OPTIMAL MANAGEMENT OF RESIDENTIAL ENERGY THROUGH IMPLEMENTATION OF REAL TIME PRICING AND DEMAND RESPONSE

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ABSTRACT

Demand response plays a crucial rule in future distribution network to facilitate the connection of low carbon technologies in a cost effective manner. This paper proposes an optimization-based automatic residential demand response controller incorporating several demand response models under a dynamic energy pricing regime that reflects network conditions. This is based on optimally schedule the energy usage of different types of domestic appliances in order to minimize the electricity payments and maximize the consumer satisfaction. Different penetration levels of the proposed demand response are applied to UK typical low voltage network. The results show that the proposed mechanisms can alleviate thermal violation in the network which allows connection of high penetration of electrical vehicles as well as electrical thermal units.

INTRODUCTION

As electricity will be increasingly generated from renewable resources, heat and transport sectors will progressively adopt low carbon technologies such as heat pumps and electrical vehicles. This will place significant additional power demands on the distribution network causing voltage drop, thermal overloading and ageing of network assets. This transition from passive to active, low carbon distribution networks requires innovative schemes to allow connecting low carbon technologies and maximise the harvesting from renewable sources. In this context, residential consumers can play a vital role in future distribution network to manage the new network participants. One of the potential mechanisms is Demand Response (DR) which is defined as the changes in electric usage of end-use customers from their normal consumption patterns in response to changes in the price of electricity [1].

The effectiveness of the demand response program is based on the proper design of the pricing signal. This design should reflect the actual market conditions based on the available resources and demand in real time, which is called Real Time Pricing (RTP). Furthermore, a threshold demand has to be assigned to the real time price at each time interval to reflect network conditions and prevent consumers from shifting most portion of their consumption to the least price intervals. However, it is difficult for the consumers to reschedule and/or reduce the usage of their appliances. Hence, automated demand response is essential to preserve a degree of flexibility for the consumers and reduce electricity bill. Fortunately, the rolling of smart meters will increase the opportunity to accommodate automated demand response programs in domestic sectors such as Residential Energy Management System (REMS) [2].

In this paper, an optimization-based automatic residential demand response controller is proposed to minimize the electricity payment for each household and maximize the consumer satisfaction to manage different models of appliances. This controller aims to optimally coordinate the scheduling and the energy usage for different type of appliances in response to real time price variations and network conditions. Moreover, different penetration levels of the proposed automated demand response program is applied to UK typical LV distribution network considering the connection of low carbon technologies such as electrical vehicles.

AUTOMATED DEMAND RESPONSE CONTROLLER MODEL

The degree of flexibility in applying demand response programs plays a vital role in increasing demand response penetration. Based on consumer preferences, the proposed controller classifies the home appliances (34 appliances) into two categories; deferrable load and curtailable load as shown in Fig. 1.

Home Appliances Models

Deferrable load includes all appliances that their starting time can be shifted across the day in response to price variations. These appliances must complete their full cycle of operation with the required energy usage. However, consumer preferences should be tackled in the design of the controller to assign a considerable level of comfort. Accordingly, each user has to set his preferred starting time and the maximum allowable tolerance time (advance/wait) to start the operation. Moreover, more differentiation can be applied to these types of appliances based on their technology features. Such appliances have to follow particular profile during the cycle of operation and there load profile can't be modified by modifying the power consumption. For instance, the washing machine during quick wash shall follow a predefined profile (power) but the starting time can be adjusted. On the other hand, the Plug-in Electrical Vehicle (PEV charging rate (Power) at each time interval can be modified but with achieving the required stored energy at the end time.

