Non-Intrusive Appliance Load Curve Disaggregation for Service Development

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***Abstract*—The popularity of reducing domestic electricity consumption is growing following the decision of several European governments to quit nuclear power in the near future. However, finding out which equipment should be replaced and more importantly which behavior should be modified to reach this goal is not a simple task, since helpful tools are not easy to find or implement. The disaggregation of the global electricity consumption could be achieved in the framework of concepts like the Internet of Things where the monitoring of each appliance is made possible using embedded power sensors. However, the implementation of such solutions in the near future will be very difficult due to the costs generated by the modification of existing appliances. Another more elegant solution to provide people with useful information about their electricity consumption consists in a single recording unit measuring the entire consumption coupled with a system able to disaggregate the appliance load curve. This is better known as non-intrusive appliance load monitoring (NIALM). The aim of this study is to investigate the feasibility of a load curve disaggregation based feedback system for consumer service development. For that purpose, a low-frequency recording unit was developed to record the global electricity consumption of fifty Swiss households. The recorded data, as well as simulated data, have been used to develop and validate a simple appliance detection technique with low computational requirements as this is a key issue for a potential future use in real-time remote feedback systems. This paper shows that the developed disaggregation technique, although simple, provides satisfactorily detection performances and could be used to provide consumers with useful information about their electricity consumption.**

***Index Terms*—Domestic Electric Consumption, Non-Intrusive Appliance Load Monitoring (NIALM), Energy Advice, Consumer Service Development.**

I. Introduction

The importance of reducing domestic energy consumption to minimize environmental footprint is growing in European countries as a consequence of the efforts engaged by several European governments to reduce their dependence on fossil energy and to phase out nuclear power following the 2011 Fukushima disaster. The potential reduction of domestic energy bills also contributes to the growing popularity of sustainable development and energy saving.

In 2010, households in Switzerland have consumed 19 TWh and a typical Swiss household of 4 people consumes about 4500 kWh yearly, representing a 1000 USD electricity bill [1]. Although Swiss households could potentially save 40 % of their electricity bills by 2035, thanks for example to the optimization of the energy efficiency of appliances [1], efficient tools to reduce this consumption are not easy to find and implement for private individuals. Different studies show that providing relevant information about the home consumption could lead to a reduction of electricity use between 4 and 15 % [2]. However, the general consumption does not provide the consumer with sufficient information about what counts for the main parts of her/his electricity invoice.

On another hand, systems able to display the energy used by the main appliances, in other words systems able to disaggregate the global consumption, would greatly help the consumer finding out which equipment should be replaced and/or which behavior should be modified. The disaggregation could be achieved using a measuring unit embedded in each appliance, in a similar way to the Web of Things [3]. This kind of solution is however very difficult to implement, especially with the already existing appliances, and generates high investments and operating costs. Another way to achieve this disaggregation is to measure the global electricity consumption of the household and to extract the most important information from this general load curve. This solution requires only one measuring unit coupled with a system able to recognize the main appliances in real-time.

This is known as non-intrusive appliance load monitoring (NIALM), in which individual appliance power consumptions are disaggregated from a central recording. Several NIALM techniques have been proposed in the last few decades. Zeifman and Roth published a NIALM review in 2011 [4]. NIALM methods can be based on low-frequency installation. These devices provide information with a typical frequency of 1 Hz and rely on changes of real power [5], changes of real power and reactive power [6], or changes of real power, reactive power, and other additional macroscopic signatures [7]. NIALM methods can also be based on higher-frequency hardware. In this case the used features can be harmonics [8], Fourier transforms [9], or wavelet transforms [10].

The HES-SO Valais-Wallis (University of Applied Sciences Western Switzerland) is currently working in this field. To develop recognition algorithms from aggregated load curves, a low-frequency acquisition system able to measure the three phases of a standard household has been built. This system has been deployed in fifty households and is acquiring data

