Data-driven Household Load Flexibility Modelling: Shiftable Atomic Loads

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Abstract— **To keep a stable power system, there should always be balance between the generation and consumption of electricity. In this study, a flexibility modelling method for atomic loads which is based on high resolution appliance measurement data is presented. The method embraces the potential variabilities of appliance use in group of households. Besides, aggregated load flexibility potential of atomic loads in defined number of households is quantified.**

Keywords—demand response; atomic loads; big data; load management; load modelling

I. Introduction

Shiftable loads can be categorized as shiftable atomic loads and shiftable interruptible loads. Shiftable atomic loads are loads that can be shifted but once they start they cannot be interrupted. Typical shiftable atomic loads are cloth washing machines, dryers and dishwashers [1]. Some recent studies claim that these loads can be interruptible if the right process step is chosen and the interruption is brief (up to 15 minutes) [2]. However, considering also the limited willingness of customers to allow the interruption of these appliances while operating, they are defined in this study as non-interruptible [3].

The practice of the shifting of load from one hour to another is not simply cutting the load of the previous hour and adding it to the new hour. Rather, especially for shiftable atomic loads, flexibility modelling requires a careful study of both the consumption profile of the individual loads to be shifted and the temporal probability of use profile of the appliance in stock of households. Washing machines cannot be interrupted and hence only the starting time of the washing machine can be shifted. Besides, in one use cycle a washing machine started operating in the previous hour can travers to the next hour until it finishes. This entails that we should look for the probability of a washing machine starting at each hour of the day. Consequently, shifting of the start of a washing machine will be the shifting of the probability of start from the specific hour to the next hour. This way, we will be assured that we are not shifting a washing machine, which was not starting in the considered hour in the first place. The aforementioned characteristics of washing machines also apply to dryers in general terms. Atomic loads can be modelled by studying closely the energy need of the different processes of a single washing cycle. Nevertheless, the variability in power demand due to the differences in washing programs and the type and the amount of clothes to be washed will essentially demand the accumulation and use of statistical data of these appliances. As the aggregated effect of these appliances are being sought for, the modelling of individual washing machines is not essential. And hence, in this study, a data driven flexibility modelling is proposed and demonstrated for selected atomic loads. Modelling techniques can be white-box, grey-box or black-box depending on the extent to which first principle physical characteristics are involved [4]. Data driven approaches are usually black-box methods. Nevertheless, the approach followed in this study considers the operating principles of the atomic loads and data-mining to extract useful information from real measurements. Hence, in the end the proposed method can be categorized as grey-box.

In some of the reviewed literature, shiftable loads are modelled using mixed integer or integer variables making the power profiles rectangular, which is far from the real consumption profiles [5], [6]. In [7], more realistic model representing one use cycle of shiftable loads with Gaussian profiles is presented. However, none of the reviewed literature use the probability-of-starting-of-use for shiftable appliances making the methods dependent on predefined base scenario for them to quantify the feasible flexibility potential. By extracting information regarding the variability in appliance operation, the differences in appliance make and by extracting the probability of use at different hours of the day from 1-minute resolution consumption measurement data, the presented method in this paper models the flexibility potential of shiftable appliances in group of households at any given time in a day.

II. Data And Method

In smart grid, the main source of big data is the advanced metering infrastructure (AMI) [8]. However, the time resolution of AMI meters at the moment is usually 15 minutes or lower. Hence, if more data resolution is required, one need to do appliance level measurements. The data used in this analysis is from a previous project called ElDeK- Electricity Demand Knowledge, in which a 1-minute resolution consumption measurements of cloth washing machines, dishwashers and dryers have been collected using dedicated plugin instrument [9]. We have analyzed the data from twenty households with measurements spanning form few days to up to one month period.

