Optimal Home Energy Management System with Mixed Types of Loads

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***Abstract*—This paper presents a novel home area energy management system (HEMS) for smart homes with different load profiles installed with photovoltaic generation, energy storage, and DC demand. The developed HEMS is shown to optimize the utilization of local renewables while minimizing energy waste between AC and DC conversions and between storage charging and discharging. Previous studies on HEMS have not considered the impact of load types. In this study, the performance of the proposed HEMS is demonstrated on different smart homes with and without electric heating. A comparative study is carried out to investigate battery behavior, characteristics of AC and DC conversion, and benefits that customers receive. A sensitivity analysis is also conducted to discuss the effects from varied energy storage capacities, AC/DC conversion efficiencies, and PV output. The results show that cost reduction in energy bills can be greatly impacted by load profiles, and customers with electric heating load coupled with sufficiently large energy storage would receive the most reduction in their energy bills.**

***Index Terms*—Consumer behavior, customer benefit, home energy management system, hybrid AC/DC system, low carbon technologies.**

I. INTRODUCTION

SIGNIFICANT low carbon technologies (LCTs), such as small- scale embedded generators, energy storage, and heat pumps, are likely to be accommodated at customer properties in the future. Since 2011, domestic PV installation in the U.K. has increased between 375–900 MW each year. Heat pump installations, although not widely deployed, have increased to approximately 33 MW capacity each year [1]. These technologies are not only changing the original network operation philosophy, but also creating great uncertainty for network operators while offering more demand flexibility to end users. In addition to increased penetration of domestic LCTs in homes, the home energy management system (HEMS) is gaining importance. HEMS offers many benefits, including

1) full utilization of renewable energy by coordinating local energy generation and consumption;
2) increased energy efficiency by introducing local DC loads;
3) accommodation of demand side response (DSR) to benefit generators and network operators [2], [3]; and
4) direct financial benefits to end customers.

The growing popularity of HEMS in smart homes has led to a research focus on designing home energy management that factors in energy storage. For example, in [4] a HEMS control strategy has been developed that coordinates energy storage and home appliances aimed at lowering total electricity cost. The design introduces a user-expected price as an indicator of the differential pricing structure for different customers. In [5] a household energy storage control strategy is presented that manages domestic electric energy consumption. The battery dispatch strategy of this design considers both energy price and network pressure to facilitate DSR. Research in [6] presents a smart home load commitment strategy, i.e., the optimal operating periods of household appliances, including a consideration of the operating modes of electric vehicles (EVs) and storage. The work in [7] presents a HEMS with EV charging that factors in peak power limiting to facilitate DSR.

There are other studies that take renewable generation into consideration. In [8], the authors design an optimal scheduling of distributed energy resource (DER) to maximize the benefit for customers. A co-evolutionary version of particle swarm optimization (PSO) is used in this study to determine the operation of several DERs, including distributed generation (DG), energy storage, and controllable load.

The work in [9] presents optimal power management for PV holders factoring in battery aging. The proposed management in this work is based on dynamic programming and is applied to real conditions. The work in [10] investigates real time scheduling of controllable loads, battery, and PV based on rule based fuzzy logic controllers. The stochastic characteristic of electricity price, temperature PV generation is considered.

The study in [11] divides the stochastic household load (including renewable generation) into two types: the inelastic and elastic. The two load types are built with different models and optimized together. Load forecasting as well as an appliance-scheduling scheme is the focus in [12] to improve demand response. The operation of the scheduled appliance shifts when solar power is available and is incentivized with time of use

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(TOU) tariff, which is then updated by the forecasted load.

The research in [13] proposes a HEMS strategy based control of a smart home to achieve DSR, including PV and availability of EV and storage. Authors in [14] propose HEMS for evaluating the collaboration of dynamic pricing, renewable generation, EV, and energy storage, in which the EV and storage facilitate the DSR by trading energy between home and grid. Finally, in [15] optimal household electrical and thermal generation scheduling is developed in a hybrid thermal/electric grid home, which includes a fuel cell with combined heat and power (CHP) and a battery as the electricity storage system.

In all the HEMS models mentioned above, however, there is no consideration given to the impact from load types, such as AC and DC loads, and with and without heat demand. With the development of LCTs, more electric vehicles and DC powered appliances involving LEDs and batteries will be connected to households. Meanwhile, customers will continue to have different patterns of demand because of the electrification of heating and transport. These various load characteristics thus become important considerations in HEMS system for determining appropriate times and quantities of load shifting and reductions. Furthermore, HEMS can also influence the choice of parameters of home appliances, such as battery size. As such, to consider HEMs without factoring in load types may generate undesirable results and limit the financial savings for customers.

