A Roadmap for Domestic Load Modelling for Large-Scale Demand Management within Smart Grids

Alexandros Kleidaras(✉) and Aristides Kiprakis

Institute for Energy Systems, School of Engineering,
The University of Edinburgh, Edinburgh, EH9 3JF, UK
{A.Kleidaras,Aristides.Kiprakis}@ed.ac.uk

Abstract. This paper discusses the potential of the domestic sector to provide Demand Side Management (DSM) services. The inherent drawback of the domestic sector is its structure, consisting of numerous small loads, the high variety of sub-types, the deviation of consumption profiles between households but also the daily variation of each household's demand. In order for DSM to be coordinated and controlled effectively there is a need to create appropraite load clusters and categories. Moreover, there is a variety of domestic loads which can be considered controllable or 'smart'. These smart loads have different characteristics, constraints and thus suitability for DSM services. Hence, typical clustering of load profiles is not optimal and the problem needs to solved on a lower level. A promising method is proposed, some initial results are shown, and finally future work and possible imporvements are discussed.

Keywords: Demand side management · Demand response · Residential loads

1 Introduction

High penetration rates of Renewable Energy Sources (RES) in the distribution side of the power system introduces considerable fluctuations, making it difficult to maintain balance between power supply and demand in the grid. At the same time, the overall power consumption is increasing over the years; in particular, the peak electric demand is rapidly growing [1–3]. Energy storage systems (ESSs) have been proposed as an effective solution to this problem, but recent research is focusing on more feasible methods, namely Demand Side Management (DSM) and Demand Response (DR) using controllable loads [1–9]. The main concept behind Demand Response derives from the potential of some loads as controllable loads, thus making use of already existing components of the grid. Demand Side Management services can be procured by electricity system operators through monitoring, aggregation and control of loads and distributed generation to maintain reliability of electric power systems.

The control strategies for Demand Response can be divided into indirect (or decentralized), where users are prompted to alter their demand profile, through dynamic tariffs or other incentives [10, 11]; and direct control (or centralized), [12], a central or automated control, such as in [10]; for cases of faults, lost generation, RES fluctuation etc., where immediate response sometimes is needed [13].

P. Pillai et al. (Eds.): WiSATS 2015, LNICST 154, pp. 33–47, 2015.
DOI: 10.1007/978-3-319-25479-1_3

The main strategies for indirect control are time of use pricing (TOUP), real-time pricing (RTP), critical peak pricing (CPP) and peak time rebate (PTR) [11, 14–16]. These can be used for peak shifting/shaving, valley filling or RES following methods. A percentage of customers is expected to alter the starting time of their appliances (or automated systems [16]). Exact response (number of customers) to dynamic tariffs and effect on load shaping depends on prices themselves and human behavior.

Direct Load Control (DLC) services can provide various services, mainly for grid reliability [14, 17]. Some of these can be load shaping (RES integration or price following) [1, 2, 4–7], frequency control [3, 4, 8, 14] voltage control [4], overload relief (transmission and distribution) [4], grid reliability [5, 9, 10], peak load reduction [9, 12], reserve (in the form of positive or negative regulation) [9]. Based on the service provided, different loads or groups of loads are utilized. For instance, T. Masuta & A. Yokoyama [3] simulate frequency control with WHs (Water Heaters) and EVs (Electric Vehicles), which can be switched on/off for short intervals without affecting the quality of service. Hernando-Gil et al. [9] utilize wet loads for DSM, but in this case shifting the appliances' operating time to achieve peak demand reduction.

2 DSM in the Residential Sector

Industrial, commercial and residential sectors have combined consumption at 91.55 % of the total. Currently, the focus of DSM is primarily on the industrial sector due its inherently large loads, existing metering infrastructure (sensors and metering technologies available) and staff with expertise on power systems. Also, the commercial sector, though it tends to have a more distributed consumption (smaller loads), facilities (or groups of them) with enough flexibility have the ability to participate. Residential loads are gaining more attention, but have not been largely used since the loads are small, distributed, and not automated [2, 4, 6, 9–12].

The major challenge lies in the domestic sector, having the highest consumption of the three (35.76 % [18]). A lot of small consumption units need to be aggregated and controlled simultaneously to achieve same results as large commercial or industrial units [4]. In addition, problems arise from the deviation in load profiles, limited knowledge of load composition (how many flexible/deferrable loads operate and at which times/conditions) and limited knowledge of their potential for DSM, including the end users' awareness and thus willingness to participate. Therefore, knowledge of the composition of the residential sector is essential. This effectively means analyzing the loads and their potential for DSM, their total volume (aggregated power), how much of it can be utilized, which times during the day, week, season and the major driving factors.