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TABLE I. NUMBER OF FULL DAY MINUTE LEVEL MEASUREMENTS OF APPLIANCES WHEN THEY OPERATE AT LEAST ONCE IN THE DAY

	Number of weekday measurements	Number of weekend measurements
Cloth washing machines	154	67
Dryers	112	52
Dish washers	226	102

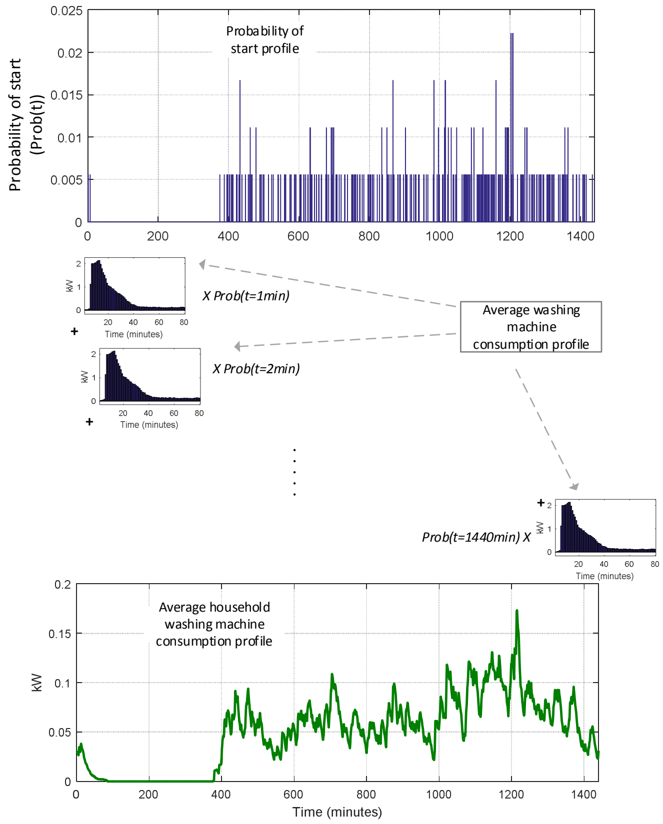

Fig. 1 Process of reconstructing the single household consumption for washing machine power consumption profile from probability of start and appliance average single-use profiles

The size and type of data is summarized in Table I. From this data two important characteristics are extracted. The first is the average appliance one-time-use profile and the second is the probability of start at each minute of the day (1440 point). These values are presented for the appliances in Sections III and IV respectively.

The method employed in this study utilizes the probability of start of the use of washing machine and one-time washing profile of an average washing machine to reconstruct the base line consumption as well as the shifted one (see Fig. 1). The main principle of the process is that demand response of atomic loads can be accomplished by shifting the probability of start of the individual appliances.

To utilize the method presented in Fig. 1, one has to remember the following considerations and assumptions:

1. According to the data, households use washing machines 1.5 times in average on a day washing machine is used. Hence, if 100 households are considered in the stock then about 150 washing activities will happen in one day. The aggregated washing machine related consumption profile is then computed from the probability of use-start profile as shown in Fig. 1.
2. The flexibility potential can only be calculated for households on washing machine use day. Therefore, further programs using the output from this model shall only use it for days when households use washing machines. Hence, the first thing the user of this model need to do is estimate the number of households involved in cloth washing activities.
3. Shifting of the start of operation of the washing machine can be conducted from one minute to another. For example, for 100 households, all washing activities that would have started at a particular minute can be shifted to the minute of choice. Nevertheless, the shifting has to be within the maximum and minimum time the operation of the appliance can be delayed.

III. SINGLE APPLIANCE MODEL

Atomic loads in households are loads which have limited or nonexistent interruptible consumption cycle. These appliances have processes where interruptions or delays may disrupt the essential task of the appliance. In this study, washing machines, dryers and dish washers are defined as atomic loads. Atomic loads normally do sequential tasks which also consume distinct level of energy. For example, a typical washing activity involves water filling, agitation, washing, spinning, rinsing and draining. For a typical washing program, the sequence of process are presented in Table II with the respective energy consumption.