This paper proposes a novel HEMS for smart homes having different load profiles and installed with PV generation, energy storage, and DC demand. The developed energy management strategy is seen to optimize the utilization of local renewables whilst minimizing energy losses between AC and DC conversions and between charging and discharging with the incentive of TOU tariff. A comparative study is also conducted to investigate the battery control strategies, the different characteristics of AC and DC conversion, and customer benefits accrued based on different types of customer loads, i.e., smart homes with or without electric heating. In addition, a sensitivity analysis is conducted to evaluate the impact from varying the energy storage capacity, AC/DC conversion efficiencies, and PV output. The main contributions of the study are:

1) development of an advanced HEMS that integrates both AC and DC demand and generation;
2) evaluation of the energy management and financial savings for different types of customers.

This paper is organized as follows: section II illustrates the different customer load types; section III introduces the structure home energy management system; section IV presents the HEMS optimization strategy; section V demonstrates the performance of HEMS on different types of customers and conducts the sensitivity analysis; and section VI draws the conclusions.

II. Customer Load Type

The domestic customers with less than 100 kW maximum demand in Great Britain are divided into two classes [16]. The main differences in customer behavior are that customers in class 1 mostly use gas to support heating demand, while customers in class 2 use electricity to heat the electric storage heaters or hot water tanks. As a result, customers in class 2 have much larger demand when the heating system is on compared to customers in class 1. Currently, in the U.K., the electric heat demand is in the overnight hours and costs less when compared to daytime hours. The demands of a normal house and an electrical heating house are shown in Fig. 1. These load profiles are obtained from a household's measurement system installed by Siemens and Western Power Distribution (WPD) in a pilot project [17].

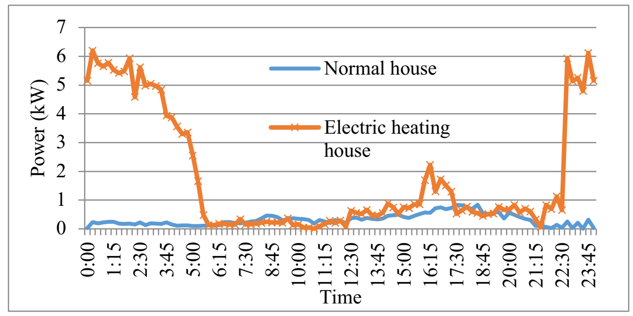

Fig. 1. Demand of houses with and without electric heating

With the electrification of heating and transport, the electricity demand of end customers will grow in the future. Additionally, the electric heat demand will become time unlimited. Both electric resistance heating and heat pumps will be widely deployed to achieve low carbon heat [18]. A recent investigation of domestic demand has shown heat pump consumption represented a significant additional electrical load when compared with a gas heating system in normal homes, accounting for 122% of total electricity consumption [19]. Additionally, demand for heat is often highest in the evening peak periods. Therefore, in the future, electric heating demand will not be seen as restricted to just overnight use. There will be increasingly large electric heating demand during the entire day. In this study, to simulate the electric heating demands of the future, a house with daytime heating and evening heating load is assumed by moving the heat load to daytime and evening peak, as shown in Fig. 2.

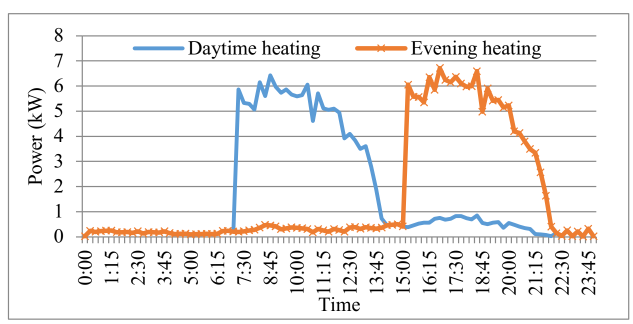

Fig. 2. House demand with daytime heating and evening heating.

III. EMS System

The simple structure of a smart home is shown in Fig. 3. A smart home will consist of the following: renewable generation, use of battery, and DC and AC loads [17]. Therefore, the entire system can be classified as AC generation/load and DC generation/load. A local DC bus is built to connect the DC powered devices and linked to the AC system by a bi-directional converter. This structure enables the direct use of the PV output via a battery and DC loads prior to AC conversion using an export inverter. This process increases energy use efficiency in the home by eliminating unnecessary AC/DC conversion losses. Additionally, with the help of a battery, PV output can be fully used to fulfill high demands during evening peak periods; in this way, customers can take advantage of tariffs to save on their electricity bills and also participate in DSR to reduce network pressure.

