Optimal Home Energy Management System with Demand Charge Tariff and Appliance Operational Dependencies

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***Abstract*—Two-way communication facilities and advanced metering infrastructure enable residential buildings to be capable of actively participating in demand side management schemes. This paper proposes a new home energy management system (HEMS), which optimally schedules the operation of home energy resources, with the aim to minimize the home's one-day electricity cost charged by the real-time pricing while taking into account the monthly basis peak power consumption penalty, charged by the demand charge tariff. To better ensure the user's lifestyle requirements, the HEMS also models lifestyle-related operational dependencies of household appliances. Numerical simulations and case studies are conducted to validate the reasonability of the proposed method.**

***[1]Index Terms*—Smart home, demand response, demand side management, building automation, smart grid**

NOMENCLATURE

Indices and Sets

a, Ω	Index and set of HERs
$\Omega^1, \Omega^2, \Omega^3, \Omega^4$	Set of HERs with the category index of 1, 2, 3, and 4;

Parameters

A	Surface area of the PV solar panel (m^2);
T	Total number of scheduling time intervals;
Δt	Duration of a time interval (hour);
σ	Energy conversion efficiency of the PV solar panel (%);
r_t	Solar radiation at time t (kW/m^2);
P_t^{pv}	Solar power output at time t (kW);
$P_a^{\min}, P_a^{\max}$	Minimum and maximum power consumption of appliance a (kW);
P_a^{rate}	Rated power of appliance a (kW);
$\varphi^{low}, \varphi^{up}$	Lowest and highest acceptable indoor temperature specified by the user (ºC);
φ_t^{out}	Outdoor temperature at time t (ºC);
λ_t^{RTP}	Forecasted real-time electricity price at time t ($/kWh);
λ^{DCT}	Demand charge tariff ($/kW);
P'	Historical peak power in previously days of the current month (kW);
ω	Weighting constant;
η^c, η^d	Charging and discharging efficiency of the RBESS (%);
$E^{ess,rate}$	Energy capacity of the RBESS (kWh);
t_a^{pmt1}, t_a^{pmt2}	Begin and end time of the user-specified permitted operation time range of appliance a;
$P^{ess,rate}$	Rated power of the RBESS (kW);
$SOC^{\min}$	Lower SOC limit of the RBESS (%);
$SOC^{\max}$	Upper SOC limit of the RBESS;
SOC^{dsr}	Minimum SOC level of ESS a at the end of the scheduling horizon;
C^{th}, R^{th}	Thermal capacitance (kWh/ºC) and reactance (ºC/kW) of the building;
E_a^{req}	Required energy consumption of appliance a (kWh);
$\tau_a^{on,\min}$	Minimum online time requirement of appliance a (hour);

Variables

$s_{a,t}$	Status of the controllable appliance a at time t (1-ON, 0-OFF);
φ_t	Indoor temperature at time t (ºC);
$\mathbf{P}_i$	Power consumption schedule of HER i;
$\tilde{\mathbf{P}}^h$	Net-house power consumption profile;
$P_{i,t}$	Power consumption schedule of HER i at time t;
SOC_t^{ess}	State-of-Charge of the RBESS at time t (%);
E_t^{ess}	Energy stored in the RBESS at time t (kWh);
P_t^{ess}	Power consumption of the RBESS at time t (kW, positive: charging, negative: discharging);

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P_t^{ac} Power consumption of the air conditioner at time t (kW);

$\tau_{a,t}^{on}$ Accumulated online duration of controllable appliance a at time t (hour);

I. Introduction

DMAND RESPONSE is one of the most important topics in smart grid. Through two-way communication facilities and Advanced Metering Infrastructure (AMI), demand side resources are capable to actively respond to certain demand side management (DSM) signals and re-shape their power consumption profiles [1]. Demand response is beneficial for both end users and the utility. On one hand, it can help end users to reduce their electricity cost and better utilize user-side energy sources; on the other hand, it can support the grid's operation in terms of balancing renewable energy, shifting system peak demand, reducing generation backup, inferring network investment, and so on.

From the utility's prospective, traditional DSM schemes can be categorized into two classes: incentive-based DSM (or known as Direct Load Control, DLC) and pricing-based DSM (or known as Indirect Load Control, IDLC). In DLC, appliances in buildings are directly controlled by the utility through remote controllers in certain time periods (e.g. peak demand or emergent periods). As subsidy, the utility provides the user certain incentive schemes, such as electricity pricing discount or customer reward. In IDLC, users are encouraged to actively shift their appliance usage time under certain dynamic electricity tariffs. The current commonly applied dynamic tariff schemes include Time-of-Use (TOU) tariff, Real-Time Pricing (RTP), critical peak pricing, etc.

In recent years, with increasing applications of building automation devices and home wireless communication facilities, Home Energy Management Systems (HEMS) [2] have been playing important roles in demand response. HEMS is essentially a kind of intelligent automation system that provides decision-support for residential users to effectively schedule and control home energy resources. HEMS can significantly help the user to tackle complexity incurred by the frequent update cycles of dynamic electricity tariffs, and also act as a delegation of the user to communicate with the utility and grid. Design and development of HEMS is extensively studied in the literature, with some representative works listed as follows. [2] proposed a HEMS that optimally schedules the operation of household appliances under a RTP scheme. [3] optimally schedules a Residential Battery Energy Storage System (RBESS) and multiple controllable household appliances to accommodate a rooftop solar power source. In [4], a household appliance commitment framework is proposed to minimize the household operation cost. In [5], a HEMS is designed, which dynamically schedule appliances in each dwelling unit based on which the power demand of the whole community was forecasted and reported to the utility. [6] proposes a two-stage HEMS where, in the first stage, the charging/discharging of a RBESS is optimally scheduled based on the forecasted solar power and, in the second stage, the actual charging/discharging of the RBESS was determined based on actual solar power output. [7] studies the coordinated scheduling of heating, ventilating, and air conditioning (HVAC) system and home plugged EV. In our recent work [8], we study the development of HEMS with vehicle-to-home (V2H) technology and residential photovoltaic solar power [8]. In [9-11], we propose a special type of residential energy management system, i.e. "demand side recommender system", which do not rely on automatic control devices, but use personalized recommendation technology to recommend energy-oriented products/services to residential users.