The activities of a washing cycle listed in Table II can vary in accordance with the type of the selected washing program. The program selectors may enable specifying the speed of washing, the temperature level of the water and the type of cloth to be washed. Accordingly, the power consumption profiles of two washing activities of similar washing machines may vary. Fig. 2 presents the power consumption profiles of four different washing machine activities. Also, in Fig. 3 the power consumption profiles of four different drying machine activities are plotted.

TABLE II. CYCLES OF CLOTH WASHING MACHINES IN ONE USE CYCLE

State	Cumulative time	Energy Consumption
Water fill	3 min	3.01 Wh
Agitation	10 min	53.9 Wh
Wash	17 min	
Drain	5 min	7.51 Wh
Spin	4 min	
Water fill	3 min	17.15 Wh
Rinse	5 min	
Drain	5 min	11.78 Wh
Spin	8 min	

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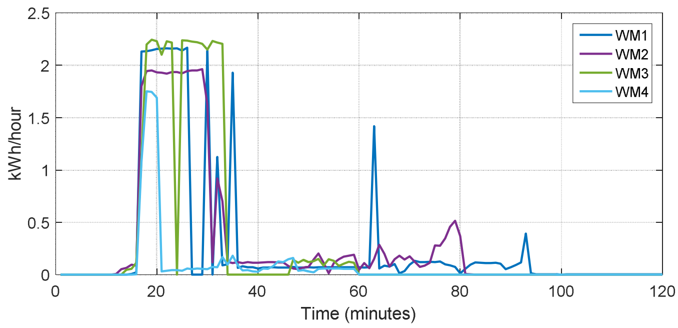


Fig. 2 Consumption profiles of single use cycle for four washing machines selected from the raw measurement data (kWh/hour)

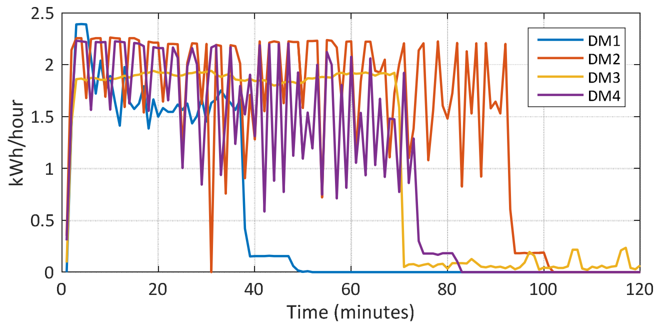
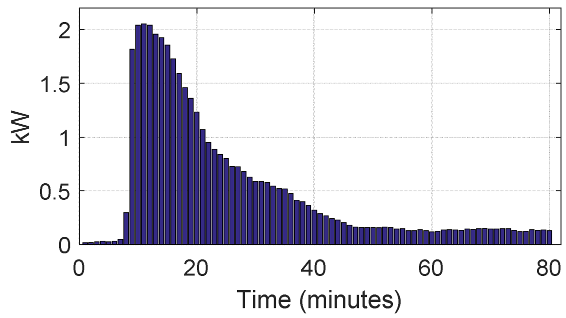
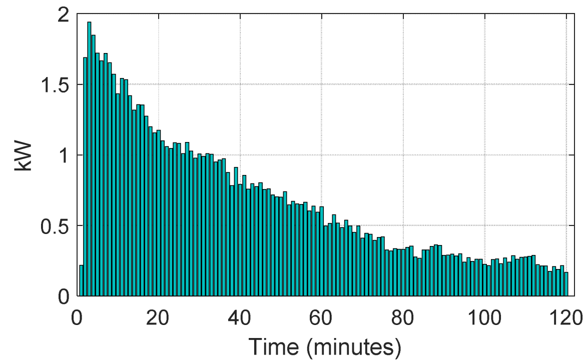