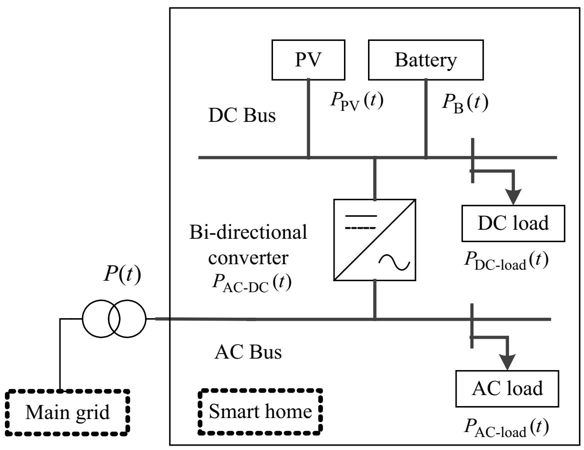

Fig. 3. Overview structure of smart homes.

To achieve optimal energy usage in the smart home, a home energy management system (HEMS) is built as shown in Fig. 4. HEMS takes the input data of forecasted customer load data, PV output, and tariffs. Then based on the objectives and constraints, it generates a strategy for both battery charging and discharging, as well as converter operations. The control strategies are sent to a charge controller and a bi-directional converter in order to achieve the needed state of charge (SOC) of the battery.

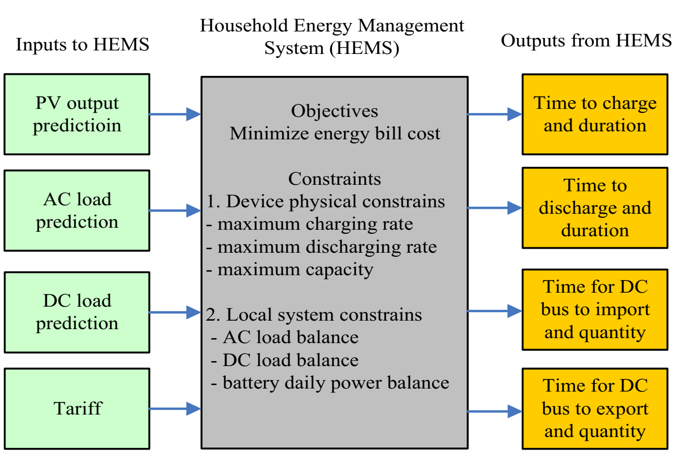

Fig. 4. Home energy management system.

In the HEMS, distributed generation and load information are derived from historical data. The methods for forecasting PV generation are widely introduced in [20]–[22]. Load forecasting methods are investigated in appliance scheduling studies, such as in [12]. For simplicity, it is assumed that forecasted PV output and load data are available at least one day ahead in the optimization model in this study. The HEMS will generate the battery and converter operation schemes in advance before the beginning of a day.

IV. Optimal HEMS Control Strategy

In this section, the mathematical formulation of household optimal AC/DC power management is presented. The objective is to minimize the total energy cost over scheduling period (one day). It is assumed that the amount of AC and DC load and PV output are available from the forecast. Thus, the battery and converter operation is designed with the response to price incentive.

1) Objective: The objective of battery operation is to minimize the cost of purchasing electricity from the main grid.

$$\mathrm{Min} \sum_{t=1}^{96} C(t)\, P(t)\, T \tag{1}$$

where $C(t)$ is the TOU rate at time t, $P(t)$ is electric power required from the main grid at time t, T is the length of time settlement, which is a constant. In this model $T = 0.25$ h.

The electrical power required from the main grid is the sum of AC load and AC to DC power, shown in (2).

During the AC/DC conversion process, AC-to-DC and DC-to-AC conversion efficiencies are considered in (3).

The AC to DC power is determined by the DC power on the DC bus. DC power can be derived from the DC load, battery input, and PV output, as in (4).

$$P(t) = P_{\text{AC-load}}(t) + P_{\text{AC-DC}}(t) \tag{2}$$

$$P_{\text{AC-DC}}(t) = \begin{cases} \eta_{\text{A/D}} P_{\text{DC}}(t) & \text{if} \quad P_{\text{DC}}(t) > 0 \\ 0 & \text{if} \quad P_{\text{DC}}(t) = 0 \\ \eta_{\text{D/A}} P_{\text{DC}}(t) & \text{if} \quad P_{\text{DC}}(t) < 0 \end{cases} \tag{3}$$

$$P_{\text{DC}}(t) + P_{\text{PV}}(t) = P_{\text{DC-load}}(t) + P_{\text{B}}(t) \tag{4}$$

where, $P_{\text{AC}-\text{load}}(t)$ is the customer's AC load at time t. $P_{\text{AC}-\text{DC}}(t)$ is the AC to DC power flow. $P_{\text{DC}}(t)$ is the DC power on the DC bus. $\eta_{\text{A/D}}$ and $\eta_{\text{D/A}}$ are AC-to-DC and DC-to-AC conversion efficiencies. $P_{\text{PV}}(t)$ is PV output at time t. $P_{\text{DC}-\text{load}}(t)$ is DC load at time t. Battery is taken as DC load; thus $P_{\text{B}}(t)$ is battery charging power at time t. When the battery charges, $P_{\text{B}}(t) > 0$; when it discharges, $P_{\text{B}}(t) < 0$; when the battery is idle, $P_{\text{B}}(t) = 0$.

