Learning from residential load data: Impacts on LV network planning and operation

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Learning from Residential Load Data: Impacts on LV Network Planning and Operation

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***Abstract*— The deployment of advanced metering infrastructure has already started in many countries around the world in order to facilitate the transition towards low-carbon economies, to improve electricity billing, to decrease distribution network operational costs, and to empower householders. In addition, the adoption of photovoltaic panels, electric vehicles and smart appliances, already being encouraged by governments, will change the way households consume and generate electricity. However, in order to adequately assess the impacts from these low-carbon technologies it is required a much better understanding of how electricity is currently consumed. This work firstly studies the effects of load characterization on the optimal selection of the conductors from the planning perspective based on a high granularity model for UK residential consumers that mimics data that could eventually be available through smart meters. Then, from the operational point of view, the benefits of load shifting (i.e., demand side management) to reduce peak demand are also investigated. The latter study is applied to a real LV network the North West of England. Results clearly indicate the potential benefits on LV network planning from high granularity data, as well as the important insights that could be gained from modeling load shifting schemes using such a data.**

***Index Terms*— LV networks, demand characterization, smart appliances, demand side management, circuit design.**

I. Introduction

REDUCTION of carbon emissions is currently a major topic in the agendas of many countries around the world. This challenge of moving towards a low carbon economy requires profound changes in the way the electricity is generated, transported and consumed.

On the one hand, the deployment of advanced metering infrastructure (or smart metering infrastructure) has already started in many countries around the world in order to facilitate the transition towards low-carbon economies, to improve electricity billing, to decrease distribution network operational costs, and to empower householders. On the other hand, the adoption of low-carbon technologies such as photovoltaic panels, electric vehicles and smart appliances is also being encouraged by governments. In Latin America, for example, the Chilean government approved the "Net Metering Law" [1], giving the legal framework to allow the energy injection and the payments for that energy at domestic scales. In the UK, feed-in tariffs have been implemented where small-scale generation (mainly photovoltaic) and corresponding exports to the grid are paid premium prices (per kWh) fixed for a number of years [2]. Incentives for electric heat pumps and electric vehicles are also in place.

If the adoption of such low-carbon technologies proves to be significant in the next few years, distribution networks are expected to experience a range of issues such as increased voltage drop, voltage rise, voltage unbalance, thermal overloads of conductors and transformers, harmonics, etc. However, due to the (very) short-term variations in demand and generation (e.g., photovoltaic panels), to assess the corresponding impacts on the low voltage (LV) distribution networks it is crucial to first a have a good understanding of the time-series electrical behavior of current domestic consumers. In addition, such models can also be used to investigate the extent to which demand side management approaches can help diminishing the impacts of future peak load scenarios.

Based on a high granularity (i.e., minute by minute) model for UK residential consumers developed in [3] that mimics data that could eventually be available through smart meters, this work first studies the effects of load characterization on the optimal selection of the conductors from the planning perspective. Then, from the operational point of view, the benefits of load shifting (i.e., demand side management) to reduce peak demand are also investigated [11]-[13].

This work is structured as follows: section II explains the main characteristics of the adopted residential load model. Section III presents the impacts on planning in terms of conductor selection when there is a better knowledge about residential loads. The importance of knowing the load behavior to carry out demand side management schemes at a residential level is discussed in section IV. In particular, a load shifting process is proposed to show the potential that similar schemes might have in decreasing peak demand. Section V shows the corresponding application of the proposed load shifting technique on a real LV distribution network with five feeders and 334 customers in the North West of England. Finally, conclusions are drawn in section VI.

II. High Granularity Load Model

To understand the real behavior of the distribution network, particularly LV feeders, domestic loads must be modeled in a way that their (very) short-term variations during the day are

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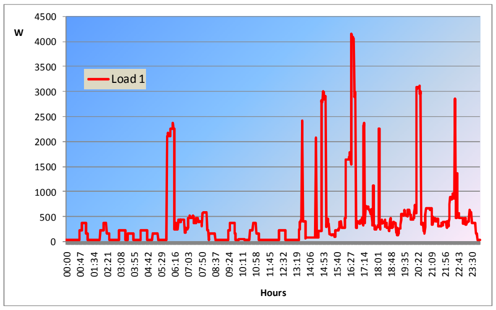

Fig. 1. Example of a minute-by-minute profile of a single UK household.