Controllable loads fall mainly into two categories: flexible and deferrable. The first type (flexible loads) are those that can provide balancing services, through altering or interrupting their cycle for a short amount of time without affecting the quality of service [12, 19–21]. For instance, electric vehicles or water heating (which usually operate for a few hours) can be switched off (or reduce their consumption) for a few minutes, as long as the battery gets fully charged or the water temperature is within the thermostat's limits respectively [3, 12, 22].

The second type, referred as deferrable loads (also found in literature as load shifting) can shift their operation in time [10, 12, 23, 24]. For instance, washing machines can be programmed to postpone (or advance) start times to favorable times (i.e. lower price due to excess RES generation or off-peak use) [11, 12, 23]. Deferrable loads are suitable for indirect load control (dynamic pricing) and is a form of decentralized DSM. Though, because of its nature, human behavior (even when assisted by automated systems [16]) plays a big part.

Table 1. DR potential of basic domestic appliance categories [12, 19–21, 25, 26]

Load type	Potential	Main factors
Cold Appliances	Flexible	Human behaviour
Electric space heating	Both	Weather
Electric water heating (excluding showers)	Both	Weather
Heating circulation pumps (Gas & Electric)	Both	Weather
Air conditioning	Both	Weather
Wet appliances	Both	Human behaviour Weather (dryers)
Cooking (ovens)	Deferrable	Human behaviour
Lighting	–	Time of day, weather
Consumer Electronics & Home Computing	–	Human behaviour

Note: Each type and each appliance has different constraints and potential. In some cases (i.e. ovens), this can be very limited.

3 Domestic Load Clustering

For the purposes of Load Clustering the main algorithms usually used are Hierarchical, Centroid and Distribution-base. Most commonly Hierarchical Agglomerative, K-means, Fuzzy C-means. The clustering algorithms prefer clusters of approximately similar size and coherent profile, as they will always assign the nearest object (distance based). This often may lead to incorrect clusters, since the main objective is to cluster similar profiles in shape and not necessarily size which have a "coherent" profile on a daily basis. The first step before clustering is thus the normalization of the load profiles.

Domestic loads aren't consistent, as the habitual patterns of users drive the main periods of loads usage, which is the main problem faced when trying to cluster them based on demand profiles. Some activities, such as laundry, don't take place on a daily basis. Thus the same households have different profiles from day to day, causing a high deviation in short term periods (weekly), unlike commercial and industrial units. Clustering domestic demand profiles on a similar manner to commercial/industrial ones, would give inaccurate results due to daily deviation.

Comparing Figs. 1 and 2, it is obvious that using average or aggregated domestic load profiles for studies on LV networks yields errors. Even though the demand profiles of individuals cannot be predicted and vary daily, on a larger scale, aggregated demand profiles do have consistency. This is due to consistency of habitual patterns, the probability of using specific appliances can be predicted on a large "homogenous" group based on historical data (and conditions such as working days, holidays, weather etc.).

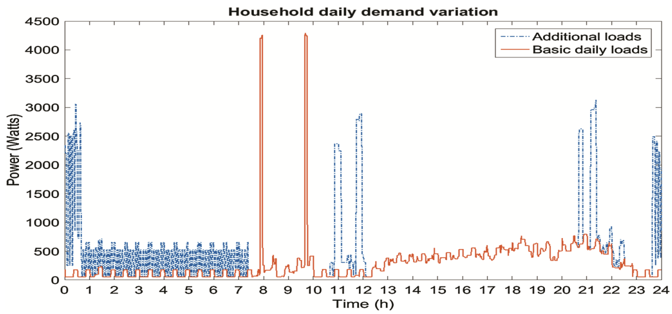

Fig. 1. Difference between two days with and without the use of Dishwasher, Washing machine, Tumble dryer, Water heater & Electric space heating

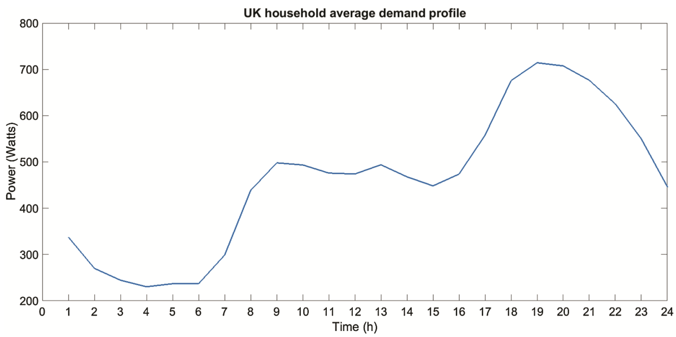

Fig. 2. Typical average household daily consumption in UK [25]

Another issue with demand response is the fact that whole load profiles do not give information about the availability of controllable loads (volume, time, etc.) but only the overall shape of profiles. Figure 2 compared to Fig. 1 has little to no information on the composition of the load profile, thus the controllable loads available. Thus, a large number of end users can be grouped in a few clusters based on their similarities, simplifying their management, supervision and forecasting. Moreover, it may allow unmonitored areas to be matched based on their characteristics to the closest template with a relatively low error (on an aggregated level) [27].

