A DATA-DRIVEN HOME ENERGY MANAGEMENT SYSTEM FOR SUB-SAHARAN AFRICA

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ABSTRACT

This work develops a home energy management system (HEMS) for regions where load shedding exists. The hardware of HEMS is mainly made from second-life materials, hence it is cheap enough for the low-income families to use. A cloud platform is developed to remotely communicate and manage the battery controlled by the HEMS. A multi-objective optimisation model is proposed to consider the trade-off between reliability improvement and bill reduction in places with time-of-use (TOU) pricing. Case studies are conducted through a simulation approach considering scheduled and unscheduled load shedding. The result shows that the HEMS can provide essential power supply during load shedding periods and reduce customers' electricity bills. The feasibility of the product has been tested in Botswana through a project with grant support from Innovate UK, EMBOSSA.

INTRODUCTION

The nature of the electricity system in most Sub-Saharan African (SSA) countries can be summarised as low security and high cost. Load shedding (also called rolling blackout) is a routine part of everyday life in more than 30 countries. Data from African Development Bank Group indicates that frequent power outages mean big losses in forgone sales and damaged equipment - 6 % of turnover on average for formal enterprises, and as much as 16% of turnover for informal enterprises unable to provide their own backstop power. From an economic point of view, the cost of electricity in some SSA countries (for example Djibouti and Gabon) are among the highest in the world [1].

Improved electricity reliability and reduced electricity bills are critical for the development of power sectors in SSA. A home energy management system (HEMS) is an intelligent technology that responds to the signals received from the grid by shifting or reducing the electricity load using energy storage [2]. Taking advantage of smart meters and new battery technologies, HEMS has quickly become a promising solution to the energy issues [3]. By controlling the charging and discharging cycles of the battery, demand will be shifted to avoid peak-time tariff and load shedding [4].

According to previous studies, HEMS can be divided into two categories: planned energy management and real-time energy management [2]. The former determines an optimal dispatch plan based on forecasted information. [2]. A classic model of this category is the day-ahead dispatch. The performance of this type of models is limited by the forecasting error. To overcome this issue, real-time energy management models are proposed [5]. However, a "greedy" planning algorithm only considers the locally optimal solution for the immediate time interval: it does not consider the influence of short term actions on future steps, through such constraints battery state of charge. This paper proposes a combined day-ahead and event-driven model. The next day's demand and price will be forecasted as well as the scheduled load shedding information. The optimisation will be implemented to minimise the overall cost of the day. If an unscheduled load shedding occurs, the optimisation will convert to a real-time management model till the load shedding ends.

The optimisation methods can be classified according to the nature of the objective. The primary objective of most HEMS is to save consumers' energy bills [6]. Dynamic programming technology is used for home energy management [6]. Other common dispatch objectives include reducing network congestion [7] and minimizing renewable curtailment [8]. This paper proposes a multi-objective optimisation which will be implemented to: i) save customers' energy bills, ii) reduce the risk of unscheduled load shedding; and iii) provide essential supply when it happens. The main challenge encountered is the uncertainty of the demand and load shedding. The optimisation module will consider unscheduled load shedding using the combined day-ahead and event-driven model. The trade-off between two functions, saving the electricity bill and increasing supply reliability, is reflected in the multi-objective optimisation through two weight coefficients which can be adjusted according to customer's preference.

ARCHITECTURE OF THE PROPOSED HOME ENERGY MANAGENMENT SYSTEM

Fig. 1 shows the proposed HEMS with two main functional modules, home battery system (HBS) and cloud service system (CSS). The HBS uses recycled materials including second-life car batteries and smartphones. It can serve at a low cost and is affordable even for poor households in SSA. The smartphone monitors the system status such as battery's state of charge and state of health. It also controls the battery to charge or discharge via a controller. The HBSs will interchange data with the CSS via the JavaScript object notation (JSON) data format through the mobile communication network. The data received by CSS