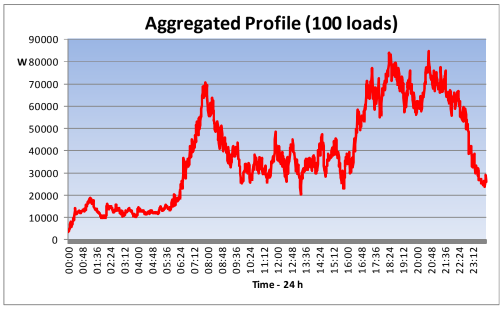

Fig. 2. Load aggregation of 100 households.

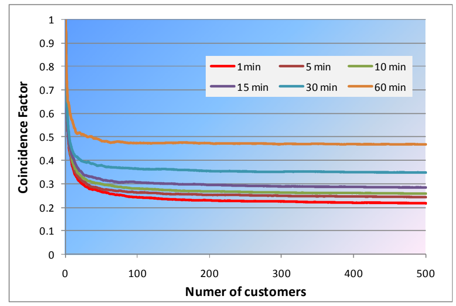

Fig. 3. Coincidence Factor

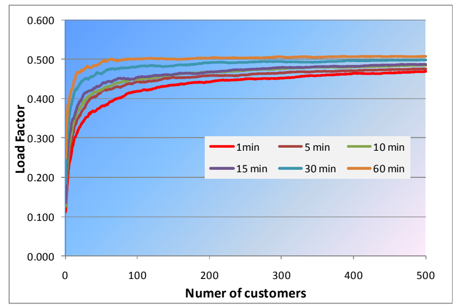

Fig. 4. Load Factor

considered. Consequently, throughout this work one minute resolution models developed in [3] for UK households will be adopted - mimicking data that could eventually be available through smart meters. This model takes into account the number of occupants, the type of day (weekday or weekend), the month, and the uses of the appliances. With such a model it is possible to have a usage breakdown of appliances. Given that the focus is on the analysis of data, for simplicity only a single day will be considered throughout this work. Fig. 1 shows the residential profile of a single household with two occupants considering a weekday in August (UK summer).

Given that the model produces a profile according to the specified characteristics of a household, it is possible to create random profiles based on a pre-defined set of main characteristics. Thus, the number of people at home was randomly allocated between 1 and 5; the available appliances are also randomly allocated in each home.

Here, all types of consumers were randomly specified to create a pool of 1000 different load profiles to be used in the impact analysis. Each of them was created using the same generic weekday and month (August). The corresponding information is then stored in a single matrix where the position P_{ijk} represents the consumption during the time i of the appliance j in the house/profile k.

$$L_{ik} = \sum_{j=1}^{m} P_{ijk} \qquad D_i = \sum_{k=1}^{N} \sum_{j=1}^{m} P_{ijk} \tag{1}$$

Thus, L_{ik} represents the load consumption of the m appliances in the house k during the time i (Fig. 1) and D_i represents the load aggregation for N houses during the time i (Fig. 2, aggregation example for 100 houses).

III. Improving LV Network Planning

The typical approach in expansion planning of distribution networks is the utilization of factors to represent the behavior of the load. This is mainly because it is not computationally efficient to carry out extensive simulations to take the corresponding investment decisions. For example, if applying a loss-based circuit design approach in order to replace network conductors, typically the distribution planner does not solve detailed power flows during the expected life time of the conductor to calculate the corresponding energy losses. The planner calculates the losses taking into account the loss load factor, which depends on the load factor [4]-[8].

The residential models described in the previous section give us the opportunity to calculate the coincidence factor and the load factor for different groups of loads. In this way, the coincidence factor and the load factor curves can be produced. The latter is particularly important to determine the optimal selection of conductors.

A. Granularity of Data

First, it is interesting to explore the effect of data granularity in the calculation of the coincidence and load factors. As mentioned previously, the adopted load model has a granularity of one minute. This means that each generated daily profile has a P_{ijk} value for each period i, with i between 1 and 1440 (24×60).

To analyze the granularity effect, the average power each five, ten, fifteen, thirty and sixty minutes is calculated in order to produce load models with the corresponding sample rate. Then, for each set of data with different granularity, the average load factor and the average coincidence factor are obtained for groups comprised by one to 500 households. The corresponding results are shown in Fig. 3 and Fig. 4.

These figures show the importance of the granularity or sample rate when assessing actual measurements. For instance, the models with 30 and 60 minute resolution converge (with 500 households) to a coincidence factor bigger than 0.3 whereas with one minute resolution it goes down to 0.2. A similar effect can be observed in the case of the load factor. Also, it is important to note that the differences in the results are not necessarily that significant when the resolution (or sample rate) is 5 minutes instead of 1 minute. This is a valuable finding that should be explored in more detail with real measurements in order to understand the importance of high sample rates when monitoring LV networks, particularly in the presence of new types of loads and distributed generators.

