Yes	5466.28	275.97	1137.58	6661.33	218.50
Case 2		No	5717.75	256	1137.58	0	7111.33
Case 3	Cloudy day	Yes	6973.11	256	423.40	4226.33	3426.18
Case 4		No	7224.57	256	423.4	0	7903.97

EC=Electricity Cost, BC=BESS Cost, PVC=PV Cost, IP=Incentive Payoffs, TC=Total Cost.

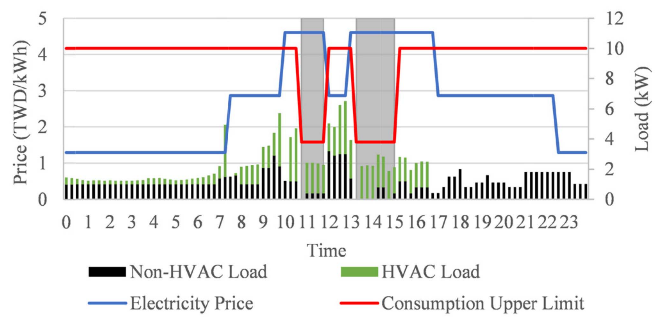

Fig. 3. Load scheduling results produced by the HEMS of household #1 – cases 1 and 3.

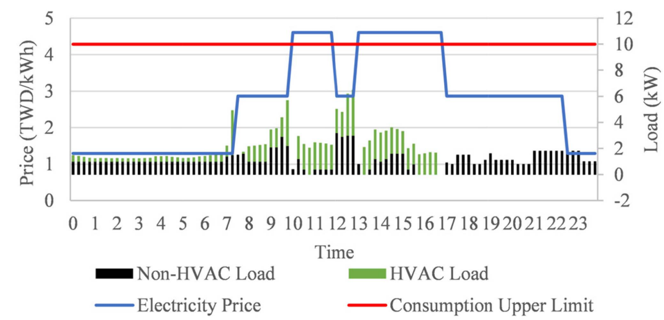

Fig. 5. Load scheduling results produced by the HEMS of household #1 – cases 2 and 4.

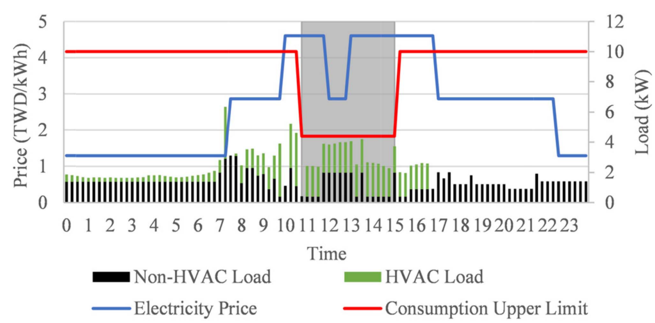

Fig. 4. Load scheduling results produced by the HEMS of household #3 – cases 1 and 3.

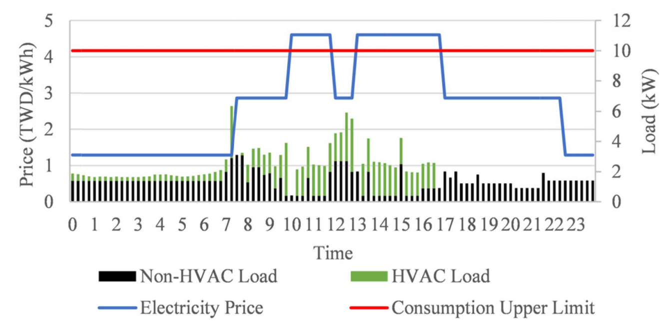

Fig. 6. Load scheduling results produced by the HEMS of household #3 – cases 2 and 4.

ensure that the PV generated power is dispatched from a global point of view. For the similar reason, the load scheduling results produced by the HEMS of household #3 in Cases 1 and 3 are identical, as shown in Fig. 4.

