Applied Energy Symposium 2020: Low carbon cities and urban energy systems
October 10-17, 2020
Paper ID: CUE2020-D-056

RESEARCH ON OPTIMIZATION OF SMART HOME PARTICIPATING IN POWER DEMAND RESPONSE IN THE CONTEXT OF INTERNET OF THINGS

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ABSTRACT

Smart home, with the Internet of Things as the core, will substantially change the time scale of residents' electricity consumption, increase the flexibility of power load, and provide more opportunity for demand response and related services, but also bring huge uncertainties. Focus on the transferable function of smart home working time, we are committed to exploring the possible changes of smart home participating in demand response. Here, we establish the smart-home integrated management model with goals of minimizing the electricity cost and peak-valley difference, and provide an optimization scheme that integrates smart home into demand response. Furthermore, the peak shaving potential of smart home participating in demand response and its impacts on power supply and grid investment are evaluated. Our results show that the time-of-use policy can reduce the peak-valley difference between -29.2% and -23.9%, and cut electricity cost by up to 9.5%, which is conducive to encouraging smart home to participate in demand response. The shift of working time in smart home may increase power consumption and increase residential electricity costs by 4.8%-11.5%. In the unconstrained dispatch mode, driven by smart home participation in demand response, it is expected to reduce the peak load of the power grid by 141 to 149 million kilowatts, and reduce power supply and power grid investment by 1.13-1.19 trillion yuan.

Keywords: Internet of Things, smart-home integrated management model, demand response, uncertainty, multi-objective optimization

Selection and peer-review under responsibility of the scientific committee of CUE2020

NONMENCLATURE

Abbreviations	
TOU	time of use
NTOU	no time of use

1. INTRODUCTION

In China, with the sustainable and rapid development of economy and society, the power consumption has been increasing, and the peak-valley difference in power consumption has also been expanding (see Fig 1). To meet the ever-increasing short-term peak demand, the investment in power supply and grid construction has been substantially increased, resulting in serious waste of resources. Therefore, it is necessary to address the contradiction between supply and demand in the power system as soon as possible [1]. Demand response can bobtail the redundant investment

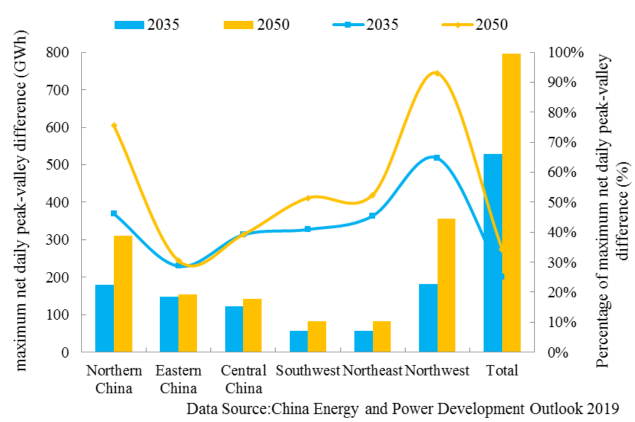


Fig 1 Maximum load peak-valley difference forecasting

and reduce the pressure of "peak shaving" on the power supply by shifting the peak load to the valley time to achieve "peak shaving and valley filling" [2].

Electricity consumption in residential sector is an important part in China, accounting for 14.17% of the total electricity consumption of the whole society in 2019. Driven the difference in residential electricity consumption between day and night, the peak-to-valley difference in the residential sector is more significant [3]. Moreover, with the popularization of household digital devices, the peak-to-valley difference in residential sector will further increase. Therefore, it is of great practical significance to increase the flexibility of residential electricity load and enhance the capability of demand response in residential sector.