2) Constraints: In the proposed model, the constraints of devices and power balance should be satisfied. The battery charging and discharging rate limit:

$$P_{\text{D}}^{\max} \leq P_{\text{B}}(t) \leq P_{\text{C}}^{\max} \tag{5}$$

where $P_{\text{C}}^{\max}$ and $P_{\text{D}}^{\max}$ are the maximum charging and discharging rates.

The battery maximum and minimum SOC limit, which is converted to maximum and minimum stored energy limit, is as follows:

$$E_{\min} \leq E_{\mathrm{B}}(t) \leq E_{\max} \tag{6}$$

$$E_{\min} = SOC_{\min} R \tag{7}$$

$$E_{\max} = SOC_{\max} R \tag{8}$$

where $E_{\mathrm{B}}(t)$ is energy stored in the battery at time t, $E_{\min}$ and $E_{\max}$ are allowed maximum and minimum energy that the battery can store; $SOC_{\min}$ and $SOC_{\max}$ are maximum and minimum SOC; R is battery capacity.

At any time, the stored energy is the sum of initial energy in the battery, and the accumulated energy is

$$\begin{cases} E_{\mathrm{B}}(t) = E\left(0\right) + \sum_{t=1}^{i} E(t) \\ E(t) = P_{\mathrm{B}}(t)T \\ E_{\min} \leq E\left(0\right) \leq E_{\max} \end{cases} \tag{9}$$

where $E\left(0\right)$ is the initial energy in the battery. $E(t)$ is the accumulated energy in battery at time t.

The battery is operated on a daily basis, and therefore the sum of charging and discharging power of the day is zero:

$$\sum_{t=1}^{96} P_{\mathrm{B}}(t) = 0. \tag{10}$$

3) The Optimization Process: The optimal operations of battery and converter are determined using mixed integer linear programming (MILP). The detailed process is shown in Fig. 5.

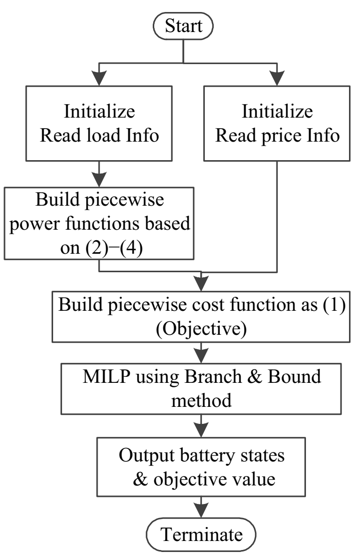

Fig. 5. Flowchart of optimization method.

V. DEMONSTRATION

In this section, the performance of the proposed HEMS is demonstrated on smart homes with and without electric heating, differing storage capacities and current limits, and converter efficiencies and PV output. The battery control strategy and benefits of bill saving of each case is shown and discussed.

Battery parameters used in HEMS framework are shown in Table I. The lithium-ion battery is chosen as the example energy storage because of its high performance, safety, and long lifetime when compared with other types of batteries.

In this study, TOU tariffs derived from wholesale energy price are used [23], as shown in Table II. The wholesale energy cost in Great Britain (GB) mainly determines the electricity bills of the customers because it accounts for over half of customers' electricity bills [24]. It is expected that this situation would continue into the future [25].

The main DC loads in the houses are LED lighting and USB sockets. The DC load profile is shown in Fig. 6. The PV capacity is 1.5 kWp, and the PV output is shown in Fig. 7.

TABLE I
BATTERY PARAMETERS

Battery Parameters	Value
Capacity	4.8 kWh
Charging current limit	20 Ah
Discharging current limit	20 Ah
Max/Min SOC	0.9/0.3
Charge/discharge efficiency	90%

TABLE II
TOU TARIFFS

Tariff Type	Time	Price (£/MWh)
Tariff 1 (low price)	00:00–06:59 14:00–16:29 21:00–23:59	146.08
Tariff 2 (shoulder price)	07:00–13:59 19:00–20:59	181.45
Tariff 3 (peak price)	16:30–18:59	241.27

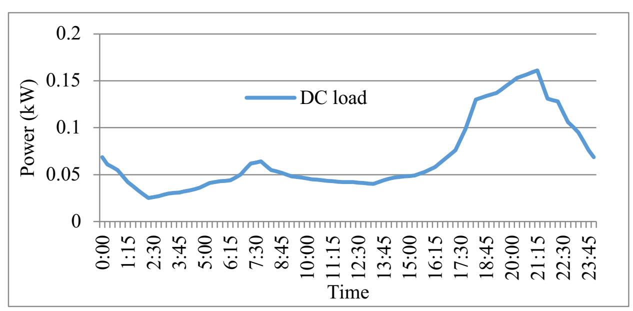

Fig. 6. DC load.