3.1 Modeling and Grouping

Knowledge of the availability of the controllable loads is essential. That means knowledge of quantity in the domestic sector. Table 2 shows ownership statistics, the model used for this paper was created for the case of UK. Things that need to be taken into consideration for the proper modelling are constrains of each type, driving factors, drawbacks and in case when loads are both deferrable and flexible how one affects the other. For example, electric heating as previously mentioned ([1–3, 5–8, 10]) can be used for DSM, but its availability depends on weather conditions (during cold weather mostly) and human behavior. If a low price signal caused the heating to operate at a t_i moment, it should be anticipated that there is extra load available for balancing services for that period. A known drawback is the rebound effect, the oscillation created when interrupted loads are switched on again, such as in [7]. Even though in this case it gets reduced over time because of random factors who affect thermal and cooling loads, initially it is still substantial, recreating similar fluctuations as the ones trying to correct.

Table 2. Appliances ownership statistics [25, 26]

Appliance	UK Ownership	EU Ownership
Fridge-freezer	69.4 %	106 %
Refrigerator	37.7 %	
Chest freezer	15.5 %	52 %
Upright freezer	31.4 %	
Electric oven	65.5 %	77 %
Electric hob	44.8 %	77 %
Microwave	93 %	–
Kettle	98 %	–
Washing machines	97 %*	95 %
Tumble dryers	56 %*	34.4 %
Dishwashers	42 %	42 %
Heating Circulation pumps	88.8 %**	70 %
Electric space heating (storage /direct)	6.13 % /0.74 %	–
Electric water heating [25]	4.8 %	–

*Includes washer dryers, ** DECC, based on number of dwellings with central heating/boilers [25], cooking, wet and heating loads are not operated every day, for example washing machines on average have 5 cycles/week and dishwasher 4.5 cycles/per week [30]

A bottom-up approach is needed, which takes into consideration the composition of the demand. One such approach has been proposed by A. Collin et al. in [28], which is driven by habitual patterns and user activities. Through the use of Markov chain Monte Carlo (MCMC) user activities profiles are generated. Then these are converted to electrical appliances use, which takes into consideration the operating cycle, power volume and other electrical characteristics of the appliances. Thus electrical load models are developed in ZIP form, which generates demand profiles.

The aggregation of those can give domestic load profiles while containing info about the composition of loads, as seen in Fig. 3. By utilizing the generated detailed demand profiles and the knowledge of the potential of smart appliances for DR, the mixture of flexible and deferrable loads during a day can be forecasted. VVPs (Virtual Power Plants) can be created, in the form of aggregated micro sources or batteries [29].

The next step is the creation of a suitable wide-scale network model. Low voltage networks differ based on many factors such as end users, number of customers, geographical location and more [9]. With the use of such LV network a larger realistic network can be created. Thus, simulations to test the potential of DSM strategies based on developed clustering of domestic loads can be evaluated. Basic DSM strategies include balancing services such as frequency control or fast reserve through central control and RES integration through decentralized control.

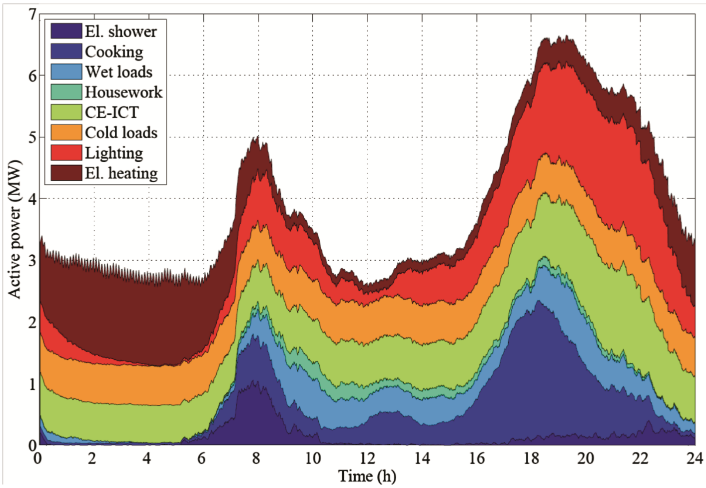

Fig. 3. Aggregated domestic demand [30] 10.000 households, bottom-up appliance specific model, urban areas

3.2 Overall Flowchart of the Methodology

In this paper, a method of combined classification and clustering is proposed, a flow chart of which can be seen in Fig. 4. Residential points with AMI (Advanced Metering Infrastructure) are assumed, with a 1 min interval of readings in the developed model for high definition, though less frequent sampling can also be used. Firstly, fixed data (classification rules) is utilized to examine characteristics that usually drive demand profiles. Then the classification rules used are estimated and analyzed for consistency. Based on the results, individuals are moved to other clusters or marked as anomalous data. The resulting clusters consist of "homogenous" individuals who have similar habitual pattern and thus aggregated demand profile.

