Demand side management considering household appliances and EV

Mr Zihao Dong, Dr Jing Jiang
Department of Mathematics, Physics & Electrical Engineering
Northumbria University, Newcastle, UK
{z.dong, jing.jiang}@northumbria.ac.uk

Dr Haiya Qian
Department of Electrical and automation Engineering
Nanjing Normal University, Nanjing, China
haiya.qian@njnu.edu.cn

Prof Hongjian Sun
Department of Engineering
Durham University
Durham, UK
hongjian.sun@durham.ac.uk

Abstract---Combination of the information technology and the power engineering is the feature of next-generation grid. Depending on bidirectional communications, demand side management (DSM) aims at optimizing the electricity usage pattern of customers to improve energy efficiency and alleviate environmental impact. In this study, a DSM optimization algorithm is designed, which can perform load shifting on a household level based on the Time-of-Use strategy. Several flexible appliances, plug-in hybrid electric vehicle (EV) charging and rooftop photovoltaic (PV), are considered. Results show that the daily electricity cost has declined by 19% after the optimization. A 12% reduction of the domestic carbon emission is also achieved from the variation of grid carbon intensity and energy provided by rooftop PV. It is validated that with the growing penetration rate of EVs and renewable energy generation, smart scheduling of household load can greatly benefit grid stability and energy efficiency.

I. Introduction

With the rapid development of internet technology and communication technology, the power grid is undergoing a thorough update. The introduction of advanced metering infrastructure [1] and automatic devices improve the controllability and stability of the grid dramatically. Based on the next-generation smart grid, DSM is supposed to further improve the energy efficiency. As nearly 20% of generation capacity exists only to meet the peak load for a short duration [2], if loads can be moved to valley period, the demand for generation capacity will be lower and less fuels are required, which means lower carbon emission and higher energy utilization rate. DSM is also supposed to interact with renewable energy. For one thing, most kinds of renewable energy are inverter-based [3], which means they are more unstable compared with synchronous generators. DSM can help to prevent drastic fluctuation of load and maintain grid stability. For another, many renewable energy sources have uncertainty [3] in nature. Combined with generation prediction and load prediction technology, DSM enables customers to make full use of clean energy by arrange more flexible loads to the period when renewable energy works, thus reaching the demand-follow-supply mode and meeting the goal of decarbonization.

Some DSM strategies have already been proposed in the present literature. Specifically, A. Vijayan et al. [4] have proposed a residential DSM algorithm based on load shifting method, which aims to minimize the daily electricity cost for customers. Another load shifting algorithm proposed by N. D. Rahate [5] focus more on peak clipping and the peak to average ratio (PAR) achieves a reduction of 22.23%. Apart from load shifting, other DSM strategies are also explored. For instance, O. M. Longe et al. [6] have discussed direct load control method on purpose of controlling the consumption. However, customers' comfort is not fully considered. Instead, S. Patil [7] suggested a priority-based DSM program. Customers can choose not to participate in load control if they do not have low priority appliances at certain time. Some studies also involve EV charging. F. Yi et al. [8] have proposed a game-theory-based EV charging model, which aims at alleviating the peak load of the grid and reducing the charging fee for customers. A. Keyhani and B. Ramachandran [9] have extended the topic further by comparing the peak shaving effect under different EV participation levels. M. Yadav [10] has evaluated EVs' performance on shaping the residential load, which indicates that EVs can either perform as a cluster or perform independently in each household. The function of PV generation with DSM is also evaluated in some papers. The performance of DSM in a microgrid with PV has been studied by J. Prasad [11]. The simulation result shows that the peak load has a reduction of 45% and the energy required from the power grid also decreases for 20%. Ye et al. [12] have judged the performance of rooftop PV in residential DSM.

