Assessment of the Cost and Environmental Impact of Residential Demand-Side Management

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Abstract—A detailed study of the potential impact of low voltage (LV) residential demand-side management (DSM) on the cost and greenhouse gas (GHG) emissions is presented. The proposed optimisation algorithm is used to shift non-critical residential loads, with the wet load category used as a case study, in order to minimise the total daily cost and emissions due to generation. This study shows that it is possible to reshape the total power demand and reduce the corresponding cost and emissions to some extent. It is also shown that, when the baseload generating mix is dominated by coal-fired generation, the daily profiles of GHG emissions and cost conflict, such that further optimisation of the cost leads to an increase in emissions.

Index Terms—Power system economics, energy management, power demand, energy conversion, power generation.

I. INTRODUCTION

CUSTOMERS' interest in the reduction of the cost of their daily power demand has increased of late. This cost describes not only the price of electricity, but also the environmental cost, defined in this paper by the generation of greenhouse gas emissions (GHG). One method of altering the cost to the consumer is through load manipulation by means of demand side management (DSM), which will impact on multiple aspects of the supply of electrical energy.

Although there have been several studies on DSM strategies and their impact on energy demand [1], they have focussed on issues such as generation planning [2]–[4], or the effect on the energy efficiency [5], [6], and there are comparatively few studies directly connected to pricing and environmental factors [7]–[9]. In the majority of existing DSM studies, the analysis is performed at higher voltage levels, using mostly industrial loads [10], with the loads treated as aggregate amounts of energy, rather than as discrete appliances with operation cycles [11]. However, the possibility of smart grid technologies has increased interest of extending DSM to residential users located within low voltage (LV) networks. As the approaches applied for industrial DSM are not appropriate for the analysis of LV networks, new methodologies must be developed and implemented.

At the LV level, the domestic energy demand depends on the mixture of the individual electrical appliances, the behaviour of the residential users and environmental aspects, such as external temperature. It is the combination of these factors which results in the stochastic nature of LV power demand and requires more detailed simulation techniques than those typically applied at the higher voltage levels. This generally requires consideration of the specific loads available for DSM, as load management must not impact on users' quality of life. The available loads, termed as 'non-critical', may be rescheduled without affecting the users. This is demonstrated in several studies that focus on specific load categories, such as electric vehicles (EV) and heat pumps, and examine how their manipulation could reduce the cost or the GHG emissions [12], [13]. However, the analysis methods for EVs and heat pumps assume that these devices allow for the interruption of their operation. This is not the case for the majority of existing domestic appliances and these techniques are not directly transferable; for example, load categories such as wet loads, operate in predefined, continuous cycles which have a distinctive start and finish time.

In this paper, an approach for the implementation of DSM on LV residential loads is presented, which includes consideration of device operation cycles. This employs a multi-objective optimisation algorithm which achieves the least economic and environmental cost of the required daily energy of a group of LV customers, and has been formulated to control the weighting of the two drivers, with the minimum effort and impact on customers' lifestyle and comfort. In this analysis, the effort is defined as the percentage of the load that is required to be managed [14] and comfort is expressed as the accumulated delay time of loads both for each household and the total group. The selection of these quantifiable indices allows for a clear picture of the effect of the approach.

As the concept of acceptable time delay will vary between different users, a penalty factor is included within the optimisation formulation to account for a user-defined allowable delay time of load operation. It is assumed that this functionality, along with the ability for the user to be able to define a priority list of DSM appliances on a centrally controlled smart meter (SM), exists within the smart home framework. The centralised system, represented by the optimisation routine in this paper, would then decide which appliance(s) to delay from the total group based on the combined user priority list. The number of deferred loads per household is controlled to ensure that the burden of energy management is equally distributed among participating customers. Prioritisation of the

loads prevents the algorithm from delaying the operation of a second load in a household unless all the other customers already have a postponed load cycle in the same day. This also bypasses the need for the user to actively participate in dynamic pricing response schemes, e.g. [15]–[17], and the possibility of rebound effects when the load is reconnected.

To demonstrate the functionality of the developed optimisation routine, the UK residential load sector is analysed for four specific periods: winter 2008/2009, summer 2009, winter 2012/2013 and summer 2012. These have been selected to investigate the effect of the sudden change in the price of coal relative to gas during 2011 (possibly attributable to the US shale gas revolution) on the price and GHG emissions profiles of UK electricity and, thus, the result of DSM actions; highlighting the sensitivity of these profiles to international energy markets. Summer and winter periods are both considered to observe differences between minimum and maximum demand conditions.

The paper is structured as follows: in Section II an overview of the problem formulation is presented; Section III describes the proposed methodology and the properties of the optimisation algorithm; in Section IV, the case study is described and the results of the application of the methodology are presented and discussed; a sensitivity analysis on the penalty factor parameter is used to highlight impact on optimisation results in Section V; conclusions and suggestions for further work are given in Section VI.

II. PROBLEM FORMULATION

The load management techniques in LV networks vary according to the different load categories and the level of their impact on people's lives. LV residential load appliances can be divided into two categories according to their necessity: critical and non-critical loads, which should be user specified. Although the use of critical loads cannot be modified without changing the behaviour of household occupants, non-critical loads can be deferred or shifted as part of load management schemes. An example of a non-critical load category is wet loads, including: dishwashers, washing machines, tumble dryers and washer-dryers. The operation of these loads can be postponed to another time of day, if needed, without noticeable obstruction to the users.