Most of home energy management techniques focus on bill reduction or utility value maximization based on TOU or RTP tariffs. Under these tariffs, energy management strategies can be designed to shift home loads from peak pricing to off-peak pricing time slots. Recently, a new type of tariff –Demand Charge Tariff (DCT), is being introduced to the residential customers. DCT has been applied on large customers for quite a long time. For commercial and industrial customers, their electricity bills usually comprise of two major components, the energy cost and the demand charge. DCT is a one-off charge based on the maximum demand (power, kW) recorded during an entire billing cycle. A typical billing cycle is usually a calendar month, while the peak demand is calculated and recorded as the moving average of the power consumption over a specific period, e.g. 15 minutes or half an hour [12, 13]. Research has focussed at studying energy management of microgrids [26] and large customer's energy storage systems [27] with DCT. For example, the authors of [26] develop an economic dispatch model for fast-responding generators in microgrids considering both TOU and DCT schemes. The authors of [27] propose a finite horizon dynamic optimization model for scheduling the charging/discharging power of a battery energy storage system to control the customer's peak power and to minimize the expected DCT charging cost. More recently, there are proposals to introduce demand charge tariff to residential users [14, 15, 28], hoping to generate effect on smoothing the peak-valley ratio for the consumption in residential sector. For example, [28] demonstrates how DCT could benefit power grids if it is applied to residential customers. Furthermore, some Australian electricity retailers have been testing DCT to residential users [30, 31], and similar trend is also seen in the U.S.A [32]. Despite this, there is still a need to develop home energy resource management techniques under DCT.

Based on above discussions, this paper is to propose a new HEMS that optimally manages the home energy resources for the user in a dynamic environment. Specific contributions of this paper include following two aspects:

(1) In this paper, we consider penetration of both RTP and DCT. Since home energy management is often performed on daily basis, as that will be shown in Section III, we propose a heuristic strategy to take into account the impact of DCT on one-day home operation. To the best of the authors' knowledge, this is the first paper that considers demand charge tariff in appliance scheduling-based home energy management;

(2) Existing literature (e.g. [3-9]) only considers operational constraints of individual household appliances, and neglects operational dependencies between different appliances, which

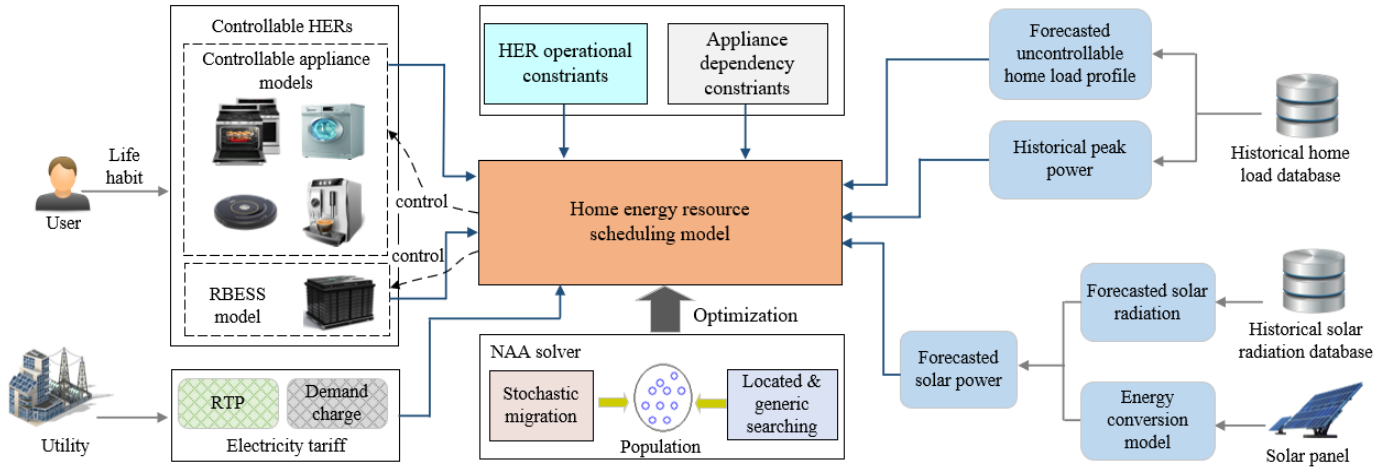

Fig. 1. Schematic of the proposed HEMS

actually reflect the user's lifestyle. The HEMS proposed in this paper models the user lifestyle-related appliance operational dependencies as a set of constraints, and is thus capable to provide better decision-support to the user.

This paper is organized as follows. Section II gives an overview of the home energy management environment; Section III presents the generalized model of appliance operational dependencies and the HEMS model; Section IV presents the solving approach; in Section V, simulation study is discussed; Section VI draws the conclusion and future work.

II. Overview of Home Energy Management Environment

The smart home environment studied in this paper is illustrated in Fig. 1. The home is equipped with a rooftop PV solar source and a RBESS. The RBESS is used to accommodate the solar power and supply power to the home. It can also absorb power from the grid for later use when the electricity price is low; it can also store the surplus solar panel. Smart meter is installed, acting as a communication agent between the home and the grid. It receives dynamic electricity tariff information and other demand response signals from the utility, and sends the utility power consumption of the house at a regular time interval.

A HEMS is deployed in the smart home, taking the role of managing home energy resources, including the RBESS and a number of controllable household appliances. It not only communicates with the home energy resources and smart meter, interact with the user, but also communicates with the external environment. In the day-ahead stage, the HEMS collects the forecasted real-time pricing data, forecasted must-run, uncontrollable home load, and forecasted solar radiation data at the site where the house is located. These forecasting tasks can be implemented within the HEMS, or they can be provided by third-party services and accessed by the HEMS through communication channels. The HEMS then uses an energy conversion model to convert the solar radiation into PV solar power output. The HEMS also accepts inputs from the user, including: a) the user's preferred time range of each controllable appliance's operation, and b) the user's lifestyle specification. The HEMS then interprets the lifestyle specification into a set of appliance operational dependency constraints. Based on above work, the HEMS solves an optimization model to determine operation plans for the controllable household appliances and charging/discharging plan for the RBESS, under both RTP and DCT.

The HEMS can be implemented in the embedded processor of smart meter or in a dedicated processor; it can interact with the user with various kinds of digital media, such as smart phone application, LED digital screen, etc. The HEMS communicates with the home energy resources through a certain short-range wireless communication protocols, such as WiFi and Zigbee, and communicates with the optional external Web services through the TCP/IP protocol. The home energy data can be stored in local or third-party databases. Technologies such as anonymous encryption [24] and cloud authentication technologies [25] can be used to ensure the data's integrity and security.