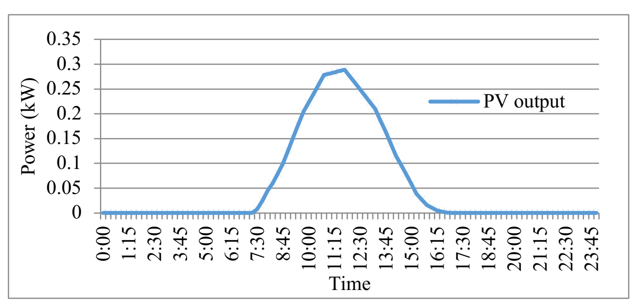

Fig. 7. PV output.

A. Performance in a Normal House

The HEMS is first tested in a house with typical load profiles. After demand adjustments, the battery control strategy and corresponding HEMS performance based on the household's typical load profile on a weekday are shown in Fig. 8 and Fig. 9. As depicted in Fig. 8, battery charges during low price times in the early morning and afternoon to 90% and 75% of SOC, respectively. It discharges in the shoulder price to 57% of SOC with lower rate in the peak price to minimum 30% of SOC with higher rate. Consequently, the demand in low price periods increases significantly as the battery charges from the AC system. The demand in the daytime decreases to zero as surplus PV and battery output power in the DC bus supports AC demands. The evening demand peak is reduced by nearly half using the battery, with the incentive of peak price.

The daily bill savings for this type of customer is £0.33. Compared to the original electricity bill, HEMS reduces the electricity bill by 19.07%.

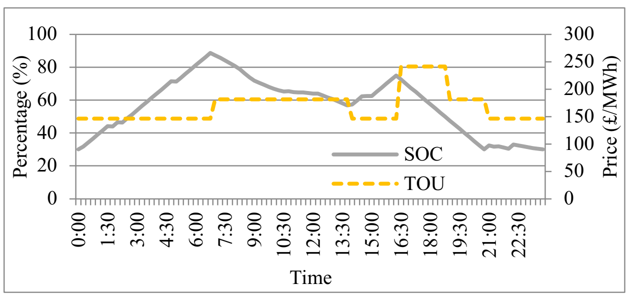

Fig. 8. SOC of battery in normal house.

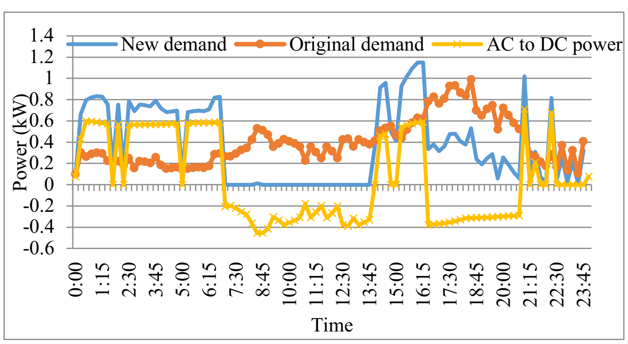

Fig. 9. Demand change in normal house.

B. Performance in Houses with Heat Load

The HEMS performances of houses with heat load are assessed in this section. The electricity demand of houses with heat load is larger than normal houses. The loads are clustered into three types to demonstrate the impacts of load characteristics: overnight heat load, daytime heat load, and evening heat load.

The battery control strategies of AC and DC system power changes are shown in Fig. 10. The overnight heating customer's battery is charged less during the overnight hours. However, it is charged more by the PV output during the morning and noon in order to support both DC and AC demand with maximum rate during the evening peak time. The battery of the daytime heating customer discharges 51% of its available stored energy in the daytime to support large daytime heat demand. The battery behavior of evening heating customer is similar to a normal customer in that it charges at a low price time and discharges with a maximum rate at high price and high demand time.

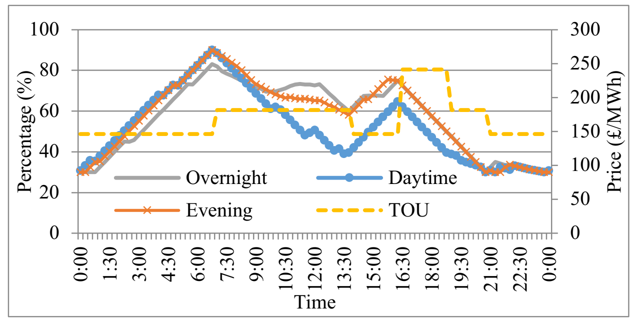

Fig. 10. SOCs of battery in houses with heat load.