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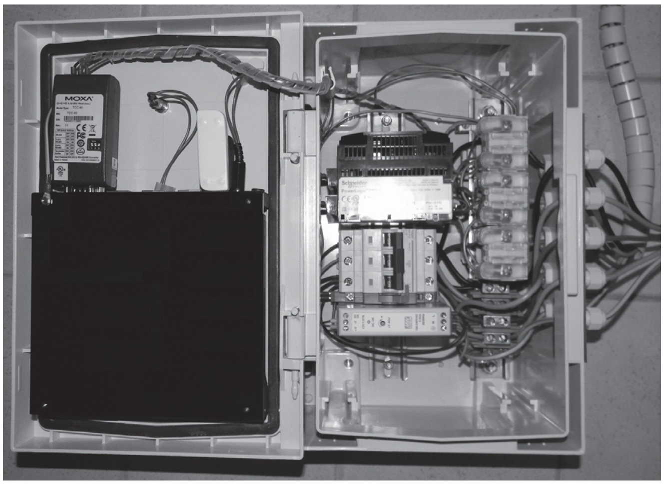
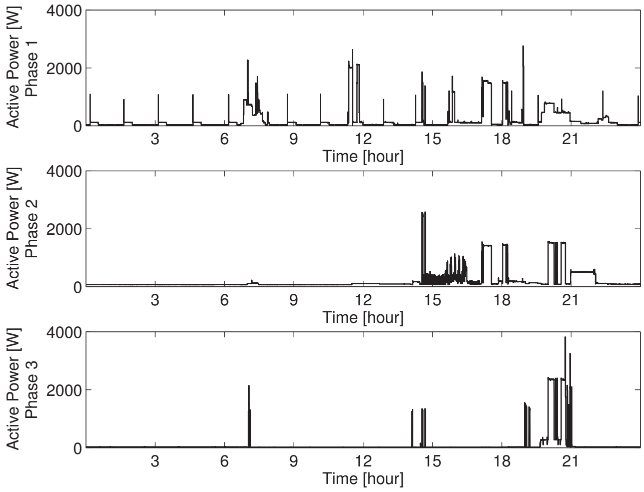
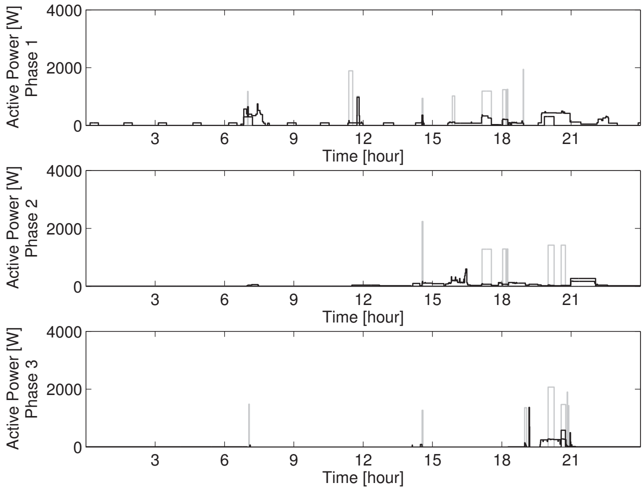


Fig. 1. Data acquisition system. The PC Engine can be seen on the left whereas the PM810 from Schneider Electric and the electric connections can be seen on the right.



(a) Typical raw 24-hour active power recorded using the measuring unit.



(b) Processed data corresponding to Figure 2(a). The high power pairs are shown in grey, the medium and low power pairs (both cumulated) are shown in black. A high power pair present on all phases can be seen before 3 pm, a few high power pairs present on phases 1 and 2 can be seen around 6 pm and a few high power pairs present on phases 2 and 3 can be seen around 9 pm.

Fig. 2. Typical raw and corresponding processed 24-hour active power.

sampled at 1 Hz for about five weeks to build a statistically relevant database. Where possible, EcoWizz [11] plugs were used to acquire disaggregated data of the main appliances in parallel to the central measure. To first tackle the complexity of the aggregated load curve, a simulator of the main contributors (washing machine, dishwasher, tumble dryer, oven, stove, etc.) was also created, thus allowing to initially test the disaggregation algorithms with an *a priori* knowledge of the contributors. This paper focuses first on the appliance detection technique and on the results for one simulated household and five real households.

As the aim of this study is to investigate the feasibility of a load curve disaggregation based feedback system for consumer service development, this paper then describes how this disaggregation technique was used to provide fifty households with relevant information about their electricity consumption. The focus was put on the robust detection of several appliances using simple solutions enabling its future use in real-time remote feedback systems. We show that the described disaggregation method, although simple, is valid and leads to good detection performances, validated by simulated data, reference values for real data, and inhabitants expectations.