III. Home Energy Management with Demand Charge Tariff and Appliance Operational Dependencies

Following the system schematic presented in Section II, in this section we firstly present the generic Home Energy Resource (HER) models; then, we formulate the proposed HEMS model without appliance operational dependencies; followed by these, we present different categories of lifestyle-related appliance operational dependencies, which are modelled as additional constraints of the HEMS.

A. Residential Photovoltaic Solar Power Model

Power output from PV solar panel is related to solar radiation, panel's surface area, and energy conversion efficiency of the panel, expressed as:

$$P_t^{pv} = A \cdot \sigma \cdot r_t \tag{1}$$

B. Generic Classification of Controllable HERs

Consider a residential unit with N controllable HER and denote the set of HER as Ω, i.e. $|\Omega| = N$. The controllable HERs are further categorized into following sets based on their operational characteristics:

- Ω^1: Set of HERs operating with power in the range of $[P_a^{\min}, P_a^{\max}], a \in \Omega^1$ and having a prescribed energy consumption that must be completed between a specific time range. Typical HERs in this set are residential energy storage systems, such as PEV and RBESS. For example, users often specify the plug-in and plug-out time of PEV, and require the SOC of the PEV battery must be larger than a threshold at the plug-out time;
- Ω^2: Set of HERs operating with power in the range of $[P_a^{\min}, P_a^{\max}], a \in \Omega^1$ but without a total energy consumption requirement. Instead, a certain disutility function is applied to measure the dissatisfaction of the user for deviating from a nominal operating point. Typical HERs in this class are thermostatically controlled appliances (TCAs) such as air conditioner, refrigerator, and heater;
- Ω^3: Set of HERs operating at the nominal power P_a^{rate} and having a prescribed energy consumption that must be completed between a specific time range. The operation of the HERs cannot be interrupted until its completion. Typical HERs in this class include appliances like coffee machine, rice cooker, toaster, and so on;
- Ω^4: Set of HERs operating at the nominal power P_a^{rate} and having a prescribed energy consumption that must be completed between a specific time range. The operation of the HERs can be interrupted and resumed later. Typical HERs in this class include appliances like washing machine, dish washer, etc.

C. Home Energy Management Model with Penetration of RTP and DCT

Denote the energy consumption schedule for each controllable HER as:

$$\mathbf{P}_i = [P_{i,1}, P_{i,2}, ..., P_{i,T}] \quad \forall i \in \Omega \tag{2}$$

The power consumption schedule of *N* controllable appliances can then be represented as a matrix with $N \times T$ dimensions, where the entry $P_{a,t}$ represents the power consumption of appliance *a* at time interval *t*. The net-power consumption of the home can be correspondingly represented as:

$$\tilde{\mathbf{P}}^h = [\tilde{P}_1^h, ..., \tilde{P}_t^h, ..., \tilde{P}_T^h] \tag{3}$$

$$\tilde{P}_t^h = P_t^{mr} + \sum_{i \in \Omega} P_{i,t} - P_t^{pv} \quad t = 1:T \tag{4}$$

where P_t^{mr} is the must-run home load at time *t* (kW).

Objective:

The proposed objective of HEM in this study is to minimize the one-day RTP cost and the DCT cost increment that might (or might not) be charged at the end of the month:

$$\min F = \sum_{t=1}^{T} \left(\lambda_t^{RTP} \tilde{P}_t^h \right) + \mu \cdot \lambda^{DCT} \max\left[\left(\max(\tilde{\mathbf{P}}^h) - P' \right), 0 \right] \tag{5}$$

where max($\cdot$) is a function that returns the maximum value among the input numbers; P' is the historically recorded peak power consumed over the previous days of the current calendar month. There are two items in model (5). The first item is the one-day electricity cost charged by RTP; the second item is the incremental cost charged by DCT, which is calculated by comparing the maximum power consumed in the current day and P'. μ is a weighting coefficient. In this study, we propose to use following formula for μ:

$$\mu = \omega \cdot \frac{d}{D} \tag{6}$$

where $D \in \{28, 29, 30, 31\}$ is the number of days in the current month; $d \in \{1, 2, ..., D\}$ is the index of the current day.

The rationale of model (5) is that the HEMS balances the two cost items charged by RTP and DCT, respectively. These two cost items are conflict to some extent. For example, cost charged by RTP can be significantly reduced by scheduling the operation of many HERs in the periods with low electricity prices; however, this may produce a peak power consumption that is potentially charged by DCT. Note that unlike the critical peak load tariff, DCT is not charged on daily basis, but only charges the peak power consumption over the whole month. This means if the peak power consumption of the current day is lower than the previous peak power in this month, then no DCT will be charged; otherwise, the DCT might be charged or not be charged, depending on the operation results of remaining days in the month. Based on this fact, we propose to introduce a day index-related weighting coefficient μ to take into account the potential effect of DCT on the daily HER scheduling. The rational of μ (Eq. (6)) is that if the scheduling result of the current day produces a larger peak power than previous days in the month, then the risk of being charged by DCT is considered in proportional to the number of remaining days in the month.

Mandatory Constraints:

The HEM model is subjected to following constraints:

1) Operational constraints of HERs in Ω^1, i.e. an RBESS in this study. The operation of the RBESS must satisfy following constraints:

$$E_{t+1}^{ess} = \begin{cases} E_t^{ess} + \Delta t \eta^c P_t^{ess} - E_t^{ess} \eta^l \Delta t & P_t^{ess} > 0 \\ E_t^{ess} - |P_t^{ess}| \eta^d \Delta t - E_t^{ess} \eta^l \Delta t & P_t^{ess} \le 0 \end{cases}, \ t = 1:T-1 \tag{7}$$

$$SOC_t^{ess} = E_t^{ess} \big/ E^{ess,rate} \quad t = 1:T \tag{8}$$

$$\left| P_t^{ess} \right| \le P^{ess,rate} \quad t = 1:T \tag{9}$$

$$SOC^{\min} \le SOC_t^{ess} < SOC^{\max} \quad t = 1:T \tag{10}$$

$$SOC_t^{ess} \ge SOC^{dsr} \quad t = T \tag{11}$$

Eqs. (7) and (8) model the variation of energy stored in the RBESS; constraint (9) specifies the RBESS's maximum charging/discharging power; constraint (10) ensures the RBESS's SOC is maintained within an allowable range; constraint (11) ensures the SOC level of the RBESS is larger or equal to a pre-specified threshold at the end of the day.