However, these loads operate with preset cycles, suggesting that the application of DSM in LV networks must facilitate loads that use cycles of certain duration and power levels, instead of theoretical bulk parts of daily energy ,to allow for a more realistic study. In this paper, a multi-objective optimisation routine is applied to schedule the use of user-defined non-critical loads in order to obtain lowest combined cost of both economic and environmental factors. This impact has to be made explicit, as the reduction in cost and GHG emissions are included in the main selling points of DSM towards customers. The problem can be stated as follows:

Given a number of downstream loads with a user specified priority list and associated time delay penalty factor, calculate the optimum use of demand manageable resources in order to obtain the lowest combined cost of price and environmental

impact of the aggregate demand for given price and emissions profiles.

III. METHODOLOGY

The proposed methodology consists of a multi-objective optimisation algorithm for shifting the load during the day. The objectives of the study are to simultaneously minimise the total daily cost of the power demand to the end-user and the GHG emissions that derive from supplying the power demand. In order to achieve these targets, the electricity price and GHG emissions profiles are combined in the optimisation algorithm and used as the drivers of the DSM actions on wet loads. A significant output is the estimation of the minimum number of shifted loads that are required for the best result.

A. Optimisation problem definition

The objective functions of the proposed algorithm can be described mathematically by (1), (2) and (3).

$$min \sum_{i=1}^{t} c_{comb} = min \sum_{i=1}^{t} (x \cdot c_{wi} + y \cdot em_{wi}) \cdot pen \quad (1)$$

$$min(t_d) \quad (2)$$

$$min(n_{swl}) \quad (3)$$

where c_{comb} is the combined cost and is calculated by c_{wi} and em_{wi} which are the weighted values of the price and GHG emissions respectively. The weighting factors x and y are used to set the ratio of participation of the two criteria in the calculation of the main driver. t defines the 1440 time steps (24 hours at 1min resolution) and pen is the penalty factor used to reduce the delay time t_d. n_{swl} is the number of shifted cycles.

The profiles of price and GHG emissions are weighted as defined by the general equation in (4).

$$f = \frac{(h \cdot P) - min(h \cdot P)}{max(h \cdot P) - min(h \cdot P)} \quad (4)$$

where f represents c_w and em_w and h can be replaced by c and em, the price in £/MWh, the GHG emissions in tonnes of CO_2 eq./MWh respectively. P describes the active power demand in MWh.

The constraints are defined in (5) - (9). The proposed load management includes only load shifting and, thus, the daily energy consumption should remain the same before (E_{old}) and after (E_{new}) the manipulation (5), while (6) maintains the operating cycle integrity of individual loads. Reduced peak demand of the new aggregate load curve is enforced by (7), and (8) avoids the possibility of concentrating all the shifted load within a short period of time. The final limitation is that the load cycle should not be reconnected during the two peak demand time periods (9).

$$E_{new} = E_{old} \quad (5)$$

$$t_{end_{new}} - t_{start_{new}} = t_{end_{old}} - t_{start_{old}} \qquad (6)$$

$$P_{max_{new}} < P_{max_{old}} \qquad (7)$$

$$P_{max_{new}} - P_{min_{new}} < P_{max_{old}} - P_{min_{old}} \qquad (8)$$

$$cyc_{wl} \notin [T_{peak}] \qquad (9)$$

where $E_{old,new}$ are the daily energy consumption before and after DSM actions, $t_{start_{old,new}}$ and $t_{end_{old,new}}$ are the appliance cycle start and stop times before and after DSM actions, $P_{max_{old,new}}$ and $P_{min_{old,ned}}$ are the peak and minimum values of the aggregate active power profile before and after DSM actions, cyc_{wl} is the time period of the shifted wet load cycle and T_{peak} include the periods of peak demand.

B. Optimisation algorithm

The price and emissions profiles are very important in the load shifting process as they define the disconnection t_{disc} and reconnection t_{rec} time step. Their direct correlation, even after the conversion of the GHG emissions profile into an equivalent cost, is not possible because of different scales. In order to be able to control the level of effect of each driver, both profiles are multiplied with the total power demand and then normalised. The resulting profile is the combined cost c_{comb}, as described by (1).

A heuristic and stochastic approach has been chosen. The t_{disc} is set by the time of day when the maximum c_{comb} occurs and the available load cycles at this time are selected for shifting. The number of available load cycles is obtained from a collated priority list, representing the DSM resource of entire modelled population. The collated priority list is accessed sequentially, beginning with highest ranked loads, ensuring that participation is distributed between all households. If no shiftable load is present during the time of maximum c_{comb}, the nearest operation cycle is selected and used to define the t_{disc}.

The time step of load reconnection t_{rec} is selected to achieve the targets above without violating the constraints. To fulfill this, the inverse of the c_{comb} is used to calculate the discrete cumulative probability, and then the predefined penalty factor is applied in order to minimise the total delay time. The t_{rec} is selected stochastically based on this probability. This results in the shifted loads being distributed more uniformly across the periods considered as appropriate for reconnection, thus avoiding the creation of a new peak.