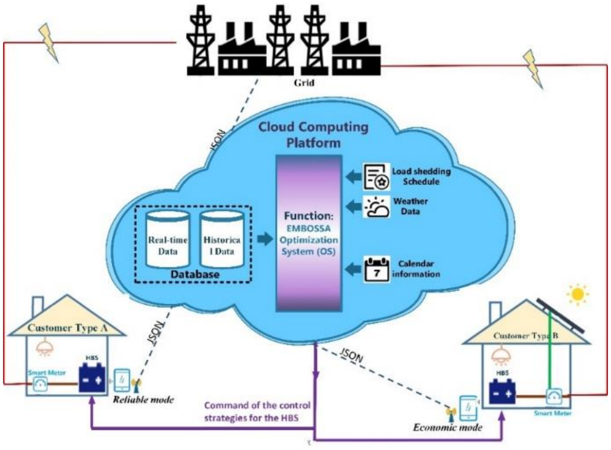


Fig. 1. Framework of proposed home energy management system.

include load shedding information published by the electricity supply companies, batteries' status and local tariff, demand, weather and network conditions. The CSS will forecast the load profiles and the price tariff of the homes for the optimisation model. The HBS will receive commands from the CSS and be dispatched accordingly.

THE CLOUD SERVICE SYSTEM

Similar-day-time load forecasting

In this study, we adopt a similar-day-time moving average method to forecast the load profile of a home. To forecast the load at time t on day d, the weighted average load on the same day of previous weeks will be considered. Also, the load at the same time t of previous days will also be taken into account.

$$\mathrm{W}_k(d,t) = (1-\alpha)\frac{1}{m}\sum_{i=k-m-1}^{k-1}\mathrm{W}_i(d,t) + \alpha\frac{1}{n}\sum_{j=d-n-1}^{d-1}\mathrm{D}_j(t) \quad (1)$$

Where, W(d,t) is the load in the weekly format, which indicate the load of the dth day and tth time in a week, d is the index of the day of the week, $d = 0, 1, \ldots, 6$. t is the time of the day in half hour, $t = 1, 2, ..., 48$. D(t) is the load in the daily format. $\alpha = [0,1]$ is a weight to balance the week's average and the day's average, when $\alpha = 0$, it will ignore the influence of similar days, on the other hand, if $\alpha = 1$, the week's part will be ignored.

Real Time Tariff

By Real Time Tariff we mean a tariff-making model in which the price of electricity varies over time and is usually designed for 48 half hours over a day. For (in contrast) a flat electricity price tariff, customers will use the appliances regardless of the time. However, for the dynamic real-time tariff structure, customers are encouraged to optimise their energy consumption response to changes in the network. The Fig. 2 shows a real-time tariff developed in UK [9].

Optimisation model in HEMS

A. Economic Cost Function

The objective is to determine the optimal amount and

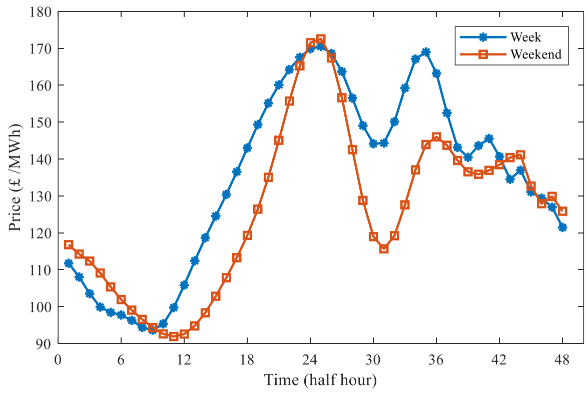


Fig. 2. Half hour price of electricity on weekday and weekend.

time of the charging and discharging actions of the battery in order to minimise the overall cost meanwhile maintaining the supply over load shedding periods and physical constraints of the battery. The overall cost includes the electricity cost and battery depreciation cost. The objective function can be expressed as follows:

$$\min\ f = \sum_{t=1}^{N_t} C_t(P_{load,t} + P_{ch,t} - P_{dch,t}) + C_{bat,t} + \lambda_t(SOC_{\max} - SOC_t) \quad (2)$$