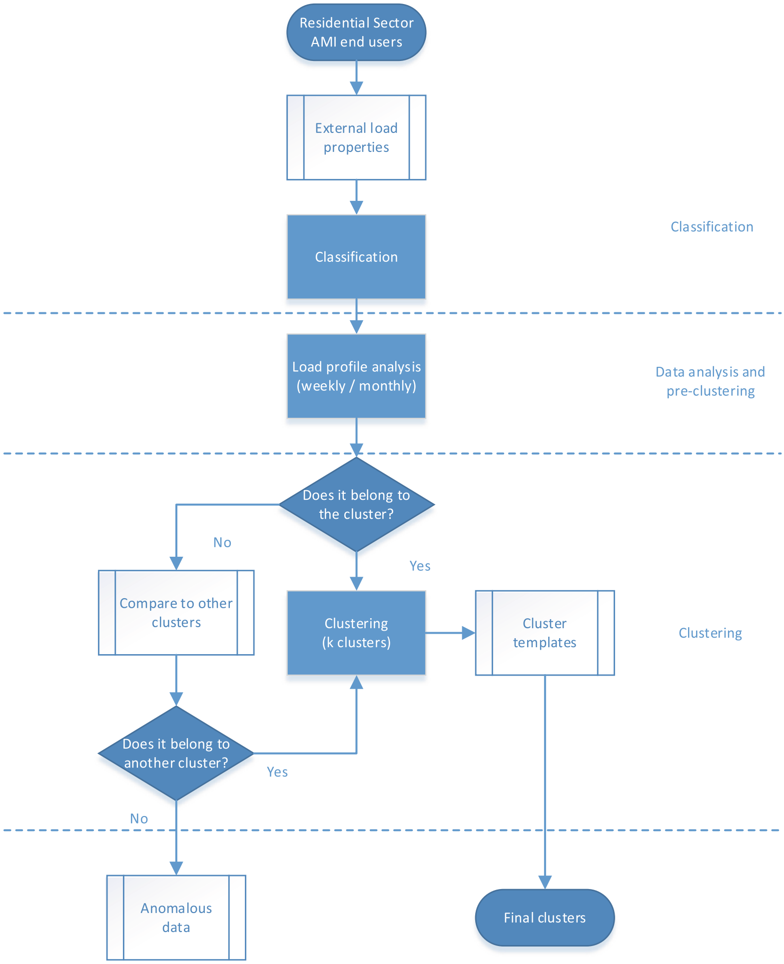

Fig. 4. Flow chart of the methodology

<u>Step 1:</u> Classification – The relationship and characteristics between households are examined. In this paper, occupation characteristics; total number and employment status, and demand characteristics; overall demand and time of use, are considered as main factors that drive the habitual behavior on a monthly basis.

Step 2: Data analysis – Similar households do not necessarily have similar habitual patterns and thus demand profiles. For instance, working occupants based from home or students (classified as non-working) being out of house during office hours, are some usual examples. Overall demand and especially demand in specific time frames of the day can be used to identify differences between similar households. In which case, historical data and analysis on monthly can be used to examine if individuals belong to their appointed cluster, another one or none (anomalous data).

Step3: Clustering - Finalizing clusters, which represent a homogenous group of individuals. On the individual level, demand profiles and thus smart appliances utilization cannot be predicted and is hard to monitor from day to day, but on an aggregated level, based on the habitual patterns of homogenous groups, the probability can be predicted. Thus, in a homogenous cluster of thousands of households, on a given day the overall use of smart appliances is known with high accuracy based on historic data and knowledge of driving factors (i.e. weather). Finally cluster templates are created, as a representative of the cluster, which can be seen as "one" micro source for VPPs, giving information on the available power for DR in specific times of the day. An important note is that households without AMI, can also be clustered based on some of the classification rules, such as occupancy characteristics and overall consumption with less accuracy.

3.3 Results

The classification used in this paper takes into consideration occupation characteristics; total number and employment status, demand characteristics; overall demand (consumption) and time of use (Table 3).

Table 3. Occupancy mixture of developed model

Number of Occupants	Working occupants				
	0	1	2	3	4
1	1210	2316	–	–	–
2	289	790	2290	–	–
3	105	395	1000	210	–
4	0	290	895	105	105

Generated through the Markov chain Monte Carlo (MCMC) method, based on UK population statistics [31]. Total number of households 10000, month January.

Combinations of household sizes of up to four occupants cover 95 % of the U.K. population [31], are thus suitable to represent the overall characteristics of the U.K. population. The correlation between occupation and consumption can be seen in Tables 4 and 5. Figures 5 and 6 are additionally presented to visualize some of these results.