IV. CASE STUDY

The methodology is applied to the UK residential load sector in order to demonstrate the functionality of the optimisation routine. For this study, 10,000 households (20 groups of 500 households, typical of highly urban networks in the UK) were used to provide a good level of aggregation and allow for marginal changes to be credible. Four specific periods, Winter (December to February) 2008/2009, Summer (June to August) 2009, Winter 2012/2013 and Summer 2012, for reasons previously discussed, and five different combinations of weighting factors (x and y in (1)) are considered to study the sensitivity of the aggregate power demand to the economic

TABLE I
TEST CASE DEFINITION: OPTIMISATION DRIVERS

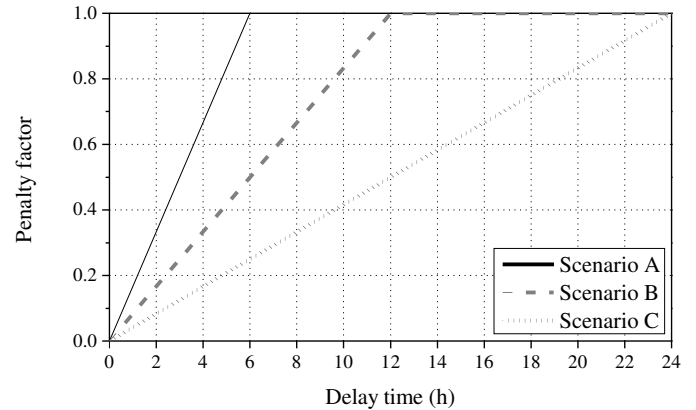| Test case	Financial criterion contribution - x	Environmental criterion contribution - y
Case 1	1	0
Case 2	0.75	0.25
Case 3	0.50	0.50
Case 4	0.25	0.75
Case 5	0	1

Fig. 1. Assumed penalty factor time delay values.

and environmental drivers. These are selected arbitrarily to demonstrate the range of possible results when either financial or environmental considerations are prioritised, or some combination of these drivers is chosen, with the weighting factors for each case shown in Table I.

All scenarios use the wet load category as the demand-manageable portion. Wet loads are responsible for a large percentage of the total daily power consumption (approximately 15%) of the annual UK residential demand [18] and exhibit pronounced seasonal variations, with daily demand around 9% higher in the winter period. Therefore, the management of such loads will potentially have an impact on the total power demand, its cost to customers and the total daily GHG emissions. This load category has to be managed differently from the loads that have often been used in similar studies on optimisation of load demand, because their operation cycles should not be interrupted. In this analysis, the user-defined priority list of shiftable loads is randomly allocated amongst wet loads. This approximation is justified as the priority list will be user input.

The optimisation time constraints are also consistent for all presented analyses. Peak time (9) is defined in this paper as the morning peak between 08:00 - 10:00 and the evening peak, during 18:00 - 22:00, based on the typical UK residential load curve. Three different scenarios of penalty factor value, which sets the allowable maximum time delay of a given load, are analysed in this paper. Three values of maximum delay time are assumed: 6hrs, 12hrs and 24hrs, as shown in Fig. 1, although any arbitrary value can be selected. In the analysis presented in this section, only Scenario B is considered. The impact of different penalty factors on the optimisation output is discussed in detail in Section V.
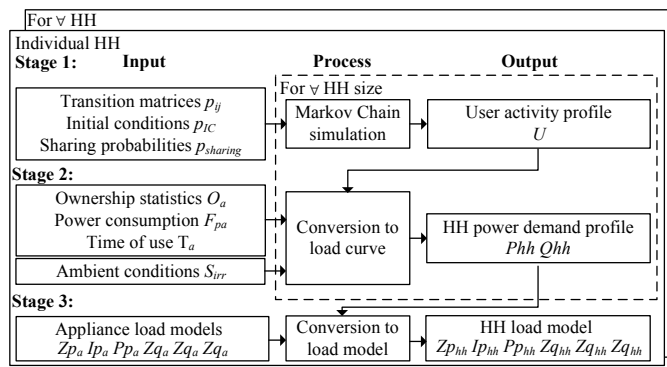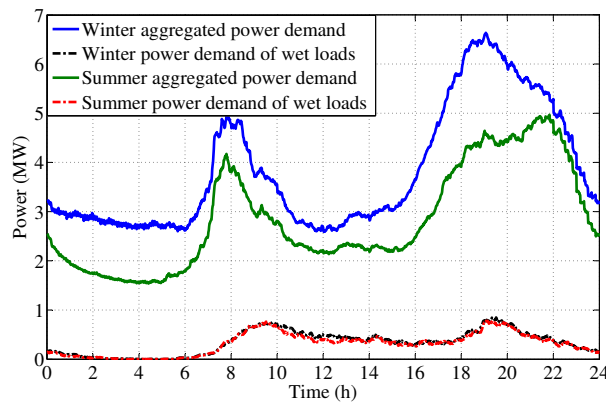
Fig. 2. Load model development work flow [19].

Fig. 3. Power demand of wet loads and the total household demand.

A. UK residential load

The calculation of active power demand before and after the load shifting requires the development of detailed power demand profiles of individual households to identify the use of 'non-critical' loads. In this paper, a previously developed combined Markov chain Monte Carlo model is implemented to generate the UK residential demand profiles [19]. The load modelling approach is presented in Fig. 2 and is summarised into three stages: user activity modelling; conversion of user activities to electrical appliance use; aggregation of the electrical appliances to build household power demand profiles and load models. Other load models are compatible with the presented optimisation methodology but they must be able to generate individual appliances profiles for a given number of households, e.g. [20].