2) Operational constraints of HERs in Ω^2, i.e. an air conditioning system in this study. We use the thermal dynamics model following in [16]:

$$\dot{\varphi}_t = \frac{1}{C^{th} \cdot R^{th}} \left(\varphi_t^{out} - \varphi_t - R^{th} P_t^{ac} \right) \quad t = 1:T \tag{12}$$

$$\varphi^{low} \leq \varphi_t \leq \varphi^{up} \quad t = 1:T \tag{13}$$

Constraint (13) restricts the indoor temperature to be controlled within a comfort range.

3) Energy consumption requirement of HERs in Ω^3 and Ω^4 :

$$\sum_{t=1}^{T} P_a^{rate} s_{a,t} \Delta t = E_a^{req} \quad \forall a \in \Omega^3 \cup \Omega^4 \tag{14}$$

4) Operation time range constraint of HERs in Ω^3 and Ω^4 :

$$P_{a,t} = 0 \quad t < t_a^{pmt1} and\ t > t_a^{pmt2}, \forall a \in \Omega^3 \cup \Omega^4 \tag{15}$$

5) Non-interruptible constraint of HERs in Ω^3 :

$$\sum_{t=t_a^*}^{t_a^* + E_a^{req}/P_a^{rate}} s_{a,t} = 1 \quad \forall a \in \Omega^3 \tag{16}$$

where t_a^* represents the time interval when HER a is first time to be turned on.

5) Minimum online time constraint of HERs in Ω^4 , in order to protect mechanical device of the HERs in Ω^4 :

$$\tau_{a,t}^{on} \geq \tau_a^{on,\min} \quad \forall a \in \Omega^4 \tag{17}$$

Constraints (7)-(17) model the individual operational constraints of the HERs. In addition to above individual operational constraints, in this study we proposed to consider the constraints representing operational dependencies among appliances, as presented in the next sub-section.

D. Modelling of Appliance Operational Dependency

It is easily observed from our life experiences that people may impose different operational dependency requirements on the household appliances. For example, in many mornings a user would require to start running the bread maker and coffee machine at the same time, so as to make his/her breakfast, i.e. bread and coffee. In literature, such operational dependencies among appliances are seldom considered. In this study, we propose to model following six modes of appliance dependencies.

Optional Constraints:

1) Dependency mode 1: The task of one appliance (denoted as x) must be started after the completion of the other appliance (denoted as y) plus a time shift. This dependency can be formulated as following constraint:

$$t_y^{end} + t_{xy}^{*1} \leq t_x^{start} \leq t_y^{end} + t_{xy}^{*2} \tag{18}$$

2) Dependency mode 2: The task of appliance x must be started after the start of appliance y plus a time shift. This dependency can be formulated as:

$$t_y^{start} + t_{xy}^{*1} \leq t_x^{start} \leq t_y^{start} + t_{xy}^{*2} \tag{19}$$

3) Dependency mode 3: The task of appliance x must be completed after the completion of appliance y plus a time shift.

$$t_y^{end} + t_{xy}^{*1} \leq t_x^{end} \leq t_y^{end} + t_{xy}^{*2} \tag{20}$$

4) Dependency mode 4: The task of appliance x must be completed after the start of appliance y plus a time shift:

$$t_y^{start} + t_{xy}^{*1} \leq t_x^{end} \leq t_y^{start} + t_{xy}^{*2} \tag{21}$$

In Eqs. (18)-(21), t_a^{start} and t_a^{end} are starting and completion time of appliance a's operation; t_{xy}^{*2} and t_{xy}^{*2} are constants where $t_{xy}^{*2} \geq t_{xy}^{*1} \geq 0$.

5) Dependency mode 5: The overlapped running time of appliances x and y cannot be larger than a threshold γ :

$$\left|\left\{t \middle| P_{x,t} > 0, t = 1:T\right\}\right| \cap \left|\left\{t \middle| P_{y,t} > 0, t = 1:T\right\}\right| \leq \gamma \tag{22}$$

6) Dependency mode 6: The overlapped running time of appliances x and y cannot be smaller than a threshold γ :

$$\left|\left\{t \middle| P_{x,t} > 0, t = 1:T\right\}\right| \cap \left|\left\{t \middle| P_{y,t} > 0, t = 1:T\right\}\right| \geq \gamma \tag{23}$$

Above dependency modes can be considered as atomic modes. More complex appliance dependencies can be created by compositing above atomic modes. For example, to specify a dependency mode that K appliances must be operated sequentially, mode (18) can be repeatedly applied K times for the appliances. As another example, to model the appliance dependency that K appliances cannot be operated simultaneously (even if their allowable operation time ranges overlap with each other), mode (22) can be iteratively applied.

IV. Solving Approach

The formulated model (5)-(23) (constraints (18)-(21)) are optional) is a mixed-integer, nonlinear, high dimensional combinatorial problem over a finite horizon. The nonlinear nature of the objective function (Eq. (5)) and constraints (12) and (17) does not lend itself for implementation with deterministic programming solvers. For this purpose, a metaheuristic optimization solver previously proposed by the authors – Natural Aggregation Algorithm (NAA) [17, 18], is used in this study to solve the model. Essentially, NAA is a biological intelligence inspired algorithm that imitates the self-aggregation behaviors of group-living animals. The main feature of NAA is it uses a stochastic migration model to dynamically migrate the individuals among multiple sub-populations, and uses both located and global searching strategies to search for the global/near-global solutions in the problem space. From a comparative viewpoint, NAA outperforms several other heuristic algorithms in solving a set of benchmark nonlinear functions and it shows satisfactory performances when dealing with power system problems (e.g. [21-23]).

Each individual in NAA represents a potential HER scheduling solution, encoded as a vector with dimension of $T + T + \left|\Omega^3\right| + \sum_{a \in \Omega^4} (t_a^{pmt2} - t_a^{pmt1} + 1)$:

- The first T dimensions are continuous variables, representing the power consumption of the RBESS;
- The next T dimensions are continuous variables, representing the power consumption of the air conditioner;
- The next $\left|\Omega^3\right|$ dimensions are integer variables, representing the starting time interval of the appliances in Ω^3. The corresponding task completion time can be calculated based on the starting time and the appliance's operation cycle;
- The last $\sum_{a \in \Omega^4} (t_a^{pmt2} - t_a^{pmt1} + 1)$ dimensions are binary variables, representing the ON/OFF status of appliances in Ω^4 ; each consequentially $t_a^{pmt2} - t_a^{pmt1} + 1$ dimensions rep-

resent the ON/OFF status of the ith appliance within its permitted operation time range $[t_a^{pmt1}, t_a^{pmt2}]$.