B. Conductor Selection

When a new LV feeder is designed, there are various techniques to design the corresponding conductors [14]. Eventually, the circuits will have to be able to withstand the peak load of the loads being fed, also considering voltage drop constraints as well as economic and in case environmental aspects.

Here, a selection algorithm is used to choose the cheapest conductor among a set of feasible conductors, i.e., those with minimum total cost that satisfy the thermal limits. The total cost can be estimated through the annuity cost, i.e., the annual payment required every year during the life span of the conductor (to pay the total investment cost) plus the energy cost (energy losses). This can be formulated as follows [5], [6]:

$$AC = INV \times \left[\frac{r \times (1+r)^H}{(1+r)^H - 1}\right] + C \times E_{Losses} \qquad (2)$$

where AC is the annuity of the total cost of the conductor, INV is the total investment cost of the conductor, C is the energy cost, E_{Losses} are the overall annual energy losses of the conductor, H is the expectance life of conductor, and r is the internal rate of return. For the sake of simplicity and since the focus is on comparing the impact of different load factors, this model assumes no load growth (although the model could be generalized to include it).

The common approach to calculate the energy losses is by using the Loss Load Factor (LLF); this factor represents the relationship between the average losses and the losses at the maximum demand.

$$LLF = \frac{E_{Losses}/T}{P_{Losses\ Max}} \qquad (3)$$

This expression is typically used in distribution planning because the losses are only calculated (through simulations and/or estimations) at peak demand. Thus, the energy losses during period T are the product of the LLF, the losses at peak demand and the length of period T.

Theoretically, the value of the LLF is between the load factor squared and the load factor (LF). A complete demonstration of this relationship is developed in [7]. One of the most common expressions to estimate the LLF is shown below [8].

$$LLF = 0.3 \times LF + 0.7 \times LF^2 \qquad (4)$$

Consequently, if the peak power losses (or corresponding peak current) of a circuit and the load factor are known (calculated or estimated), then it is possible to determine the Annuity Cost.

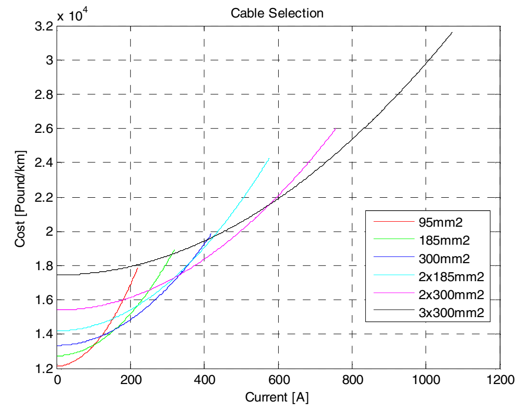

Fig. 5. Cable Selection – Load Factor equal to 0.48

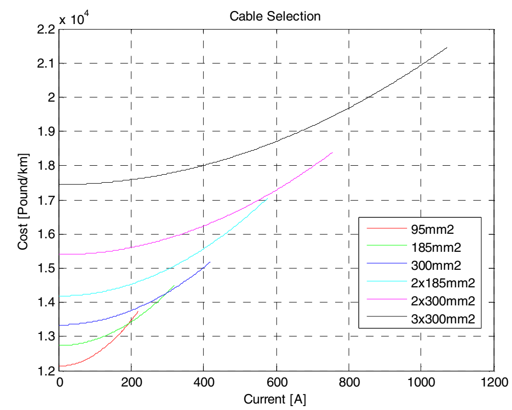

Fig. 6. Cable Selection – Load Factor equal to 0.20

Here, two different cases are analyzed to obtain the Annuity Cost. The first one considers just one value for the load factor, which corresponds to the typical approach in distribution planning [4]-[6]. The second case uses the load factor curve calculated in the previous section (Fig. 4). The corresponding data required to calculate the Annuity Cost for each conductor is presented in the Appendix.

1) Constant Load Factor

Distribution Network Operators (DNOs) often use the load factor of medium voltage (e.g., 33kV/11kV and above) distribution substation because energy and power demand measurements are commonly available.

Let us assume that our typical 11kV/0.4kV distribution transformers have in average four main (underground) feeders, each of them with 100 consumers. Hence, the average number of customers fed by each distribution transformer is 400. In this case, using the load factor curve for five minute resolution (Fig. 4), the corresponding value would be 0.48. Using this load factor and the annuity cost equation, it is possible to determine the annuity cost curve for each conductor under analysis (six types of conductors – see Appendix). The corresponding curves are shown in Fig. 5 for different peak currents (a proxy of energy losses).