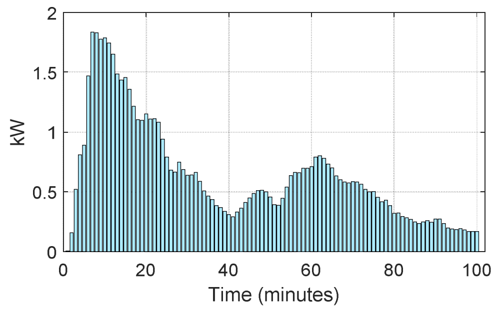
Fig. 3 Consumption profiles of single use cycle for four drying machines selected from the raw measurement data (kWh/hour)



a)



b)



c)

Fig. 4 Averaged Single use load profiles for a) Cloth washing machines (WM), b) Dryers (DRY) and c) dish washing machines (DM)

As it can be seen in both Figs 2 and 3 power consumption profiles of washing machines and dryers can vary significantly depending on the size of the load (clothes to be washed) and the selected program on the machine. Hence, the use of an average profile for washing activity can be used to model the consumption profile for aggregated group of households. Accordingly, using the average of individual consumption profiles, representative power consumption profiles are calculated for the different types of atomic loads (see Fig. 4).

IV. Probability of Use start

The average number of wash cycles in an average European household is calculated to be 3.8 washes per week based on the 2011 figures [10]. The probability of households to use these appliances at each day of the week varies and even more these probabilities can vary at each minute and hour of the day. Usually the washing machine use intensifies at the early hours of the day and evening hours of the day in weekdays. However, in weekends the start of use for washing machines intensify at late hours in the morning and subsides in the evening. The attempt to quantify the DR potential of washing machines and their respective rebound effects can be accomplished once the probability of start of use profile on the average base day is known.

Based on the high-resolution data, we have compared the washing and drying machine use-habits and its dependency on the day type of the week. In average, there is about 48.7% chance of washing activity to take place in any of the weekdays. The differences among the day types is not much. Nevertheless, it seems that washing and drying activities intensify on Sundays and Thursdays while Tuesday is the least favorite day to do washing or drying activity. The small differences among weekdays' probability of use of the appliances suggest that developing a probability of use-start for different hours of an average weekday and weekend should be adequate to quantify the demand response potential and the rebound effects of washing machines and dryers. The probability-of-use-start as extracted from the 1-minute resolution measurement data are presented in Fig. 5 for three atomic loads on an average weekday and weekend. In the profiles, one can observe that washing related activities start at late hours of the morning in weekends than weekdays. In addition, peak probability of use values for dryers are observed just after the peak probability of use values for washing machines (see Figs 5a and 5b).

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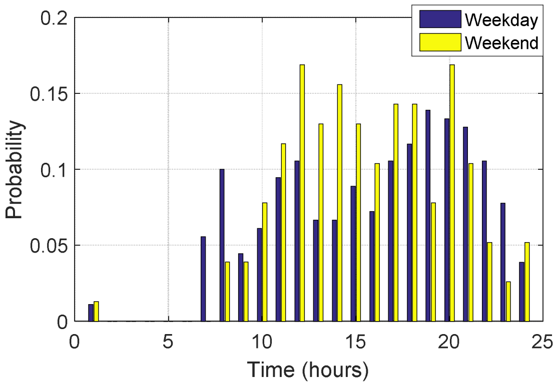
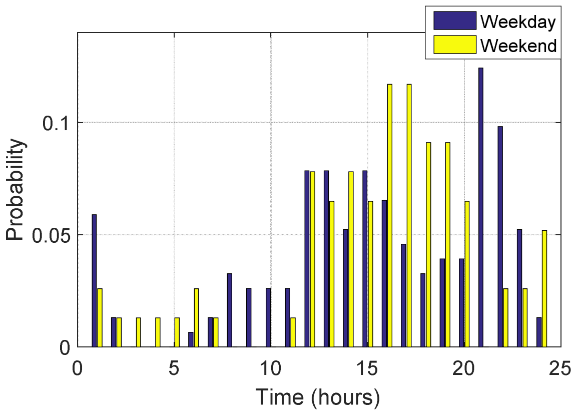
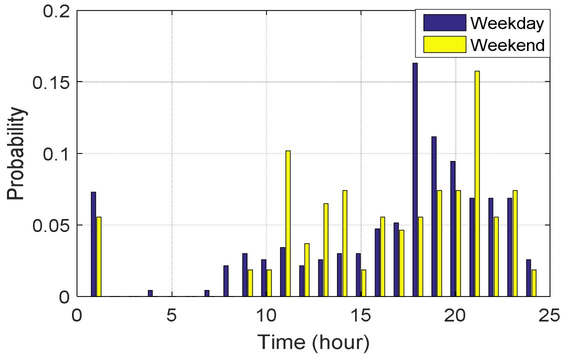