Table 4. Consumption (kWh), random day January

Number of Occupants	Working occupants				
	0	1	2	3	4
1	8.416	6.553	–	–	–
2	11.134	9.850	8.962	–	–
3	12.599	11.063	10.658	10.085	–
4	–	12.588	11.761	11.387	11.617

Table 5. Relative standard deviation

Number of Occupants	Working occupants				
	0	1	2	3	4
1	32.9 %	36.7 %	–	–	–
2	30.4 %	32.1 %	36.2 %	–	–
3	53.3 %	31.6 %	34.9 %	29.9 %	–
4	–	27.1 %	28.7 %	28.2 %	28.4 %

Households of the same size, consisting of non-working occupants generally tend to have higher consumption, since the time spend in the house increases. Cases such as work based at home or students (classified as non-working) being out of the house on working days during office hours are just a few to name.

The approach suggested is a combination of occupancy characteristics and overall monthly consumption (historical data). For example, this allows case A to be placed in

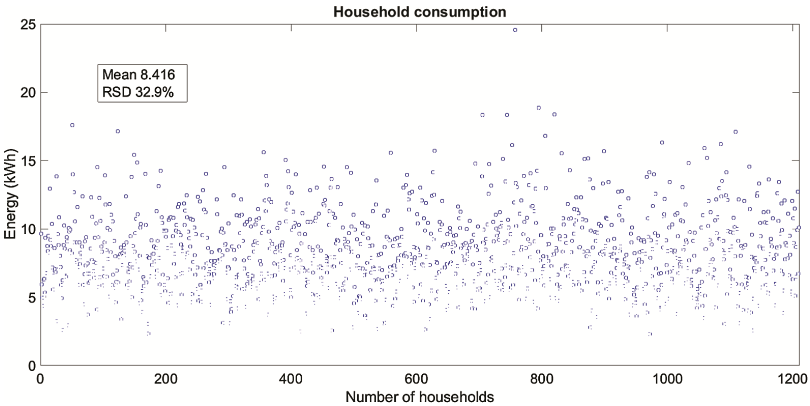

Fig. 5. Household consumption: 1 working occupant, random day in January

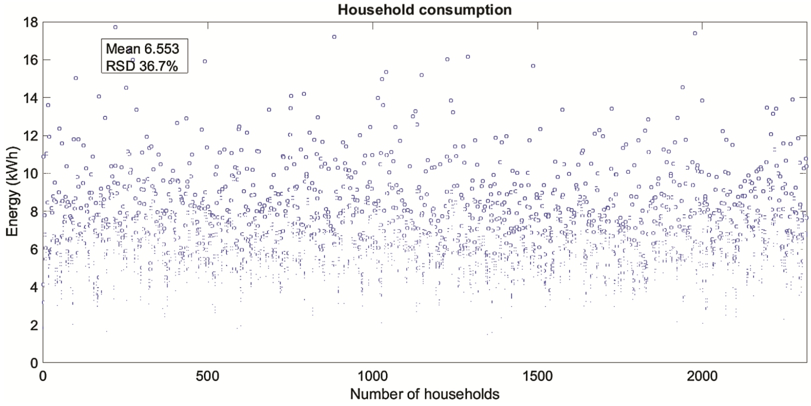

Fig. 6. Household demand: 1 non-working occupant, random day in January

a "non-working occupants" dominant group and case B in a "working occupants" dominant group, assuming similar consumption characteristics.

From Table 1, it can be seen that the households of 3 non-working, 3 working, 3 working & 1 non-working, 4 working occupants are small in number, thus their RSD values are examined with caution to avoid wrong conclusions (i.e. 3 non-working occupants has high RSD value compared to similar households). Nonetheless, we observe decrease in RSD values as the household size increases and as the number of working occupants decreases. The first one can be attributed to more consistent use of appliances, e.g. more frequent use of washing machine within a week for a bigger household thus less demand deviation. The second one can be attributed to occupants sharing more activities (habitual patterns) due to higher time flexibility opposed to working occupants, especially in cases where their working hours do not align.