From Fig. 5 is it possible to choose the cheapest conductor for a given peak current. For example, if the current through the line is 200 A, then the 300 mm^2 conductor must be selected. However, it is important to highlight that this result is sensitive to the load factor. Indeed, if the load factor is 0.2 (Fig. 6), for the same 200 A, the optimal conductor would be

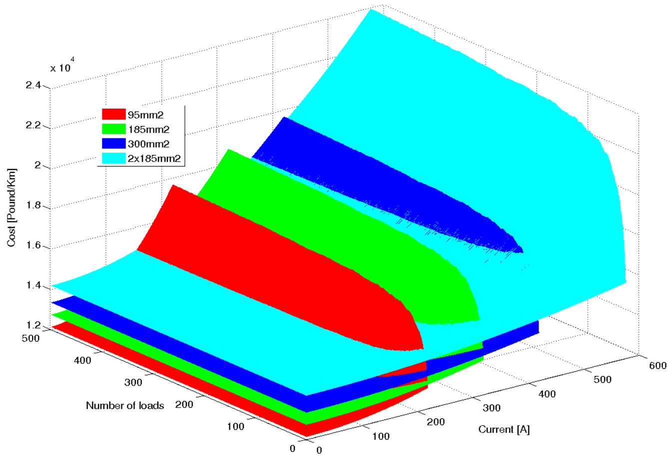

Fig. 7. Optimal Surface Selection

185 mm^2. Therefore, considering a more realistic load factor based on load profiles and actual number of customers would lead to true optimal solution, i.e., the most cost-effective conductor.

2) Load Factor Curve

A load factor curve is important in the conductor selection process because each feeder (or section) supplies different numbers of customers. Consequently, each feeder has a different load factor. Hence, the corresponding annuity cost depends on the number of customers supplied by the feeder and its peak current. Because of this, the annuity cost for each conductor can be represented as a surface rather than a bi-dimensional curve.

Fig. 7 shows the annuity cost surface for each of the conductors considered and indicates the relationship among cost, current and number of customers (the LLF depends on the LF and this in turn depends on the number of customers). For example, in the zone between 400 A and 500 A, the cheapest surface is the surface cost of 300 mm^2 (blue surface) only if the number of customers is lower than 100. However, if the number is higher, then the surface cost of 2x185 mm^2 (light blue surface) will be the cheapest one. Thus, a better conductor selection is done when the load factor curve is taken into account.

These results may encourage DNOs to carry out measurement campaigns in order to get a better understanding of their LV electricity consumption and with that potentially improve investment decisions.

IV. Improving LV Network Operation

A better understanding of residential load profiles is not only important for planning purposes. In order to implement demand side management (DSM) schemes, as part of the transition towards Smart Distribution Networks, such an understanding is also fundamental. In liberalized, fully unbundled electricity markets such as in the UK, DSM schemes could in the future be used by DNOs to defer new infrastructure investment due to load growth (e.g., due to electric heat pumps and electric vehicles), ultimately bringing reduced tariffs to consumers.

In particular, the amount of aggregated power (from

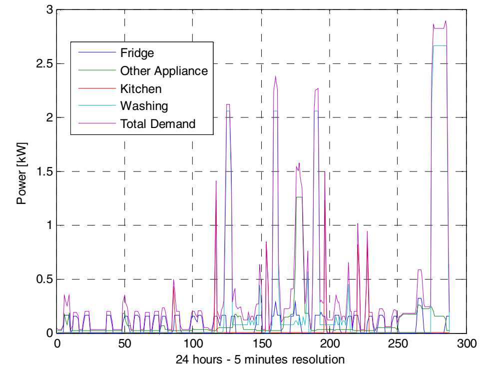

Fig. 8. Demand profile of each appliance group – single household.

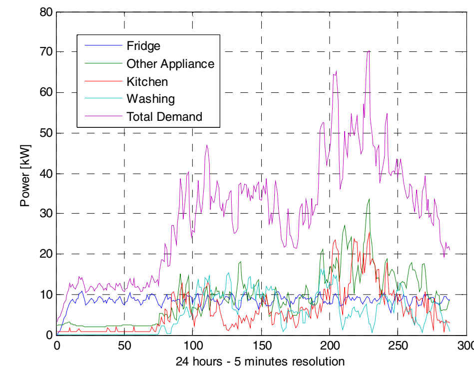

Fig. 9. Demand profile of each appliance group – 100 households.

common household appliances) able to be 'easily' shifted thorough the day in order to decrease the peak demand at the distribution transformer (also known as peak shaving) will be investigated.