The compared load profiles before and after HEMS and the converted AC/DC power are shown in Figs. 11–13. The HEMS effectively removes the demand from high price and shoulder price time to low price time as shown. Apart from fulfilling the DC load, the battery puts much of its effort on supporting the large heating demand. However, the amount of demand reduction and shifting is limited compared to the large electric heating load during the daytime or evening.

The daily bill savings for the overnight heating, daytime heating, and evening heating are all approximately £0.33 compared with the case without HEMS, which is equal to that of a normal house. As a result, use of HEMS provides a reduction of 4.86%, 4.43%, and 4.15%, respectively, in the electricity bills.

It can be observed that significant demand differences do not bring significant differences in battery control strategies and energy bill savings between normal and electric heating houses. However, all LCTs in the HEMS can impact the results. Thus, it is worthwhile assessing the influence of LCT characteristics on battery control strategy, AC/DC power flow, and bill savings.

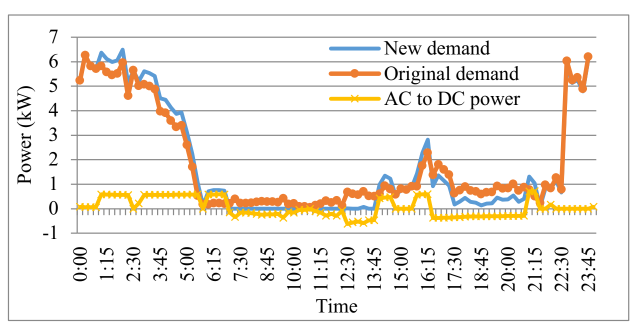

Fig. 11. Demand change in overnight heating house.

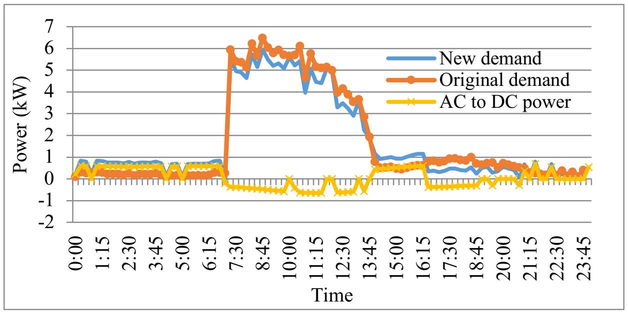

Fig. 12. Demand change in daytime heating house.

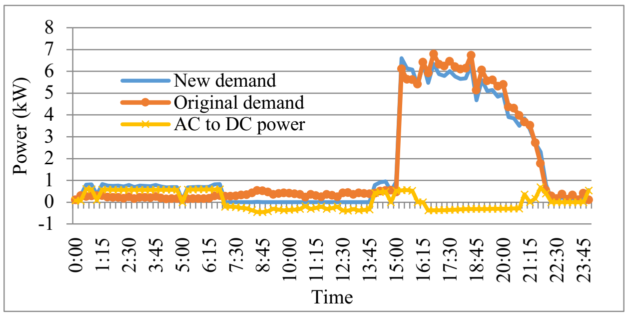

Fig. 13. Demand change in evening heating house.

C. *Sensitivity Analysis and Discussion of Results*

A sensitivity analysis is performed to assess the impact of LCT characteristics on HEMS performance in different types of houses. The parameters of battery capacity, current limit, and converter efficiency, as well as PV output are changed to demonstrate the corresponding effects. The resulting change in battery control strategies and bills savings are plotted and listed.

1) Impact of Battery Capacity and Current Limit: Battery capacity and current limit are important factors that determine the capability of demand shifting and bill savings. It is seen that the battery capacity increases to 19.2 kWh and the resulting charging/discharging limit increases to 180 Ah, as shown in Table III.

TABLE III
BATTERY PARAMETERS

Battery Parameters	Value
Capacity	19.2 kWh
Charging current limit	180 Ah
Discharging current limit	180 Ah
Max/Min SOC	0.9/0.3
Charge/discharge efficiency	90%

The battery control strategies with a large battery are shown in Fig. 14. In normal and overnight heating houses, the battery capacity is not fully used, with a maximum SOC of 50% and 56%, respectively, because the demand in shoulder and high price time are relatively small. In daytime heating and evening heating houses, the batteries are charged to 90% of SOC during ahead of low price time to support the large heat demand in shoulder and high price time.

By increasing the battery capacity, the bill savings of houses increase, as shown in Table IV. Bill savings increase is shown in the parentheses when compared with previous base cases. In the normal house, the savings increase comes from larger demand shifting in high price time compared with previous scenarios. Among all the houses with heat load, the saving in evening heating house is the largest because of significant demand shifts in high price times. It is noticeable that the saving of a daytime heating house is less than that of an overnight heating house. The reason is that a daytime heating house has larger energy loss (money loss) caused by larger AC/DC converted energy and more battery behaviors. Although the battery shifts more of the demand from shoulder price time to low price time, this benefit is offset by larger energy loss.