Although many DSM strategies and models have been presented in the past literature, most of them focus on one aspect of residential load, EV or PV generation only. However, with the growing proportion of EV and PV, it is important to explore how different elements can interact with each other on a household level as it is directly related to customers' willing to engage in DSM, which falls into this paper's research area. Apart from that, most studies set their objectives as saving cost for customers, clipping peak load and stabilizing the grid, while the carbon emission control effect of DSM is rarely evaluated. As DSM enables a higher utilization rate of PV and other clean energy, the benefits it can bring on reducing carbon emission is very important because of the global target of decarbonization and more cases are required in this aspect to quantify them.

Different from the past literature, this project aims to analyze the benefits of DSM in a more comprehensive way. The main contributions of this project are:

- A residential DSM optimization model is proposed. The model combines popular DSM elements and the benefits it can bring are analyzed. All the data involved is real

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demand data, which means the practicability of proposed model is generally high.

- The optimization algorithm is based on simplex method. Compared with some heuristic algorithms which are used in some previous DSM models, simplex method is more rigorous mathematically. Its mathematical complexity is also lower than some polynomial algorithms and already has fledged applications. Therefore, it is easy to apply and more stable in practical use.
- Carbon emission concern is met by considering grid carbon intensity. PAR is regulated as well to bring benefits to grid operators. As a result, a multi-objective optimization is presented. The pareto front is also given to see how these objectives affect each other.
- Simulation is divided into different scenarios and the reduction of cost and carbon dioxide in each scenario are calculated. The results indicate that combination of load shifting and rooftop PV can reduce bill payment and carbon emission of a household considerably without disturb customers' comfort.

The reminder of this paper is organized as below: Section II presents the proposed model and methodology. Section III illustrates simulation results and discussions. Section IV draws conclusions.

II. System Model and Methodology

In the present study, a residential energy management system is proposed as shown in Fig. 1. It considers 3 smart appliances (washing machine, dishwasher, electric water heater), EV charging and rooftop PV. The 3 certain appliances are chosen because their operation time is flexible. People do not care about the exact time slots that these appliances work in. In this case, the discomfort caused to customers can nearly be ignored and no compensation is required. In the proposed model, the household is equipped with smart meters to collect consumption data and all the equipment can be controlled automatically. By performing load shifting based on a time-of-use price strategy, the optimization algorithm is expected to achieve cost saving for the family and peak load alleviating for the power grid. Specially, the carbon emission is also treated as an optimization objective. The reduction of carbon emission is achieved by introducing the idea of grid carbon intensity and the utilization of rooftop PV.

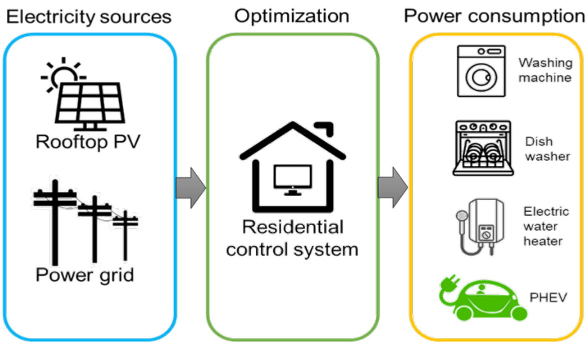


Fig. 1 Proposed residential energy management system

A. Problem formulation

The proposed residential energy management system is an optimization problem essentially. Firstly, all the elements involved are expressed by mathematical equations so that they can be solved by the algorithm.

For washing machine and dishwasher, both of them are uninterruptible loads and we use integers to represent this characteristic:

$$S_{wm}^{t}=\begin{cases}0\\1\end{cases},\quad S_{dw}^{t}=\begin{cases}0\\1\end{cases},\quad t=0,1,2,\dots,23 \tag{1}$$

When $S_{wm}^{t}=1$, it represents that the washing machine is operation on that time slot t, while $S_{wm}^{t}=0$ represents it is off at that time slot. S_{dw}^{t} represents the same for dishwasher. To simplify, one time slot is chosen to be an hour. The rated power consumption of washing machine and dishwasher is assumed to be a constant value, and their operation time is set to be one hour, that is:

$$W_{wm}=500Wh,\quad W_{dw}=900Wh \tag{2}$$

Washing machine should operate one time a day, while dishwasher is assumed to operate two times a day.