In the evolution process of NAA, after each iteration, certain constraint handling strategies are applied on each individual. If the BESS's SOC range constraint is violated in a time slot (constraint (10), the charging/discharging power of the BESS in that time slot is adjusted to the boundary value that makes the SOC to be the lower/upper allowable limit. If the indoor temperature limit is violated (constraint (13)), the status of the air conditioner is adjusted to be ON or OFF. If the minimum online/offline constraint of an appliance is violated in a time slot (constraint (17)), the ON/OFF status of the appliance in adjacent time slots is adjusted to satisfy the constraintrequirement. For other constraints (i.e. mandatory constraints (11), (14), and optimal constraints (18)-(23)), the "check-and-abandon" strategy is applied. That is, if a constraint is violated, the individual is then assigned as a very large fitness value before entering into the individual selection process. The very large fitness value helps the algorithm to identify that the individual is not feasible in the current iteration.

The overall optimization procedures are shown in Fig.2.

V. Simulation Study

A. Simulation Setup

A smart home is simulated that consists of a 4kW-capacity rooftop solar panel, a RBESS, and multiple controllable household appliances. A normal summer day is considered; the scheduling horizon starts from 7am when the user starts one day life, and ends on 7am of the next day. The scheduling interval is set to 10 minutes. Therefore, there are totally 144 scheduling time intervals. We use the RTP tariff based on [19], shown in Fig. 3. The DCT is set to be \$8.03kW/month. The one-day forecasted solar power profile is shown in Fig. 4.

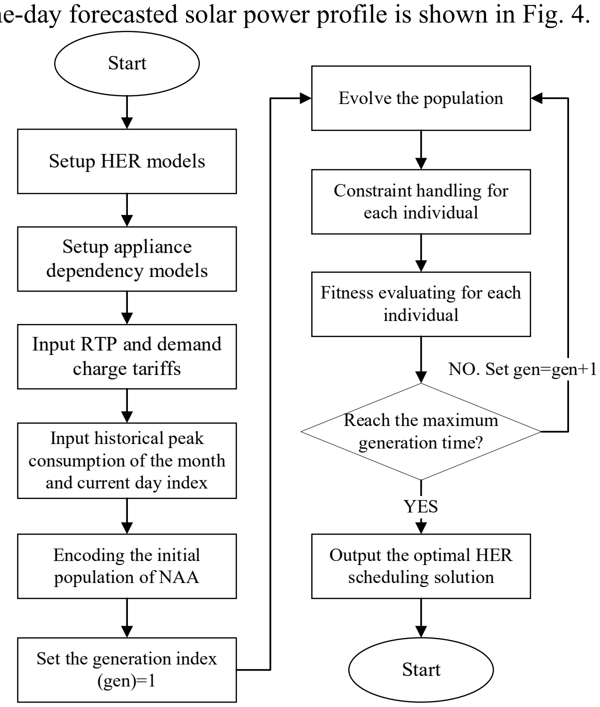

Fig. 2. Workflow of the NAA based solving procedures

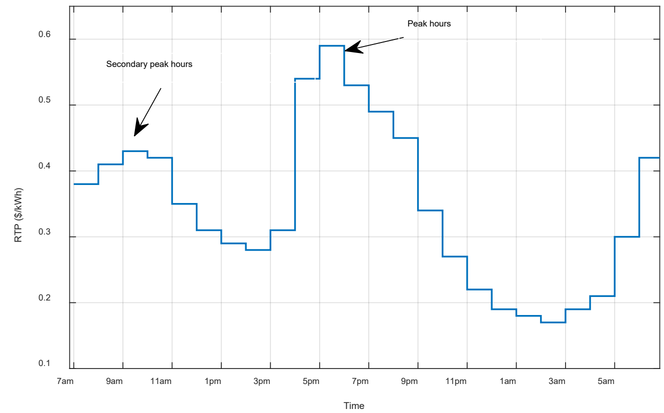

Fig. 3. 24-hour real-time pricing

TABLE I RBESS Model

Rated power	Energy capacity	Initial SOC
4kW	8kWh	30%
Charging/discharging efficiency	SOC^{min}	SOC^{max}
0.9	10%	90%

TABLE II
Configurations of Controllable Household Appliances

Name	Operation duration	Operation time range	P_a^{ca}	Interruptible
Pool pump (PP)	3hours	[10am, 6pm]	1.5 kW	YES
Dish washer (DW)	1hour	[8pm, 7am]	1kW	YES
Washing machine (WM)	1.5hours	[10am, 7pm]	0.9 kW	YES
Clothes dryer (CD)	1.5hours	[10am, 7pm]	2.5 kW	YES
Coffee machine (CM)	10minutes	[7:30am, 8:30am]	0.8kW	NO
Dehumidifier (DH)	20minutes	[5pm, 8pm]	0.3kW	NO
Bread maker (BM)	10minutes	[7:30am, 8:30am]	0.5kW	NO

TABLE III
Parameters of Building and Air Conditioner

Building Parameters		
R_{TH}	C_{TH}	
18 ºC/ kW	0.525 kWh/ºC	
Air Conditioner Parameters		
Power range		
[0, 1.5KW]	23 ºC	25.5 ºC

Configuration of the RBESS is shown in table I; settings of non-thermostatically controllable appliances are shown in table II; parameters of the air conditioner and the building are shown in table III. The one-day must-run uncontrollable load profile of the home is extracted from the Australian "Smart Grid, Smart City" dataset [20]. Control parameters of NAA are set as follows: population size =5,000, maximum generation time =3,000， N^S =20; Cp^S =250; δ =1; Cr_{local} =0.9; α =1.2; Cr_{global} =0.1. All programs are implemented in Matlab and executed on a DELL workstation with 128-G memory and two Intel Xeon processors.

B. Home Energy Management with Appliance Dependencies

It is assumed that the user specifies the lifestyle-related appliance dependencies listed in table IV. The optimal operation

TABLE IV

LIFESTYLE RELATED APPLIANCE DEPENDENCIES

Index	Dependency	Explanation
1	$t_{CM}^{start}+0 \le t_{BM}^{start} \le t_{CM}^{start}+0$ (constraint (19))	The user requires to simultaneously make coffee and bread in the breakfast time
2	$\left\|\{t \| P_{PP,t}>0, t=1:T\}\right\| \cap \left\|\{t \| P_{DW,t}>0, t=1:T\}\right\| = 0$ (constraint (22))	The user specifies the pool pump cannot be operated simultaneously with clothes dryer due to the big noise
3	$t_{WM}^{end}+0 \le t_{DH}^{start}$ $t_{CD}^{end}+0 \le t_{DH}^{start}$ (constraint (18))	The dehumidifier in the laundry cannot start to work until both washing machine and clothes dryer finish their tasks

*Note: notations t_x^{start} and t_x^{end} representing the starting and completion time interval of the appliance 'x', where x is an abbreviation in table II.