As a result, with large battery capacity and current limit, the HEMS performance is significantly influenced by load profiles. Customers with electric heating load receive more reduction in their energy bills, especially for customers with evening electric heating. However, increasing the battery capacity and current limit in these houses has less impact in the daytime heating house because the increase in bill savings is minor, shown in Table IV.

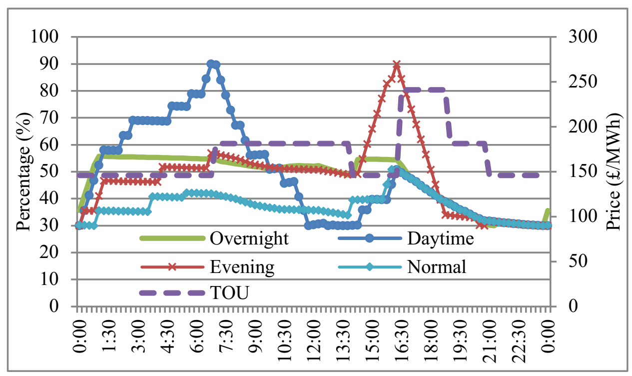

Fig. 14. SOC of larger battery.

TABLE IV
BILL SAVINGS WITH LARGER BATTERY

Customer Type	Daily Bill Saving (£)	Saving Percentage (%)
Normal	0.39 (+0.06)	22.53 (+3.46)
Overnight heating	0.42 (+0.09)	6.20 (+1.34)
Daytime heating	0.40 (+0.07)	5.36 (+0.93)
Evening heating	0.85 (+0.52)	10.76 (+6.61)

2) Impact of Converter Efficiency: Converter efficiency determines the energy loss in the AC-DC system, and thus is an important factor in electricity bills. The converter efficiency is set as 89%, i.e., AC-to-DC efficiency and DC-to-AC efficiency are both 89%.

As shown in Table V, the daily savings are generally equal (very slight decrease) to that with 90% AC-to-DC and DC-to-AC efficiencies. Moreover, the daily savings of the four types of houses are exactly the same in the HEMS with 89% efficiencies. However, a decrease in efficiencies increases the total electricity bill because customers have to pay for more

AC-to-DC and DC-to-AC energy losses. Therefore, the bill saving percentage decreases.

TABLE V
BILL SAVINGS WITH 89% EFFICIENCIES

Customer Type	Daily Bill Saving (£)	Saving Percentage (%)
Normal	0.33 (−0)	18.79 (−0.28)
Overnight heating	0.33 (−0)	4.80 (−0.06)
Daytime heating	0.33 (−0)	4.37 (−0.06)
Evening heating	0.33 (−0)	4.10 (−0.05)

The battery control strategies of all the houses are changed when compared to the base cases, as shown in Fig. 15. The batteries for four types of houses are not fully used (maximum of 66% of SOC) and they follow a common pattern:

1) charges 10%–15% of SOC from AC system during low price time overnight and discharges slightly to support DC demand;
2) discharges to support DC demand in the morning;
3) charges 25% of SOC from PV output;
4) discharges to support AC demand during high price time;
5) discharges to support DC demand during shoulder price time.

Additionally, the AC-DC power exchanges in the four types of houses are the same.

The battery does not shift the demand in shoulder price under this efficiency condition because the money losses (caused by energy losses) during the inefficient demand shifting are larger than the benefits brought by demand shifting. The battery only shifts demand during peak price times. With the battery current limit and peak price time limit, the shifted AC demand is limited. In this case, the shifted AC demand and DC demand only account for a maximum of 70% of battery capacity. It can be predicted that if the efficiencies keep decreasing, the battery may not work since the money loss cannot be compensated for by the benefit brought by demand shifting between peak price and low price.

To conclude, because of low conversion efficiencies, the impacts of different load profiles cannot be identified on HEMS. In addition, under a given TOU price condition, the efficiencies in AC/DC HEMS system not only determines the bill savings, but also influences the battery charging and discharging behaviors. In order to make full use of the battery in shifting AC demand in the HEMS system, the efficiencies should be set with the consideration of price differences.

3) Impact of PV Output (Capacity): In the proposed HEMS, PV plays an important role in demand reduction. The PV output power is set to increase 2.5 times to present large PV capacity.

The battery control strategies with large PV output are shown in Fig. 16 and Fig. 17. Instead of charging significant amount of power from the AC system, the batteries are mainly charged by the PV output, except in the morning heating house. In the morning heating house, the discharge rate at shoulder price time becomes slow since surplus PV output facilitates reducing the large heat demand.