It is important to highlight that the actual implementation of a DSM scheme where household appliances are actively managed for peak shaving purposes will certainly require (among many aspects) the corresponding communication infrastructure, adequate control algorithms, and suitable value propositions for consumers to engage. This is not the focus of this section. This section aims at highlighting the potential that certain loads might have in similar future schemes as part of the Smart Grid vision.

A. Power Available from Household Appliances

In order to estimate the aggregated power that could be used for peak shaving purposes it is necessary to identify the different types of appliances in the dwellings. The appliances already incorporated in the adopted load model can be classified in the following groups:

- Fridge: chest freezer, fridge freezer, upright freezer.
- Cooking: hob, oven, microwave, kettle, small cooking appliance.
- Washing: dish washer, tumble dryer, washing machine, washer/dryer.
- Other Appliance: CD player, phone, iron, vacuum, fax, PC, printer, TV, receiver, etc.

Using the daily profiles already produced for section II (that includes a breakdown of loads), it is possible to show the aggregated behavior of the appliance groups for a single (Fig. 8) and 100 households (Fig. 9).

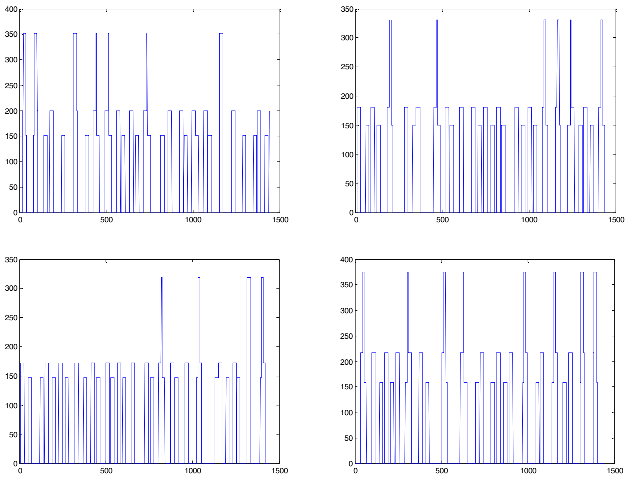

Fig. 10. Electrical consumption for different fridge loads.

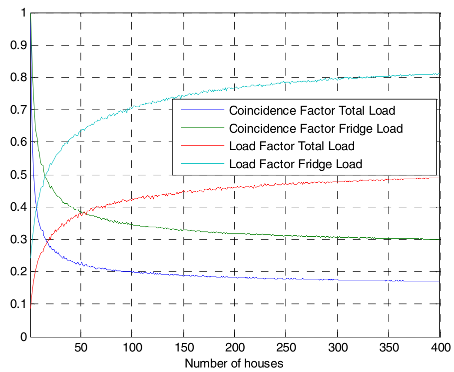

Fig. 11. Load Factor and Coincidence Factor for Fridge load and total load

Two important characteristics can be observed from the aggregated demand of 100 households (Fig. 9). Firstly, the fridge group is almost constant in comparison with the other loads. Secondly, the washing group has an important presence along the day, especially during peak hours for the distribution transformer. These two characteristics could be exploited by the DNOs in a potential DSM scheme given that correspond to household appliances that do not significantly affect the comfort level of the occupants if externally managed.

B. Potential of the Fridge Group

Each fridge load has a cycle consumption pattern through the day; the duration and the amplitude of each period depend mostly on the temperature inside of the fridge. If the fridge door is closed the duration and amplitude of each period is almost the same. However, when the door is open the inside temperature starts to increase and therefore the electrical consumption is higher. Fig. 10 shows the electrical consumption of different fridges (one minute resolution) from the adopted load model.

From Fig. 10 it can be observed that these loads are present almost during the whole day. Indeed, if we compare the load factor and the coincidence factor calculated in section III with those for the fridge loads only (Fig. 11), it is clear that the values are respectively much higher and lower than for the total load.

It is worth noting that, similarly to opening and closing fridges' doors, reducing their temperature or cutting them off as part of a potential DSM scheme, means that once back to normal operation, more power will be required (for them to restore their specified temperatures). Consequently, the thermal behavior of the load needs to be understood in order to really apply fridge load control in peak demand reduction.

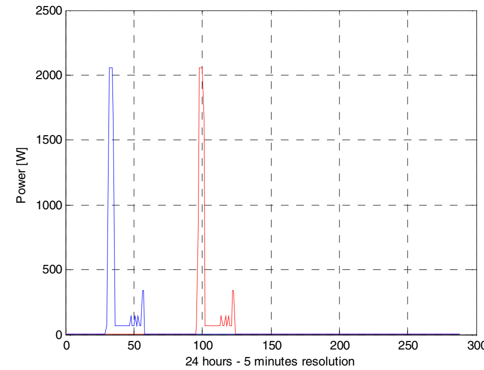

Fig. 12. Shifting process for a washing machine.