a) Cloth Washing Machine



b) Dryer



c) Dish washer

Fig. 5 The probability of starting to use appliances at each hour of weekday and weekend average day is presented for a) cloth washing machine, b) dryer and c) dish washers

V. FLEXIBILITY MODEL

In flexibility or demand response modelling the first important task is to model the base line or the reference load profile. Once the probability of use-start of washing machine and drying machine is computed, we can then synthetically reconstruct the 24-hour consumption profile of a single household using single washing machine and single dryer one-time average consumption profiles and following the developed method as outlined in Fig. 1. Brief description of the reconstructing process of average household level washing machine related power consumption is presented in Fig. 6. The comparison of an average household consumption reconstructed as described above and the average of real-measurements are presented in Fig. 7. This approach is capable of calculating the aggregated effect or the average household consumption profiles since the probability data and single-use consumption profiles comprise information such as the different wash and dry programs and the variation on the use of these appliances among group of households.

In order to quantify the DR potential and to study the rebound effect of DR programs, a Matlab script is written, which uses only the average one use profile of a washing machine (Fig. 4) and the probability of start profile in Fig. 5. The main principle of the flexibility modelling method is that the shifting potential in the consumption of washing machine and dryers shall essentially be estimated from the shifting of the probability of use profile as illustrated in Fig. 1. This approach preserves the probable availability of a washing machine which will start operating at the time when shifting is required in the distribution system.