The individual demand profiles have been selected to represent typical UK households based on the overall demographic characteristics of the UK population for the analysed periods [19]. Weekdays have been selected as they have the most frequent use of wet loads [21]. The contribution of the wet load category to the aggregate power demand of the selected group is illustrated in Fig. 3. It can be seen that the two daily peaks of the power demand of the wet load category coincide approximately with the two daily peaks of the total household demand during winter and are close to the peaks during summer. This verifies that managing this load should help to reduce the overall power demand peaks.

B. Generation price and GHG emissions

1) Generation price: Although the cost of electricity to the end-user consists of a lot of factors, it is mostly derived from the cost of generation. For the purposes of this paper, the average electricity price is used. These values are derived from market information published online by the balancing mechanism reporting agent [22]. This depends on the contribution of all types of generation plants and remains constant due to long term contracts. In the UK, the electricity price is largely set by the power plants that work with fossil fuels, such as oil and coal, because of their high marginal cost. Any load shifting of this magnitude will create changes to the generation of these plants as they respond faster to the demand changes. Therefore, the average values of price can be used instead of the marginal values.

In Fig. 4a, it can be seen that the profiles vary significantly between the seasons and across the years. Winter profiles are identified by a high peak early in the evening which is lower in magnitude for 2012/2013 due to the drop in worldwide coal prices, linked to the increase in fracking for shale gas in the USA [23], [24]. The summer price profile of 2012 has a similar trend to the summer of 2009, but the magnitude is closer to those of winters. The general trend is summarised as follows: the price of electricity increases during morning load pick up and continues until around midday when it will start to reduce, with significant early evening peaks observed in the presented winter periods. In all analysed periods, the electricity is cheaper during the night highlighting the need to decongest the daytime load.

2) GHG emissions: The GHG emissions curves are the short-term marginal emissions derived from operational and market data for generation plants on the British grid [22]. Marginal data is required for this analysis because the shift in non-critical loads will not affect the operation of baseload plants, but only those operating on the margin, which tend to have higher GHG emissions intensities. These curves represent the average marginal emissions factor for the given time of day across every day in the dataset for the considered period. Corresponding curves of average emissions factor were also calculated from the total emissions and output, which were used to estimate the total GHG emissions before DSM was applied. The calculation method is based on [25] and it is described in detail in [26].

It can be seen in Fig. 4b that during both the summer of 2012 and the winter of 2012-2013 the GHG emissions fluctuated significantly, but with a trend of being higher at times of low demand. This is likely to be due to high-emission coal-fired plants providing both baseload and marginal generation at these times, while lower-emission gas-fired generation provides a greater proportion of marginal generation during times of high demand, providing a greater proportion of the marginal generating mix when coal-fired plant are already at full output. This relationship is mostly determined by the relative prices of coal and gas, with coal-fired plant taking on a higher proportion of the baseload when coal is cheaper than gas. In contrast, it can be seen that during the summer of 2009 the trend of the GHG emissions was the inverse to that of 2012,
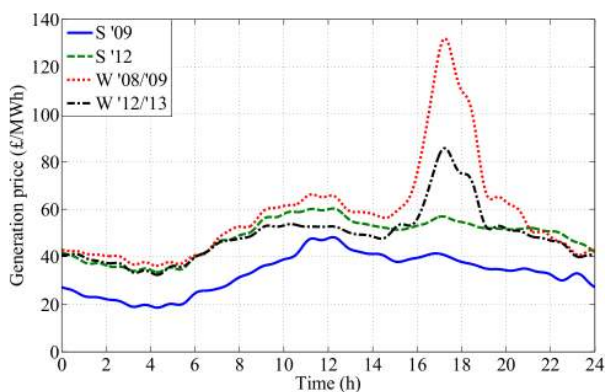
(a) Price profiles
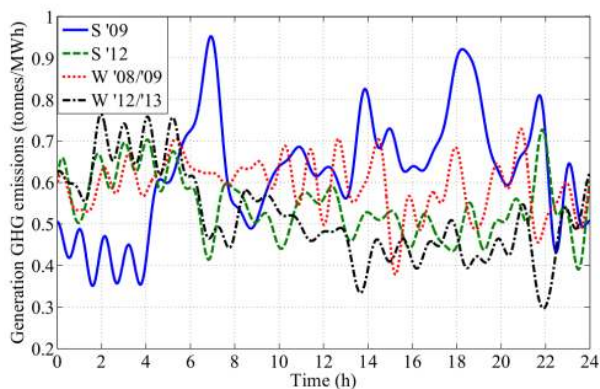
(b) GHG emissions profiles

Fig. 4. Daily profiles of price (a) and GHG emissions (b) per MWh [22], [26] for the selected periods and the typical winter (W) and summer (S) profiles.

being higher at times of high demand, suggesting that gas-fired plant was taking on a higher proportion of the baseload generation, and that coal was more expensive. This was before the drop in coal prices that has been reported since 2011.

3) Combined: Fig. 5 depicts the normalised combined cost of the price of electricity and the equivalent cost of the GHG emissions for each case according to (1) and (4). In the majority of periods the price and GHG emissions profiles conflict, such that they combine to produce a relatively flat combined cost curve when price and emissions have the same weighting (case 3), although the high peak in price in winter evenings makes the price profile appear to dominate. In the summer of 2009 the GHG emissions and price profiles did not conflict, instead combining to create a clear curve.