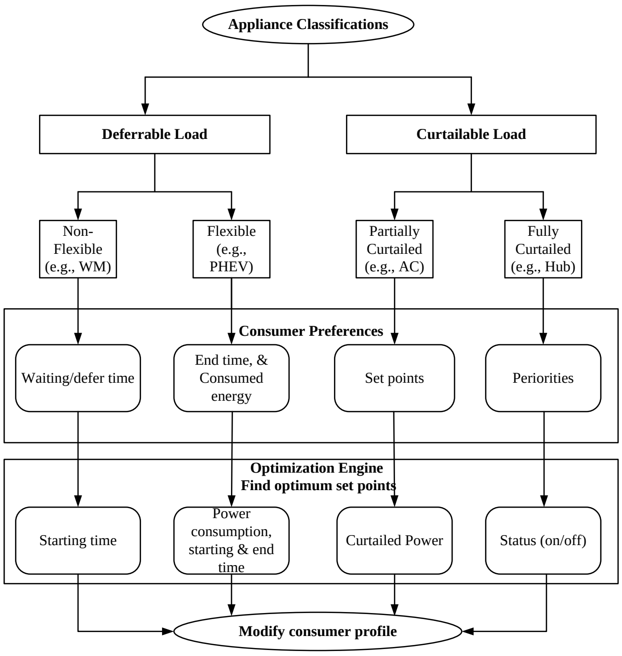

Fig 1. The proposed home appliances classifications

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Curtailable load falls into two types; partially curtailable load include a category of appliances that can be interruptible (curtail a percentage of the required power) but without shut it down completely such as Air Conditioning (AC) that its power consumption can be controlled according to its temperature set point. In addition, according to the consumer priorities, there are particular types of appliances that can be switched off without the need of re-turned them on such as light bulbs.

The remaining appliances are categorized as a set of *critical loads* such that their operation can't be interrupted at any time interval.

Methodology

A multi-objective optimization problem is solved to achieve a trade-off between the daily electricity payment and the consumer satisfaction. The consumer preference (satisfaction) is measured in terms of deferral time from the consumer preference and the reduction of the required curtailed energy. The optimizer will solve this problem as mixed integer linear programming to specify, the optimal values of the starting time for each deferrable appliance, as well as the power consumption, at each time interval within the optimization time horizon, for each of flexible and curtailable appliances. In other words, it will cover the coordination between all dwelling appliances and their inter-temporal relation in the time horizon of a single day. The objective function is subject to the corresponding power limit that is associated with the price signal. The controller is novel to optimally mange the home appliances such that the critical loads have to be operated without intervention. The Optimization is implemented in the AIMMS [3] optimization model environment, a high level modelling language.

IMPACT OF THE PROPSED CONTROLLER

To investigate the effectiveness of the scheduler in managing home appliances and achieve trade-off between minimum electricity payment and maximum user satisfaction, the following case study will consider controlling the four appliances categories and the coordination of their operation during 96-time intervals (24 hours). This includes deferrable loads with fixed profile (e.g., Washing Machine (WM)), deferrable loads with flexible profile (e.g., Electrical Vehicle (EV)), partially curtailable loads (e.g., Air Condition (AC)) and fully curtailable loads (e.g., kettle and hob).

Single dwelling daily load profile

The model in [4], that characterizes 33-appliance events in details, is adopted to generate daily load profiles with 1 minute resolution. This model is modified to include electrical heating appliances and electrical vehicles. In order to reduce the computational burden of the scheduler, the demand profile is sampled in 15-minute frequency. The result daily load profile is generated for the coldest weekend in January as shown in Fig. 2.

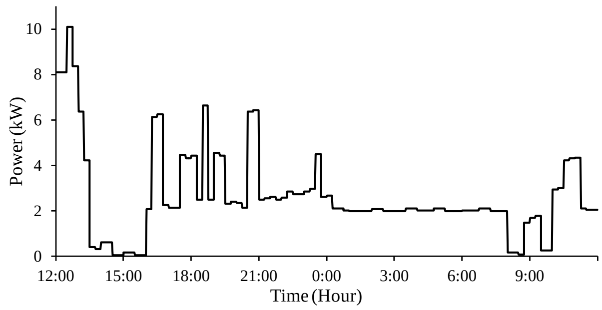


Fig 2. Daily load profile for a single dwelling.

Price Signal

A 15-minute daily price signal is announced by the utility for each day at 12:00 noon that reflect the network status and as shown in Fig. 3. This price signal at each time interval will be valid up to certain dwelling power level. The price signal will be doubled at each time interval in case the corresponding power consumption exceeds the allowed power level.