Smart home will make smart demand response possible [2]. The emergence of smart home makes it possible to shift or even re-arrange power demand on a time scale. More specifically, it can transfer the demand for a certain appliance at a specific time to other periods without affecting the enjoyment of services provided by this appliance. Taking cooking appliances as an example, traditionally, user have to cook by the appliance at a specific time (such as 11:00-12:00) to obtain the service for food at 12 noon. Due to restrictions on the flexibility of electricity use, it is likely to form a peak load and increase the operating pressure of the grid, with a large number of users intensively using electricity consumption in a short period of time. In the era of smart home, appliance can automatically choose to complete the cooking process at any time before 12 o'clock through the user's setting or the driven of external conditions, and adjust the appropriate power to keep the food warm. This function substantially improves the flexibility of power load and is conducive to demand response with the participation of smart home. The role of smart home in demand response is mainly reflected in two aspects: first, it can achieve the effect of "peak shaving and valley filling" to stabilize the load by the shift of load; second, it is benefit to save household electricity cost by transferring the load to the low electricity price time. However, it is undeniable that the new services and experiences brought by smart home, while improving comfort and convenience for user, may also increase electricity demand and offset potential saving in electricity cost [4]. In other words, the impact of smart home participation in demand response has greater uncertainty. Additionally, the uncertainty of the number and types of smart home will also directly affect the effect of residents' demand response [5]; users' time utilization and behavior are affected by household structure [6,7], occupation [8], electricity price policy [9] and so on, also brings uncertainty for the effect of demand response.

We contribute to the existing studies from three aspects. First, focus on the transferable function of smart home working time, we specifically accommodate for the new energy consumption demand, which may generate from appliance power state conversion during the process of realizing advance or delay of energy consumption time. Meanwhile, there are many types and quantities of appliances with the function above. Therefore, within a specific time window, we aim to optimize all appliances on the entire network so that it can achieve the optimization of load peak-valley difference and electricity cost. Second, this research has built a smart-home integrated management model (smart-home integrated management, SIM) with the goal of minimizing the cost of power consumption on the demand side and minimizing the peak-valley difference in power consumption. Rearranged and proposed a set of optimized solutions that incorporate smart homes into power demand response. Second, we establish smart-home integrated management (SIM) model with goals of minimizing the electricity cost and peak-valley difference, and provide an optimization scheme that integrates smart home into demand response. Third, the peak shaving potential of smart home participating in demand response and its impacts on power supply and grid investment are evaluated.

2. MATERIAL AND METHODS

2.1 Data source

Driven the uncertainty of residential electricity consumption behavior, research needs to be supported by more accurate household energy consumption data. To obtain research data, we conducted a "Household Energy Consumption and Resource Allocation Survey" on Chinese urban and rural households from February to March 2016. In this survey, respondents were asked to fill in data including the type, quantity, model, and power of appliances in their homes. And then we tracked the use frequency of various household appliances on a certain day, as well as the length of each operation and the operating time range (in terms of 15 minutes interval). The survey covered 466 households in 28 provinces in China, and a total of 1,025 valid personal questionnaires were collected.

2.2 Smart-home Integrated Management Model

To analyze the dispatch and management process of smart home participation in demand response in the context of the Internet of Things, we establish the smart-home integrated management (SIM) model with goals of minimizing the electricity cost and peak-valley difference, which can allocate and re-arrange the working time of smart home electricity tasks, show the changing process of each smart home operating state in various time periods detailly, and calculate the changes of load fluctuations and electricity cost based on the optimal state.

Before conducting model scheduling management on smart home, we first introduce the concept of set theory to describe and define the related assumptions and constraints of smart home power consumption tasks in the model, and then classify the types of power consumption tasks of different appliances. On this basis, combining the power task types and operating characteristics of appliances, three smart home scheduling modes are designed.