The consumption upper limit of household #1 being reduced to the baseline load $\bar{P}_{u,base}$ at certain interval, while that of household #3 being reduced to the baseline load $\bar{P}_{u,base}$ throughout the entire IBDR interval. This is because household #1 chooses to participate in IBDR at certain time intervals, rather than over the entire IBDR interval while household #3 chooses to participate in IBDR throughout the entire IBDR interval. During the time intervals that household #1 or 3 opts out of IBDR, their consumption upper limit is restored from $\bar{P}_{u,base}$ to the maximum contracted load $P_u^{\max}$. This justifies the effectiveness of (16) in varying the upper limit of household consumption according to the λ_u^j and $\bar{P}_{u,base}$. The household load during the time intervals when household #1 and #3 opts to participate in IBDR is purposely reduced to maximize incentive payoff. This due to the inclusion of the negative incentive payoff cost function in the HEMS optimization in (19) and the fact that the optimization is of minimization problem. When the optimization is solved, the incentive payoff will be maximized in order to minimize the objective function of the HEMS optimization. However, the HAVC load during the time interval when household #1 and 3 opt to participate in IBDR is not reduced substantially. The reason being that the outdoor temperature is high, so that the HVAC need to operate extensively to ensure that the temperature constraint in (13) is not violated.

Fig. 5 presents the load scheduling results produced by HEMS of household #1 in Cases 2 and 4. Fig. 6 presents the load scheduling results produced by HEMS of household #3 in Cases 2 and 4. The load scheduling results produced by the HEMS of household #1 in cases 2 and 4 are identical because the PV power P_{PV}^j is dispatched by GEMS instead of HEMS, as already discussed earlier. For the similar reason, the load scheduling results produced by the HEMS of household #3 in cases 2 and 4 are identical.

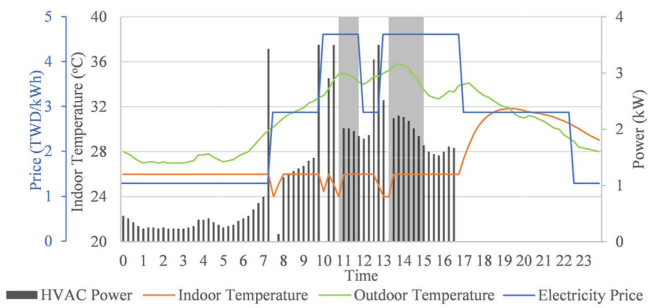

Fig. 7. HVAC scheduling results produced by the HEMS of household #1 – cases 1 and 3.

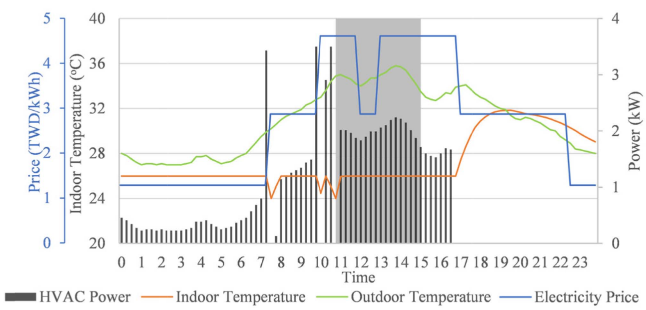

Fig. 8. HVAC scheduling results produced by the HEMS of household #3 – cases 1 and 3.

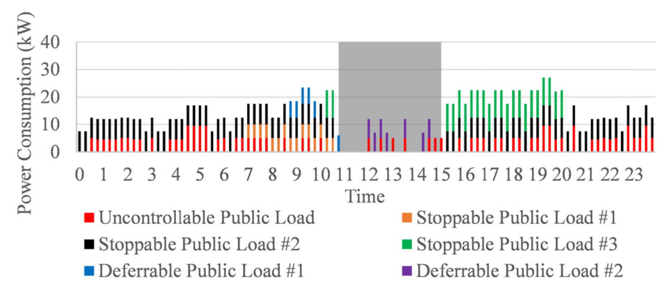

Fig. 9. Public load scheduling results produced by the GEMS–case 1.

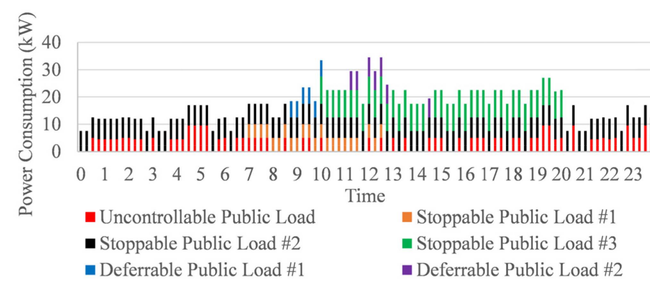

Fig. 10. Public load scheduling results produced by the GEMS–case 2.