$$\sum_{t=0}^{23}S_{wm}^{t}=1\quad,\quad\sum_{t=0}^{23}S_{dw}^{t}=2 \tag{3}$$

Electric water heater is an interruptible appliance, which means the power consumption per hour can vary from 0 to full operation power. The rated power of electric water heater is 2200W with a capacity of 60L. Water is assumed to be heated to $55^{\circ}C$. Take the environment temperature to be $25^{\circ}C$ Therefore the power required is $Q=cm\Delta t$ =7560kJ=2.1KWh. To simplify, it is assumed that the daily consumption of the electric water heater is 2.2KWh,

$$0\le W_{ewc}^{t}\le 2200Wh \tag{4}$$

$$\sum_{t=0}^{23}W_{ewc}^{t}=2200Wh \tag{5}$$

For the PHEV, it is assumed to adapt AC level 1 charging with a rated power of 1.92kW. The battery capacity is 16.5kWh, which is the maximum power charged daily. EV charging is also interruptible. The case that PHEV sells back the energy stored to the grid is not included in this study. As a result, energy consumed by PHEV per hour should always be a positive number.

$$0\le W_{ev}^{t}\le 1920Wh \tag{6}$$

$$\sum_{t=0}^{23}W_{ev}^{t}\le 16.5kWh \tag{7}$$

For rooftop PV, the output power is related to the solar irradiance, size of the PV panel and the transform efficiency, which can be calculated as:

$$W_{pv}^{t}=K\times A\times I^{t} \tag{8}$$

Where K refers to the transform efficiency, A refers to the PV size and I^{t} refers to the solar irradiance at time slot t. K is set to be 0.12 and A is $6.5m^{2}$. The expense of PV energy is taken to be 0. Therefore, the total power demand from the grid per hour can be calculated, which is:

$$W_{sum}^t = S_{wm}^t W_{wm} + S_{dw}^t W_{dw} + W_{ewc}^t + W_{ev}^t + W_b^t - W_{pv}^t \tag{9}$$

Where W_b^t is the based load at time slot t, which is non-shiftable. It is noticeable that W_{sum}^t should always be a positive number or 0. When the energy provided by PV surpass the demand at that hour, W_{sum}^t is taken to be zero, which means the model does not consider the case that PV sell the surplus energy back to the grid. Then the daily electricity cost EC is calculated as below:

$$EC = \sum_{t=0}^{23} EP^t \times W_{sum}^t \tag{10}$$

Where EP^t is the electricity price at time slot t. A time-of-use price strategy is adapted and the price curve is shown in Table I.

TABLE I. GRID ELECTRICITY PRICE [13]

Time of Day	0:00-8:00	8:00-16:00	16:00-24:00
Price (¥)	0.35	0.45	0.55

In order to smooth the load curve and avoid creating new peaks because of load shifting, the peak to average ratio (PAR) limit is considered. It is calculated as the peak load divided by the average load of a day, that is:

$$PAR = \frac{\max_{0\le t\le 23}\{W_{sum}^t\}}{W_{average}} \le \alpha \tag{11}$$

$$W_{average} = \frac{\sum_{t=0}^{23} W_{sum}^t}{24} \tag{12}$$

α should be a number not much larger than 1 to achieve peak clipping effect.

B. Carbon emission

In order to minimize the carbon emission of the household, the concept of grid carbon intensity is considered. Table II [14] shows carbon intensity factors of different generation types, where CCGT refers to combined cycle gas turbine power stations and OCGT refers to open circle gas turbine plants.

TABLE II. CARBON INTENSITY BY GENERATION TYPE [14]

Generation Type	CO_2(g/KWh)
coal	910
Nuclear	0
CCGT	360
Wind	0
Pumped Storage	0
Hydro	0
Biomass	300
Oil	610
Solar	0
OCGT	480

As different generation sources all connect to the power grid, the carbon intensity of the grid varies from hour to hour when the proportion of different sources changes. The grid carbon intensity is calculated as:

$$C_g^t = \sum_{k=1}^{K} \frac{D_k^t \times C_k^t}{D_{total}^t} \tag{13}$$

Where C_g^t is the grid carbon intensity at time slot t. k represents generation types. D_k^t represents the power generated from k at time slot t. C_k^t is the carbon intensity factor for k and D_{total}^t is the total power generated by all sources.