C. Results and discussion: Cost

The results of cost optimisation for all time periods and cases for the penalty factor B are presented in Fig. 6 to 9. The curves of total daily cost of demand preserve the trend of reducing the price, even when it is not used as a guide in the optimisation algorithm. The characteristics of each year or period generate some very interesting results; for example, it is visible that the total daily cost of demand has decreased 20% between winter 2008/2009 and 2012/2013 while it increased 18% between the summers of 2009 and 2012.
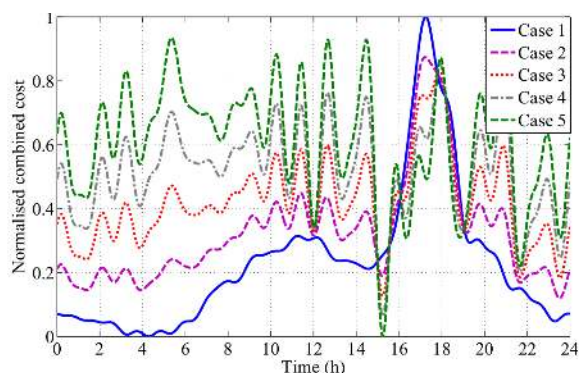
(a) Winter 2008/2009
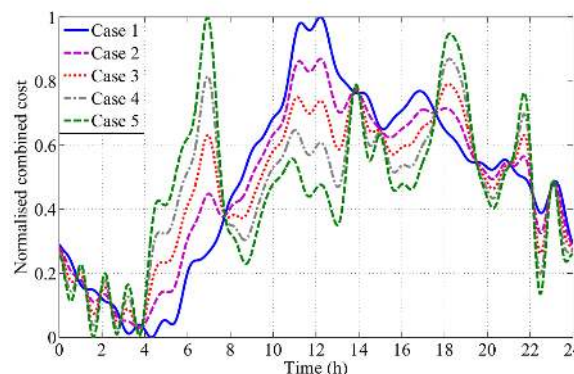
(b) Summer 2009
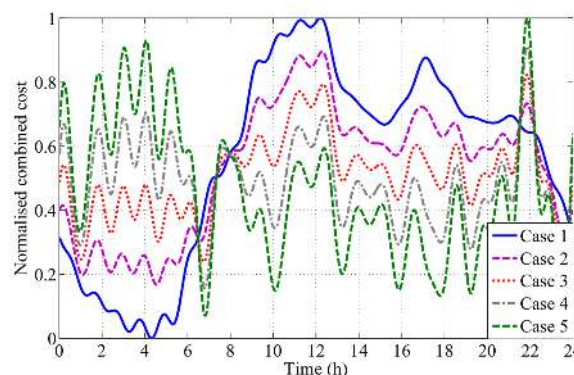
(c) Summer 2012
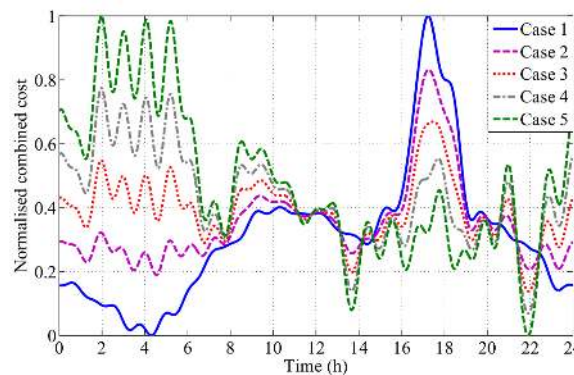
(d) Winter 2012/2013

Fig. 5. Normalised combined cost profile for each case calculated using (1) through (4) for the selected periods.
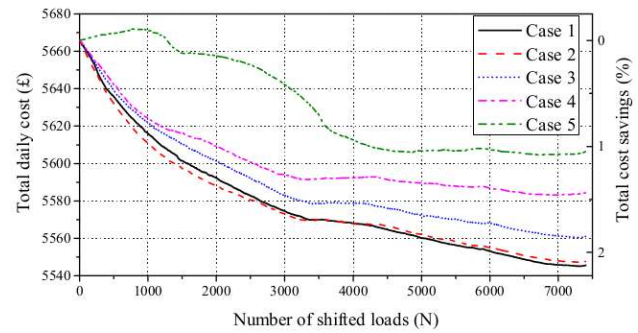
(a) Total cost due to price
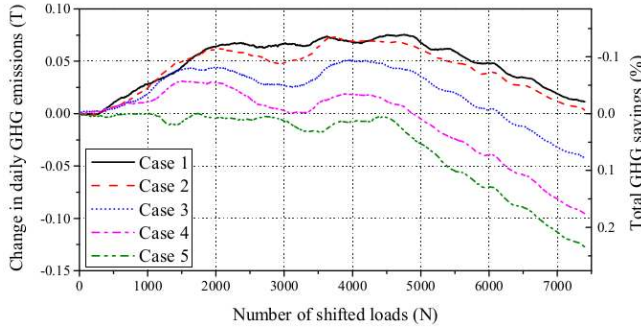
(b) Total GHG emissions

Fig. 6. Total price and GHG emissions during winter 2008/2009 after DSM implementation.