Since the community does not participate in IBDR, the households do not participate in IBDR. Therefore, the upper limit of the household consumption remains at the maximum contracted load $P_u^{\max}$ throughout the day. Due to the reason that the HVAC needs to operate extensively throughout the day to obey the temperature constraints in (13), the HEMS of household #1 and #3 fails to substantially reduce the household load at the times when the electricity price is the highest. Nevertheless, the peakiest household load is not scheduled at the time when the electricity price is the highest. This justifies the fact that the HEMS of household #1 and #3 schedules the household load according to the time-varying electricity price. The inclusion of electricity cost function $C_{u,1}^{j}$ into the HEMS optimization in (19) equips the HEMS of household #1 and #3 with the ability to minimizes the electricity cost under time-varying electricity price.

Fig. 7 presents the HVAC scheduling results produced by the HEMS of household #1 in Cases 1 and 3. Fig. 8 presents the HVAC scheduling results produced by the HEMS of household #3 in Cases 1 and 3. The indoor temperature is kept within the preassigned lower and upper bound during the operation interval of HVAC. This justifies the effectiveness of the temperature constraint in (13).

The public load scheduling results produced by the GEMS for Cases 1 and 2 are presented in Figs. 9 and 10, respectively. Referring to Fig. 9, Stoppable Public Load #1 should operate for at least 22 sampling intervals from 0700–1230. However, it eventually operates for 15 sampling intervals only. The reason is that it is forced to stop during the IBDR interval. The stoppable public loads are intended to be stopped during the IBDR interval in any case, as demonstrated in (21). For the similar reason, Stoppable Public Load #2 and Stoppable Public Load #3 are stopped during IBDR interval, causing them to fail to fulfil their minimum operating duration. In contrast, deferrable public loads are intended to fulfil their minimum operating duration in any case, as shown in (23). In Fig. 10, the stoppable public loads are not stopped during the IBDR event for the reason that the community does not participate in the IBDR event. Nevertheless, it is proven that the GEMS schedule public loads appropriately by considering all the constraints imposed on the public loads and whether or not the community participates in IBDR event.

The power dispatch results produced by the GEMS in Cases 1–4 are presented in Figs. 11–12, respectively. The consumption upper limit of the community is reduced to the baseline load $\bar{P}_{base}$ of the community during the IBDR interval in Fig. 11. On the contrary, the consumption upper limit of the community remains at $P^{\max}$ throughout the day in Fig. 12. This is because the community participate in IBDR in Fig. 11 but does not participate in IBDR in Fig. 12. The consumption upper limit of the community is intended to vary according to the IBDR participation of the community, as demonstrated in (32).

In Figs. 11 and 13, power purchases are not reduced substantially during the IBDR interval, although one of the GEMS objectives is to maximize the incentive payoff. This is because the HVAC of every household operates extensively during the IBDR interval to comply with the temperature constraint in (13), resulting in high aggregated household load during the IBDR interval. The high aggregated household load during the IBDR interval disallow the GEMS to substantially reduce the power purchases during the IBDR interval. Nevertheless, the power purchases of the community during the IBDR interval lies

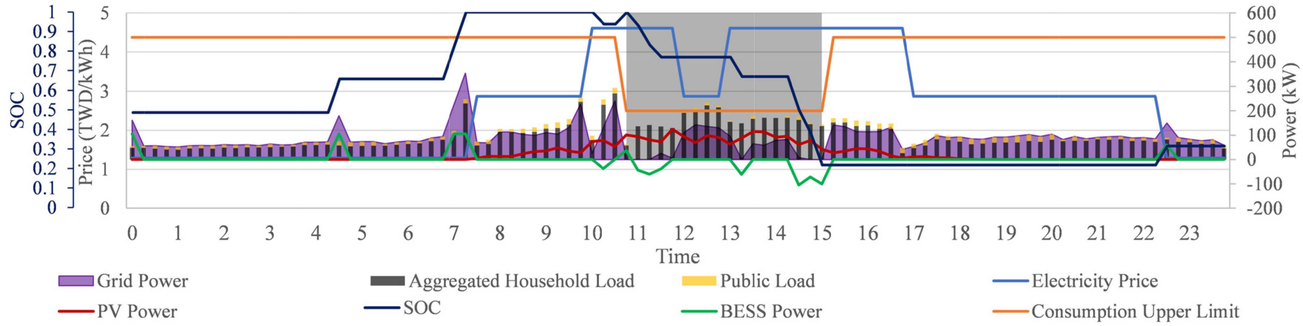

Fig. 11. The power dispatch results produced by the GEMS–case 1.