PV generation does not produce carbon dioxide. Therefore, the daily carbon emission of the household E_{carbon} can be calculated as:

$$E_{carbon} = \sum_{t=0}^{23} C_g^t \times W_{sum}^t \tag{14}$$

In this project, the optimization based on both cost and carbon emission target will be carried out. Therefore, the optimization objective function is expressed as:

$$\min k_1\, EC + k_2 E_{carbon} \tag{15}$$

Where k_1 and k_2 are weight coefficients. By giving different values to them, cost saving and carbon emission will have different priorities.

III. RESULTS AND DISCUSSION

In this section, the simulation set up is specified to give the scope of this project. Then the simulation results are presented with some discussion.

A. Simulation set up

The residential consumption data is obtained from the NREL data catalog [15]. It includes the load profile of a household in the mid-west region of the United States. Consumption data is recorded at 10 minutes intervals and covers the whole year, which is aggregated as typical residential load curves and treated as predicted consumption data for load shifting. As shown in Fig. 2, two different typical load curves are used as input of the algorithm, respectively in summer and winter. It can be found that the consumption in summer is always higher than that in winter and high peaks occur at night because of EV charging.

To calculate the output power of rooftop PV generation,

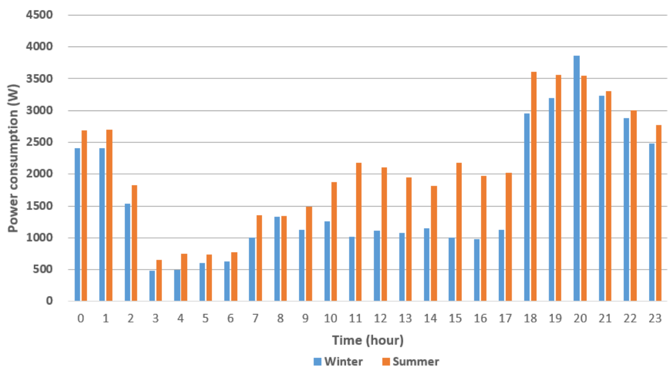


Fig. 2 Typical load curve

the data of solar irradiance is obtained from NREL data log [16]. For simplification, only clear sunny day is considered.

Generation data of year 2021 for grid carbon intensity calculation comes from GridWatch [17]. The source provides generation data at 5 minutes intervals of most generation types. In this project, the data of one month is aggregated and calculated as equation (13).

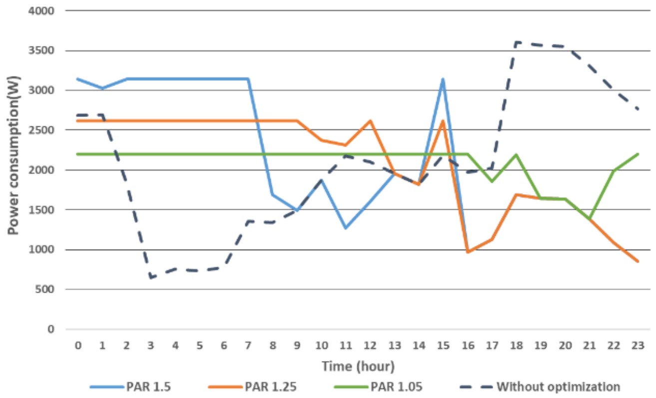
In order to fully analyze the effect of load scheduling and rooftop PV on both cost saving and carbon emission control. Simulations are divided into 4 different scenarios as shown in Table III.