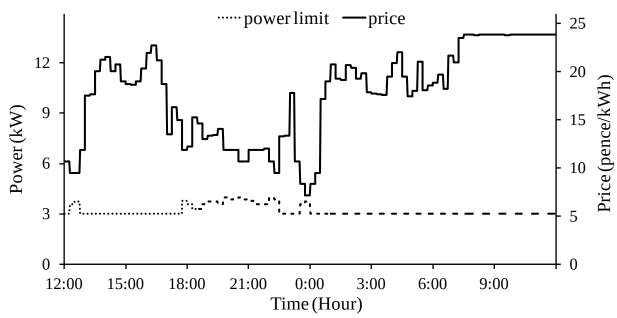
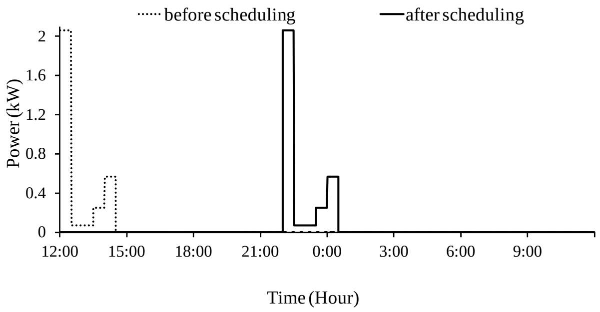


Fig 3. Daily power limit (left) and price signal (right).

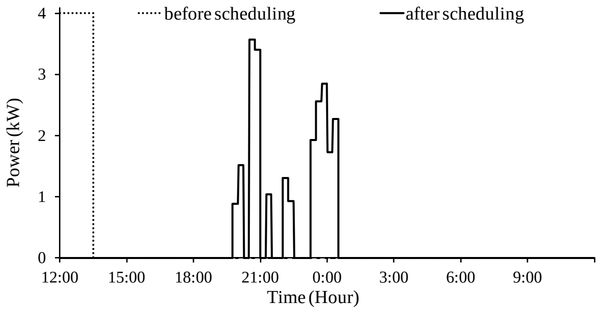
Scheduler results

The peak demand of the daily profile is 10.1kW and is occurred at 12:30. The total daily energy consumption is (63.77 kWh) with total cost of (£14.64). The preferred operation time and settings of the appliances are considered in the scheduler. The starting time of WM is required to take place at 12:00 and within a tolerance limit of ten hours. With a 4kW smart charger, the controller has to manage the EV charging profile in order to fill the daily depleted energy (6kWh). The user defines the arrival time at 12:00 noon, and the departure time at 10:00 and the expected driven distance (6miles). For a 2.5 kW air condition, the user prefers to maintain the indoor temperature close to 70F. Moreover, the user allows the controller to turn-off the hob and the kettle if necessary in order to minimise the electricity payment.

As the controller manages the scheduling for the four categories, the starting time of the WM will take a place at (22:00) instead of starting at (12:00) with preserving its demand profile as shown in Fig. 4 (a). Furthermore, the charging scheme of the EV will be modified to minimize the electricity payment as shown in Fig. 4(b). The curtailed energy for the AC is reduced by 17% of its daily consumption. Furthermore, the 2.29kW hob and the 1.74kW kettle have been considered to operate concurrently, the scheduler decides to turn-off the hob for 87% and to prevent the kettle to be turned on all the time, in order to be within the power limit while minimizing the required curtailed energy.



(a)



(b)

Fig 4. Daily profile before and after scheduling for (.a) washing machine and (b) electrical vehicle.

The electricity payment is reduced down by 44% compared with the base case (before deploying the proposed controller). As a result, Fig. 5 shows the daily load profile after the deployment of the proposed automated demand response controller. It can be observed that the demand will not exceed the power limit at any time interval during the day.

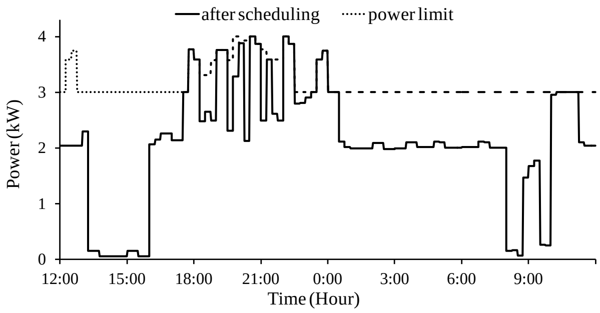


Fig. 5 Daily power limit and load profile after applying the proposed automated demand response controller.

CASE STUDY

The proposed demand response is investigated in a UK typical low voltage distribution network in an urban area with load density greater than (4MVA/km^2). In order to assess the effectiveness of the proposed scheduler, different penetration levels of automated demand response program are applied. A radial residential distribution feeder is shown in Fig 6. A 250 kVA 33/0.4 kV step-down transformer is used to supply 100 residential consumers. The circuit has been modelled using OpenDSS [5] with a three-phase representation.

