A Sustainable and User Behavior Aware Cyber-Physical System for Home Energy Management

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There is a growing trend for employing cyber-physical systems to help smart homes to improve the comfort of residents. However, a residential cyber-physical system is differed from a common cyber-physical system since it directly involves human interaction, which is full of uncertainty. The existing solutions could be effective for performance enhancement in some cases when no inherent and dominant human factors are involved. Besides, The rapidly rising interest in the deployments of cyber-physical systems at home does not normally integrate with energy management schemes, which is a central issue that smart homes have to face. In this paper, we propose a cyber-physical system based energy management framework to enable a sustainable edge computing paradigm while meeting the needs of home energy management and residents. This framework aims to enable the full use of renewable energy while reducing electricity bills for households. A prototype system was implemented using real world hardware. The experiment results demonstrated that renewable energy is fully capable of supporting the reliable running of home appliances most of the time and electricity bills could be cut by up to 60% when our proposed framework was employed.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability;

Additional Key Words and Phrases: cyber-physical sysmtem, human interaction, scheduling, energy management, renewable energy

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1 INTRODUCTION

A cyber-physical system (CPS) is a system of systems to allow physical phenomena to be probed or controlled via information-based approaches. The system generally includes processing modules that are responsible for acquiring data from sensors in a timely manner and issuing commands to operate actuators meet user needs. In recent years, CPS applications can be found on a wide spectrum of daily activities, including but not limited to home automation, smart grid, healthcare, vehicular applications and smart cities. Despite the primary purpose of the design of such a system being to enable bidirectional object-object interactions, human-object interactions are increasingly integrated into the expanding apparatus of the applications. With the involvement of human activities and interactions, expanded CPS (human-in-the-loop CPS, or HilCPS) would offer a great opportunity for restoring or augmenting human interaction with the physical world [Schirner et al. 2013].

As a popular CPS application associated with significant human interactions, smart home introduces enhanced monitoring and control functionality into residential environments. The energy consumption of households is always a noticeable issue since it accounts for around 35% of the overall consumption of all activities [Venkatesh et al. 2013]. Multiple studies have shown that residential energy consumption can be effectively reduced by dynamically adjusting the power demands of home appliances and electric vehicles. For example, the use of CPS-based home energy systems [Zhou et al. 2016] has successfully helped residents to reduce their electricity bills by shifting loads from peak hours to non-peak hours. However, the dual characteristics of regularity and variability of residents' behaviors could degrade the performance of most existing solutions when the human factor is not fully addressed. It is also vital to determine the willingness of residents to change their behaviors in cooperation with the energy management schemes without affecting their daily activities. Otherwise, the potential benefits gained from those energy management schemes may not be able to deliver as promised. It is also important to note that a significant portion (over 80%) of today's energy is still generated by fossil fuels (brown energy) [Eco [n. d.]]. As is well known, the widespread use of fossil fuels is implicated in global climate warming. Carbon taxes have helped to reduce the rapid anthropogenic release of carbon dioxide from fossil fuel, but also to drive up electricity prices for residents. To effectively lower the electricity bill in a sustainable way, the employment of renewable energy (green energy) is equally important to reduce the total energy demand of households from utility grid. With the growth of distributed power generators, they are capable of powering an increasing number of residents from green energy sources. Typical examples of these small on-site energy generators include rooftop solar panels, microturbines, and micro-wind generators. Advanced energy storage, e.g. thin-film batteries and super-capacitors, have become more mature and are usually used in combination with these green energy sources to better utilize them. These technologies open a new avenue for supporting various applications of smart homes.

In this article, we propose a framework design by integrating multiple renewable energy sources with smart homes to form a HilCPS environment in households by explicitly considering the human factor so as to reduce the electricity bill efficiently while still meeting the needs of the residents. In this design, we developed a smart appliance scheduling-based approach to manage residential energy based on user behavior constraints. These behavior constraints are represented by user willingness, which is formally modelled as the flexibility of the residents using different appliances. We adopted an information theory approach to analyze the cumulative distribution functions (CDF) of the starting time of various types of smart appliances. To obtain a quantitative measure, the entropy value of a CDF is used to indicate how a given appliance can be used, e.g. no flexibility, 1h-3h flexibility, etc. With these deadline values, we can treat the use of smart appliances as automatic jobs that can be scheduled to use the energy resource. We convert flexibility into deadlines and then assign reasonable deadlines to different appliance in different households and the underlying assumptions on user behaviors can be eliminated. In addition to that, we integrate with load determination and scheduling techniques to maximize the use of renewable energy harvesting from the ambient environment to minimize the electricity cost to a household. Our framework is able to achieve 75% energy savings and cut 60% from the electricity bill in a household, compared to the case where no such appliance scheduling is deployed.

2 RELATED WORK

Cyber-physical systems have been widely studied in the past and extensively used in industrial applications. Recently, researchers have started paying attention to investigating the interactions between human beings and CPS systems. In [Schirner et al. 2013], the human-in-the-loop CPS (HilCPS) is introduced as a specific type of CPS to denote the CPS systems that are involved with human factors. HilCPS is increasingly used in multiple domains, e.g. residential applications [Aksanli and Rosing 2017] and healthcare applications [Nunes et al. 2015].

One of the residential applications of HilCPS is to manage the energy consumption of home appliances based on the study of the historical activities of users. To extract the behavior patterns from residents, multiple approaches were developed accordingly to achieve the same goal. In [Cottone et al. 2015], [Muratori et al. 2013], the authors used common available activity data sets to group the users' behavior into different categories based on multiple criteria, e.g. age, gender, head counts in a house and employment status. With the help of these datasets, the researchers can either determine the sequences of a set of activities by using machine learning approach [Keshtkar and Arzanpour 2017], or which activity is most likely related to what appliance in a household [Delzendeh et al. 2017]. After that, the starting time of a given appliance and its operating conditions can be further estimated. The overall energy consumption of a household is then simply summed up on all the appliances. The major issue of this type of approach is that no realtime information about users can be obtained so that it becomes an offline design. Other studies collect the behavior of users directly. In [Yin et al. 2016], the user behavior is defined as the user's preference. In [Lee et al. 2013], user behavior is extensively studied in considering their willingness to use appliances. However, in this study the factor of flexibility was not addressed and the privacy concern was triggered since it is necessary to collect personal profiles from smart phone. By far, only a few studies [Aksanli and Rosing 2017], [Zhai et al. 2018] have conducted quantitative analysis on the flexibility of appliances. Most of those approaches just utilize the power consumption of smart appliances. Besides, controllability is usually only considered for energy hungry appliances, e.g. HAVC (Heating, Ventilation and Air Conditioning) and electric vehicles (EV). In addition, both existing research work and developed home energy management systems (HEMS) rarely address the integration of sustainable energy.

In an effort to address the issue of using sustainable energy to support the running of HEMS, we propose a low-cost sustainable HilCPS design as a home-level extension of the exploratory design of our sustainable edge computing systems [Li et al. 2018], which can not just reduce the electricity tariff, but also meet the needs of smart home applications and home energy management. In our HilCPS, the physical devices are the appliances and the sensing devices that provide the essential information, the cyber part is the appliance management functionalities running on the portable computing device and the residents frequently interact with the physical devices during their daily routines.

3 SYSTEM DESIGN OUTLINE

This section illustrates the HilCPS-based energy management framework for home appliances. We first introduce the overall design of the system. Then we provide the details of the function of the system modules and the interactions between them.