TABLE III. CARBON INTENSITY BY GENERATION TYPE

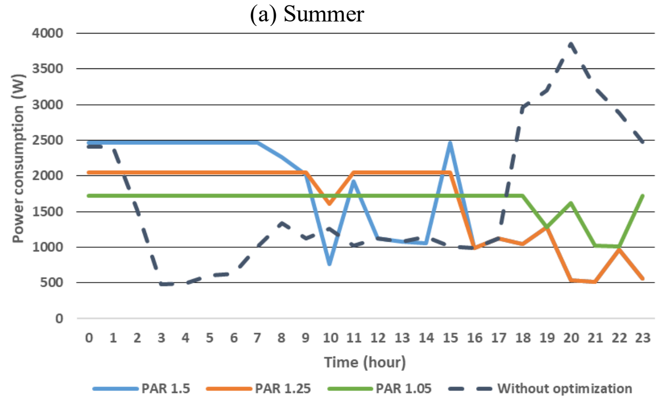
	Cost Objective	PV Generation	Carbon Emission Objective
scenario 1	Yes	No	No
scenario 2	Yes	Yes	No
scenario 3	Yes	No	Yes
scenario 4	Yes	Yes	Yes

B. Simulation results

1) Scenario 1: After optimization, the load profile under different PAR limits is shown in Fig. 3.



(a) Summer

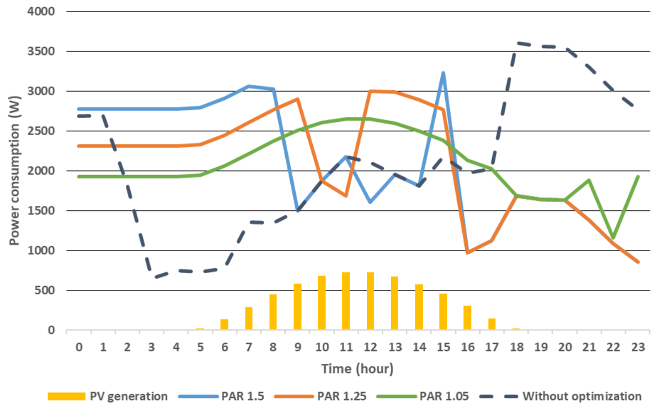


(b) Winter

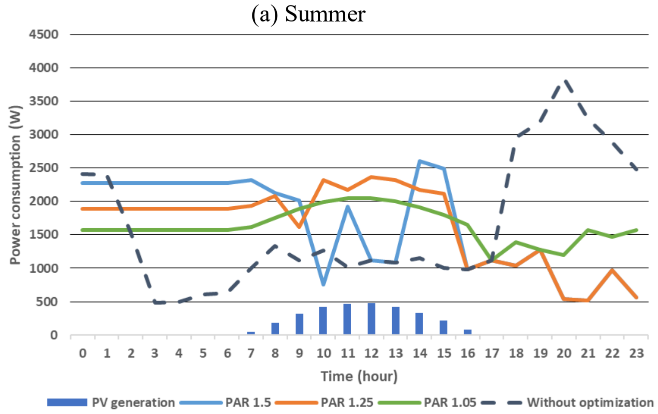
Fig. 3 Scenario 1 optimization results

It can be seen that with a mild PAR limit (1.5), most load is shifted to low price period, bringing maximum cost saving to customers. When PAR limit becomes stricter, the load curve becomes smoother. The results indicate the load curve shaping ability of EV is strong if given higher flexibility. It is clear that EV charging takes a large proportion of residential load and provide considerable flexibility. Therefore, it is feasible to shape the load curve with EV and several high-flexibility appliances. It does not bring any inconvenience to customers as the operating schedule of other critical appliances (e.g., lighting, air conditioner, TV, electric cooker) is not changed.

2) Scenario 2: With the engagement of rooftop PV. The optimized load curve is shown in Fig. 4. It can be found that whatever the PAR limit is, some load is always shifted to meet the supply of PV as it is free of charge. Although it will cause



(a) Summer



(b) Winter

Fig. 4 Scenario 2 optimization results

a peak load at noon, the extra load is actually covered by PV generation, which means the demand from the power grid is still flat with a strict PAR limit and grid stability can be maintained. Apart from that, the solar irradiance is weaker in winter compared with summer, which results in a lower PV generation output and less load is covered.