(a) Total cost due to price

(b) Total GHG emissions

Fig. 7. Total price and GHG emissions during summer 2009 after DSM implementation.
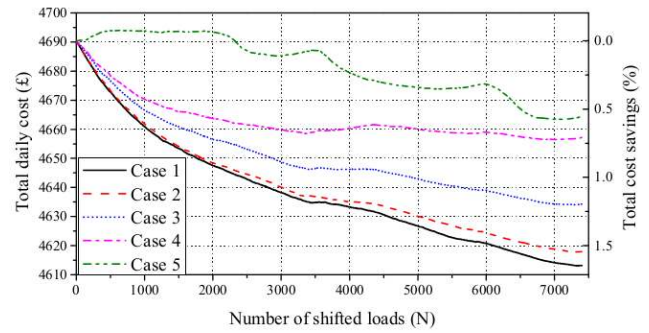
(a) Total cost due to price
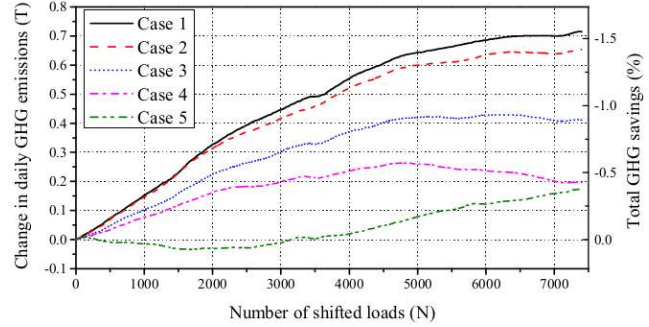
(b) Total GHG emissions

Fig. 8. Total price and GHG emissions during winter 2012/2013 after DSM implementation.
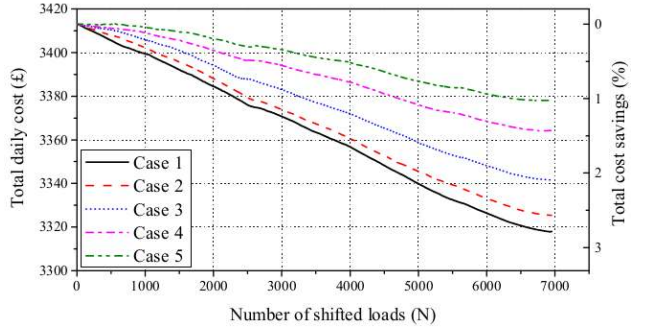
(a) Total cost due to price
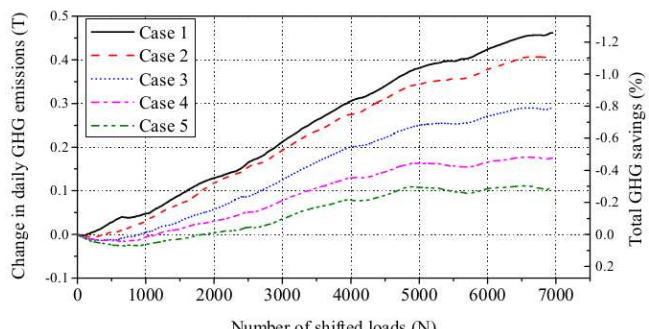
(b) Total GHG emissions

Fig. 9. Total price and GHG emissions during summer 2012 after DSM implementation.

This can be explained by the change in generation mixture between these two years (Fig. 4a). However, while the cost due to price is following the total daily cost of demand, the GHG emissions seem to reduce in volume after the introduction of fracking both in winter and summer by 17% and 20% accordingly.

The results, summarised in Table II, also indicate that DSM actions can have an impact on the cost due to price, with

the maximum savings varying between 0.58% and 3.75% depending on the season and price profile. The results also demonstrate similar trends for each season (Figs. 6, 7, 8 and 9): in the winter there is a rapid decrease in total daily cost of demand as the number of shifted cycles is increased to 3500, beyond which it is either stabilised or decreases with a slower rate; in summer the minimum combined cost is achieved at the maximum number of shifted cycles - this is because the power demand for electric heating and lighting is higher during winter at reconnection time of the shifted loads, allowing for more shifted cycles during summer.

Regarding the GHG emissions, different effects of the DSM actions are observed for each of the four selected periods of time. Table III shows the maximum GHG emissions savings as a proportion of the emissions before any DSM actions (the latter calculated from the average emissions factors), and it can be seen that these are modest for all periods except summer 2009. When a large number of cycles are shifted, it was also found that this could result in an increase in GHG emissions of up 1.5%. Furthermore, it is observed that there are differences between the same seasons of different years: in the winter of 2008/2009, the emissions were found to increase at low numbers of shifted cycles in cases 1 to 3, while they are more constant in cases 4 and 5, where there is a weighting in favour of the GHG emissions profile over the price profile. Then, after approximately 4500 cycles, the emissions reduce to the minimum values. In contrast, in the summer of that year, the daily GHG emissions profile was very different, and allowed for a much greater reduction by taking advantage of all possible shifted cycles. In Fig. 7b, it can be seen that case 3 seems to provide the maximum emissions reductions.

This result can be explained by Fig. 5b and the fact that, when both drivers are equally weighted in the combined cost, they create a distinctive curve in favour of shifting loads to the night time. As for the winter of 2012/2013 and summer 2012, it is interesting that the GHG emissions actually increase as more cycles are shifted, due to the increased marginal emissions at times of low demand as a result of cheaper coal. For these years, the cases where the combined cost is based on the GHG emissions profiles are the only ones that provide some reduction in the emissions, but only for a limited number of shifted cycles.