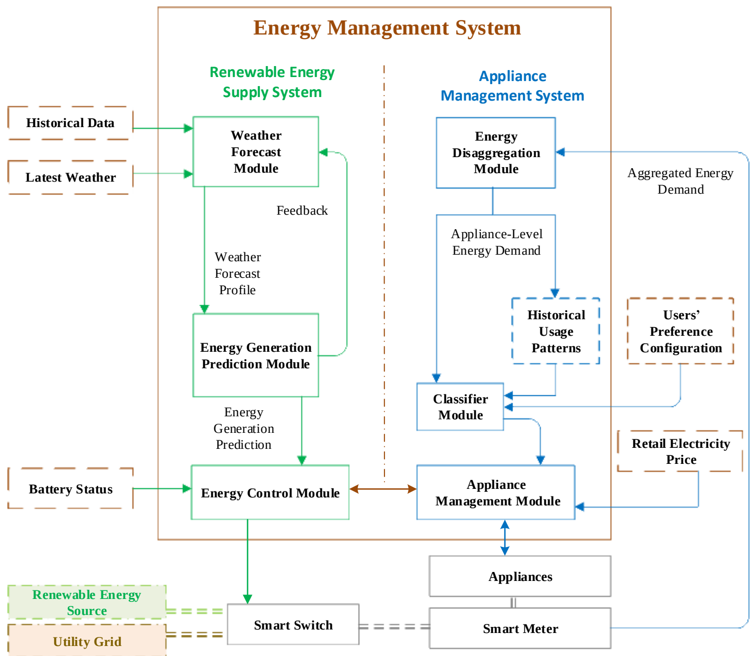

Fig. 1. The System Framework

3.1 System Overview

The proposal of our energy management system is designed for greening smart appliances, which aims to maximize the use of renewable energy in ordinary households while still conforming to users' needs. The overview of our design is depicted in Fig. 1, which contains two sub-systems, namely renewable energy supply system and appliance management system. With such a design, the operation time of smart appliances is automatically scheduled based on users' preferences, day-ahead electricity price, and historical usage profiles. Meanwhile, the system takes advantage of renewable energy harvesting techniques, the converted and stored renewable energy are used to minimize energy consumption from the utility grid in peak hours.

The renewable energy supply sub-system aims to maximize renewable energy utilization with an optimal energy allocation scheme. The major challenge of the sub-system is the intermittency of renewable energy generation, which is caused by the fluctuation of sunlight intensity. To address this issue, the sub-system integrates three modules with the functions of weather forecast, energy generation prediction and renewable energy management respectively. Receding horizon control strategy [Mattingley et al. 2011] is used for both the forecasting module and the renewable energy management module to achieve optimal renewable energy allocation.

The appliance management sub-system aims to minimize drawing electricity from the utility grid, particularly in peak hours when the energy price is high. In this sub-system, a smart meter is used to collect the overall load of a household and pass it to the energy disaggregation module. The voltage and current of individual appliances can be derived from the overall load in the energy disaggregation module. By analyzing the changes in current, the energy disaggregation module provides the real-time status of each appliance in the household. Then the appliance-level energy demand is passed to the classifier module, where the appliances are classified by users' preference profiles and historical usage records of appliances. The classifier filters the operating requests of appliances according to user requirements and the features of the appliances, only the selected information is passed to the appliance control module. In the appliance control module, the operation time of appliances is scheduled in order to maximize utilization of renewable energy.

3.2 System Components

Weather forecast module: The weather forecast module is responsible for providing coefficients associated with renewable energy generation, e.g. sunlight intensity, wind intensity, temperature and global horizontal irradiance. At the initial stage, the weather forecast module loads historical data that includes location information and day-ahead historical weather data. Then a weather forecast is generated based on the initial inputs. However, the uncertainty of cloud has a significant impact on renewable energy generation. It is hard to predict the formation, movement and dissipation of cloud only based on historical data. To reduce the deviation from the weather forecast module, a receding horizon control strategy is adopted in this module. The weather forecast is repeatedly computed on a pre-defined time granularity with the latest information, and the latest result will then be passed to the energy generation prediction module for further processing.

Energy generation prediction module: In this module, the output of renewable energy harvesting is estimated by the inputs from the weather forecast module and the hardware specifications of the renewable energy generator. For example, solar energy is a common type of renewable energy source. As is well known, the power generation of a solar panel is based on the volt-ampere characteristics of solar cells. In open-circuit solar cells, voltage decreases with temperature rise while other factors remain constant [Cuce et al. 2013]. Thus, with the prediction weather profile and renewable energy generator properties, energy generation from renewable energy sources can be predicted accordingly. Then the result is passed to the energy control module.

Energy control module: In the energy control module, there are three input profiles, including battery status, real-time energy demand and energy generation prediction. In this module, we aim to maximize the utilization of renewable energy by reducing conversion loss from charging and discharging batteries. Electricity from the renewable power system is given priority over the utility grid, with the surplus renewable energy stored in batteries. In our system design, smart appliances can be purely powered by either renewable power system or utility grid. A smart switch is equipped to connect both types of energy sources but only draws power from one source in any given time period.

Energy disaggregation module: Before stepping into appliance scheduling, our proposed system needs to be aware of historical details of execution time of each appliance for deducing user activities on a typical day. Based on this fine-grained appliance-level information, usage patterns of each appliance can also be derived and given a high priority so that the schedule plan generated from the appliance control module will retain a resemblance of customers' daily routines. Hence, for getting appropriate scheduling strategies for a household, usage patterns and features of each appliance are key information in need of timely acquisition as inputs. In general, Appliance Load Monitoring (ALM) approaches [Hosseini et al. 2017] can be employed to obtain this information. ALM approaches can be divided into two types, namely Intrusive Load Monitoring (ILM) and non-Intrusive Load Monitoring (NILM). For ILM, tremendous numbers of metering devices and sensors are deployed to achieve energy monitoring on each appliance in a distributed way, which leads to high cost of capital investment and increases complexity of system installation and maintenance. In contrast, NILM techniques have gained increasing popularity in both research and industry in recent years, and conduct energy disaggregation only based on overall energy consumption [Giri and Bergés 2015]. Advanced NILM techniques can be categorized into supervised NILM and unsupervised NILM. Most supervised NILM algorithms need extensive data sets for training and modeling of each appliance, which is hard to retrieve for household scenarios. As for the unsupervised NILM algorithms, like factorial hidden Markov models and artificial neural networks, they are computationally intensive. Considering these factors, a location-aware NILM approach [Uttama Nambi et al. 2015] is employed in our design, which not only reduces the complexity of computation, but also requires much less historical data for appliance modeling.

Classifier module: This module is designed for classifying the smart appliances into shiftable and unshiftable, and passing the information of shiftable appliances with adjustable range to the next module. The purpose of such classification is to satisfy householders' needs while completing the rescheduling of the appliances. The classification process is mainly based on flexibility. Flexibility refers to the extent to which the start time of an appliance can be adjusted, which depends on distribution of appliance usage during a day. Appliances with uniform usage distribution have better flexibility than those appliances that are always used around a certain preferable usage period. For example, lighting is a kind of rigid demand so that lamps theoretically have low flexibility. In contrast, dish washers might have higher flexibility as people are normally not in rush with those demands. Unshiftable appliances with low flexibility can be scheduled to another time only with difficulty. Thus, in our design, the system only reschedules the running of shiftable appliances with high flexibility.

To quantitatively obtain the flexibility of each appliance, we used an approach similar to that in [Aksanli and Rosing 2017] to modeling user flexibility. Based on historical data derived from the energy disaggregation module, the start times of each appliance are first extracted. Then we plot the graph of cumulative probability density function (CDF) for start times of each appliance, which presents the load distribution of a specific appliance and its usage patterns. After that, each CDF graph is assigned with an entropy value between 0 to 5. Each entropy value is associated with a threshold of time period to be adjusted, during which the start time of a given appliance job can be shifted accordingly. Each threshold not only reflects the flexibility of an appliance, but also determines job deadline. On the other hand, correlation is another coefficient to be considered during the scheduling process to satisfy user demands. It indicates the associations between different appliances, such as relevance and execution order. For example, radiant-cooker and range hood are usually used together. At the initial stage, the classifier module generates a preset user preference profile based on the variety of appliance and historical records. But householders are able to modify the profile at all times to better conform to their own habits.

In addition, appliances can be further classified into adjustable and unadjustable, which is based on user preferences. For an adjustable appliance, the setpoints or working mode can be dynamically altered based on user preferences. An unadjustable appliance always works in a fixed mode. Different to flexibility, user preference profiles can be set manually based on the personal habit of each resident.