The daily electricity cost of scenario 1 and scenario 2 is calculated and presented in Table IV. It can be found that even with a strict PAR limit, there is still a saving of 6-7% for load shifting alone compared with no optimization scenario. With a mild PAR limit, the saving can grow to 11-12.5%, and the PAR in this case is still lower than the original load curve. When PV generation is involved, the cost of different PAR limit can have a further reduction of 6-10%. In winter, cost saved by PV is not as much as that in summer due to a lower PV power output.

TABLE IV. DAILY ELECTRICITY COST

Season	Case	Daily electricity cost (¥)			
		PAR=1.5	PAR=1.25	PAR=1.05	No optimization
Summer	Senario 1	21.14	21.55	22.35	23.83
	Senario 2	18.77	19.14	19.82	
Winter	Senario 1	16.45	16.78	17.52	18.83
	Senario 2	15.26	15.57	16.25	
		Save in %			
Summer	Senario 1	11.29%	9.57%	6.21%	0%
	Senario 2	21.23%	19.68%	16.83%	
Winter	Senario 1	12.64%	10.89%	6.96%	0%
	Senario 2	18.96%	17.31%	13.70%	

To analyze the relationship of PAR and daily cost clearly, the pareto front of scenario 2 summer load curve is given in Fig. 5. It is obvious that the curve has two linear parts which correspond to the two steps in electricity price. When the PAR is above 1.18, the expense of reducing PAR is relatively low.

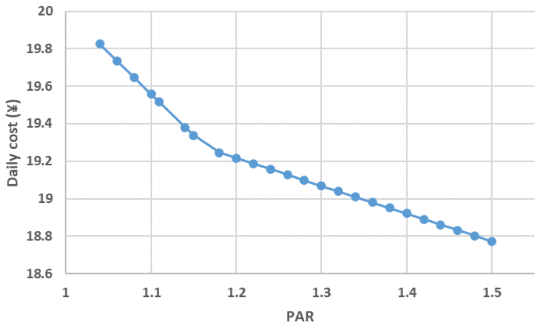
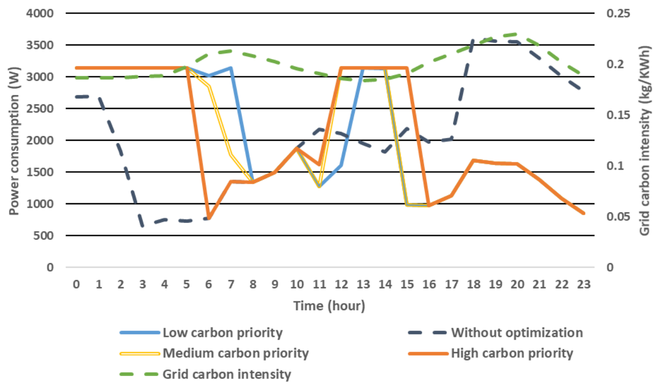


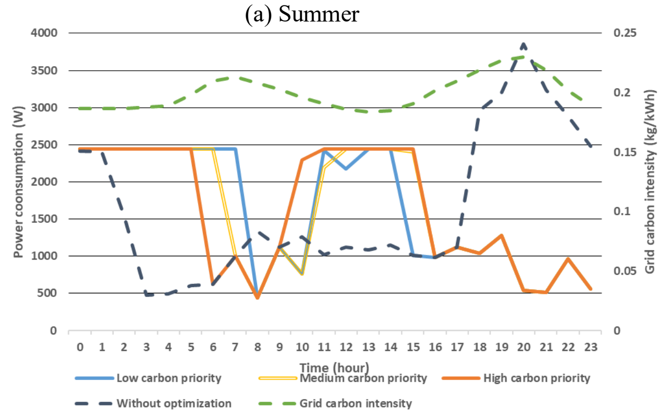
Fig. 5 Pareto front of cost and PAR

After that, the cost grows quickly when a lower PAR is required.