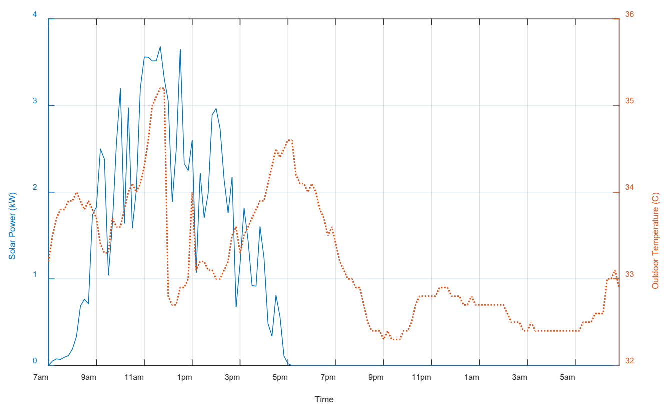

Fig. 4. 24-hour solar power and outdoor temperature profiles

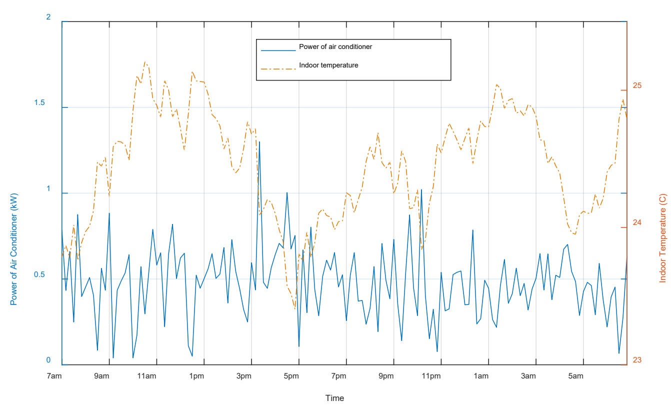

Fig. 5. Scheduling results of the air conditioner

of the air conditioner, RBESS, and non-thermostatically controlled appliances are shown in Figs. 5-7, respectively. Fig. 5 clearly show that by properly controlling the power consumption of the air conditioner, the indoor temperature is well controlled within the comfort range specified by the user (i.e. [23ºC, 25ºC]. From Fig. 3 and Fig 5, it can be seen that the time intervals of peak power consumption of the air conditioner (i.e. larger than 1kW) are scheduled to avoid the peak RTP hours. Fig. 6 shows that the RBESS is scheduled to discharge to serve the home load in the morning and evening when there is little or no solar power. From around 11am to around 3pm, the RBESS is charged by the surplus solar power. In the evening period, the RBESS is discharged to serve the air conditioner load, must-run load, and some controllable appliances.

Fig. 6. Scheduling results of the RBESS

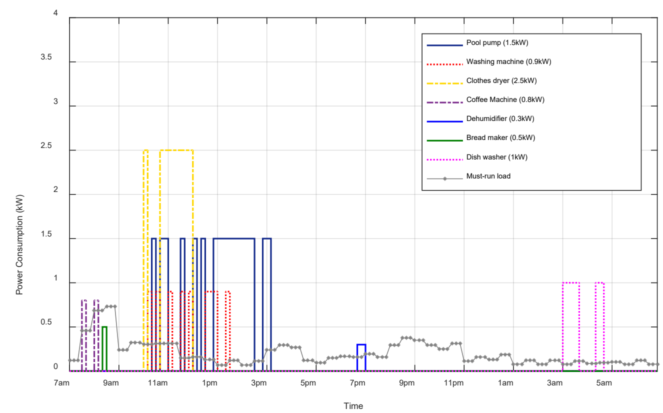

Fig. 7. Scheduling results of household appliances

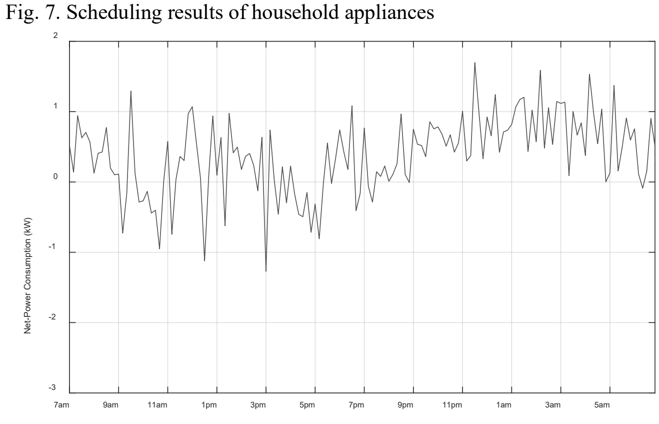

Fig. 8. Net-power consumption profile

Then in the mid-night, the RBESS is charged again to ensure the desired SOC low limit is achieved. Fig. 7 shows that as expected, all three dependency constraints of the household appliances are satisfied by the HEMS, indicating that the user's lifestyle requirements are sufficiently respected.

We now evaluate the computational cost and solution quality of the proposed model with different NAA settings. In this experiment, the maximum generation time is fixed at 3,000 and the population size varies between 1,000 and 5,000. The results are shown in table V. It can be seen that in all cases, the optimization solver ensures that there is no extra DCT cost increment. With the increase in population size, more optimal HER operation plans can be found to reduce the RTP cost and, as a trade-off, the execution time increases. When the population size reaches 5,000 (i.e. the setting used in the case study reported above), the total execution time is around 6.5 hours.

TABLE V
OPTIMIZATION RESULTS WITH DIFFERENT POPULATION SIZE SETTINGS IN NAA

Population Size	RTP Cost ($)	DCT Cost Increment ($)	Execution Time (minutes)
1,000	3.40	0	74
2,000	2.84	0	151
3,000	2.68	0	227
4,000	2.13	0	303
5,000	1.91	0	391

Considering the proposed application is a day-ahead HER scheduling application, this is assumed to be acceptable.