Where, C_t is the electricity price; P_{load} is the forecasting load of consumer; $P_{ch,t}$, $P_{dch,t}$ are the charging and discharging power of battery; SOC_t is the state of charge of the battery; SOC_{max} is the maximum SOC of the battery; λ_t is a penalty coefficient in regard to battery SOC, which is intended to support energy security; $C_{bat,t}$ is the battery depreciation cost, given as:

$$C_{bat,t} = (P_{ch,t} + P_{dch,t}) I_{bat} \Delta T / 2E_{\max} N_{cycle} \quad (3)$$

Where, I_{bat} is the investment cost of battery; ΔT is the length of a timeslot; E_{max} is the capacity of battery; N_{cycle} is the standard cycle life of battery.

B. Constraints for battery

The charging and discharging power are constrained between zero and the maximum power of the battery:

$$0 \le P_{ch,t} \le P_{ch,\max} \quad (4)$$

$$0 \le P_{dch,t} \le P_{dch,\max} \quad (5)$$

The step change of SOC is constrained by the maximum changing rate as expressed in (6) and the upper and lower bounds of SOC are also constrained in (7):

$$SOC_t = SOC_{t-1} + (\eta_{ch} P_{ch,t} - \eta_{dch} P_{dch,t}) E_{\max} \quad (6)$$

$$SOC_{\min} \le SOC_t \le SOC_{\max} \quad (7)$$

In order to ensure the introduction of HEMS will not create another peak load, a peak load constraint should be added as:

$$P_{ch,t} + P_{load,t} \le \max\{P_{load,t} \mid t = 1,2,\ldots,N_t\} \quad (8)$$

If there is a scheduled load shedding, HEMS should provide as much power as possible during the power outage. Hence, it need a constraint for the total stored energy by the end of online interval:

$$SOC_{N_t} = \begin{cases} SOC_{\max} & if\ (SOC_{\max} - SOC_{\min})\eta_{dch}E_{\max} \le E_{load} \\ E_{load}/(E_{\max}\eta_{dch}) + SOC_{\min} & if\ (SOC_{\max} - SOC_{\min})\eta_{dch}E_{\max} > E_{load} \end{cases} \quad (9)$$

Where, $P_{ch,max}$, $P_{dch,max}$ are the maximum charging and discharging power; $\eta_{ch,max}$, $\eta_{dch,max}$ are charging and discharging efficiency; E_{load} is the total load during the future offline period.

C. Dispatching method

In order to dispatch the HBS on time, the load shedding information, the state of charge and state of health of the HBS will be updated and sent to the CSS every 5 minutes. Fig. 3 shows the flowchart of the proposed dispatching method. If the state of grid is changing from off to on, it will trigger an event-based dispatch immediately, reflecting the recovery from a load shedding. The day-ahead dispatch is a time controlled event. When the time is half of the interval of the update period (2.5 minutes in this case) to the midnight, the day-ahead dispatch will be updated. The optimisation system will schedule the dispatching of battery for the next two days if no load shedding is scheduled. The minimal length of the dispatching is 48 points (24 hours), and the maximum is 96 points (48 hours). If there is a scheduled load shedding within 48 hours, only the duration between midnight and the load shedding will be dispatched by the optimisation system. The electricity price in the dispatched period will be forecasted based on the tariff data. The similar-day-time moving average method will be used to forecast the load profile of the home. If there is a scheduled load shedding, the essential energy required during the load shedding period will be considered as another input for optimisation. This process will iterate until a stop command is set to the HEMS.