Although measurements are required to actually understand the real potential and behavior of fridge loads in a given region, the high load factor of these particular appliances is an indication of their potential for DNOs. Because of the fact fridges are common is most households around the world, most of the research has been focused on system-level frequency demand response [10].

C. Potential of the Washing Group

The washing group corresponds to what can be called passive loads, i.e., loads that can be shifted without disturbing the normal behavior of the household occupants. In this work, it is considered that the use of this group of appliances can be moved through the day through a DSM scheme in order to decrease the peak demand.

Fig. 12 shows an example of the potential shifting process for one washing machine from the original period (red color) to a new period (blue color).

Assuming that the DNO is able to control the washing group appliances and can also forecast the aggregated load profile for a particular number of customers, it is possible to propose an algorithm to minimize the peak demand. The problem to solve is formulated as follows:

$$\text{minimize}\left\{ max \sum_{k=1}^{N} \sum_{j=1}^{m} P_{ijk} \right\} \qquad (5)$$

The minimization is achieved by shifting the washing appliances in each home. To solve this problem a heuristic methodology is presented in [11] using 30 houses. Also a linear programming (LP) solution is presented in [12], solving the general problem (different appliances to be shifted) for 10 users, and the extension of [12] to integer LP is presented in [13] using four dwellings. These works show the potential in peak demand reduction using different appliances; however, they do not show the implications in real LV distribution systems (nearly 100 loads per feeder). Thus, different group of loads with different available appliances (not everyone has washing requirements the same day) have different impacts on peak demand reduction and on the LV distribution system.

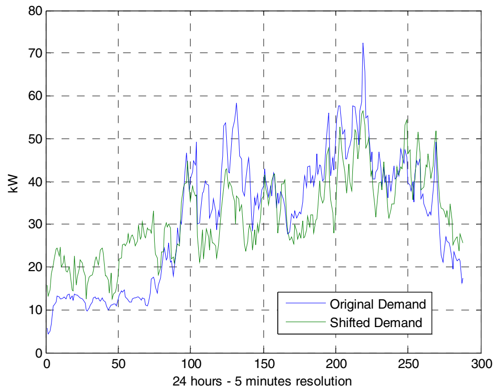

Fig. 13. Original demand and demand after the shifting process.

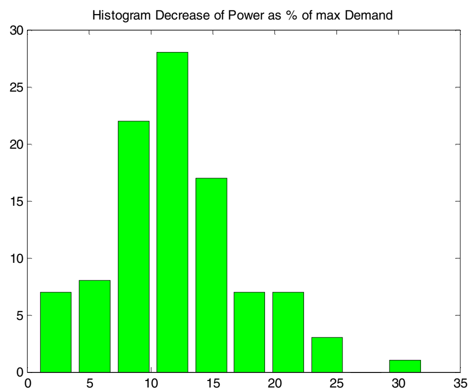

Fig. 14. Histogram of peak shaving benefits

To exemplify the potential impact of load shifting on LV network operation and planning, in this paper a basic procedure is developed. The washing appliances are shifted randomly and the peak demand is calculated, the process is repeated thousands of times and the final solution will be the one corresponding to the lowest peak. The procedure to appreciate the peak reduction is:

- Creation of *N* profiles using the load model.
- Identification of the washing appliances in each of the *N* houses.
- Re-allocation of the washing appliance in order to decrease the peak demand by using the basic heuristic.

This process was first applied to a feeder with 100 households and resulted in a 15% reduction of the peak demand as shown in Fig. 13. It can also be observed that a significant part of the washing load was shifted to early hours of the day.

Each household profile is different, so the peak shaving for one feeder with 100 houses could be different from another equal in size – each household uses the washing appliances differently (this is captured in the load model).

In order to understand how the peak shaving benefits vary for different groups of households, the proposed shifting algorithm is applied to 100 different groups each with 100 households.

The maximum reduction found in this analysis was 32%, corresponding to a group with many washing appliances available. The minimum reduction was 2% and the average reduction was 12 %. This particular case study provides a very interesting insight to the DNO: in 50% of the cases the peak is shaved by more than 11.4 %, and in 95% of the cases this reduction is bigger than 3.6 %. By understanding the potential contribution from these particular loads, DNOs can decide on whether to go ahead with a DSM scheme based solely on them or in combination with other appliances or loads.