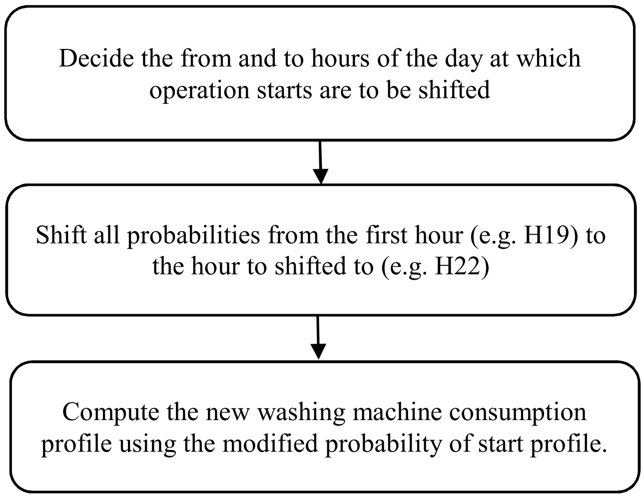


Fig. 6 Quantifying DR potential

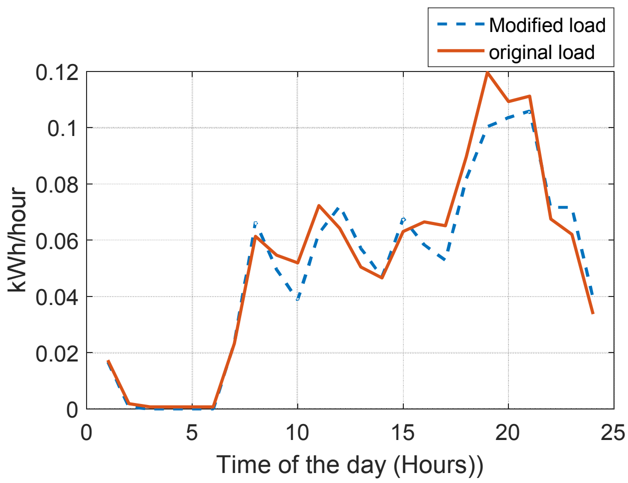


Fig. 7 Comparison of original cloth washing machine related consumption and the profile generated using the method in Fig. 1.

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Using the average single-use profiles of the appliances and the probability of start values, one can write a script to calculate the aggregated flexibility potential of atomic loads without the concerns with the variability in the type of appliances and the differences in appliance use pattern. Flexibility potential, in this study, refers to the amount of power one can reduce from the system by shifting the would-be operations of appliances to different times of the day. The script can also be used to calculate the rebound effect for the implemented shifting operation. An example shifting operation of cloth washing machines from hour 20 to hour 21 and for 100 households is plotted in Fig. 8.

A delay in washing activity would most likely result in a delay in drying activity. Hence, it gives much sense to combine washing and drying related consumption as a combined resource of demand response and their respective rebound effects. Nevertheless, the drying activity can also be delayed independently from the washing activity.

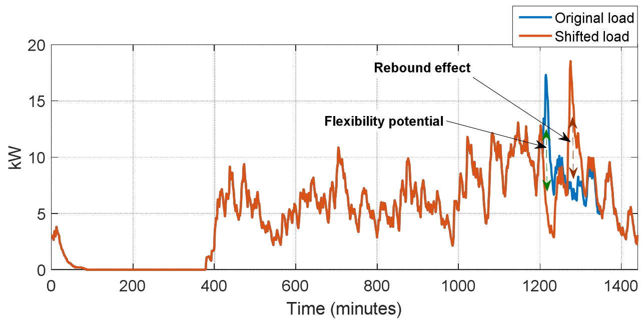

Fig. 8 Impact of shifting cloth washing activities from hour 20:00-20:15 to hour 21:00-21:15 for 100 households

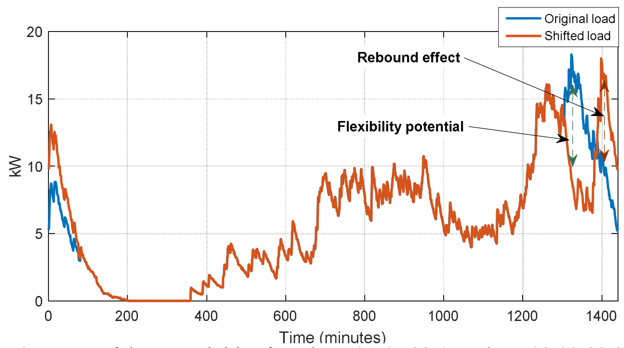

Fig. 9 Impact of dryers activities from hour 21:45-22:15 to hour 23:00-23:30 for 100 households

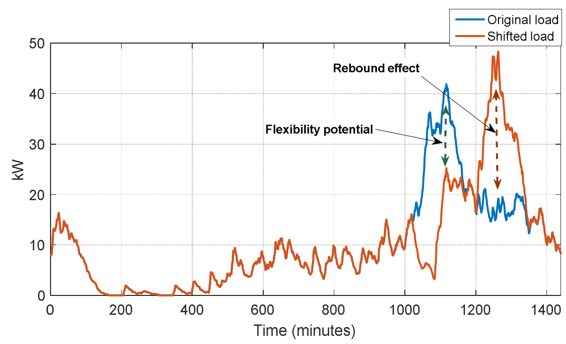

Fig. 10 Impact of shifting dish washer activities from hour 17:00-17:59 to hour 20:00-20:59 for 100 households