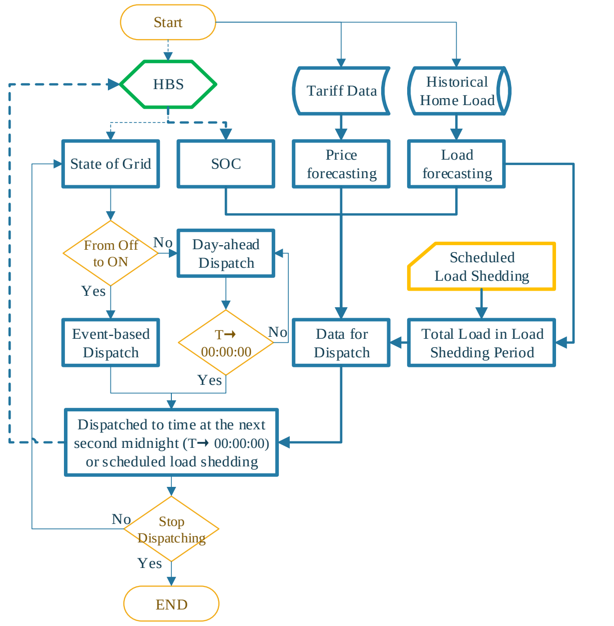


Fig. 3. The flowchart of proposed dispatching method.

CASE STUDY

In the test, a second-hand vehicle battery with capacity of 1 kWh is used to build the HBS. The maximum charging and discharging power of the battery is 0.2kW. The charging and discharging efficiency are both 0.88. The depreciation of the battery is £5 per cycle. Six days of load profiles are randomly simulated for a home. Two load shedding events are simulated where the first one is scheduled at period from 61[th] half-hour (hh) to 79hh, and another is unscheduled, from 161hh to 173hh as shown in Fig. 4(a). During the 6 days, the CSS updated the dispatching strategies (D1 to D7) for the HBS as shown in Fig. 4(b). D1 is the initial dispatching and D2 is a day-ahead dispatching. Both D1 and D2 ended at 61hh when the scheduled load shedding happened. The system updated itself by D3 to take account of the load shedding event. D4, D5 and D7 are the regular day-ahead dispatching. When there is a new dispatching action, the overlapped part with previous dispatch will be replaced by the new one. Fig. 4(c) shows the result of the charging or discharging power for the battery.

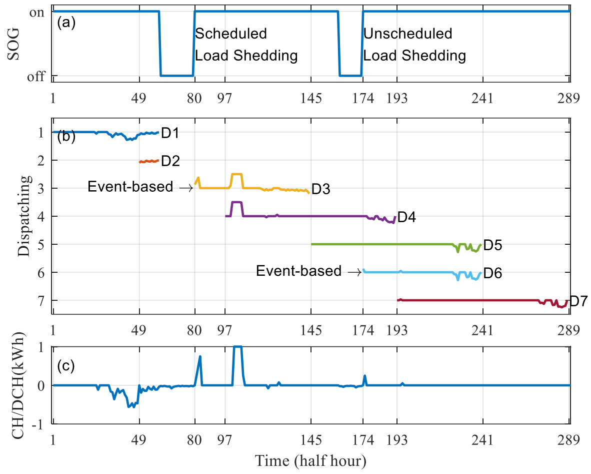
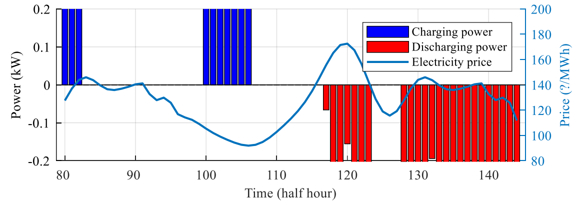
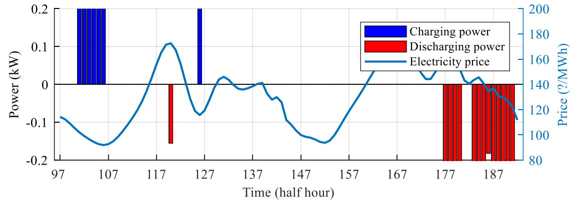


Fig. 4. Dispatching for HEMS in 6 days with a scheduled load shedding (61hh ~79hh) and an unexpected load shedding (161hh ~ 173hh) (a) state of grid (b) dispatching events (c) charging or discharging load for the battery.