By combining the aforementioned HER scheduling plans, the overall net-consumption profile of the home is obtained, shown in Fig. 8. Since the current day index is sent to be 28, close to the end of the current month; the weight of the DCT cost is therefore large in model (5). As a result, the HEMS successfully control the maximum one-day net-consumption of the house to less than the recorded historical maximum power consumption of the current calendar month (i.e. 1.7kW), which helps the user to avoid the high risk of the large DCT penalty. The final total RTP cost of the home is $1.91, and DCT cost is zero.

We further compare the proposed HEMS with three other benchmark cases:

(a) Case 1: the HEMS with appliance dependencies and DCT (the proposed HEMS in this paper);

(b) Case 2: the HEMS without appliance dependencies but with DCT;

(c) Case 3: the HEMS with appliance dependencies but without DCT.

(d) Case 4: The case without HEMS in which: the BESS does not be scheduled to serve the home load; each controllable appliance is switched on at the first time slot of its allowable operation time rage, and it is turned off when it finishes the task; the air conditioner is regularly switched on and off, for example, it remains in the ON status until the lower limit of the comfort indoor temperature range is reached).

The cost comparison results obtained from the simulations are shown in table VI. For Case 2, that does not consider the appliance dependency, the home electricity cost can be slightly reduced even if without satisfying the user's lifestyle requirements. Without the DCT, a significant reduction in RTP cost can be achieved. This will lead to much higher peak power levels than the recorded historical peak power of the current month, leasing to a $4.1 possible DCT cost increment. When there is no HEMS (Case 4), very large RTP and DCT costs are incurred. Due to absence of BESS and the lack of coordination for appliances' operations, the household is charged $8.72 by RTP. This un-coordinated scenario leads to a peak power of 5.6kW and to a consequent high DCT penalty ($31.3).

We now compare the efficiency of the NAA solver on the proposed model with two other well-known heuristic algorithms: Particle Swarm Optimization (PSO) and Differential Evolution (DE). The Matlab codes of PSO and DE are implemented by the authors and used in our previous work [17, 18]. For all three algorithms, the population size and maximum iteration time are fixed as 5,000 and 3,000, respectively. Five trials are performed for each algorithm, and the averaged fitness value (i.e. value of the objective function (5)) is obtained. The results are plotted in Fig. 9. It can be seen that the searching performance of PSO is significantly worse than DE and NAA. Although it seems that NAA stops improving the solution after around 1,700 iterations, it still generates better solution than DE. The average computational cost of NAA, PSO, and DE is 395, 373, and 378 minutes, respectively. Although NAA spends around 20 minutes more than PSO and DE, due to its relatively high optimization performance, it is acceptable for the day-ahead scheduling application considered in this paper.

TABLE VI
HOME OPERATION COSTS OF THREE CASES

	RTP Cost	DCT Cost Increment
Case 1	$1.91 (21.9%)	0 (0%)
Case 2	$1.77 (20.3%)	0 (0%)
Case 3	$1.02 (19.7%)	$4.10 (13.1%)
Case 4	$6.72	$25.9

*The values in brackets indicate the corresponding percentage of the cost items in the unscheduled case, i.e. Case 4.

TABLE VII
HOME OPERATION COSTS WITH DIFFERENT DAY INDEX SETTINGS

Day Index	RTP Cost	DCT Cost Increment
3	$1.12 (12.8%)	$3.11 (9.9%)
15	$1.54 (17.7%)	$1.05 (3.3%)
28	$1.91 (21.9%)	0

*The values in brackets indicate the corresponding percentage of the cost items in the unscheduled case, i.e. Case 4 in table VI.

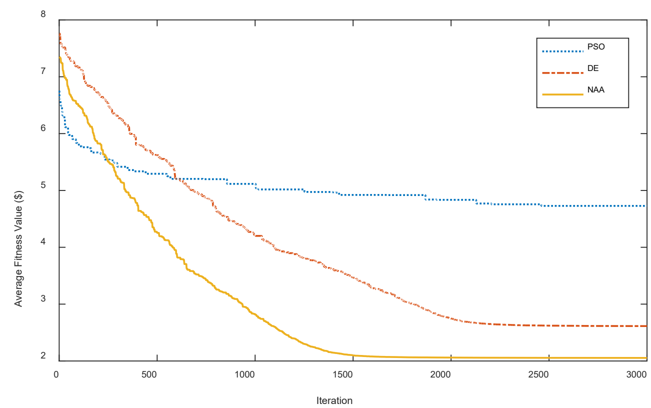

Fig. 9. Optimization performance comparison of the three algorithms

C. Home Energy Management with Different Day Indices

We fix the historical recorded peak power consumption of the current calendar month to be 1.7kW, and then assign three typical day indices to the simulation program: 3, 15, and 28, which represent an early, middle, and late day of the current calendar month, respectively. The home operation costs are shown in table VII. Note that in both table VI and VII, only the RTP cost is the deterministic cost; as fore the DCT cost, it just represents a possible increment compared with the historically recorded peak power in the current calendar month. In other word, if the overall peak power of the current month occurs in the later days of the current month, then for this current day, only the RTP cost will be charged.

As expected, when the current day is in the beginning of the month, the HEMS pays much more attention on minimizing the RTP cost. This is because there are still 27 days remaining in the current month, indicating a large chance that the monthly peak power will occur in the later days. With the move of the day index, the effect of DCT is increasingly considered by

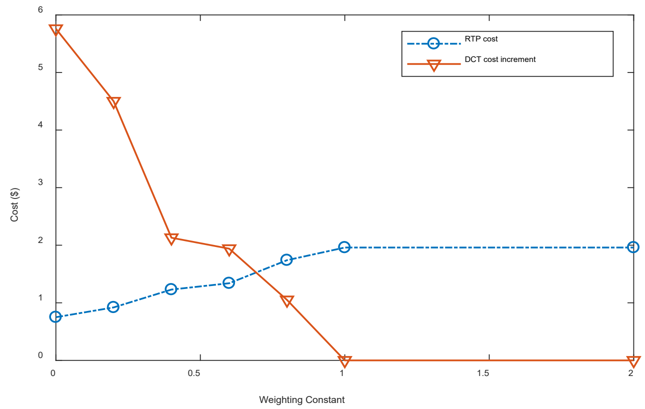

Fig. 10. Sensitivity study of weighing constant

the HEMS. When the current day is in the middle of the month, the HEMS controls the DCT cost increment to be 1.05, significantly smaller than that when the current day index is 3. Finally, when the end of the month is approaching (day index of 28), the HEMS ensures there is no any further DCT cost increment, avoid the risk of incurring high DCT expense. This is reasonable, because the DCT rate is often several times higher than the TOU or RTP rate.