Appliances management module: This module plays a vital role in this system, which is mainly responsible for job allocation and online scheduling. Once an appliance job is released, it will be allocated in an appropriate queue based on the allocation algorithm presented in Section 5. Thus, the energy source for powering the running of this appliance can be determined. After that, online scheduling will be achieved by employing the scheduling strategies in Section 5. During this process, the permutation as well as the energy source for jobs could be adjusted to guarantee system-level and appliance-level requirements. On the other hand, the start time of each job within the corresponding queue can also be shifted. Based on the profile from the classifier module, the type of any given appliance can be identified. For jobs released by unshiftable appliances, this module cannot change its start time. Instead, the start time of the jobs released by shiftable appliances can be adjusted within the corresponding threshold period obtained from the classifier

Table 1. Key Parameters

Notation	Definition
α	Appliances set in a household.
α_{shift}	A set of shiftable appliances.
$\alpha_{unshift}$	A set of unshiftable appliances.
α_i	The ith element in the set α (for short, we use α_i to denote as an appliance from now on).
η^d	The number of total appliances in a household.
$P_{\alpha_i}^{max}$	Maximum power consumption of an appliance α_i.
$P_{\alpha_i}(t)$	The real-time power consumption of appliance α_i at operation time t.
T_{α_i}	Maximum tolerance duration of a particular job released by appliance α_i.
L_{α_i}	Maximum operation time for appliance α_i to finish a particular job.
m_{α_i}	A set of working modes or setpoints of appliance α_i.
ρ_{α_i}	A set of values of power consumption, each of which matches up to a particular working mode of appliance α_i.
ω_{α_i}	A set of possible performance impacts made by appliance α_i.
ψ	A set of renewable energy sources used in household environment to generate electricity.
η^s	The number of renewable energy sources in the set ψ.
ψ_i	The ith element in ψ.
$P_{\psi_i}(t)$	Power generation from renewable energy source ψ_i at time t.
$P_{\psi_i}^{max}(t)$	Maximum total output power from each renewable energy source at time t.
$P_{\psi_i}^{d}(t)$	Actual output power supplied to appliances at time t.
P_c^{min}	Minimum charging power of the battery.
P_c^{max}	Maximum charging power of the battery.
P_d^{max}	Maximum discharging power of the battery.
$P_c(t)$	Actual charging power at time t.
$P_d(t)$	Actual discharging power at time t.
E_{max}	Battery capacity, representing the maximum amount of energy that can be stored in the battery.
$P_{loss}(t)$	Power dissipation on battery at time t.
$P_{grid}(t)$	Actual supplied power from utility grid at time t.
P_{grid}^{max}	Maximum supplied power from utility grid.
$C_{grid}(t)$	Real-time electricity price at time t.
λ_{α_k}	Appliance job released by appliance α_k.
$t_{\alpha_k}^r$	Release time of the job λ_{α_k}.
$t_{\alpha_k}^l$	Latest start time of the job λ_{α_k}.
σ	The smallest time unit.
ξ	The smallest power unit.
$Q_{release}$	A queue containing appliance jobs newly released by corresponding appliances.
Q_{ready}^r	A queue containing appliance jobs ready to be executed and powered by renewable energy
Q_{ready}^g	A queue containing appliance jobs ready to be executed and powered by utility grid
Q_{run}^r	A job queue containing appliance jobs currently running and powered by renewable energy
Q_{run}^g	A job queue containing appliance jobs currently running and powered by utility grid

model. Besides, to minimize energy consumption of an appliance, each appliance will be set to the most energy efficient mode before starting its operation. The details of scheduling strategies will be provided in the following sections.

4 SYSTEM MODELING

In this section, we first detail the models which are used in our proposal, including power demand and power supply. Afterwards, the problem formulation is formally given to describe the core problem addressed in this paper. The notations used in the rest of the paper are also listed in Table 1.

4.1 Power Demand

We model appliances in a typical household as follows, each of which entails variant power-demand operations at different time periods during a day. In a household, there is a set of smart appliances $\alpha = \{\alpha_1, \alpha_2, ..., \alpha_{\eta^d}\}$, where η^d denotes the number of total appliances. Each $\alpha_i \in \alpha$ can be modeled by a tuple $\{P^{max}_{\alpha_i}, T_{\alpha_i}, L_{\alpha_i}\}$, where $P^{max}_{\alpha_i}$ represents its maximum power consumption, T_{α_i} is maximum tolerant duration within which operations for a job of α_i are supposed be finished after the job is released, and L_{α_i} denotes its maximum operation time which is less than or equal to T_{α_i}. As presented in the last section, these appliances can be categorized into two types, shiftable appliances α_{shift} and unshiftable appliances $\alpha_{unshift}$. The start time of a job for a shiftable appliance is flexible and can be shifted within a constrained time period only if the job can be finished before the deadline. In contrast, the start time of a job from an unshiftable appliance is fixed. Therefore, if $\alpha_i \in \alpha_{shift}$, $L_{\alpha_i} > T_{\alpha_i}$, whereas $L_{\alpha_i} = T_{\alpha_i}$ if $\alpha_i \in \alpha_{unshift}$.

Both shiftable appliances and unshiftable appliances can further be classified into two groups, adjustable appliances α_{adjust} and unadjustable appliances $\alpha_{unadjust}$. Because setpoints and working modes of adjustable appliances can be selected, another three parameters $\{m_{\alpha_i}, \rho_{\alpha_i}, \omega_{\alpha_i}\}$ are required to model appliance α_i, where $\alpha_i \in \alpha_{adjust}$. m_{α_i} is a set of working modes or setpoints which can be set. ρ_{α_i} denotes different values of maximum power consumption and each $\rho^j_{\alpha_i} \in \rho_{\alpha_i}$ can be identified once a particular $m^j_{\alpha_i} \in m_{\alpha_i}$ is selected. ω_{α_i} represents a set of possible performance impacts when the working status of appliances is varied accordingly. Considering the dynamic nature of human behavior, it is assumed that each appliance α_i can be operated multiple times, thus for each job instance, the real-time power consumption of appliance α_i during operation period can be represented as $P_{\alpha_i}(t)$.

4.2 Power Supply

As mentioned in our proposed system architecture, we practically adopt a hybrid power-supply system comprised of three major components: (i) utility grid which is responsible for distributing electricity in a centralized manner, (ii) a set of renewable energy generators, such as rooftop renewable energy generators, microturbines, and micro-wind generators, (iii) household energy storage devices. Significantly lowering the carbon footprint of smart homes requires maximizing the utilization of renewable energy at each household. Thus we use renewable energy as the primary and brown energy from utility grid as the secondary energy supply. The specific model of this home-centric power-supply system is depicted as follows.

As we take multiple renewable energy sources into account, let $\psi = \{\psi_1, \psi_2, ..., \psi_{\eta^s}\}$ denote a set of renewable sources, where η^s is the number of elements in this set. At time t, power generation from renewable energy source ψ_i can be represented as $P_{\psi_i}(t)$. Besides, output power from each renewable energy source at t is limited to its power bound $P^{max}_{\psi_i}(t)$, which is normally less than $P_{\psi_i}(t)$ due to energy transition loss. Let $P^d_{\psi_i}(t)$ denote actual output power satisfying appliance demand. Considering uncertain nature of renewable energy, reliable forecasting techniques are supposed be employed as means to obtain the power generation of each energy source at different time period.

In the case of $P^d_{\psi_i}(t) < P^{max}_{\psi_i}(t)$, surplus supplied power from renewable energy sources will be distributed to the energy storage device for further employment in peak hours. The use of storage in conjunction with renewable energy sources is helpful to optimize the cost effectiveness of smart homes. Based on characteristics of the energy storage device, such as lithium-ion battery, the device is modeled with minimum charging power P_c^{min}, maximum charging power P_c^{max}, maximum discharging power P_d^{max}, battery capacity E_{max}. Let $P_d(t)$ and $P_c(t)$ denote the actual discharging power and charging power respectively, $E(t)$ is the actual battery status showing energy left. Due to the fact that there is always power dissipation $P_{loss}(t)$ on battery during the power supply at t, we need to improve utilization of energy accommodated in the battery by reducing the energy dissipated by internal resistance. According to the extensive study of the battery model by [Hredzak et al. 2014], the reduction of current could potentially reduce energy loss and extend the time for power supply.

With respect to electricity from utility grid, let $P_{grid}(t)$ denote the actual supplied power which is limited to the power bound P_{grid}^{max}. Rather than sporadic powering method of renewable energy sources, utility grid can provide stable supplied power at any time period, thus the supplied power only varies along with power demand from customers. Besides, the electricity price at time t is represented as $C_{grid}(t)$ varying constantly in accordance to real-time price adjustment from utility.