The dispatching action D3 (80hh~144hh) is zoomed in Fig. 5(a). When the load shedding ends at 80hh, the battery starts charging regardless of the high electricity price till the SOC reaches a safe level at 83hh. This is to ensure the minimum SOC in case of another load shedding. The charging stops from 83hh until the price goes to a lower range at 100hh.



(a) Event-based dispatching (D3)



(b) Day-ahead dispatching (D4)

Fig. 5. Dispatching actions D3 and D4

However, when the time of CSS receives a message from

HBS within half of the update interval (the update interval is 5 minutes in this study), a new dispatching, D4 (97hh~192hh) as shown in Fig. 5(b), will replace the part overlapping with D3. This is to reflect the updated information on the battery and the forecasted price and load. The results of the simulation is shown in Fig. 6. The demand (blue line) is the power consumed by the user and the real (red line) is the power withdrawn from the grid. The result shows that the demand at peak-time is shifted and the HBS provides supply when load shedding happens. At the beginning and the ending of the simulation, the SOCs of the battery are kept at 100%.

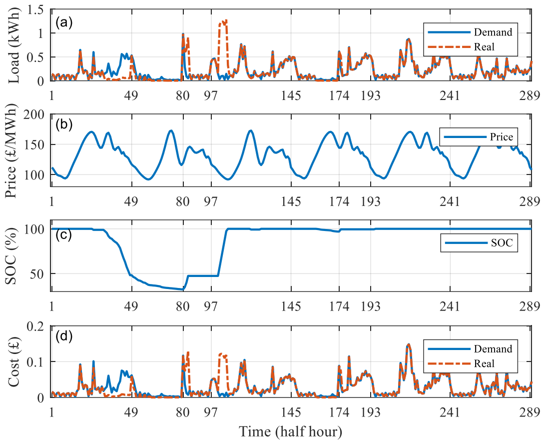


Fig. 6. Simulation results of cost and load for a HEMS in 6 days with a scheduled load shedding (61hh ~79hh) and an unexpected load shedding (161hh ~173hh).

Table I lists the benefit analysis of the proposed method. Customer with the HEMS saves £0.024 over the testing period and received essential power supply during a total of 16-hour load shedding period.

Table. I. Statistics table of cost and extra supply time in the simulation.

Time	Electricity cost(£)			Extra supply time (hour)
	Demand	Real	Saving	
1hh~48hh	1.378	0.740	0.639	0.000
49hh~96hh	0.596	0.678	-0.082	9.500
97hh~144hh	1.535	2.063	-0.528	0.000
145hh~192hh	1.254	1.253	0.001	6.500
193hh~240hh	2.006	2.012	-0.006	0.000
241hh~288hh	1.179	1.179	0.000	0.000
Total	7.948	7.924	0.024	16.000

FIELD TESTING

We went to Botswana, a country in SSA. There we procured a used car battery and a used smartphone, and we assembled them (with a minimum of special-purpose battery management hardware) into an HBS. We demonstrated the HBS communicating with and being directed by the CSS via a local GSM network and the Internet. We also simulated unscheduled load shedding, during which the HBS powered essential domestic lighting and other DC domestic services.

CONCLUSIONS

In this study we proposed a home energy management system for domestic customers with load shedding and cost-sensitive. The HBS is dispatched by multi-objective optimisation based on the energy price, scheduled load shedding and predicted load demand. The HEMS will provide the essential supply during power cuts, and help them to reduce energy bills. It also helps electricity companies to make fewer power cuts during peak time. The recycled hardware used in the system will not only stimulate local recycling economy but also reduce air pollution by enabling local poor households to reduce the use of kerosene.

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