An important finding of this study is that it is difficult to quantify the savings in GHG emissions and cost that can be expected by the implementation of DSM, and that these are highly dependent on the changing generation mix. Before the US shale gas revolution, there were greater potential savings due to DSM actions on wet loads; however, the increase in shale gas production affected fuel prices and the generation mix (and corresponding GHG profiles) in the UK, indicating the global nature of the problem. As a result, after 2011, it can be seen that the extensive use of DSM results in an increase in GHG emissions, while the cost, to some extent, retains the pre-fracking savings.

D. Results and discussion: Power demand

The effect of the reformed power curve of the wet load category on the aggregate power curve for winter 2012-2013

TABLE II
PERCENTAGE SAVINGS AMONG PERIODS AND TEST CASES

Period	Test Case	Total daily cost of demand	Total cost savings	Total GHG emissions savings
W08/09	Case 1	**1.63**	**2.13**	<0.01
	Case 2	1.56	2.10	<0.01
	Case 3	1.44	1.86	0.08
	Case 4	1.29	1.46	0.18
	Case 5	1.11	1.08	**0.23**
S09	Case 1	2.70	**3.75**	1.49
	Case 2	**2.91**	3.57	1.76
	Case 3	2.89	3.58	1.65
	Case 4	2.43	2.87	1.82
	Case 5	2.19	2.42	**1.96**
W12/13	Case 1	**0.85**	**1.65**	<0.01
	Case 2	0.83	1.55	<0.01
	Case 3	0.72	1.20	<0.01
	Case 4	0.53	0.72	<0.01
	Case 5	0.44	0.58	**0.07**
S12	Case 1	**1.65**	**2.79**	<0.01
	Case 2	1.54	2.57	0.02
	Case 3	1.30	2.09	0.04
	Case 4	0.99	1.43	0.04
	Case 5	0.78	1.02	**0.07**
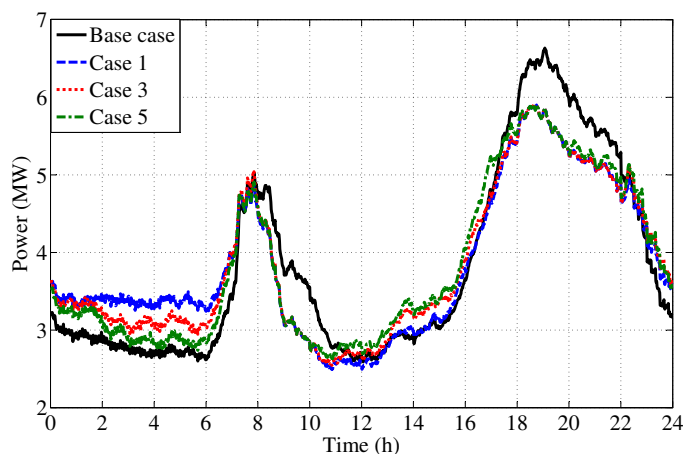
Fig. 10. Active power demand of total residential demand before and after load shifting for minimum daily cost.

is illustrated in Fig. 10. The power during the peak hours has reduced around 11.9% in the evening and 22.7% in the morning which will help to alleviate stress in the electrical network, and the duration of the morning peak has also been reduced. The power demand during the night time has increased significantly by 16.7 to 23.5%, depending on the case and time. The power demand decreases or remains constant during midday for case 1 and increases by up to 12.4% for cases 3 and 5, showing the influence of the weighting between the financial and environmental criteria. The ratio of max to min load, defined in constraint (8), reduces from 2.54 for the base case to 1.79, 1.97 and 2.10 for Case 1, 3, and 5, respectively, clearly indicating a reduced variation in the power demand profile.

V. STUDY ON PENALTY FACTOR

In this section, further investigation on the impact of the penalty factor, which represents a user-defined maximum time delay limit, is presented. The same base case study is used data but now a comparison is drawn between the total cost savings and delay times obtained using the two extreme cases of the penalty factor, denoted A and C (c.f. Fig. 1), and the average penalty factor B. Penalty factor A places a more stringent constraint on the optimisation process, while penalty factor C will allow load reconnection to be deferred for up to 24hrs.

The results presented in Table III illustrate that the more stringent constraint will return the lowest cost saving, although it should be noted that a saving is still achieved. This can be explained by the fact that, for this case study, the DSM load portion (i.e. wet load category) is used consistently throughout the day; therefore, short term load shifting will only allow reconnection to periods with, possibly, equally as high combined cost. Accordingly, not all load may be shifted. All three figures show a large amount of households that have either not used their wet appliance(s) or not participated in the DSM implementation, i.e. the sum of summation of the histogram is less than the total number of available DSM resource within the modelled population.