2.2.1 Definition of task set

a. Time range set *T* of smart home task

Assuming that the time range set of smart home tasks is *T*, the scheduling time range of smart home power-using task is 24 hours a day (0:00-24:00), with 15 minutes as an interval, thereby the length of one day is divided into 96 time periods, and the number code is 1~96 in sequence, that is $T=\{1,2,3,\ldots,95,96\}$。

b. Electricity task set K

Assuming that *K* is the set of all electricity -using tasks in the time range set T, such that $K=\{task1, task2, task3, \ldots, taskM\}$, and |K|=M, M is the total number of tasks.

c. Residential electricity task load set *L*

Assuming that Residential electricity task load set is $L=\{L_m|m\in K\}$, where $L_m=\left(l_{1,m},l_{2,m},\ldots,l_{t,m},\ldots,l_{\gamma_m,m}\right)$, $1\le t\le\gamma_m$。 $l_{t,m}$ is the load power of the m-th task in the t-th time period, and $l_{t,m}>0$。

d. The state set *Z* of the residential electricity task

Assuming that *Z* is the state set of the residential electricity task, that is, the solution set of all residential electricity tasks. Where $z\in Z$ is the matrix of electricity task status, that is, the operating state set of the corresponding task in the t-th time period：

$$z=\begin{pmatrix} z_1\\ z_2\\ \vdots\\ z_m\\ \vdots\\ z_M \end{pmatrix}=\begin{pmatrix} z_{1,1} & z_{2,1} & \cdots & z_{t,1} & \cdots & z_{96,1}\\ z_{1,2} & z_{2,2} & \cdots & z_{t,2} & \cdots & z_{96,2}\\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots\\ z_{1,m} & z_{2,m} & \cdots & z_{t,m} & \cdots & z_{96,m}\\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots\\ z_{1,M} & z_{2,M} & \cdots & z_{t,M} & \cdots & z_{96,M} \end{pmatrix} \tag{1}$$

Here, $m\in K$, $t\in T$, $z_{t,m}\in\{0,1,\delta_m\}$, When m-th task is in normal operation state during the t-th time period, $z_{t,m}=1$, when m-th task is in the low-power operating state during the t-th time period, $z_{t,m}=\delta_m$, δ_m is the power conversion factor when task m is in the low-power operating state, when m-th task does not run in the t-th time period, $z_{t,m}=0$;

Assuming that the initial operating time range of electricity-using task m is $T_m^{in}=\{\varepsilon_m,\varepsilon_m+1,\ldots,\varphi_m-1,\varphi_m\}$, where $\varepsilon_m,\varphi_m\in T$, $\varepsilon_m\le\varphi_m$, The operating time of m-th task is $\lambda_m=\varphi_m-\varepsilon_m+1$; assuming the schedulable time range of each appliance electricity-using task is $T_m^{rang}=\{\alpha_m,\alpha_m+1,\ldots,\beta_m-1,\beta_m\}$, $\alpha_m\le\beta_m$, $\left|T_m^{rang}\right|=\beta_m-\alpha_m+1$, $1\le\lambda_m\le\beta_m-\alpha_m+1$; T_m^{on} is the actual operating time range set of m-th task, where $T_m^{on}\subset T_m^{rang}$; λ_m^{on} is the actual operating duration of m-th task, where $\lambda_m^{on}=\lambda_m+\lambda_{z_{t,m}=\delta_m}$, $\lambda_{z_{t,m}=\delta_m}$ is the duration of m-th task operating in the low-power state, where $\lambda_{z_{t,m}=\delta_m}\ge 0$。

2.2.2 Electricity task types

According to the above-mentioned concepts and load characteristics, residential electricity tasks are divided into three categories:

a. Continuous task K_{con} : for $\forall m\in K_{con}$, $\forall t\in\left\{\min T_m^{on}+1,\min T_m^{on}+2,\cdots,\max T_m^{on}-2,\max T_m^{on}-1\right\}$, let $z_{t,m}=1$, that is, appliances in this task type will participate in scheduling optimization. And in the scheduling process, once it starts operating, it will not stop until the task is completed.

b. General task K_{gen}: $K_{gen}=\left\{i\,|\,i\in K, T_m^{on}=T_m^{rang}\right\}$, that is, appliances in this task type participate in the optimization process, but are not scheduled by program, just operate according to the time range and the working duration set by the user.

c. Interruptible task K_{irp} : $\forall m \in K_{irp}$, $\forall t \in \{\min T_m^{on}+1, \min T_m^{on}+2, \cdots, \max T_m^{on}-2, \max T_m^{on}-1\}$, let $z_{t,m}=1$, appliances in this task type participate in scheduling optimization under the control of program, and can be interrupted during the tasks operating.