4.3 Problem Statement

The major problem for advanced energy management is defined as follows:

$$\max \frac{\int_0^T \left[\sum_{\psi_i \in \psi} P_{\psi_i}^d(t) + P_c(t) \right] dt}{\int_0^T \sum_{\psi_i \in \psi} P_{\psi_i}(t)\, dt} \tag{1}$$

subject to

$$\sum_{\alpha_i \in \alpha} P_{\alpha_i}(t) - P_{grid}(t) = \sum_{\psi_i \in \psi} P_{\psi_i}^d(t) \tag{2}$$

$$\sum_{\psi_i \in \psi} P_{\psi_i}^{max}(t) - \sum_{\psi_i \in \psi} P_{\psi_i}^d(t) \geq P_c(t) \tag{3}$$

$$P_{\psi_i}^d(t) \leq P_{\psi_i}^{max}(t) \tag{4}$$

$$P_c^{min} \leq P_c(t) \leq P_c^{max} \tag{5}$$

$$\int_{\Gamma}^{\Gamma+\sigma} P_c(t)\, dt + E(\Gamma) \leq E_{max} \tag{6}$$

$$P_{grid}(t) \leq P_{grid}^{max} \tag{7}$$

The primary objective of this work as shown in (1) is to maximize the utilization of renewable energy, which is supposed to satisfy the constraints (2), (3), (4), (5), (6), (7). $\sum_{\psi_i \in \psi} P_{\psi_i}^d(t)$ and $P_c(t)$ are control variables in objective function (1), whereas $\sum_{\psi_i \in \psi} P_{\psi_i}(t)$ is not, because renewable energy generation is mostly affected by multiple weather factors which cannot be manipulated by our system. At time t, only partial appliances releasing jobs are fully powered by renewable energy sources, and the remaining running appliances draw energy from utility grid. As shown in constraint (2), $\sum_{\psi_i \in \psi} P_{\psi_i}^d(t)$ can be identified once the number of appliances supplied by renewable energy sources is determined. To achieve it, an effective scheduling strategy is required to make a decision on selecting the energy source for each appliance. In order to balance the demand and power supply and maximize utilization of renewable energy, the start time of each shiftable appliance is supposed to be scheduled within tolerant duration T_{α_i}. Considering the constraints

(4) and (7), $P^d_{\psi_i}(t)$ for each renewable energy source ψ_i and $P_{grid}(t)$ are not supposed to exceed the corresponding power bound.

With respect to another control variable $P_c(t)$, once the total power demands $\sum_{\psi_i \in \psi} P^d_{\psi_i}(t)$ purely drawing from renewable energy and maximum output power $\sum_{\psi_i \in \psi} P^{max}_{\psi_i}(t)$ from renewable energy sources are obtained, it can be determined based on constraints (3) and (5). In order to maximize the utilization of renewable energy, surplus power is supposed to be assigned to the battery as much as possible only if the limitation on charging power is gratified. Apart from these two constraints, battery capacity is another factor that would affect decision making on the amount of power charged at time t. As shown in the constraint (6), total energy charged into battery from Γ to $\Gamma + \sigma$, where σ is the minimum arrival time unit of surplus renewable energy, also depends on the remaining energy in battery at Γ. At any time, it is expected to be guaranteed that the total energy stored in the battery cannot exceed the maximum energy capacity.

5 APPROACH AND SOLUTION

Because this energy management system resembles a quasi-real-time system, we matched the appliance scheduling problem with a real-time task scheduling problem. The two are similar, as a series of operations, contained in a job of each smart appliance, can be deemed as tasks in the applications, the deadline constraint for which is always to be satisfied. The sum of energy generation for appliance operations matches the available computing and storage resources in support of task processing. To achieve the objective presented in the last section, we first presented our designed scheduling framework for all appliance jobs in the household, and then defined appliance-level and system-level scheduling rules. This not only guaranteed meeting the deadlines for appliance operations, but also balanced the supply and demand for power. Based on these two scheduling rules, we developed three algorithms for real-time job scheduling, which was implemented across three critical stages, contained in the scheduling framework, and effectively maximized the utilization of renewable energy. In addition to the scheduling of appliance jobs, the algorithm for energy management of the battery will be presented in this section, aiming to achieve reduction of energy cost and peak demands.

5.1 Scheduling Rules

For this system, we propose appliance-level and system-level scheduling rules, which aim to guarantee all appliance operations are able to be completed before deadlines. Meanwhile, the power-supply system will not suffer power shortages at different time instants. Before introducing the appliance-level scheduling rule, we first define the maximum energy demanded by an appliance α_i during time period T as $f(\alpha_i, T, t_s)$, which can be calculated by Eq. (8) and Eq. (9) as follows:

$$f(\alpha_i, T, t_s) = P^{max}_{\alpha_i} \cdot \left\lfloor \frac{T}{T_{\alpha_i}} \right\rfloor \cdot L_{\alpha_i} + P^{max}_{\alpha_i} \cdot \max(0, T - \left\lfloor \frac{T}{T_{\alpha_i}} \right\rfloor \cdot T_{\alpha_i} - (T_{\alpha_i} - L_{\alpha_i})) \tag{8}$$

$$f(\alpha_i, T, t_s) = P^{max}_{\alpha_i} \cdot \min(L_{\alpha_i}, t_s + T - t^s_{\alpha_i}, t^s_{\alpha_i} + L_{\alpha_i} - t_s) \tag{9}$$

Given that α_i can be an appliance that releases jobs periodically, such as refrigerator and air-conditioner, it thus can operate multiple times during T. Because jobs of this type of appliances are mostly unshiftable, we separate this calculation into two parts. The first part of Eq. (8) is used to calculate the energy demands of appliance jobs, the duration of which is fully included within the period T starting from time instant t_s, and $\left\lfloor \frac{T}{T_{\alpha_i}} \right\rfloor$ implicitly represents the number of jobs of the appliance α_i during that time period. The second part shows the energy demands of the appliances whose operating duration is partially included within the period T. Regarding to the appliances that operate sporadically, the energy demands during the period T can be calculated by Eq. (9). The operating duration is the minimum interval length of L_{α_i}, $(t_s + T - t^s_{\alpha_i})$ and $(t^s_{\alpha_i} + L_{\alpha_i} - t_s)$, where $t^s_{\alpha_i}$ is the start time for α_i to operate, and formally we use the latest start time. In addition, we use $P^{max}_{\alpha_i}$ as the power consumption at each time instant in both Eq. (8) and Eq. (9), the maximum energy demands can thus be obtained.

Based on Eq. (8) and Eq. (9), the appliance-level scheduling rule can be defined as follows:

$$\chi_{\alpha_k} = \frac{\sum_{\alpha_i \in Q^T_\alpha} f(\alpha_i, T_{\alpha_k} - L_{\alpha_k} + \sigma, t^r_{\alpha_k})}{\int_{t^r_{\alpha_k}}^{t^l_{\alpha_k}+\sigma} \left[\sum_{\psi_i \in \psi} P^{max}_{\psi_i}(t) + P^{max}_d - P^{max}_{\alpha_k} + \xi \right] dt} \tag{10}$$

$$t^l_{\alpha_k} = t^r_{\alpha_k} + T_{\alpha_k} - L_{\alpha_k} \tag{11}$$

where $\alpha_k \in \alpha$ denotes the appliance in need of deadline guarantee analysis, $t^r_{\alpha_k}$ represents the release time of the job produced from appliance α_k, $t^l_{\alpha_k}$ denotes its latest start time which can be calculated by Eq. (11), Q^T_α is a set of appliances that are powered by renewable energy and operate during the time period T from $t^r_{\alpha_k}$ to $(t^l_{\alpha_k} + \sigma)$, σ is the smallest time unit, the same as the definition in constraint (6), and ξ represents the smallest power unit. For this appliance-level scheduling rule shown in Eq. (10), the numerator part of the fraction on the right hand side is able to calculate maximum renewable energy demands from running appliances except for α_k from $t^r_{\alpha_k}$ to $(t^l_{\alpha_k} + \sigma)$, and the denominator part is used to calculate the minimum renewable energy demands from other appliances that exactly prevent α_k from starting its operation. On the left hand side of Eq. (10), χ_{α_k} refers to the ratio of these two parts, which is a metric responsible for estimating the complexity of finishing job α_k without experiencing operation delay. The larger value of χ_{α_k} indicates more difficulties for appliance α_k to complete the job before the deadline only using power from renewable energy sources.

To avoid operation delay for the appliance α_k, the start time of its job should be strictly no later than $t^l_{\alpha_k}$. Thus we need to check if there is time instant within the period from $t^r_{\alpha_k}$ to $t^l_{\alpha_k} + \sigma$ for α_k to start its job effectively. We always consider the worst case where each appliance $\alpha_i \in Q^T_\alpha$ draws maximum energy from renewable energy sources during duration $(T_{\alpha_k} - L_{\alpha_k} + \sigma)$. Therefore, only if $\chi_{\alpha_k} < 1$ is satisfied, implying that sufficient energy generation from renewable energy sources can surely power α_k, α_k is able to start its operation before $t^l_{\alpha_k}$. However, if $\chi_{\alpha_k} \geq 1$, α_k will not guarantee to complete the job before the deadline.