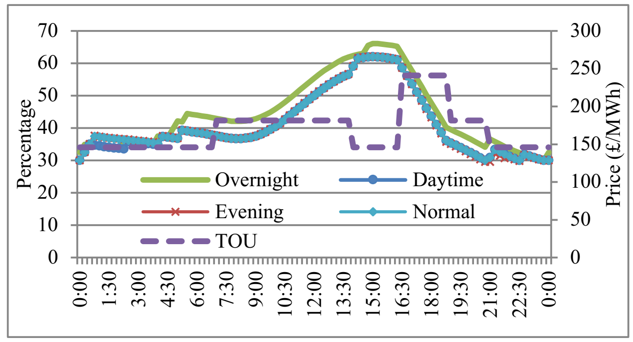

Fig. 15. SOC of battery in EMS system with 89% efficiencies.

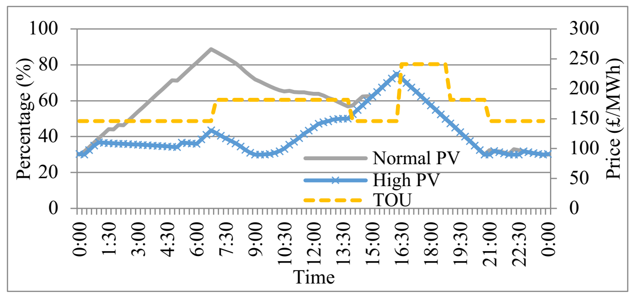

Fig. 16. SOC of normal house with large PV output.

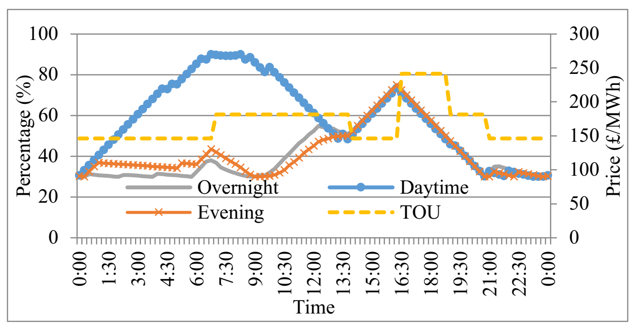

Fig. 17. SOC of electric heating house with large PV output.

However, it can be concluded in this case that both battery capacity and current limit influence the performance of HEMS as follows:

1) The batteries of normal, evening, and overnight heating houses are not fully used.
2) The discharge rates are the same at maximum limit during peak price time for four types of houses.

By increasing the PV output, the bill savings of houses increase dramatically, as shown in Table VI. Nearly all the houses double the savings. The overnight heating house has relatively lower increases. There is less shifting of demand from shoulder to low price in overnight heating houses for lower demand during shoulder price times (daytime).

In summary, the battery control strategy of the daytime heating house is significantly different from others with large PV outputs. The energy bill savings between normal and electric heating houses are similar, partially because of the limitation of battery current limits. However, overnight heating houses have less reduction increases because of lower daytime demand.

TABLE VI
BILL SAVINGS WITH LARGE PV INSTALLATION

Customer Type	Daily Bill Saving (£)	Saving Percentage (%)
Normal	0.67 (+0.34)	38.48 (+19.41)
Overnight heating	0.65 (+0.32)	9.58 (+4.72)
Daytime heating	0.67 (+0.34)	8.96 (+4.53)
Evening heating	0.67 (+0.34)	8.39 (+4.24)

VI. CONCLUSION

In this paper, a new HEMS in a smart home with PV, battery storage, and DC demand is presented. Compared with the previous approaches, this HEMS considers the different load types in optimizing the home AC and DC energy usage. It considers and discusses the impact of different load profiles in HEMS, i.e., the smart home with and without electric heating load. Additionally, it minimizes the energy losses between AC and DC systems and between battery charging and discharging in achieving the minimal energy cost for end users.

The results show that the proposed HEMS effectively reduces the energy bill and the bill reduction can be greatly affected by load profiles. For customers with and without electric heating load, the HEMS performance is different in the presence of reasonable parameters of LCTs. Generally, with sufficiently large battery capacity and current limit or PV installation, customers with electric heating loads would receive more energy bill savings. In detail, the key findings are as follows:

1) With large battery capacity and current limit, the HEMS performance of different types of load is significantly different. Consumers' energy bills can be greatly reduced, particularly for homes with evening electric heat demand. However, with small battery capacity, the HEMS performance is similar between all types of customers.
2) Within certain range of efficiencies, the HEMS performance is the same for all types of customers.
3) In a given TOU, the unreasonable converter efficiencies limit the function of HEMS.
4) PV installation capacity significantly impacts the battery control strategy of daytime electric heating customers. In comparison, the increased PV capacity has less impact on overnight heating houses with lower daytime demands.

The results are useful for consumer homes of different load profiles to use energy storage, while taking advantage of local renewables and cheap central supply. Future work will focus on long-term HEMS operations and calculation of benefits, as well as the impact of uncertainty (forecast error of PV and load) on customers.

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