The collected data allow a better understanding of the main contributors to the electricity bill as well as the useful characteristics to recognize them. Both the database of real-world signals and the simulator are powerful tools for further research on load curve disaggregation and consumer service development.

II. Experimental method

A. Measuring unit

The measuring unit is a power meter PowerLogic Series 800 PM810 from Schneider Electric. This power meter is equipped with 40/5 current transformers and with RS485 communications for integration into any power monitoring/control system. The PM810 is a true RMS meter capable of accurate measurements of highly non-linear loads. The sampling frequency is 6.4 kHz (128 samples per 50 Hz cycle) and the sampling technique enables accurate measurements through the 31^{st} harmonic [12], [13]. The data is integrated, finally sampled at 1 Hz, and values of voltage, current, active power, reactive power, and power factor are recorded for the three phases. The system also allows to store the value of the total active energy. The data is stored through a Modbus communication on a small PC platform (PC Engines, http://www.pcengines.ch/) running Voyage Linux (http://linux.voyage.hk/), a very stripped-down Debian Linux. More details about the measuring unit can be found in [14].

The data is stored in CSV files (Comma Separated Values) and is saved on two flash drives for redundancy. The data is composed of two timestamps (one from the PM810 and one from the PC Engine), the 3 voltages values, the 3 current values, the 3 active power values, the 3 reactive power values, the 3 power factor values, and the cumulated active energy. The system generates one CSV file for every period of 24 hours, each CSV file consists thus of 86400 entries. The recordings are finally synchronized with a data server at the HES-SO Valais-Wallis that provides the final storage location. Figure 1 shows the details of the acquisition system, the PC Engine can be seen on the left whereas the PM810 and the electric connections can be seen on the right. The measuring unit has been deployed in fifty households to create a statistically relevant database and it recorded the general electricity consumption for about five weeks. The recording campaign started in December 2012 and ended in November 2013. The selected households were all located in the Sion area (Switzerland) and only a few of them were using electric power for heating or domestic hot water. In some households, EcoWizz plugs [11] were used to acquire the load curve of specific appliances in parallel to the central measure provided by the measuring unit.

B. Simulator

To first tackle the complexity of the aggregated load curve, a simulator of the main contributors (washing machine, dishwasher, tumble dryer, oven, stove, boiler, etc.) has been created. The simulator aims at producing realistic load curves by combining different electrical appliances. The format of the generated data is the same as the format of the real data recorded by the measuring unit. The simulator is based on configuration files defining the set-up of the simulations (start and stop times, appliances to be used, phase(s) on which the appliances will appear, etc.), and models of the different appliances. Every electrical appliance used is the simulator is either generated using a statistical model or directly extracted from a database containing previously recorded measurements of the specific appliance. Two main aspects are simulated: the occurrence probability and the load curve. The occurrence probability varies during time (e.g. the dishwasher is more likely to be used around 1 pm and/or 7 pm rather than in the middle of the night). The statistical models contain parameters representing the appliance (number of cycles, duration of the cycle(s), duration of the different functioning states of the cycle, power levels of the different states, etc.). The output of the simulation is stored in different files. The global load curves, similar to real data, can be used to test different disaggregation algorithms. The specific load curves of every appliance used in the simulation can be used for quantitative evaluations of the disaggregation algorithms. More details about the simulator can be found in [14].

C. Disaggregation algorithm

1) Data processing: Raw active power data sampled at 1 Hz and either recorded using the measuring unit or generated using the simulator are first filtered using a 1 minute median filter to remove high frequencies. At that time, the baseload is evaluated for all three phases. The baseload is the minimum power continuously consumed in the 24-hour window. After subtraction of the baseload, the next step consists in detecting all power changes of more than 10 W (edge detector) and lasting more than 10 seconds. The active power data is then reconstructed using these power changes to obtain a "square wave". The power changes are then grouped in pairs according to the following rule: any positive power change must be followed by a later very similar negative power change. Once all power changes are paired, the next step consists in grouping the pairs according to the amplitude of the power change: high power pairs above 750 W, low power pairs under 250 W and medium power pairs in between. The final data processing step is to check for every high power pair if there is a synchronized high power pair similar in duration on one or both other phases. The result is high power pairs grouped according to the fact that they appear on all phases, two phases, or a single phase. Figure 2(a) shows a typical raw 24-hour active power recording (all three phases) and Figure 2(b) shows the corresponding processed data. The high power pairs are shown in gray, the medium and low power pairs (both cumulated) are shown in black. A high power pair present on all phases can be seen before 3 pm, a few high power pairs present on phases 1 and 2 can be seen around 6 pm, and a few high power pairs present on phases 2 and 3 can be seen around 9 pm.