The appliance-level scheduling rule only guarantees that any appliance powered by renewable energy can operate before the latest start time of a particular job, but it cannot guarantee that power generation is sufficient to complete all operations. Thus, the system-level scheduling rule is introduced to avoid power shortage during the operation time of each appliance. We define this rule as Eq. (12):

$$\sum_{\psi_i \in \psi} f(\psi_i, \Gamma, t_0) \geq \sum_{\alpha_i \in Q^\Gamma_{run}} f(\alpha_i, \Gamma, t_0) + f(\alpha_k, \Gamma, t_0) \tag{12}$$

$$f(\psi_i, \Gamma, t_0) = \int_{t_0}^{t_0+\Gamma} P^{max}_{\psi_i}(t)dt + E(t_0) \tag{13}$$

where Γ is the least common multiple of maximum tolerant operating duration T_{α_j}, $\alpha_j \in Q^\Gamma_{run} \cup \{\alpha_k\}$, Q^Γ_{run} contains jobs that start execution before a new job of α_k but their operation time partially overlaps with the job of α_k, t_0 denotes the earliest start time of α_i, $\alpha_i \in Q^\Gamma_{run}$. The total energy demanded by appliances contained in $Q^\Gamma_{run} \cup \{\alpha_k\}$ can be calculated by using Eq. (8) and Eq. (9). Eq. (13) is used to calculate the sum of available energy from renewable energy sources. Only if inequality Eq. (12) is satisfied, entire operations within the lifecycle of a particular job from appliance α_k can be feasibly accomplished without suffering power shortage.

5.2 Allocation Strategy for Appliance Jobs

On the basis of the critical scheduling rules presented above, we propose two algorithms which contribute to achieve maximum utilization of renewable energy in household scenarios. The first algorithm is to initially allocate released jobs of all smart appliances to an appropriate queue for further scheduling. The pseudo code is shown in Algorithm 1.

Algorithm 1 Job Allocation

```
1:  Initialize: Set up priority queues:
    Q_release Q^r_ready Q^g_ready Q^r_run Q^g_run;
2:  Assign each queue with value of ∅
3:  The following operations will be performed once any appliance releases new job
4:  for each λ_{α_k} released at time t do
5:      Q_release ← Q_release ∪ {λ_{α_k}}
6:  end for
7:  Sort Q_release according to the value of χ
8:  for each λ_{α_k} ∈ Q_release (with largest χ_{α_k} selected first)  do
9:      if f(α_k, Γ, t_0) meets rule (12) then
10:         if χ_{α_k} < 1 then
11:             Q^r_ready ← Q^r_ready ∪ {λ_{α_k}} (any insertion for Q^r_ready and Q^g_ready are according to the usage priority)
12:             for each α_i ∈ Q^r_ready do
13:                 if χ_{α_i} ≥ 1 or inequality (12) is not satisfied then
14:                     Q^g_ready ← Q^g_ready ∪ {λ_{α_k}}
15:                     Q^r_ready ← Q^r_ready \ {λ_{α_k}}
16:                 end if
17:             end for
18:         else
19:             Q^g_ready ← Q^g_ready ∪ {λ_{α_k}}
20:         end if
21:     else
22:         Q^g_ready ← Q^g_ready ∪ {λ_{α_k}}
23:     end if
24: end for
```

In Algorithm 1, λ_{α_k} denotes a particular job of the appliance α_k. Initially, Lines 1-2 set up five queues. $Q_{release}$ is used to contain the jobs to be finished released by appliances. Two ready queues Q^r_{ready} and Q^g_{ready} are comprised of appliances which are ready to operate and powered by two different energy sources, namely renewable energy and energy from utility grid. Another two running queues Q^r_{run} and Q^g_{run} contain the currently-running appliances powered by these two energy sources. Once any appliance releases a job, it will be first allocated to $Q_{release}$ and then this queue will be sorted based on χ of each appliance in the $Q_{release}$, which is presented in lines 4-7. Lines 8-22 are used to filter out the appliances completely powered by renewable energy based on the appliance-level and system-level scheduling rules, and insert these appliance jobs into Q^r_{ready} based on different usage priorities which corresponds to the deadlines. As mentioned before, the earlier deadline a job has, the higher priority it is assigned. Therefore, this allocation method implicitly ensures that the job with higher priority in Q^r_{ready} will be executed earlier, which not only simplifies the work in the following scheduling stage, but also significantly lowers the risk of sacrificing users' comfort. Once the job newly inserted in Q^r_{ready} is assigned with higher priority than some existing jobs in the same queue, the execution order of these jobs would be adjusted, leading to the deadline violation. To avoid this case, the system needs to individually check the satisfaction of the appliance-level scheduling rule for all these jobs as shown in Lines 12-17. For other appliances violating these two scheduling rules, the system will put them into Q^g_{ready}.

5.3 Scheduling Strategy for Appliance Jobs on Q^r_{ready}

Algorithm 2 Job Scheduling on Q^r_{ready}

1: **while** System is on **do**
2:   **for** each $\lambda_{\alpha_k} \in Q^r_{ready}$(with high priority selected first) **do**
3:     **if** $P^{max}_{\alpha_k} < \sum_{\psi_i \in \psi} P^{max}_{\psi_i}(t) + P^{max}_d - \sum_{\alpha_i \in Q^r_{run}} P^{max}_{\alpha_i}$ **then**
4:       Search for $\omega^{\zeta}_{\alpha_k} \in \omega_{\alpha_k}$ corresponding to users preference
5:       Search for a working mode $m^{\zeta}_{\alpha_k} \in m_{\alpha_k}$ mapping to $\omega^{\zeta}_{\alpha_k}$
6:       $Q^r_{run} \leftarrow Q^r_{run} \cup \lambda_{\alpha_k}$
7:       $Q^r_{ready} \leftarrow Q^r_{ready} \backslash \lambda_{\alpha_k}$
8:       **for** each $\lambda_{\alpha_i} \in Q^r_{ready}$ **do**
9:         **if** $\chi_{\alpha_i} \geq 1$ or inequality (12) is not satisfied **then**
10:           $Q^g_{ready} \leftarrow Q^g_{ready} \cup \{\lambda_{\alpha_i}\}$
11:           $Q^r_{ready} \leftarrow Q^r_{ready} \backslash \{\lambda_{\alpha_i}\}$
12:         **end if**
13:       **end for**
14:     **end if**
15:   **end for**
16:   The following steps will be executed only if any appliance finishes its job
17:   **for** each λ_{α_j} finished at time t **do**
18:     **if** $\lambda_{\alpha_j} \in Q^r_{run}$ **then**
19:       $Q^r_{run} \leftarrow Q^r_{run} \backslash \{\lambda_{\alpha_j}\}$
20:     **else**
21:       $Q^g_{run} \leftarrow Q^g_{run} \backslash \{\lambda_{\alpha_j}\}$
22:     **end if**
23:   **end for**
24: **end while**

After selecting the appropriate power source for each released appliance job, the system is supposed to realize online scheduling on Q^r_{ready} and Q^g_{ready}. Algorithm 2 presents the detailed procedure of performing job scheduling on Q^r_{ready}. To maximize the utilization of renewable energy, the difference between total renewable energy generation and total energy consumption of appliance jobs from the running queue is taken into account. When the energy generation is greater than the maximum power consumption of an appliance α_k, the new job λ_{α_k} will be added to the running queue and the appliance will start its operations immediately, as depicted in lines 3-7. In this procedure, if the selected appliance is an adjustable one, it needs to be set to an appropriate working mode which not only reduces energy drawn from utility grid, but also meets users' preferences. Considering cases where appliance jobs with lower priority may be executed first only if the requirement shown in line 3 is satisfied, the actual operation sequence of the appliances in

Q^{r}_{ready} would be changed accordingly. Thus, the system is required to check the appliance-level scheduling rule for each appliance in Q^{r}_{ready} once a new job is added into Q^{r}_{run} in case of causing operation delay. Once the appliance finishes all operations of a job, the job is removed from the running queue as depicted in lines 16-23.