The detailed classification of some appliances tasks is shown in Table 1.

Table 1 Classification of appliances task types

task types	Codes of appliances
Continuous task	1 Rice cooker 2 Water heater 3 Microwave oven 4 Electric oven 5 Electric pressure cooker 6 Induction cooker 7 Range hood 8 Electric heater/electric floor heating 9 Air conditioner 10 Electric fan 11 Electric blanket 12 Washer/dryer 13 Vacuum cleaner
General task	14 personal computer 15 TV 16 light 17 refrigerator
Interruptible task	18 Humidifier 19 Air Purifier

2.2.3 Scheduling mode

Adjust the operating time rang of appliances task to realize the scheduling of different power-consumption tasks. Here, three scheduling modes are designed as follows:

Mode M1: This is an unconstrained dispatch mode. Continuous tasks and interruptible tasks are allowed to operate with the largest schedulable time range, but general tasks are not scheduled.

Mode M2: On the basis of M1, the operational termination time of appliances coded as 1-11 in Table 1 are restricted, ceteris paribus. The operational termination time of the appliances is same as the actual operational termination time in survey.

Mode M3: This mode is derived from a survey on the acceptability for the time range of appliances dispatching. On the basis of M2, starting time of the appliances coded as 3-11 in Table 1 is further restricted.

Additionally, the setting of δ_m in formula (1) for all scheduling modes is as follows:

Here, only appliances with low-power operation function is set up. In this research, the heat preservation power of rice cookers and electric water heaters is uniformly set to 10% of normal power; the low-frequency operation power of air conditioners is uniformly set to 20% of normal heating/cooling power.

2.2.4 Objective function

The smart home integrated management (SIM) model is a multi-objective planning, and the objective functions need to meet the minimum of power load peak-valley difference and electricity cost:

$$\min F(z)=\begin{cases}\max\limits_{t\in T}(\sum\limits_{m\in K}(z_{t,m}*l_{t,m}))-\min\limits_{t\in T}(\sum\limits_{m\in K}(z_{t,m}*l_{t,m}))\\ \sum\limits_{t=1}^{96}(PR_t*\sum\limits_{m\in K}(z_{t,m}*l_{t,m}))\end{cases} \tag{2}$$

Here, PR_t is the real-time electricity price for the t-th time period.