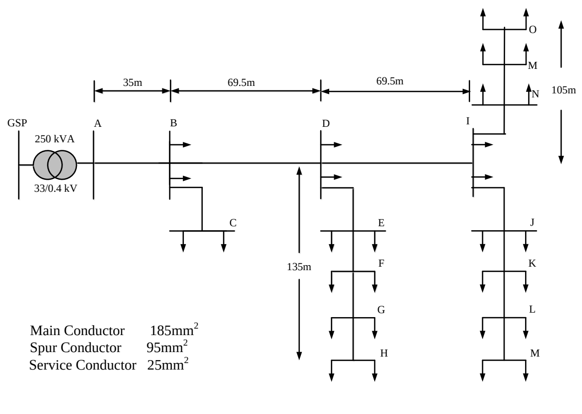
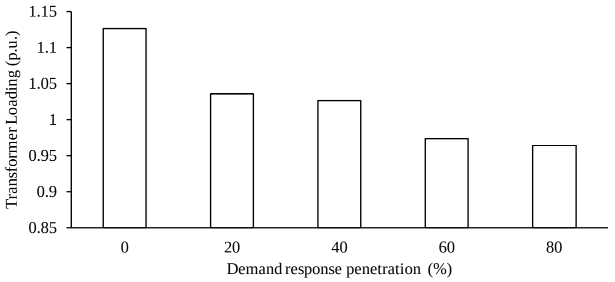


Fig 6. Typical UK residential LV feeder (test circuit)

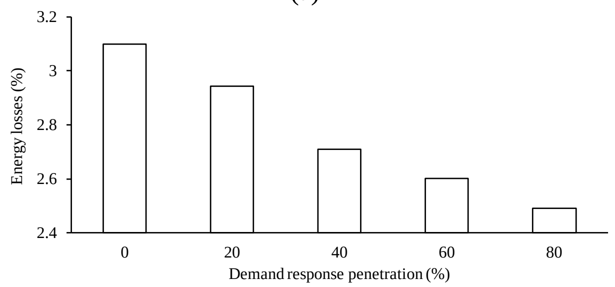
The modelling of electrical heating appliances and the electrical vehicles tackles the variations and the diversity in the consumer preferences. At the penetration of 50% for the EV and the thermal units, the peak demand of the network is increased from 153kW to 282kW. This is heavily overloading the transformer beyond its capacity.

Case Study Results

The simulations run at different demand response penetration level take into the account different consumer preferences. Automated demand response is sited randomly across the users, but the assigned consumers are held constant over the increasing penetration scenarios. Fig. 7 shows the loading percentage of the distribution transformer and the daily rate of the energy losses at different penetration levels. It can be shown that applying 40% or more of the proposed controller is capable to decrease the peak demand below the transformer thermal capacity as well as to reduce the energy losses. At demand response penetration of 80%, the use of line A-B falls below the thermal capacity as shown in Fig. 8.



(a)



(b)

Fig 7. (a) Transformer loading in p.u. and (b) energy losses% for different automated demand response penetration levels.

The proposed demand response can effectively benefit both the users and the utilities. For the consumers, it was found that a reduction in the electricity payments by 23% is associated by only curtailing 4.3% of the dwelling energy.

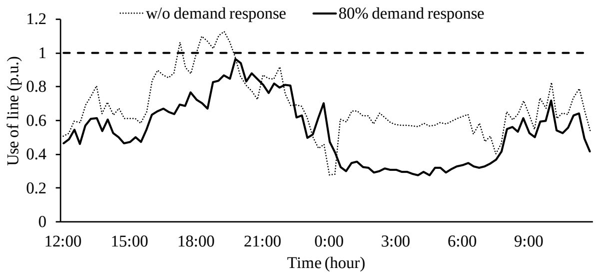


Fig 8. Use of line A-B in p.u. with 80% automated demand response penetration.

CONCLUSION

The proposed automated demand response controller proves its effectiveness in managing home appliances of a single dwelling and achieves trade-off between minimising electricity payment and maximising user satisfactions. Moreover, the proposed scheduler can manage effectively the thermal constraints for a typical low voltage distribution network in the UK and allow connecting high penetration of low carbon technologies. This work will be extended to medium voltage network to investigate the potential benefits of the proposed controller from the planning perspective.

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