TABLE I
PERCENTAGE OF PEAK REDUCTION CONSIDERING BANNED TIMES

Temporal Constraint	Percentile 5th	Percentile 50th	Mean	Std Dev
Base Case	3.55	11.30	12.13	5.52
(1-6)	1.68	9.16	9.58	4.95
(0-6)	1.50	9.42	9.46	4.94
(0-8)	1.45	8.83	9.01	4.51
(18-20)	5.61	12.85	13.32	5.44

In addition, if washing appliances are capable of communicating to the DNO (or the DSM scheme itself) their availability (i.e., a customer is ‘requesting’ use of the appliance), then the DNO could apply the shifting algorithm and have more certainty on the expected reduction of the peak.

It is important to note that the above proposed algorithm is considering the whole day to allocate the new washing process (i.e., the use of the appliance can be shifted to times that could disturb household occupants or neighbors). Thus, some periods of the day could be banned. To model that effect the following banned times are defined:

- (1-6) no washing between 1 and 6 am.
- (0-6) no washing between 0 and 6 am.
- (0-8) no washing between 0 and 6 am.
- (18-20) no washing between 6 and 8 pm.

The adapted shifting algorithm is applied again for 100 different groups each with 100 households. The results for each case are presented in Table I.

The best solution is found when the peak time period is banned. It is also possible to appreciate that the % of reduction decreases when the number of hours during the off-peak period are increased.

V. REAL LV NETWORK APPLICATION

The shifting algorithm with the peak time period banned is applied on a real low voltage distribution network from the North West of England, owned and operated by Electricity North West Limited (ENWL). This network has five low voltage feeders, 334 costumers and 8 km (Fig. 15).

In order to understand the effect of the number of customers, the methodology is applied to each feeder separately. First of all, one profile is created for each costumer; the aggregation of these profiles produces the demand profile of the feeder. After that, the shifting algorithm is applied; this creates modifications in some costumer profiles (those with washing appliances) and therefore it produces a new demand profile of the feeder. The difference between the old and new demand profile peak is the peak reduction. To observe the impact of that peak reduction in each segment of the real network, two time series power flow

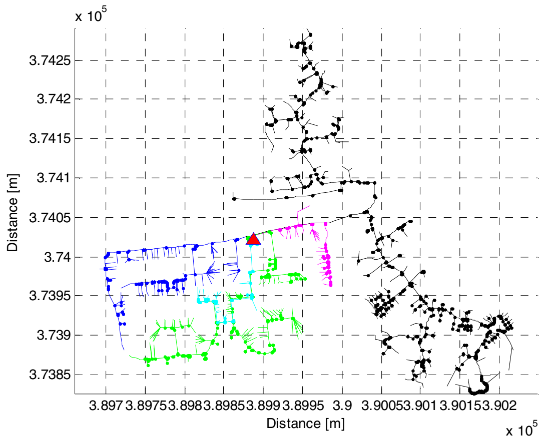

Fig. 15. ENWL Low Voltage Distribution Network

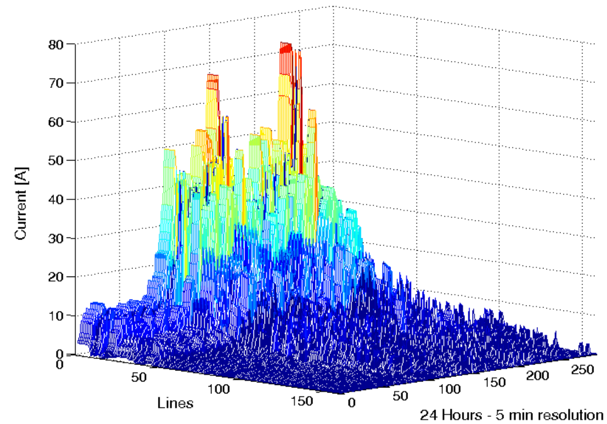

Fig. 16. Currents considering business as usual operation – Feeder 1.

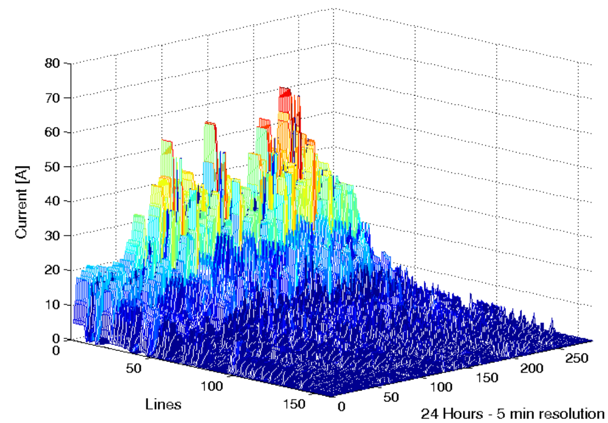

Fig. 17. Currents after applying the load shifting algorithm – Feeder 1.

simulations are carried out for each feeder, one for the profiles before the methodology application and one after the shifting process.