Algorithm 3 Job Scheduling on Q^{g}_{ready}

1: The following operations will be performed once new appliance job is inserted into Q^{g}_{ready}
2: Search for $\omega^{\zeta}_{\alpha_k} \in \omega_{\alpha_k}$ corresponding to users preference
3: Search for a working mode $m^{\zeta}_{\alpha_k} \in m_{\alpha_k}$ mapping to $\omega^{\zeta}_{\alpha_k}$
4: Search for a working power $\rho^{\zeta}_{\alpha_k} \in \rho_{\alpha_k}$ mapping to $m^{\zeta}_{\alpha_k}$
5: $\lambda_{first} \leftarrow Q^{g}_{ready}[0]$
6: $\lambda_{last} \leftarrow Q^{g}_{ready}[n]$
7: $\tau_0 \leftarrow t^{r}_{\alpha_{first}}$
8: $\tau_n \leftarrow t^{r}_{\alpha_{last}} + T_{\alpha_{last}}$
9: $F(\tau_0, s(\tau_0)) = 0$
10: **for** $\tau_i = \tau_0 \ to \ \tau_n$ **do**
11:     **for** each possible system state $s(\tau_i)$ at τ_i **do**
12:         **for** each $\lambda_{\alpha_k} \in Q^{g}_{ready}$ **do**
13:             **if** $t^{r}_{\alpha_k} \leq \tau_i \leq (t^{r}_{\alpha_k} + T_{\alpha_k} - L_{\alpha_k})$ **then**
14:                 **if** $\tau_i \leq (t^{r}_{\alpha_k} + T_{\alpha_k} - L_{\alpha_k}) \leq \tau_{i+1}$ **then**
15:                     $Q^{g}_{run} \leftarrow Q^{g}_{run} \cup \{\lambda_{\alpha_k}\}$ (not real scheduling)
16:                     $Q^{g}_{ready} \leftarrow Q^{g}_{ready} \backslash \{\lambda_{\alpha_k}\}$ (not real scheduling)
17:                 **else**
18:                     Add λ_{α_k} into the job set $\Lambda[\ ]$ as a candidate
19:                 **end if**
20:             **end if**
21:         **end for**
22:         Calculate all possible subsets of $\Lambda[\ ]$
23:         **for** each possible job set $\phi \subset \Lambda$ **do**
24:             **for** each $\lambda_{\alpha_j} \in \phi$ **do**
25:                 **if** $(\sum_{\lambda_{\alpha_i} \in Q^{g}_{run}} P^{max}_{\alpha_i} + P^{max}_{\alpha_k}) \leq P^{max}_{grid})$ **then**
26:                     $Q^{g}_{run} \leftarrow Q^{g}_{run} \cup \{\lambda_{\alpha_j}\}$ (not real scheduling)
27:                     $Q^{g}_{ready} \leftarrow Q^{g}_{ready} \backslash \{\lambda_{\alpha_j}\}$ (not real scheduling)
28:                 **end if**
29:             **end for**
30:         **end for**
31:     **end for**
32:     Gain all possible system states $S(\tau_{i+1})$ at τ_{i+1} after above operations
33:     **for** each possible system state $s(\tau_{i+1})$ at τ_{i+1} **do**
34:         $F(\tau_{i+1}, s(\tau_{i+1})) \leftarrow \min\{F(\tau_i, s(\tau_i)) + W(s(\tau_i), s(\tau_{i+1}))\}$;
35:     **end for**
36: **end for**
37: Schedule the jobs in Q^{g}_{ready} based on critical path reaching to $s(\tau_n)$

5.4 Scheduling Strategy for Appliance Jobs on Q^g_{ready}

For the appliance jobs assigned to Q^g_{ready}, we also develop an optimal scheduling strategy, which can substantially reduce the energy cost for each household. Before getting into the details of the algorithm, we first model the scheduling problem as follows.

$$\min\left\{\sum_{\lambda_{\alpha_i}\in Q^g_{ready}}\left[\int_{t^s_{\alpha_i}}^{t^s_{\alpha_i}+T_{\alpha_i}} C_{grid}(t)\cdot\ P_{\alpha_i}(t)dt\right]\right\} \tag{14}$$

subject to

$$t^r_{\alpha_i} \le t^s_{\alpha_i} \le (t^r_{\alpha_i} + L_{\alpha_i} - T_{\alpha_i}),\ \forall\alpha_i \in Q^g_{ready} \tag{15}$$

$$\sum_{\lambda_{\alpha_i}\in Q^g_{ready}} P_{\alpha_i}(t) \le P^{max}_{grid} \tag{16}$$

As shown in (14), the objective of the scheduling is to minimize the total energy cost of the jobs currently within Q^g_{ready} . $t^s_{\alpha_i}$ denotes the start time of a certain appliance job λ_{α_i}, which is a decision variable in this optimization problem. Thus the number of decision variables is equal to the number of appliance jobs within Q^g_{ready}. Meanwhile, there are two critical constraints (15) and (16) as basic scheduling principles that the system should satisfy when deriving job schedules. The employment of constraint (15) guarantees that each job is able to finish its entire operations no later than its deadline, and the constraint (16) indicates that total power consumption at a given time instant cannot exceed a certain power bound which depends on the power capability of the utility grid. In an effort to derive cost-effective schedules for the whole system, we developed a dynamic programming (DP) based strategy in Algorithm 3.

In Algorithm 3, $S(\tau_i)$ denotes a set of possible system states at time instant τ_i, and $s(\tau_i)$ is one of the elements within that set, recording the state of each job either in Q^g_{run} or Q^g_{ready}. $F(\tau_i, s(\tau_i))$ is the cost-to-go for this system when the DP algorithm is employed, which represents minimum total energy cost to reach system state $s(\tau_i)$ from the beginning of runtime, and $W(s(\tau_i), s(\tau_{i+1}))$ denotes the optimal transition cost from $s(\tau_i)$) to $s(\tau_{i+1})$), which is used to calculate $F(\tau_{i+1}, s(\tau_{i+1}))$. The entire procedure in Algorithm 3 will only be performed once a new appliance job is inserted into Q^g_{ready}. In the procedure, we firstly identify the operating duration of appliance jobs, starting from the release time of the first job and ending at the deadline of the last job within Q^g_{ready}. We also select the appropriate working mode for the appliances that have job(s) currently allocated in the Q^g_{ready} as shown in lines 2-4, which aims to reduce energy consumption while guaranteeing performance satisfaction. Then, the system is expected to iteratively search for cost-effective schedules at different stages. As depicted in lines 11-31, based on constraints 15 and 16, the system will filter out a set of appliance jobs $\Lambda[\ ]$ that could be added into Q^g_{run} at certain stage τ_i and search for all possible system states at τ_{i+1} by dispatching different combinations of candidate appliance jobs into Q^g_{run}. For each possible system state at τ_{i+1}, optimal energy cost can be calculated by employing the formula shown in line 34. Ultimately, minimum total energy cost at the final state $s(\tau_n)$ can be calculated and the optimal job schedules at different stages are effectively generated as well.

6 A PROOF-OF-CONCEPT CASE STUDY

To evaluate the feasibility and the performance of our design, we set up a small-scale testbed powered by a hybrid energy supply, which includes renewable energy generators and the utility grid. In this testbed, we used real-world

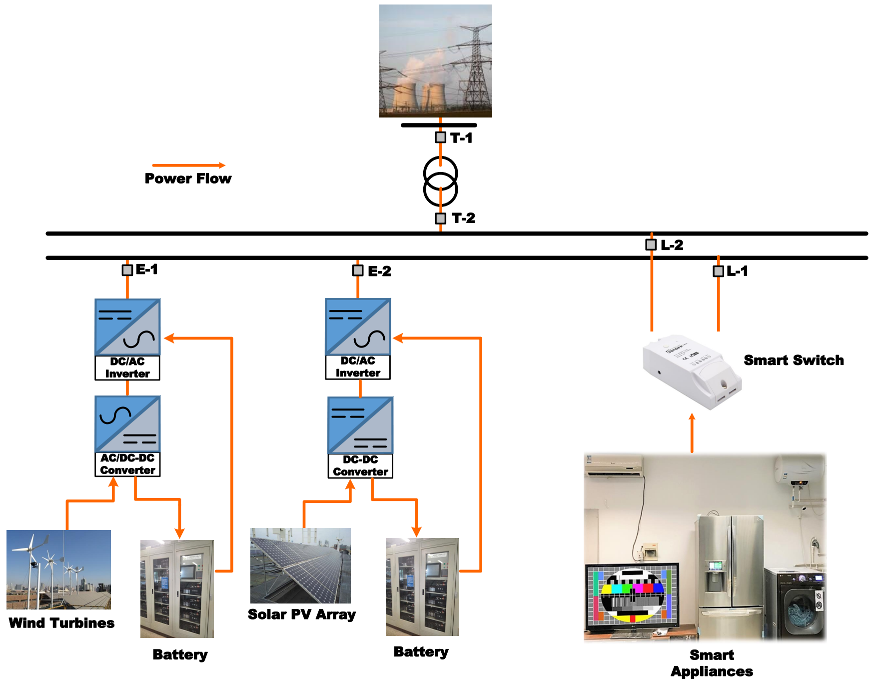

Fig. 2. Experiment Setup

smart appliances to emulate a household scenario. In this section, we firstly introduce the details of our experiment setup and the implementation of our proposed framework. Then the results of the performance evaluation will be discussed.