The correlation between occupation and time of use (mainly controllable loads) can be seen in Figs. 7 and 8. The first one showing a typical office hours working occupant

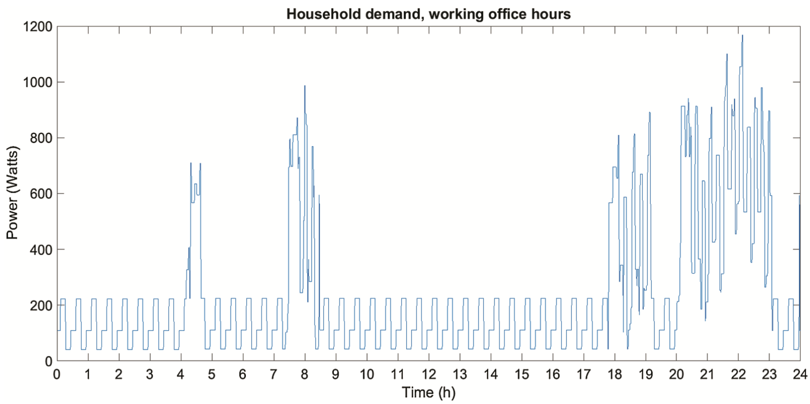

Fig. 7. Household demand: 1 working occupant

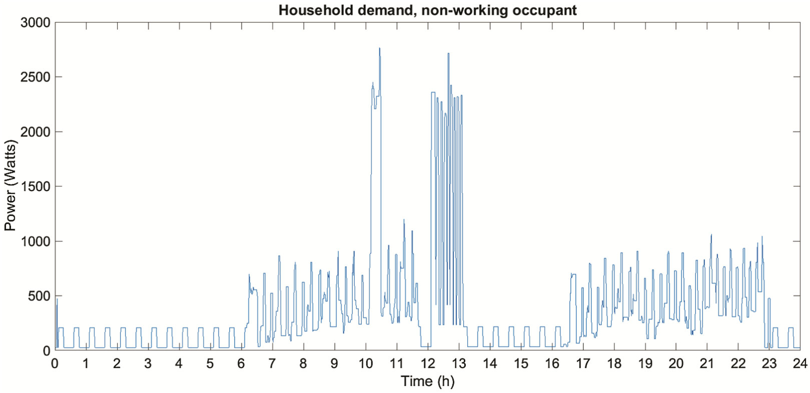

Fig. 8. Household demand: 1 working occupant

and the household demand which consists of cold loads and power electronics in a power down state (such as a TV which is plugged) between 8.30 am and 17.50 pm, the household can be considered in a "passive" consumption state. On the other hand, the second one has "active" consumption within the above hours.

A household with non-working occupants might match better a group consisting mainly of working occupants and vice versa as mentioned above. The approach suggested is a combination of occupancy characteristics and smart meter historical data. A comparison between households with different characteristics in an aggregated level can be seen in Fig. 9. In this case, two groups of the same household size but different occupancy characteristics. Night hours, from 20 pm till early morning hours, 8 am have small differences to almost none is certain hours, while the rest of the day has a substantial gap.

The low demand exhibited during office hours from the second group ("working occupant") is, mainly due to passive consumption. An important conclusion is that the

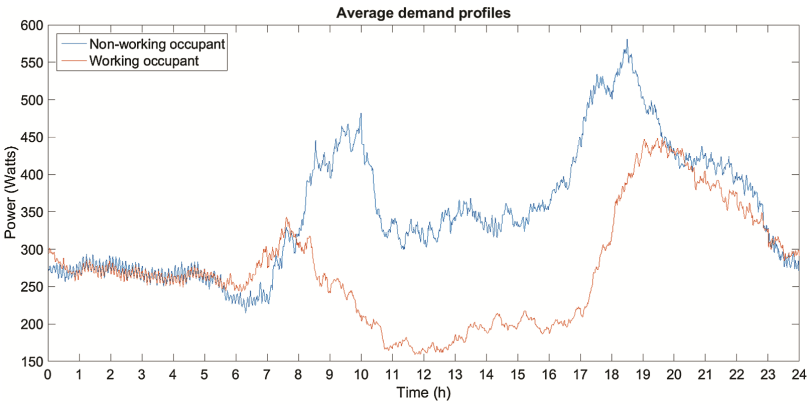

Fig. 9. Household demand differences

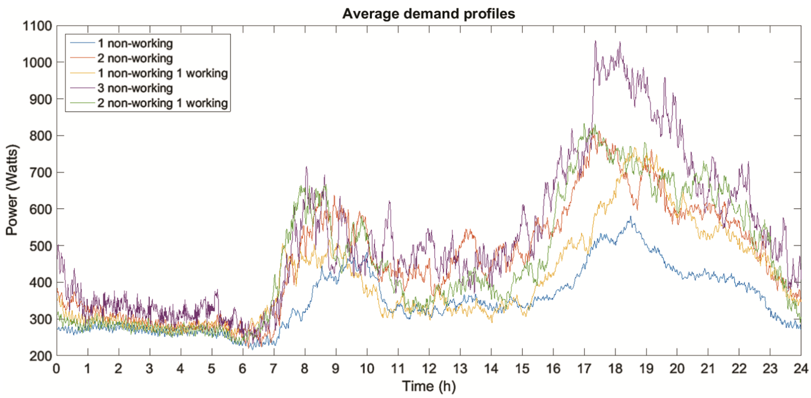

Fig. 10. Household demand similarities: non-working occupants Rest 4 combination follow the same pattern, not included for better visualization

second group ("working occupant") would have less interruption on cold loads (such as door opening or loading goods), thus higher availability than the first group ("non-working occupants"). In case a DSM service is needed, suitable to flexible loads such as cold loads, e.g. Frequency Control Demand Management (FCDM), sending signals to the second group would be the first choice.