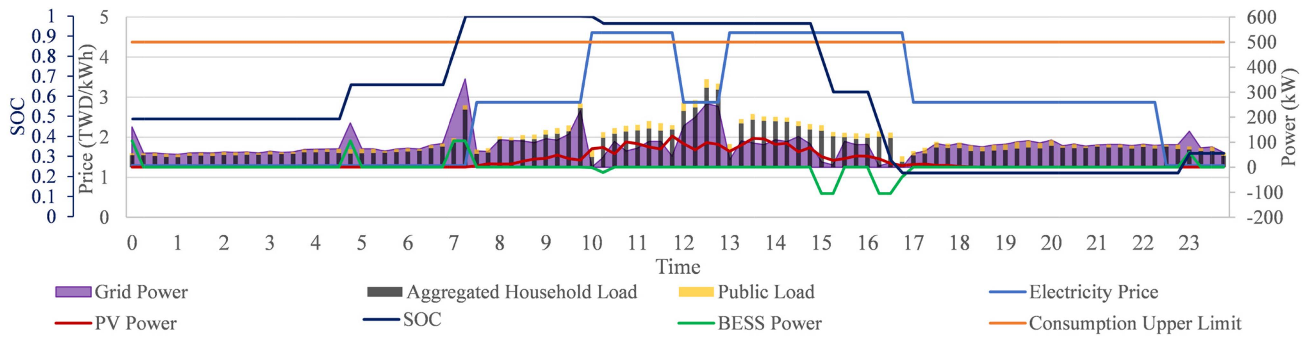

Fig. 12. The power dispatch results produced by the GEMS–case 2.

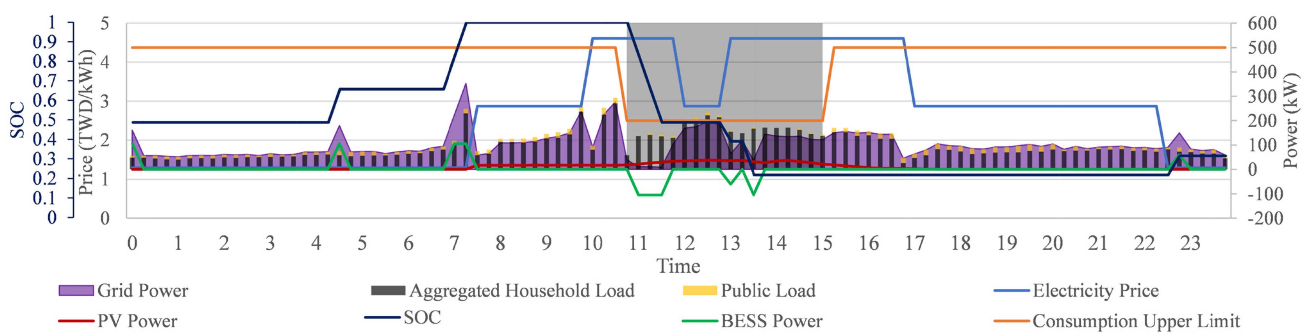

Fig. 13. The power dispatch results produced by the GEMS–case 3.

below the consumption upper limit, indicating the consumption upper limit constraint in (32) is effective. The BESS is charged to the maximum before the IBDR interval so that there is enough BESS power for use during the IBDR interval to ensure that the power purchases during the IBDR interval lies below the baseline load $\bar{P}_{base}$.The total load is accurately supplied by the power from grid, BESS and PV panels at every sampling interval, indicating that the power balance constraints (30) of the GEMS optimization problem are effective.

In Figs 12 and 14, power purchases are not substantially reduced during the time when the electricity price is the highest, although the GEMS should minimize the electricity cost under the time-varying electricity price. The high aggregated household load resulting from high HVAC load disallows the GEMS to substantially reduce the electricity purchases during the time when electricity price is the highest. Nevertheless, the highest electricity purchase is not scheduled at the time when electricity price is the highest. This justifies that the GEMS schedules power purchases according to the time-varying electricity price. This is due to the inclusion of the time-varying electricity price ρ_b^j in the GEMS optimization (44) and the fact that the GEMS optimization is of minimization. When the GEMS optimization is solved, the electricity cost associated with the time-varying electricity price will be minimized.