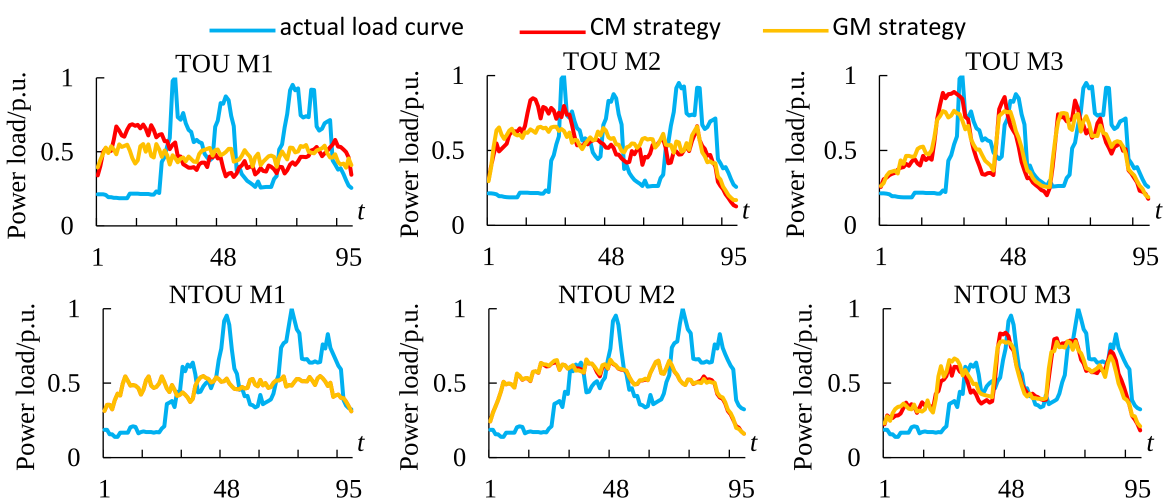


Fig 2 The power load fluctuations in different strategies

3. RESULTS

3.1 *Transfer characteristics of power load on time scale*

The solution of multi-objective planning is a set of Pareto frontier solutions, in which each solution corresponds to a load curve. To clearly show the transfer characteristics of electricity load on the time scale, according to two strategies, we select the solutions from the Pareto front solution set for comparative analysis. One of them represents the minimum peak-valley difference (GM strategy), and the other is the minimum electricity cost (CM strategy). The power load fluctuations in different strategies are shown in Fig 2. Here only the transfer status of the electricity price policy group is shown.

It can be seen that the peak load is reduced driven by the load transfer on the time. More specifically, for the TOU group, it is likely to form a new peak load under the CM strategy as the electricity demand shifting to low price periods. For the NTOU group, it is equivalent to a single-objective optimization without electricity price incentives. It can be seen that the load curves of the GM strategy and the CM strategy overlap in mode M1, but in mode M2 and M3, driven by the usage of appliances with the function of heat preservation or low frequency, electricity cost continue to change, thereby the load curves under the two strategies are misaligned.

3.2 *Change of electricity cost and load fluctuation*

The effect of smart home participation in demand response is significantly affected by electricity price policy, family structure and occupation. Here, only the first two effects are shown (see Fig 3), in which 3(a) and 3(b) respectively show the changes in peak-valley difference and electricity cost in different groups and different modes.

Taking the electricity price policy group as an example, the peak-valley difference is possible to be reduced by 23.9%~80.7% in the time-of-use (TOU) group, and the range in NTOU group is- 72.9%~-29%; but for electricity cost, it is possible to change the cost of the TOU in the range of -9.5%~4.4%, and the range of electricity cost for the NTOU group is 0%~11.5%.

It is worth noting that the electricity cost of modes M2 and M3 are both higher than that of mode M1. The increase in electricity cost generates from the usage of appliances with heat preservation or low frequency function. That is, the transferable function of smart home working time may increase the electricity consumption and lead to an increase in electricity costs by 4.8%~11.5%