On the other hand, heating loads, such as space heating (heating circulation pumps or electric heaters) and water heating loads are mainly expected to be operating within office working hours in the first group ("non-working occupants"). Additionally, for the second group, wet loads might potentially have a wider window to shift their operation, since ccupants will be absent during working hours.

Comparing clusters of different household sizes Figs. 10 and 11, consisting of similar occupants, the overall demand profile is similar with increased consumption. Oscillations increase is observed, an expected outcome for working occupants due to different

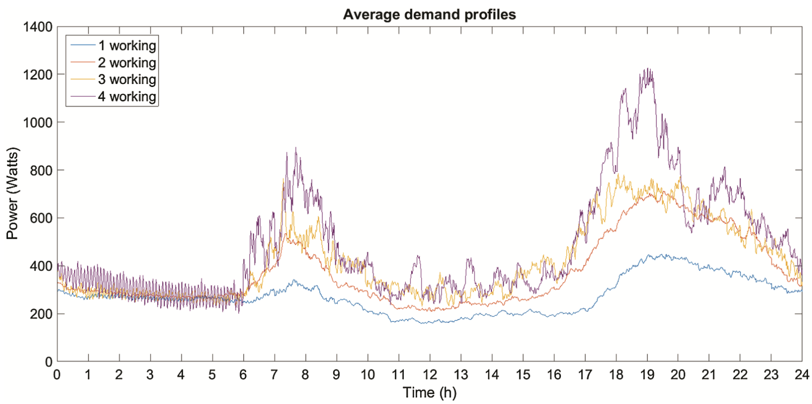

Fig. 11. Household demand similarities: working occupants

working hours, working from home or annual leave. Though the opposite would be expected from non-working occupants due to higher frequency of appliances usage such as wet loads and more shared activities.

4 Conclusions

This paper discusses the potential of domestic sectors to participate in DSM strategies in order to provide certain balancing services and load shaping. These are of great important for grid reliability, RES integration, reduction of cost and greenhouse gas emissions. Smart appliances are considered and their potential and suitability for DR and DSM strategies is discussed. Due to the wide variance of their ratings, electrical characteristics and use pattern, there is a need for a better modelling and then coordination and aggregation of domestic appliances for effective DSM. Due to the high deviation of the demand profile of single households on a daily basis, proposed clustering techniques in the literature are not always effective. However, it was observed that when aggregating similar types of domestic loads, the aggregated demand profile is more coherent, due to the habitual patterns of users which has a weekly /monthly frequency. The approach suggested in this paper is to cluster similar households based on external factors as well as demand profiles, creating a "homogenous" cluster, which on an aggregated level can be predicted and modelled using the probabilities of habitual patterns. The results show that classification based on occupancy and consumption is a good starting point but further analysis is needed. Additionally, demand during specific times of the day can be used to improve the homogeneity of the clusters. As such, a cluster can be used to identify available controllable loads (flexible and deferrable) with higher accuracy and thus based on the DSM service needed in specific times of the day, the proper cluster(s) can be selected to provide the service effectively.

Acknowledgments. The research leading to these results has received funding from the European Community's Seventh Framework Programme (FP7-PEOPLE-2013-ITN) under grant agreement no 607774.

References

1. Kawachi, S., Hagiwara, H., Baba, J., Furukawa, K., Shimoda, E., Numata, S.: Modeling and simulation of heat pump air conditioning unit intending energy capacity reduction of energy storage system in microgrid. In: Proceedings of the 2011 14th European Conference on Power Electronics and Applications (2011)
2. Kajgaard, M., Mogensen, J., Wittendorff, A., Veress, A., Todor, A., Biegel, B.: Model predictive control of domestic heat pump. In: American Control Conference (2013)
3. Masuta, T., Yokoyama, A.: Supplementary load frequency control by use of a number of both electric vehicles and heat pump water heaters. IEEE Trans. Smart Grid **3**, 1253–1262 (2012)
4. Starke, M., Letto, D., Alkadi, N., George, R., Johnson, B., Dowling, K., Khan, S.: Demand-side response from industrial loads. In: 2013 NSTI Nanotechnology Conference and Expo, vol. 2 (2013)