The total BESS throughput, i.e., the total amount energy charged into and discharged from the BESS throughout the day, when considering and disregarding BESS degradation cost, is shown in Table V. Table VI shows the total energy generated from the PV system throughout the day when considering and disregarding PV degradation cost. In all cases, the total BESS

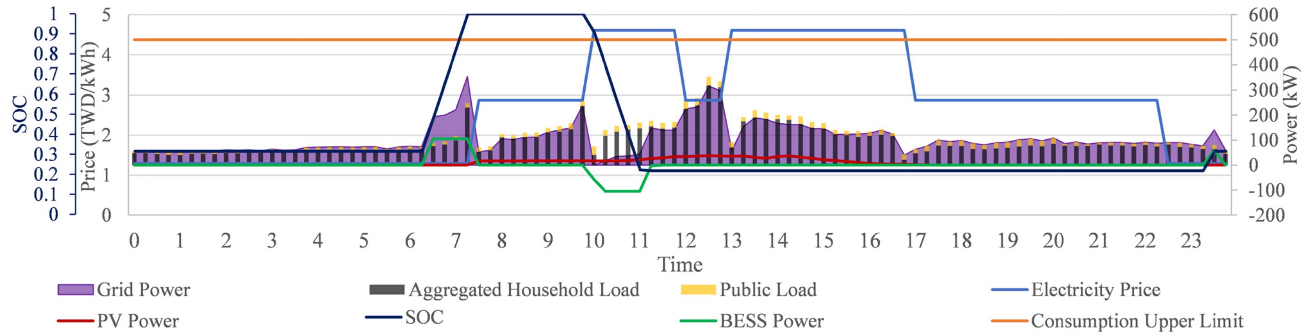

Fig. 14. The power dispatch results produced by the GEMS–case 4.

TABLE V
TOTAL BESS THROUGHPUT

Cases	Total BESS throughput (kWh)	
	With BESS cost	Without BESS cost
Case 1	258.73	1829.99
Case 2	240	1866.05
Case 3	240	1843.92
Case 4	240	1824.66

TABLE VI
TOTAL ENERGY GENERATED FROM PV SYSTEM

Cases	Total PV generated energy (kWh)	
	With PV cost	Without PV cost
Case 1	568.79	584
Case 2	568.79	584
Case 3	211.7	238
Case 4	211.7	238

throughput is lower if BESS degradation cost is considered. This is because the BESS degradation cost depends on the total BESS throughput, as shown in (43). In addition, the GEMS optimization in (44) is a minimization problem. When it is solved, the BESS throughput will be minimized in order to minimize the BESS degradation cost. Similarly, the total energy generated from the PV system is lower if PV degradation cost is considered.

V. CONCLUSION

A resident-centric distributed CEMS has been proposed, which allows each resident household to act autonomously, while securing the collective goals of the community to certain extent. The proposed CEMS minimizes electricity cost under TOUP regardless of the community participation in IBDR. When the community participates in IBDR, the proposed CEMS also maximizes incentive payoff. If the community participates in IBDR, the proposed CEMS stops the stoppable public loads during IBDR interval. Regardless of the community participation in IBDR and weather, the proposed CEMS performs power dispatch optimally. The computation time is not an issue as the proposed CEMS is solved in a distributed manner.

As electric vehicles become more and more popular, electric vehicle charging infrastructure is starting to appear in communities. Since electric vehicles are high-powered appliances, uncoordinated electric vehicle charging tends to create additional electricity demand. In this context, CEMS with electric vehicle charging scheduling will be a worthy subject of research. In future work, the mathematical models for electric vehicles can be incorporated into the proposed resident-centric distributed CEMS, equipping it with the ability to schedule electric vehicle charging. The proposed work considers the fully-dependent architecture, meaning that no energy trading is allowed among residents. For communities allowing energy trading between residents, the proposed framework could still be applicable after incorporating the constraints or objective functions that serve energy trading among residents. This can be another future direction of the proposed work.

In this paper, both residential uncontrollable loads and public uncontrollable loads are assumed to be predictable in the real-time optimization models for HEMS and GEMS. Machine-learning based load forecast approaches can be applied to predict these uncontrollable loads. This could serve as a good further research direction for the extension of the proposed research.

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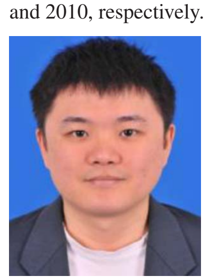

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