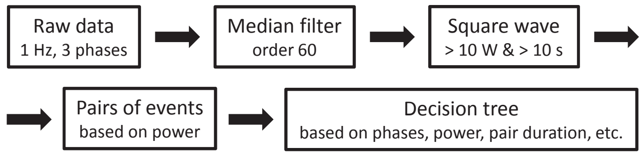


Fig. 3. Algorithm flowchart. The raw data are filtered and transformed into a square wave. Then the events are paired based on power and finally the pairs are classified using a decision tree.

2) Detection: As already mentioned, the aim of this study is the robust detection of several appliances using simple techniques enabling their future use in real-time remote feedback systems. The detection algorithm first evaluates the three baseloads and is then able to detect cold chain appliances (fridges and/or freezers), dish washers, washing machines, and tumble dryers. The lunch (11 am to 1 pm) and dinner (6 pm to 8 pm) cooking energy are then estimated based on the remaining high power pairs and the remaining low energy is considered to mainly regroup lighting and electronics. Finally the energy not associated to any of the previously listed appliances is labeled as "other". This would typically include a hair dresser, a vacuum cleaner or any not previously listed appliance consuming more than 250 W. Parameters for appliance detection including the phase(s) on which the different appliances appear are manually evaluated using the first few days of the recording period and the automatic detection is then performed on the entire recording period. Typical parameters are power and duration of the working

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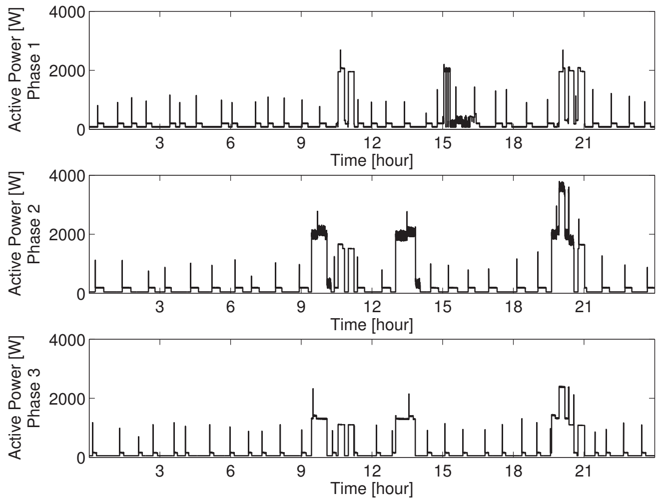

Fig. 4. Typical raw-24 hour active power simulation. A fridge and an baseload can be seen on each phase, one washing machine cycle can be seen on phase 1, three tumble dryer cycles can be seen on phases 2 and 3 and two dish washer cycles can be seen on all three phases.

period of the compressor for a fridge, or power and duration of the heating period(s) and duration of the cycle for a washing machine or a dish washer. The detection, based on decision tree learning [15], scans all pairs generated during the data processing step. The characteristics of a given pair, and possibly "neighbor" pairs located in a specific time window (the cycle duration of the appliance), are compared to the manually evaluated parameters of an appliance. If the characteristics of the analyzed pairs sufficiently match the appliance's parameters, they will be considered to belong to that specific appliance. If not, they will be left unlabeled and compared to the parameters of another appliance until they are associated with an appliance. The analyzed pairs might be located on different phases in the case of appliances using power from more than a phase. At the end of the detection process, the remaining pairs are labeled as "other". For the simulated household, the ground truth is known both in terms of number of cycles (how many times the compressor of the fridge was on or how many times the dish washer was used on a particular day) and energy (the energy consumed by the fridge or the dish washer on a particular day). For the real world households, the ground truth is partially known thanks to the EcoWizz plugs and is completed by manual annotation. The flowchart in Figure 3 summarizes the main steps of the disaggregation algorithm.