As expected, the distribution of delay times becomes more uniform as the penalty factor constraint is relaxed. This is clearly visible in Fig. 11, which presents the cumulative delay time experienced per individual household. As the values are the total delay time per household, the total delay time can be greater than the penalty factor specified for each individual load. However, the majority of households experience a total delay time less than individual load penalty factor; demonstrating the correct implementation of the reconnection process described in Section III-B.
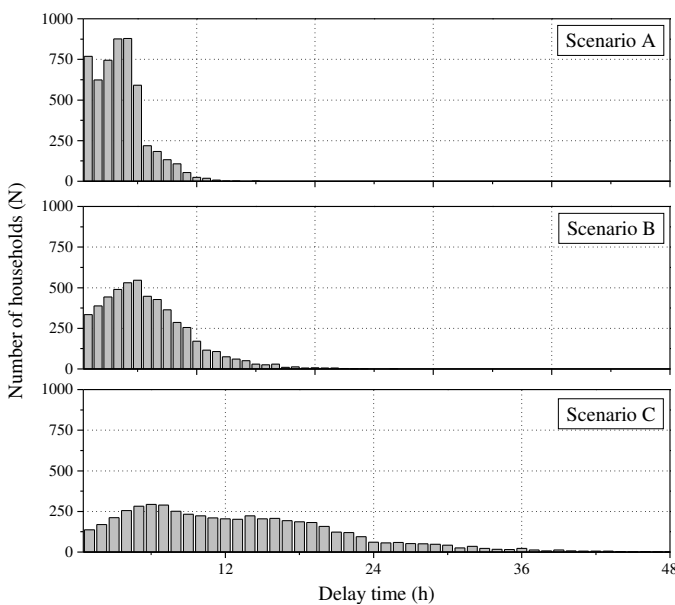
TABLE III
INFLUENCE OF PENALTY FACTOR ON TOTAL COST SAVINGS

Period	Test Case	Penalty factor scenario A	B	C
W'08/09	Case 1	1.39	**1.63**	1.18
	Case 2	1.38	1.56	1.17
	Case 3	1.32	1.44	1.12
	Case 4	1.24	1.29	1.05
	Case 5	0.17	1.11	0.14
S'09	Case 1	1.82	2.70	1.55
	Case 2	1.89	**2.91**	1.61
	Case 3	1.91	2.89	1.62
	Case 4	1.82	2.43	1.55
	Case 5	1.77	2.19	1.50
W'12/13	Case 1	0.68	**0.85**	0.58
	Case 2	0.66	0.83	0.56
	Case 3	0.65	0.72	0.60
	Case 4	0.57	0.53	0.48
	Case 5	0.42	0.44	0.36
S'12	Case 1	1.07	**1.65**	0.91
	Case 2	1.01	1.54	0.86
	Case 3	0.95	1.30	0.81
	Case 4	0.86	0.99	0.73
	Case 5	0.78	0.78	0.66

TABLE IV
IMPACT OF PENALTY FACTOR ON TOTAL DELAY TIME

Period	Test Case	Penalty factor scenario A	C
W08/09	Case 1	-46.5%	90.8%
	Case 2	-47.0%	94.3%
	Case 3	-45.7%	93.8%
	Case 4	-45.8%	89.8%
	Case 5	-41.3%	88.6%
S09	Case 1	-43.4%	90.7%
	Case 2	-43.8%	87.2%
	Case 3	-42.8%	86.4%
	Case 4	-40.3%	88.0%
	Case 5	-38.0%	93.1%
W12/13	Case 1	-42.0%	91.7%
	Case 2	-41.0%	92.2%
	Case 3	-41.6%	87.1%
	Case 4	-40.2%	84.4%
	Case 5	-39.8%	81.0%
S12	Case 1	-43.3%	94.0%
	Case 2	-40.0%	90.0%
	Case 3	-38.2%	90.8%
	Case 4	-33.7%	92.6%
	Case 5	-37.9%	91.3%

The total delay time is summarised in Table IV, displaying the difference in total delay time of the aggregate population for different penalty factor values. The total delay time experienced by the aggregate group almost doubles for penalty factor scenario C; but a consistent reduction of between 30 - 50% is observed for the more stringent penalty factor scenario A.

VI. CONCLUSION

This paper has shown that management of LV loads can allow for significant reductions in cost but is only effective in reducing GHG emissions when coal is supplying the marginal generation during the day. The study has combined daily profiles of the average values of electricity price and marginal GHG emissions with detailed models of LV residential loads, through a multi-objective optimisation algorithm, including customers' comfort among the priorities. The results show

Fig. 11. Impact of penalty factor on the distribution of individual household cumulative delay time.

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ASSESSMENT OF THE COST AND ENVIRONMENTAL IMPACT OF RESIDENTIAL DEMAND-SIDE MANAGEMENT   9

that the financial factor has a greater impact in shaping the combined total cost, suggesting that it is more difficult to achieve GHG emissions savings than cost reductions by shifting residential load. This may explain the current situation of generation, where price is the main objective and GHG emissions reductions are difficult. Also, the change in the profiles and the generation mixture after the fall in coal prices in 2011, had a substantial impact on the potential savings in cost and GHG emissions. The resulting contradictive profiles caused an increase in GHG emissions after an extensive application of the DSM actions. This highlights the necessity of using detailed power demand profiles and the difficulty of forecasting the total impact of DSM actions without considering up-to-date cost and emissions profiles.

The presented methodology can be applied on contiguous days' demand profiles for forecasting and DSM planning studies. The constrained reconnection periods, taken as peak demand periods in this study, can be set to any arbitrary time and can be coordinated with, for example, scheduled short-term maintenance tasks. The calculated magnitude of potential reductions suggests that DSM actions on non-critical loads applied at both the LV level and at a larger scale can lead to reductions in price and GHG emissions comparable to those achieved by distributed generation (DG). This will become more important if EVs become prevalent, as they will present a considerable demand increase. Although the presented methodology has been demonstrated on the wet load category, it is more generally applicable and can be used to coordinate the operation of any loads that operate in fixed cycles, including first generation commercial EVs which do not currently have the functionality to adjust their charging current as assumed by several works in this area.

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ASSESSMENT OF THE COST AND ENVIRONMENTAL IMPACT OF RESIDENTIAL DEMAND-SIDE MANAGEMENT   10

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