The power flow simulation takes into account the network topology, the conductor information and the location of the loads; it is important to remark that the load behavior is coming from the load model presented in Section II, which represents just residential loads, and therefore it is not the actual behavior of the corresponding ENWL customers. However, this is a suitable approach to test the potential benefit of the proposed load shifting technique.

Another important feature of the power flow simulation is the capability to solve the problem for one whole day with 5 minutes resolution (288 periods during the day). With this it is possible to observe the current through each line for each period of time. As an example, Fig. 16 and Fig. 17 show the currents through the feeder 1 (blue line in Fig. 15) before and after the shifting algorithm, respectively.

In Fig. 16 and Fig. 17, the lines are sorted from the transformer to the last line. For that reason, the current circulation is bigger in the first lines (main feeder) and decreases till the last lines (connection lines for the customers). Obviously, this aggregation effect happens because of the radial structure of the LV feeders.

Fig. 16 shows that the morning peak current is about 65 A and the afternoon one is about 70 A. Also, it is possible to observe that the consumption during the night time is small and the aggregation effect in the first lines is not significant during the night time. On the other hand, Fig. 17 shows a decrease in the peak demand. In fact, the morning peak current is about 55 A and the afternoon peak current is 60 A, which means a reduction of 14% in the maximum peak demand.

The change in the current profiles because of the load shifting algorithm can be observed in Fig. 17; the consumption is moved to the off peak period by shifting part of the passive loads to the night time period. Indeed, the aggregated effect in the first lines during the night period is twice the same effect before the algorithm application. The same features described in this section can be observed for the rest of the feeders.

It is important to recall that the previous result corresponds to one particular population of loads with certain amount of passive loads able to be shifted. Therefore, to have a more accurate assessment of the potential benefits from the proposed load shifting algorithm considering different load populations, a Monte Carlo analysis is carried out. 1000 populations are simulated for each feeder. The main outcomes are shown in Table II.

TABLE II
PERCENTAGE OF PEAK REDUCTION PER FEEDER

	Customers	Percentile 5th	Percentile 50th
Feeder 1	63	2.43	12.05
Feeder 2	113	5.21	12.49
Feeder 3	28	0.64	12.54
Feeder 4	98	4.57	12.38
Feeder 5	24	0.41	12.98

Table II indicates that independently of the load number, in 50% of the cases the peak decreases by more than 12%. However, the percentage of peak reduction in the 5^{th} percentile (5% of the cases) increases if the number of load increases; this is an expected result because the probability to have passive loads available increases with the number of customers.

With this analysis the DNO is able to know the most likely peak reduction (about 12%) and also the lowest contribution according to the number of customers per feeder. Consequently, this analysis can inform operational decisions when implementing similar DSM schemes.

VI. Conclusions

This work presented a set of potential (positive) impacts in LV network planning and operation considering the availability of high granularity consumer demand data (data that could eventually be available through smart meters).

From the planning perspective, in terms of the effects of the data granularity level on the load factor and coincidence factor, it was found that hourly 'sampling rates' produces an overestimation of those factors. On the other hand, 1 and 5 min data do not show significant differences. This is crucial in determining the right level of data to be monitored or stored for similar purposes. In terms of optimal conductor selection, it was also demonstrated that taking historical values for the load factor rather than those based on measurements could lead to suboptimal investments.

From the operational perspective, it was shown through the coincidence and load factor curves that the fridge loads are above those for the total loads, making them a feasible load to be controlled. However, considering only the washing appliances, a load shifting algorithm was proposed to assess the potential peak reduction from demand side management strategies. Results using a real LV network showed that it is possible to estimate the most likely peak reduction as well as the lowest contribution according to the number of customers per feeder. This analysis can inform operational decisions when implementing similar demand side management schemes.

VII. Acknowledgment

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VIII. Appendix

The installation cost for every underground cable is 140,000 ₤/km. The cost of energy losses cost is 45.3 ₤/MWh. The internal rate of return is 7%. The life expectancy is 30 years.

TABLE III
Conductor Parameters

Size (mm^2)	Capacity (A)	R (ohm/km)	X (ohm/km)	Cost per km (£k)
95	220	0.3200	0.0690	10.5
185	320	0.1640	0.0685	18.0
300	420	0.1000	0.0675	25.5
2x185	576	0.0820	0.0343	36.0
2x300	756	0.0500	0.0338	51.0
3x300	1071	0.0333	0.0225	76.5

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