III. Experimental results

A. Simulated household

To first test our disaggregation algorithms with an *a priori* knowledge of the appliances, we simulated 15 days of the electric consumption of an imaginary household using the simulator. The simulation includes a baseload for each phase, 3 fridges (one on each phase), one washing machine on phase 1, one tumble dryer on phase 2 and 3, and one dish washer on all phases. Figure 4 shows a typical raw 24-hour active power simulation (all three phases). A fridge and a baseload can be seen on each phase, one washing machine cycle can be seen on phase 1, three tumble dryer cycles can be seen on phases 2 and 3 and two dish washer cycles can be seen on all three phases.

TABLE I
Cycles detection performances. For each appliance (three fridges, a dish washer, a washing machine, and a tumble dryer), the table shows the total a priori number of cycles, the total number of detected cycles, and the percentage of false positives (F. P.) and false negatives (F. N.).

	Cycles			
	Reality	Detection	F. P. [%]	F. N. [%]
Fridge/Freezer 1	466	466	1.7	1.7
Fridge/Freezer 2	350	347	0.3	1.2
Fridge/Freezer 3	527	526	0.4	0.6
Dish washer	22	22	0.0	0.0
Washing machine	29	29	0.0	0.0
Tumble dryer	15	15	0.0	0.0

Table I shows the detection performances in terms of number of cycles. For each appliance (three fridges, a dish washer, a washing machine, and a tumble dryer), the table shows the total *a priori* number of cycles, the total number of detected cycles, and the percentage of false positives (F. P.) and false negatives (F. N.). With F. P. and F. N. both below 2 %, the performance of the algorithm is really noticeable. This is in particular true for high power appliances such as the dish washer or the tumble dryer.

TABLE II
Energy detection performances. For the baseload and each appliance (three fridges, a dish washer, a washing machine, and a tumble dryer), the table shows the total a priori energy, the energy of all the detected cycles, and the error rate.

	Energy [kWh]		
	Reality	Detection	Error [%]
Total energy	234.1	235.3	0.5
Baseload	69.4	69.8	0.6
Fridge/Freezer 1	14.3	14.0	2.1
Fridge/Freezer 2	16.5	16.2	1.8
Fridge/Freezer 3	9.1	8.8	3.3
Dish washer	65.3	63.0	3.5
Washing machine	21.0	21.1	0.5
Tumble dryer	38.5	38.3	0.5

Table II shows the detection performances in terms of energy. For the baseload and each appliance (three fridges, a dish washer, a washing machine, and a tumble dryer), the table shows the total *a priori* energy, the energy of all detected cycles, and the error rate. The total energy consumed during the 15 days of the simulation is 234.1 kWh. The detected total energy is 235.3 kWh, representing a 0.5 % error. Finally, 4.1 kWh were not assigned to any appliance, representing 1.8 % of the total energy. With such small error rates, the ability of the system to evaluate the consumption of the different appliances is demonstrated.

B. Real households

All fifty households recorded data were analyzed using the aforementioned technique to provide the households inhabitants with advice on their electricity consumption. Five of them

TABLE III
TOTAL TRUE NUMBER OF CYCLES AND TOTAL NUMBER OF DETECTED CYCLES FOR EACH HOUSEHOLD (H1 TO H5) AND EACH APPLIANCE. A HYPHEN MEANS THAT THE APPLIANCE WAS NOT PRESENT IN THE HOUSEHOLD.

		H1	H2	H3	H4	H5
Fridge / Freezer 1	Reality	988	629	1326	287	696
	Detection	934	575	1311	300	686
	F. P.	0.1	0.6	0.5	6.6	1.0
	F. N.	5.6	9.2	1.6	2.1	2.4
Fridge / Freezer 2	Reality	-	-	-	718	531
	Detection				720	505
	F. P.				1.1	1.5
	F. N.				0.8	6.4
Dish washer	Reality	6	39	21	19	23
	Detection	6	39	23	20	24
	F. P.	0.0	0.0	9.5	5.3	8.7
	F. N.	0.0	0.0	0.0	0.0	4.4
Washing machine	Reality	10	17	31	21	25
	Detection	9	15	28	19	22
	F. P.	0.0	0.0	3.3	9.5	0.0
	F. N.	10.0	11.8	10.0	19.1	12.0
Tumble dryer	Reality	3	12	-	-	-
	Detection	3	11			
	F. P.	0.0	0.0			
	F. N.	0.0	8.3			
Lunch	Reality	10	31	29	25	25
	Detection	10	31	31	25	25
	F. P.	0.0	0.0	6.9	0.0	4.0
	F. N.	0.0	0.0	0.0	0.0	4.0
Dinner	Reality	22	31	41	27	28
	Detection	22	31	38	27	31
	F. P.	0.0	0.0	0.0	0.0	10.7
	F. N.	0.0	0.0	7.3	0.0	0.0