D. Sensitivity Study on the Weighting Constant

The weighting constant ω in Eq. (6) controls the consideration degree of the DCT cost in the daily home energy management. The smaller value of ω indicates the HEMS will pay more attention to the RTP cost. However, this would lead to high DCT penalty; the larger value of ω can well controls the DCT cost. However, recall that the DCT cost is charged for the peak power of the whole month instead of one day, too large value of ω will therefore make the HEMS overrates DCT's impact and result in unnecessary RTP cost.

Above justification is reflected in the sensitivity study results reported in Fig. 10, where we set the current day index as 28 and observe the optimized RTP cost and DCT cost increment under different settings of ω. Fig. 9 clearly shows that with the increase of ω, the one-day DCT cost increment decreases while the one-day RTP cost increases. Therefore, the choice of the value of ω reflects the compromise between the daily basis RTP cost and monthly basis DCT cost.

E. Long Term Evaluation

One-month home energy management is simulated. The one-month home load profile is modified from an Australian household in the Australian "Smart Grid, Smart City" dataset, shown in Fig. 11. One-month solar radiation is obtained from the SoDa database [29] and is converted to the solar power output according to model (1), shown as Fig. 12. The controllable appliances listed in table II are then scheduled day-by-day, subjected to model (5). Based on the life experience of an Australian family (see the acknowledgement section), the pool pump is set to run once every two days; the washing machine and clothes dryer are set to run 4 times per week; other controllable appliances are operated once every day. Two settings of the weighting constant ω is used: a small value ($\omega = 0.4$) and a large value ($\omega = 1.5$), respectively. For comparison purpuses, the home operation result under the case of no HEMS (i.e. no RBESS and no appliance scheduling) is also calculated and listed.

The peak power consumption in each day is shown in Fig. 13, and the relevant one-month optimization result is shown in table VIII. The results show that when there is no home energy management, very high values of daily peak power consumption are resulted, and these lead to high RTP cost and DCT cost over the month. With the penetration of RBESS and appliance scheduling, the household's electricity cost is significantly reduced. With $\omega = 0.4$, the peak power over the month occurs in the 25th day (2.6kW), leading to $20.9 DCT cost and $31.5 RTP cost. With a value of $\omega = 1.5$, the monthly peak power occurs in the 7th and 11th day (2.4kW) and this produces lower DCT costs ($18.4) and higher RTP cost ($36). These results confirm that the choice of the value of ω reflects the compromise between the RTP cost and DCT cost).

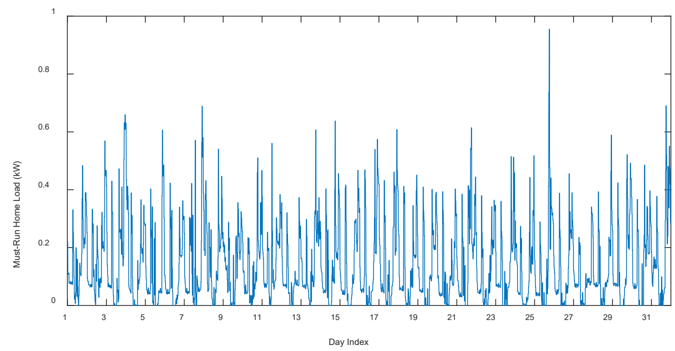

Fig. 11. One-month household must-run load

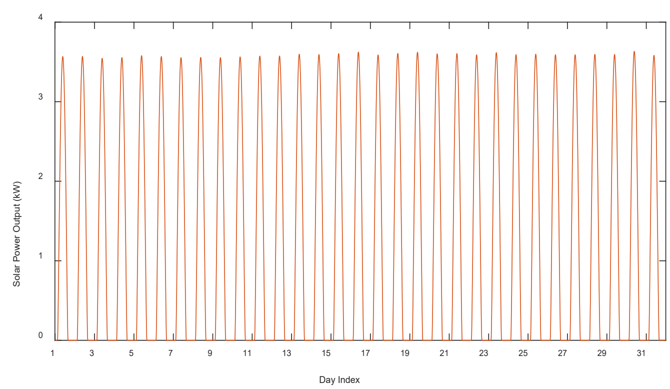

Fig. 12. One-month solar radiation

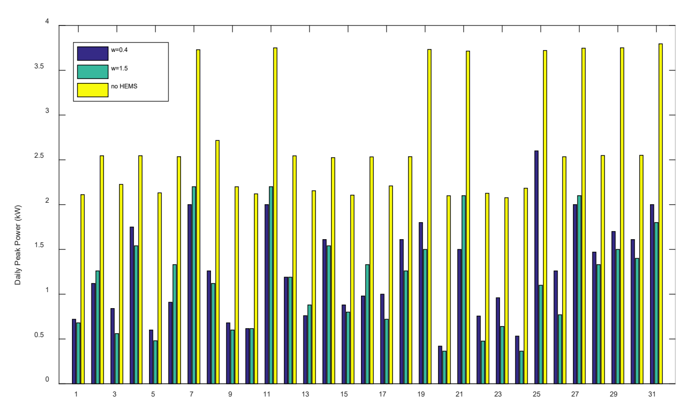

Fig. 13. Daily household peak power consumption under 3 cases

TABLE VII
ONE-MONTH COST EVALUATION UNDER THREE CASES

	RTP Cost	DCT Cost	Total Cost
$\omega = 0.4$	$31.5	$20.9	$52.4
$\omega = 1.5$	$36.0	$18.4	$54.6
Without HEMS	$110.6	$38.1	$148.7

VI. CONCLUSION AND FUTURE THOUGHTS

This paper proposes a home energy management system that considers the penetration of both real-time pricing and demand charge tariff. The HEMS also takes into account the operational dependencies of appliances, which reflect the user's lifestyle requirements. Numerical studies are conducted, which show compared with the case that is only with RTP, DCT poses extra impact on the home energy management that must be sufficiently considered. In the meantime, the appliance dependencies are also unneglectable factors when designing user-oriented HEMSs.

As presented, this is an ongoing discussion in industry to apply DCT to the residential sector. Therefore, the work in this paper can be considered as an academic reference for DCT practice in residential buildings.

Currently, the authors are working on extending the home energy management to the residential community scale by considering the penetration of DCT. In this scenario, we consider the DCT is charged based on the peak power consumption of the whole residential community, and all units share the DCT cost based on their power consumption proportions. Since compared with the industrial customer (which is the current application domain of DCT), a single residential unit's power capacity would be too small, applying DCT on community scale would be a possible option in the practice of DCT in the residential sector.

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