5. Papaefthymiou, G., Hasche, B., Nabe, C.: Potential of heat pumps for demand side management and wind power integration in the German electricity market. IEEE Trans. Sustain. Energy **3**, 636–642 (2012)
6. Malík, O., Havel, P.: Active Demand-side management system to facilitate integration of res in low-voltage distribution networks. IEEE Trans. Sustain. Energy **5**(2), 673–681 (2014)
7. Lu, N., Chassin, D.: A state-queueing model of thermostatically controlled appliances. IEEE Trans. Power Syst. **19**, 834–841 (2004)
8. Kim, Y., Kirtley, J., Norford, L., Leslie, K.: Variable speed heat pump design for frequency regulation through direct load control. In: 2014 IEEE PES T&D Conference and Exposition (2014)
9. Hernando-Gil, I., Hayes, B., Collin, A., Djokic, S.: Distribution network equivalents for reliability analysis. Part 1: Aggregation methodology. In: 2013 4th IEEE/PES Innovative Smart Grid Technologies Europe (ISGT EUROPE), 6–9 October 2013
10. Chang, T., Alizadeh, M., Scaglione, A.: Real-time power balancing via decentralized coordinated home energy scheduling. IEEE Trans. Smart Grid **4**, 1490–1504 (2013)
11. Albadi, M.H., El-Saadany, E.F.: A summary of demand response in electricity markets. Electr. Power Syst. Res. **78**(11), 1989–1996 (2008)
12. Subramanian, A., Garcia, M., Callaway, D., Poola, K., Varaiya, P.: Real-time scheduling of distributed resources. IEEE Trans. Smart Grid **4**, 430–440 (2013)
13. National Grid: Frequency Control by Demand Management, 2015. http://www2.nationalgrid.com/uk/services/balancing-services/frequency-response/frequency-control-by-demand-management/
14. Strbac, G.: Demand side management: Benefits and challenges. Energy Policy **36**(12), 4419–4426 (2008)
15. Faruqui, A., Harris, D., Hledik, R.: Unlocking the €53 billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investment. Energy Policy **38**(10), 6222–6231 (2010)
16. Du, P., Lu, N.: Appliance commitment for household load scheduling. IEEE Trans. Smart Grid **2**(2), 411–419 (2011)
17. National Grid: Short term Operating Reserve (STOR), 2015. http://www2.nationalgrid.com/UK/Services/Balancing-services/Reserve-services/Short-Term-Operating-Reserve/STOR-Runway/
18. Department of Energy and Climate Change (DECC) statistics, Electricity, 2013. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/337649/chapter_5.pdf
19. Shan-shan, Q., Jing, C., Xiao-hai: Interruptible load management in power market. In: 2014 China International Conference on Electricity Distribution (CICED 2014)
20. Tuan, L., Bhattacharya, K.: Interruptible load management within secondary reserve ancillary service market. In: 2001 IEEE Porto Power Tech Proceedings
21. Nistor, S., Wu, J., Sooriyabandara, M., Ekanayake, J.: Capability of smart appliances to provide reserve services. In: International Conference on Applied Energy (2013)
22. Pan, X., Li, Y., Wang, L.: Research on coordinative optimal dispatch of interruptible load on multi time scale. In: China International Conference on Electricity Distribution, CICED (2012)
23. Niyato, D., Dong, Q., Want, P., Hossain, E.: Optimizations of power consumption and supply in the smart grid: analysis of the impact of data communication reliability. IEEE Trans. Smart Grid **4**, 3–4 (2013)
24. Y, Z., Jia, L., Murphy-Hove, M., Pratt, A., Tuong, L.: Modeling and stochastic control for home energy management. IEEE Trans. Smart Grid **4**(4), 2244–2255 (2013)
25. Department of Energy & Climate Change, Energy consumption in the UK statistics. https://www.gov.uk/government/statistics/energy-consumption-in-the-uk

26. Stamminger, R., Broil, G., Pakula, C., Jungbecker, H., Braun, M., Rüdenauer, I., Wendker, C.: Synergy potential of smart appliances. In: D2.3 of WP 2 from the Smart-A project, November 2008
27. Li, R., Gu, C., Li, F., Shaddick, G., Dale, M.: Development of low voltage network templates — part I: substation clustering and classification. IEEE Trans. Power Syst. **30**(6), 3036–3044 (2014)
28. Collin, A., Tsagarakis, G., Kiprakis, A., McLaughlin, S.: Development of low-voltage load models for the residential load sector. IEEE Transa. Power Syst. **29**(5), 2180–2188 (2014)
29. Hao, H., Sanandaji, B., Poolaa, K., Vincent, T.: Aggregate flexibility of thermostatically controlled loads. IEEE Trans. Power Syst. **30**(1), 189–198 (2014)
30. Collin, A., Tsagarakis, G., Kiprakis, A., McLaughlin, S.: Modelling the electrical loads of UK residential energy users. IEEE Trans. Power Syst. **29**(5), 957–964 (2014)
31. 2011 census: Population and household estimates for the United Kingdom, Office for National Statistics, March 2013