TABLE III. FLEXIBILITY POTENTIAL FOR 100 HOUSEHOLDS WHERE ALL OF THEM HAVE AT LEAST ONE TIME APPLIANCE USE AT THE PARTICULAR DAY

	Time shifted (from-to)	**Flexibility potential (kW)**
Cloth Washing machines	20:00-20:15 to 21:00-21:15	11.45
Dryers	21:45-22:15 to 23:00-23:30	9.28
Dishwashers	17:00-17:59 to 20:00-20:59	16.7

Certain shifting times are selected for the individual appliances to show case their flexibility potential as it is plotted in Figs 8 to 10. Table III presents the kW flexibility aggregated potential from the individual atomic loads in 100 households. Nevertheless, the appropriate time for shifting can be selected by reviewing the impact on the total load as the total load peak is the main driver. In this analysis, when a shifting operation occurs from 20:00-20:15 to 21:00-21:15 it effectively means all the probable atomic load use-starts in the first period are shifted to the second period. Practically this happens when the probabilities of the first period are shifted to the second period.

VI. DISCUSSIONS

This paper essentially present a method to quantify the flexibility potential of shiftable non-interruptible appliances. In effect the presented method will inform stakeholders how much power (kW) they can reduce by shifting the potential operation of the appliances. The activation of such flexibility resources, on the other hand, requires its own in-depth investigation as it may depend on the availability of communication channels to both customers and appliance, the willingness of customers, the market arrangement and the smartness of the appliances. Also, smart activation of the resources shall be executed to avoid rebound effects; for example, by distributing the shifting of group of appliances over time than executing all resources at once. The rebound effect mainly arises from an increase in consumption due to the superimposing of shifted appliances on top of the already operating appliances. Hence, rather than spreading the shifting of the appliances overtime, one need to observe the probabilities of start operation for the next hours to decide the appropriate hour to shift to.

When flexibility potential of aggregated loads in a distribution network is calculated, careful consideration of the interdependencies of the individual activities within the house is needed. For example, a delay in washing activity would most likely result in a delay in drying activity. Hence, it gives much sense to combine washing and drying related consumption as a combined flexibility resource and also for their rebound effect analysis. Nevertheless, the drying activity can be delayed independently from the washing activity.

The average number of wash cycles in an average European household is calculated to be 3.8 washes per week based on the 2011 figures [10]. The flexibility model for atomic loads is provided for an average single appliance (say cloth washing machine) with one operation per day. Let us say 100 households

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are connected in a distribution network and 70 of them conduct in average 1.2 times washing activity in a particular day, then the probability of start values for cloth washing machines need to be multiplied by 1.2. Then after, the flexibility potential of the 70 households at any particular time of the day can be calculated leaving the rest of the 30 households with zero flexibility.

The presented method for shiftable loads can be used by aggregators to forecast or estimate the flexibility potential (in kW) which they can get from group of households at any time of the day. These estimations help them in their participation to the power market. The method can also be used by a DSO preparing to incentivize the shifting of atomic loads from peak-hours to other hours. The presented method in general enables the estimation of flexibility potential one can get from shiftable atomic loads. The application areas can be short and long term planning of the network (e.g. distribution network planning) involving the participation of flexibility resources.

VII. Conclusion

The flexibility potential of aggregation of household shiftable appliances mainly depends on the power rating of the appliance and the coincidence for the appliance to operate at the same time in different households. Although the rebound effects show higher peaks for the appliance consumption, being the integral part of the total household, the overall effect will level out the total load by shaving the peak. The computed flexibility potentials encompass the variability in program selection of the specific atomic loads such as cloth washing machines, dryers and dishwashers. The presented data driven method of flexibility modelling involves data mining of existing measurements to extract important characteristics of the appliance use such as probability of use-start and average single-use consumption profiles.

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