6.1 Experiment Setup

In this experiment, we designed a testbed as shown in Fig. 2, which can be deemed as a household. The smart appliances used in this testbed include smart refrigerator, washing machine, air-conditioner, TV and water heater. The average power consumption of a TV is 100W and the air-conditioner consumes 665W in an hour. For the washing machine, two washing programs were considered in this experiment, which are daily wash (137W) and delicate (147W) respectively. The smart refrigerator can also work in two different modes, which on average consume 98W and 78W respectively. Regarding the water heater, we selected three setpoints, 60°C, 65°C and 70°C, any of which is possible to be set in our daily life. Based on a long-term measurement, we figured out that the average power consumption of these three setpoints are 1216W, 1330W and 1551W respectively. A Raspberry Pi 3B device with a quad-core CPU and 1 GB RAM was used for running our proposed framework. In addition, this testbed was equipped with multiple smart swtiches to remotely control the running of corresponding appliances and adjust their working modes. To store the surplus energy from the renewable energy source, we used a Lithium-ion battery with capacity of 1.5KWh in our experiments.

In this testbed, a hybrid power supply system was employed to power these smart appliances, which combines renewable energy generators and utility grid. To generate renewable energy, we set up photovoltaic arrays as a solar energy source and three wind turbines as a wind power source. The phtovoltaic arrays have peak output power of 600W

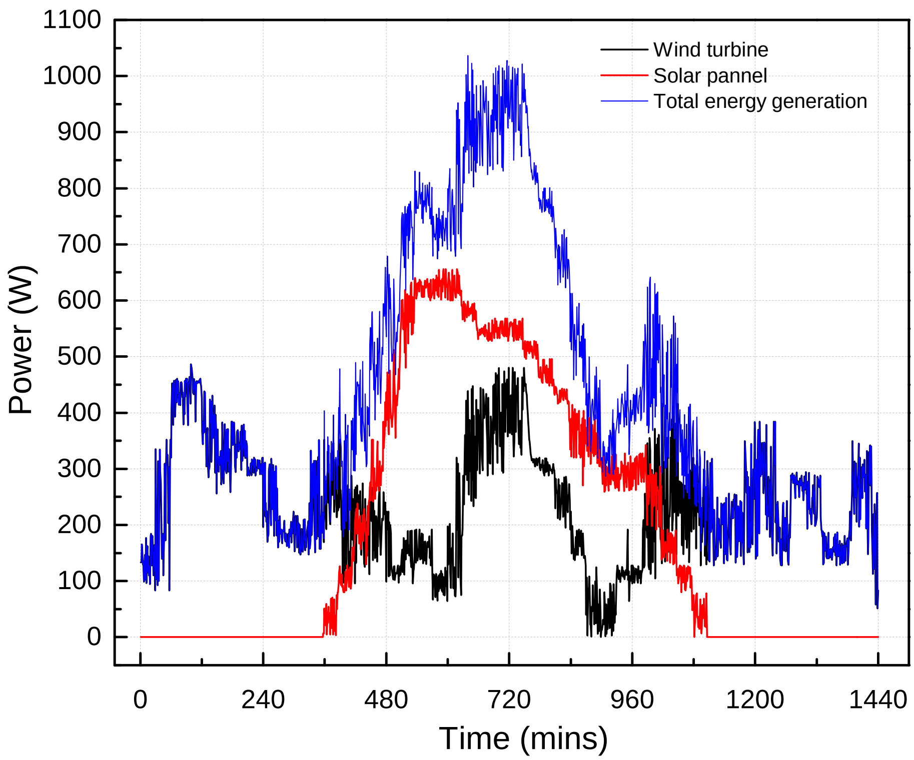

Fig. 3. Power Generation

Table 2. Energy Consumption

Experimental case	Renewable energy generation	Total energy consumption	Renewable energy consumption
Case 1	10.03KWh	6.75KWh	3.15KWh
Case 2	10.03KWh	6.38KWh	4.79KWh

and the peak power output of each wind turbine can be 150W. To enhance reliability of the whole system and derive optimal appliance schedules, we conducted intra-day energy generation prediction based on weather forecasts acquired from Solcast [Sol [n. d.]] and Windfinder [Win [n. d.]]. Both of them provide API for users to retrieve forecasting information of sunlight intensity, temperature, wind gusts and wind speed from a given location. As is well known, day-ahead pricing information is supposed to be periodically retrieved from the utility company. In Australia, the electricity prices over a day that residential users get from energy retailers are three static values, matching up with three fixed time periods, peak hours, off-peak hours and shoulder hours respectively. With respect to aggregated energy consumption, we used one smart meter measuring energy consumption of all appliances, and then derived fine-grained appliance-level information by using the NILM algorithm employed in one of our previous works.

To benchmark the performance of our design, we also conducted experiments without any schedule strategies on each appliance, simply aligning with users' behavior in daily routine. The results of this experiment will be compared with the case employing the proposed scheduling strategies.

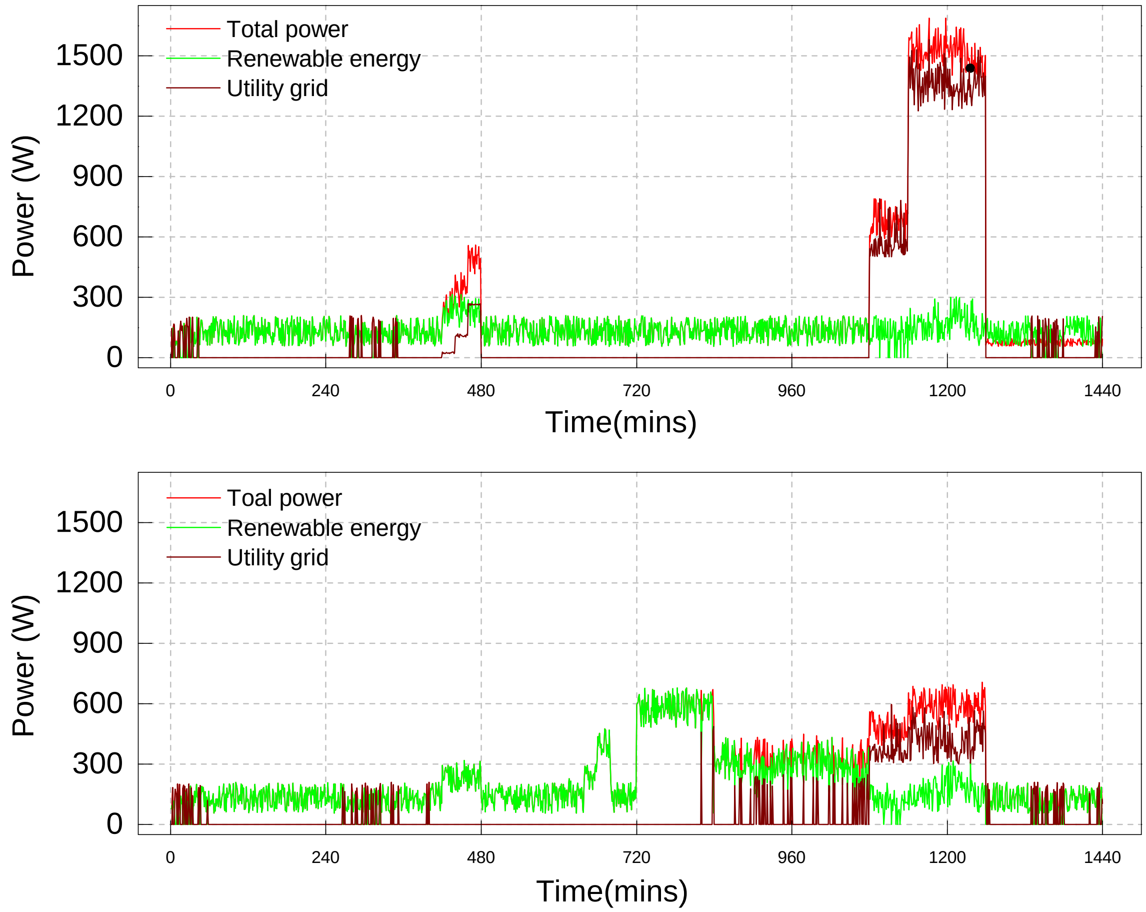

Fig. 4. Power Consumption

6.2 Performance Evaluation

We evaluated the performance of our proposed HilCPS-based energy management system over five weekdays and collected corresponding data. Fig. 3 shows the renewable energy generation on one day. The largest proportion of renewable energy generation comes from 9AM to 4PM and the peak output power of this solar-wind hybrid power supply can reach to 1020W at around 1PM. Actual energy consumption from both renewable energy sources and utility grid are shown in Fig. 4. In this experiment, we compared renewable energy usage between two experimental cases realized by two different scheduling strategies.