3) Scenario 3: Load curves after optimization are presented in Fig. 6. The PAR limit is set to be 1.5. By setting different k_1 and k_2 in formula (15), carbon emission is given different priorities. k_1 is fixed to be 1. For low carbon priority, k_2 is 0.1. For medium carbon priority, k_2 is set to be 5 and for high carbon priority k_2 is 10. The results show that under a low carbon priority, the algorithm still shift most load to low price period, which is from 0 to 8 a.m. While for a medium and high carbon priority. Some load is shifted from high carbon intensity period (i.e. 6-9 a.m.) to low carbon intensity period from 11 to 16 p.m. Some load remains the same as the low price and low carbon period are coincident from 0-5 a.m.



(a) Summer

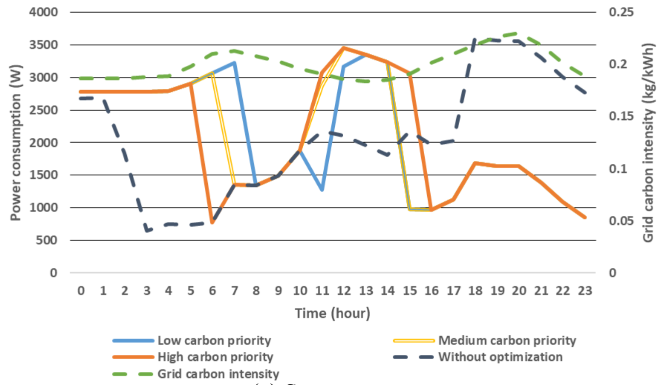


(b) Winter

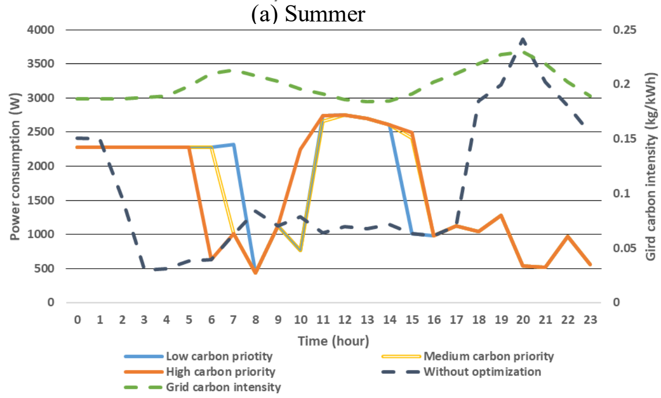
Fig. 6 Scenario 3 optimization results

4) Scenario 4: When involving PV generation, the simulation results is shown in Fig. 7.

Similar to scenario 2, some load is shifted to the noon to meet the generation of rooftop PV while maintaining the required PAR. With a higher carbon priority, more load goes to low carbon intensity priority just like scenario 3. The daily electricity bill and carbon emission is calculated and



(a) Summer



(b) Winter

Fig. 7 Scenario 4 optimization results

presented in table V. It can be found that without using PV, the cost saving is around 10% for summer and 11% for winter, while the reduction of carbon emission is relatively lower, which is about 2.5% for summer and 4.4% for winter. This is due to the marginal variation of grid carbon intensity within a day. However, with the proportion of wind and solar energy increasing continuously, the fluctuation of carbon intensity may become more drastic in near future, which means the proposed load shifting algorithm can bring more benefits. Besides, more carbon reduction comes from rooftop PV, with the engagement of which the carbon emission has a reduction of 13.8% averagely in summer and 11.5% averagely in winter. The difference mainly comes from the total demand and PV generation output. By combining the load shifting strategy and PV, the daily cost achieves a maximum reduction of 21.11% and the daily carbon emission can also achieve a reduction of 13.44%, which is quite considerable. It is noticeable that the original consumption data obtained in this project is relatively high and PV energy is fully used in all cases. In practical use, the PV energy may exceed the consumption at some time slot.