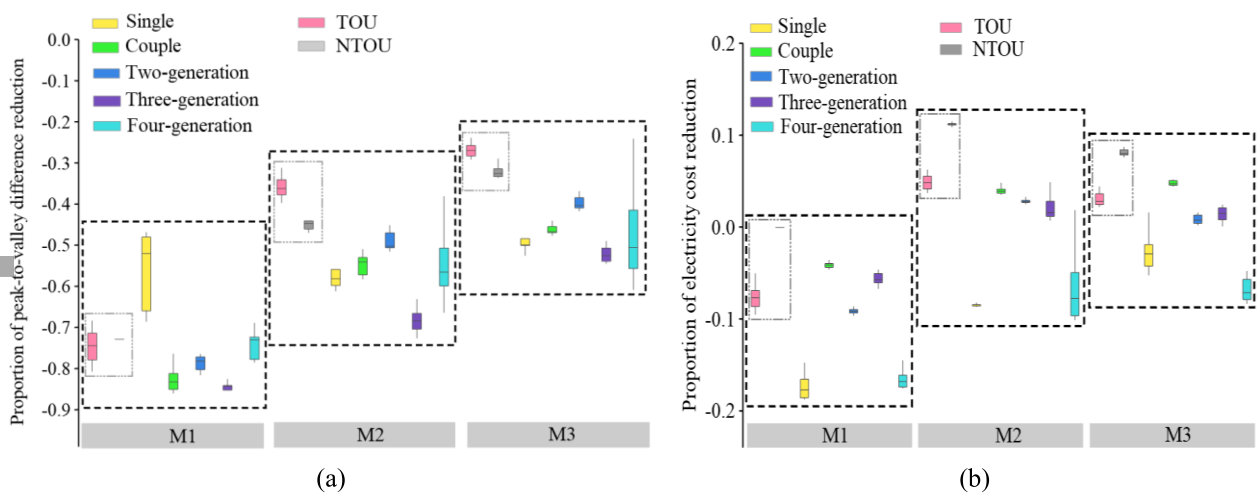
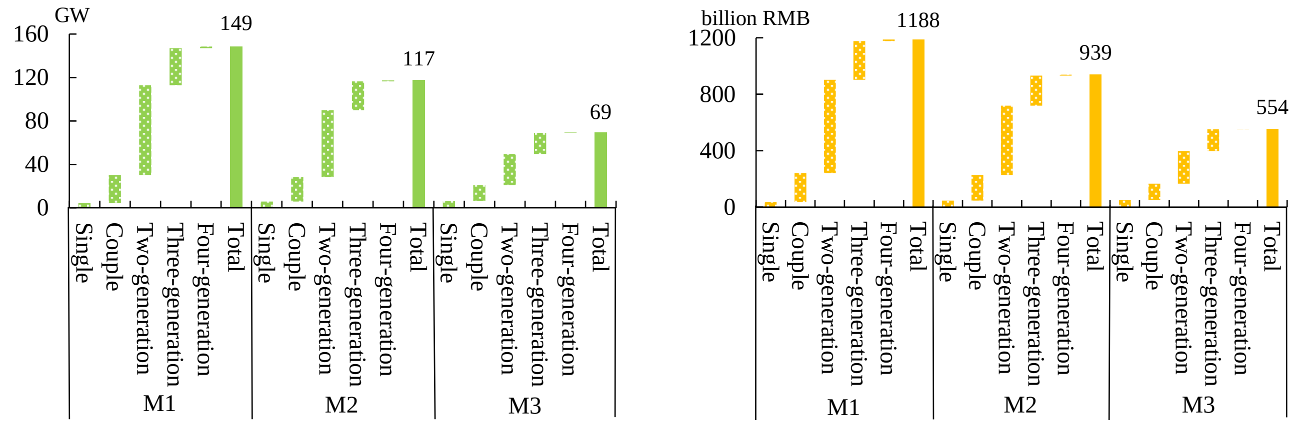


Fig 3 The change of peak-velley difference and electricity cost

3.3 *The potential of smart home participation in demand response*

To analyze the impact of smart home participation in demand response on the operation of power grid and the investment of power supply and power grid in China, based on China's sixth national census data in 2010, this part accounts for the potential of smart home in demand response from the perspectives of electricity price policy and family structure. Here, only part of results is shown in Fig 4. In the unconstrained mode M1, the participation of smart home in demand response can reduce the peak load of the power grid by 141 to 149 million kW, and save the investment of power supply and grid by about 1.13-1.19 trillion yuan.



(a) (b)

Fig 4 The potential of smart home participation in demand response

4. CONCLUSIONS

This study focuses on the transferable function of smart home working time, establishes the smart-home integrated management model, with goals of minimizing the electricity cost and peak-valley difference, to provide an optimization scheme that integrates smart home into demand response. At last, the potential of smart home participating in demand response is evaluated. The results show that the time of use policy can reduce the peak-valley difference between -29.2% and -23.9%, and cut electricity cost by up to 9.5%, which is conducive to encouraging smart home to participate in demand response. The transferable function of smart home working time may increase power consumption and thereby increase residential electricity costs by 4.8%-11.5%. In the unconstrained dispatch mode, driven by smart home participating in demand response, it is expected to reduce the peak load of the power grid by 141 to 149 million kilowatts, and reduce power supply and power grid investment by 1.13-1.19 trillion yuan.

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