As shown in the upper part of Fig. 4, we emulated the daily routine of a typical family and the appliances ran immediately once the jobs were released, without employing any scheduling strategies. The schedule profile generated from the appliance control module was based on residential habits in a typical day. Within the selected day, the smart refrigerator mostly drew energy from renewable energy sources except for the period 0AM-1AM and 6AM-7AM. During the daytime from 6AM to 5PM, most energy consumption was covered by renewable energy, and the surplus energy generated from photovoltaic arrays and wind turbines was stored in batteries for future use. However, from 7AM to 8AM, renewable energy was not sufficient to support the running of the washing machine, thus it fully drew power from utility grid during that time period. From 6PM to 9PM, as user activities significantly increased, a set of appliances was turned on, including air-conditioner, TV and water heater. The available renewable energy was not sufficient in that time period, and the energy stored in the battery was quickly depleted by 7PM. The energy consumed by appliances is mainly supplied by utility grid. In this case, as shown in Table 2, the sum of energy consumption is 6.75KWh and renewable energy generators produced 10.03KWh energy in total. Only 3.15KWh renewable energy, however, was consumed by the appliances, which represents 46% of total energy consumption. Thus, only 30% of total renewable energy generation was used, but more renewable energy was wasted.

The bottom part of Fig. 4 shows the energy consumption of appliances that followed the schedule strategies proposed in the last section. In this experiment, the appliances are firstly classified into two types, shiftable appliances and unshiftable appliances. The unshiftable appliances, including TV, air conditioner, and refrigerator, need to run immediately once the jobs were released. In contrast, the shiftable appliances deployed in our testbed, including washing machine and water heater, are more flexible to adjust their operation time. Therefore, the operation time of both appliances could be arranged to work during the period when the renewable energy supply was plentiful. To meet the deadlines of the jobs, as shown in Fig. 4, the washing machine was scheduled to operate from 9AM to 10AM, and water heater started working at 1PM and finished the job before 9PM. By doing so, the deadline of each appliance job was thus guaranteed. In addition, the battery was fully charged by 5PM before the solar energy generation dropped down to zero. Since most workloads of appliances are shifted to daytime, the energy demands at peak hours were significantly alleviated. From 6PM to 9PM, most energy supply from utility grid was drawn by the air-conditioner due to its low flexibility. The remaining workload could be fully powered by the battery and the renewable energy generated from wind turbines until 10PM, exactly avoiding the peak hours. In this experiment, because wthe ater heater and washing machine were adjusted to a relatively low working mode based on user preferences, total energy consumption dropped down to 6.38KWh. As shown in Table 2, the total renewable energy usage reached 4.79KWh, which takes up to 48% of total renewable energy generation and 75% of total energy consumption. Compared to the previous experiment, this experiment employing the effective online scheduling strategies not only shows significant improvement on the utilization of renewable energy, but also shows high reduction of energy demands.

6.3 Cost Reduction

To study the cost reduction when the proposed scheduling strategies are employed, we analyzed the distribution of appliance loads in two different experimental cases during the selected day, which were powered by utility grid. As shown in the upper part of Fig. 5, the blue line represents the variation of the real-time electricity price within a day. In Australia, the electricity market is operated by the Australian Energy Market Operator, which offers electricity to the energy retailers at every five minute interval with the average price over the past 30 minutes. As shown in Fig. 5, most energy consumption occurred at the peak hours (6PM-9PM) when the electricity price was high, leading to high energy cost. In the bottom part of Fig. 5, partial workloads from appliances were shifted to the period from 3PM to 6PM when the electricity price was lower. Furthermore, every appliance was adjusted to a lower setpoint or working mode without jeopardizing users' comfort. Comparing these two different cases, the energy cost was significantly reduced by 60%.

7 CONCLUSION

We propose a HilCPS based energy management system in this article, which explicitly take human interactions into consideration to guarantee the needs of users are fully met. In this system, we support analysis of user preference on each appliance and use an entropy-based solution to convert the flexibility of appliances into deadlines. Moreover, on

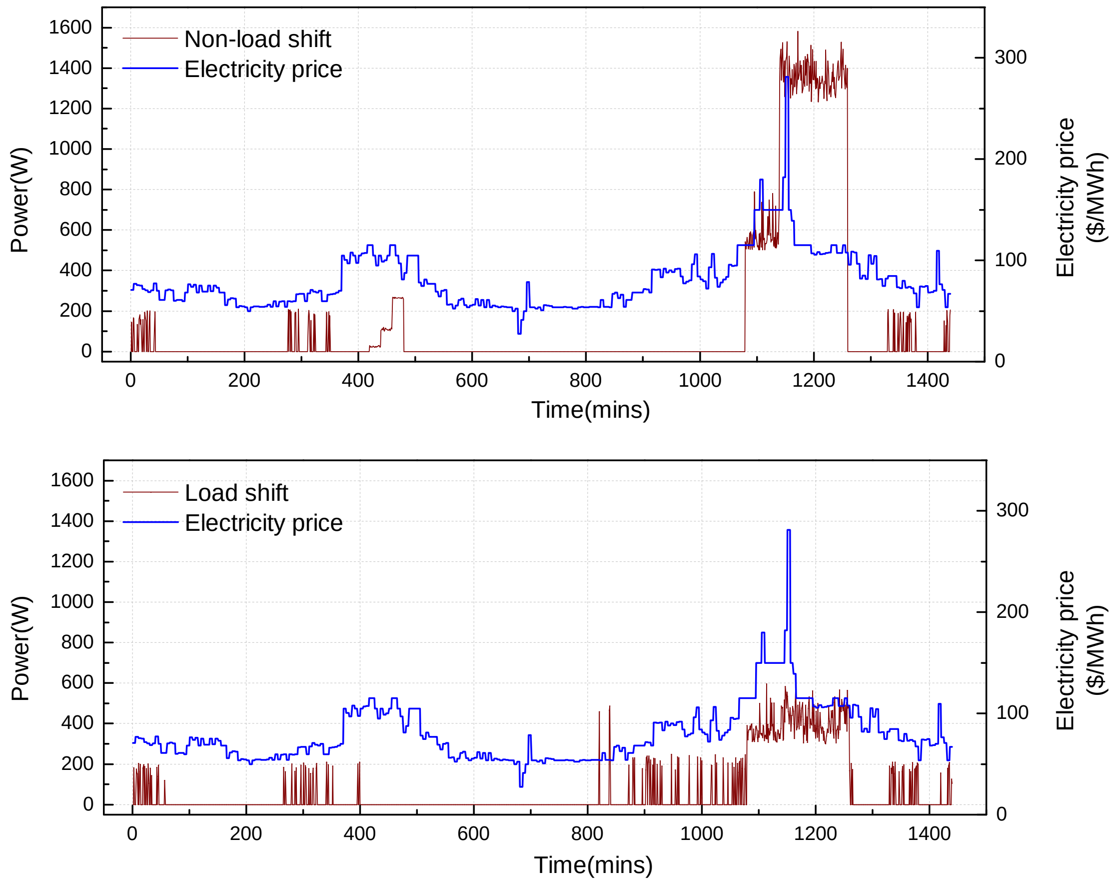

Fig. 5. Cost Reduction

top of a traditional load shifting approach, an optimal scheduling strategy for appliance jobs is presented, which is helpful to achieve energy management in a sustainable way without jeopardizing users' comfort. To conduct evaluation of this system framework and proposed scheduling strategy, we implement a testbed with real smart appliances, and practically prove that this system can effectively maximize the utilization of local renewable energy and significantly lower energy cost.

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