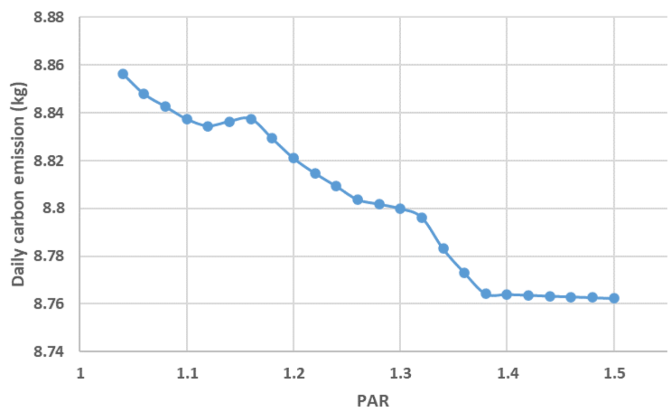


Fig. 8 Pareto front of carbon emission and PAR

TABLE V. DAILY ELECTRICITY COST AND CARBON

Season	Case	Low carbon priority	Medium carbon priority	High carbon priority	No optimization
		Daily electricity cost (¥)			
Summer	Senario 3	21.14	21.29	21.54	23.83
	Senario 4	18.8	18.99	19.22	
Winter	Senario 3	16.47	16.61	16.79	18.83
	Senario 4	15.26	15.39	15.56	
		Save in %			
Summer	Senario 3	11.29%	10.66%	9.61%	0%
	Senario 4	21.11%	20.31%	19.35%	
Winter	Senario 3	12.53%	11.79%	10.83%	0%
	Senario 4	18.96%	18.27%	17.37%	
		Daily carbon emission (kg)			
Summer	Senario 3	9.9399	9.899	9.8502	10.1727
	Senario 4	8.8051	8.7623	8.7188	
Winter	Senario 3	7.732	7.699	7.6721	8.0529
	Senario 4	7.1532	7.1243	7.1004	
		Save in %			
Summer	Senario 3	2.29%	2.69%	3.17%	0%
	Senario 4	13.44%	13.86%	14.29%	
Winter	Senario 3	3.98%	4.39%	4.73%	0%
	Senario 4	11.17%	11.53%	11.83%	

In this case, the proposed load shifting algorithm can further improve the energy efficiency and make full use of surplus PV energy.

The Pareto front of daily carbon emission and PAR under medium carbon priority is presented in Fig. 8. Unlike the case of bill payment, the change of carbon emission is nonlinear with PAR. The PAR can be regulated to 1.38 almost without the expense of carbon emission. After that, the slope changes frequently. Specifically, at the period of 1.6-1.2 PAR, the carbon emission has a slight decrease. It should be resulted from the high price but low carbon intensity period (i.e., 22-24 p.m.). The reduction in carbon emission is at the scarifice of electricity cost.

IV. CONCLUSTION

In this project, a residential load management system is proposed based on simplex algorithm. The system involves EV charging and several flexible appliances. Several scenarios are considered and the benefits of proposed DSM optimization method are analyzed comprehensively. The results indicate that EV charging takes a large proportion of total household consumption and can lead to high peaks without optimization. By performing load shifting, the peak load can be alleviated effectively and higher energy efficiency can be achieved. Based on a Time-of-Use price strategy, grid carbon intensity curve and rooftop PV, the load shifting algorithm also brings lower electricity cost and carbon emission to users. The reduction of cost and carbon emission is related to PAR limit suggested by grid operators and the carbon priority. Averagely, a reduction of 19% in cost and 12% in carbon emission can be achieved. (i.e., PAR is 1.25 and medium carbon priority). Rooftop PV is the main contributor of carbon reduction since the variation of grid carbon intensity is not significant. While load shifting still helps to make full use of PV generation. With a growing proportion of renewable energy, it is strongly suggested that smart scheduling of EV charging and other flexible load help to improve the energy efficiency of households dramatically and minimize environmental impact.

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