(H1 to H5) were however more thoroughly studied to serve as ground truth to evaluate performances of the technique on real data. All households include a fridge, a dish washer, and a washing machine. Households 4 and 5 include a second fridge or a freezer, Households 1 and 2 include a tumble dryer, and all households use their stove/oven for lunch and/or dinner cooking. Table III shows the total true number of cycles partially based on manual annotation, the total number of detected cycles, and the percentage of false positives (F. P.) and false negatives (F. N.) for each household and each appliance. A hyphen means that the appliance was not present in the household. Errors on real data are noticeably higher than on simulated data. Although the accuracy is certainly improvable, an error rate of 10 % is still sufficient to provide the consumer with a good overview of the repartition of his electrical consumption between the main appliances. Moreover, as the number of cycles per appliance can be as low as 3, the statistical significance of these results still has to be confirmed on a larger panel of households. The results remained however valid and really useful for the consumers.

Table IV shows the energy of all detected cycles for each appliance. It also shows the total energy and the number of recorded days for each households. A hyphen still means that the appliance was not present in the household. The comparison with true values is only possible in the case of the number of cycles, thanks to the EcoWizz plugs completed by manual annotation. This comparison is not possible in the case of the energy since the EcoWizz plugs did not systematically

TABLE IV
APPLIANCE SPECIFIC ENERGY, TOTAL ENERGY, AND NUMBER OF RECORDED DAYS FOR EACH HOUSEHOLD.

	H1	H2	H3	H4	H5
Baseload	11.9	102.5	37.5	35.4	65.4
Fridge/Freezer 1	38.4	19.4	40.8	29.0	22.6
Fridge/Freezer 2	-	-	-	18.4	30.0
Dish washer	6.8	65.7	19.5	23.0	28.6
Washing machine	6.2	7.8	21.0	9.9	10.9
Tumble dryer	4.5	18.5	-	-	-
Lunch	5.1	42.2	16.8	36.5	22.9
Dinner	25.3	50.2	38.1	19.9	27.5
Low power	42.5	91.5	134.1	51.8	99.7
Other	1.9	35.7	9.7	21.3	13.7
TOTAL	**142.6**	**433.5**	**317.5**	**245.2**	**321.3**
# of days	34	34	46	27	33

provide a reliable recording and manual estimation of the energy would only be very approximate. Variations among the different households are high, especially with the baseload and the dish washer consumption, which can vary from a factor of 10. This small overview already shows the high variance of the households consumption behaviors. A factor of 3 can be observed between the minimum and maximum total electricity consumption.

C. *Overall consumption*

Following the data presented in the previous sections to demonstrate the disaggregation technique validity, this section aims to provide an overview of consumption behaviors encountered during this pilot study. The box plot in Figure 5 shows the overall detection results extrapolated to a year of the fifty households through their quartiles. The horizontal whiskers indicate variability outside the upper and lower quartiles and crosses show outliers. Appliances not present in a household was considered to consume 0 kWh. The yearly consumption of high power appliances (washing machines, dish washers, and tumble dryers) is relatively low and shows a moderate variance. The baseload and the low power appliances are the two main contributors to the electricity bill and both show a large variance.

The pie chart in Figure 6 shows the distribution of the overall detected consumed energy. The baseload and the low power appliances, categories with possibly the best potential of consumption reduction, represent together nearly 50 % of the consumption. The high power appliances (washing machines, dish washers, and tumble dryers) only represent 15 % of the consumption.

Finally, the minimal total consumption extrapolated to a year was as low as 1’184 kWh, whereas the maximum was close to 11’204 kWh. It was not possible to link this variation to the volume of the house or the number of people in the household. These variations are clearly linked to differences of consumption behaviors.

IV. DISCUSSION

A. *Simulated household*

To first test the performances of the disaggregation method using *a priori* reference values both in terms of number

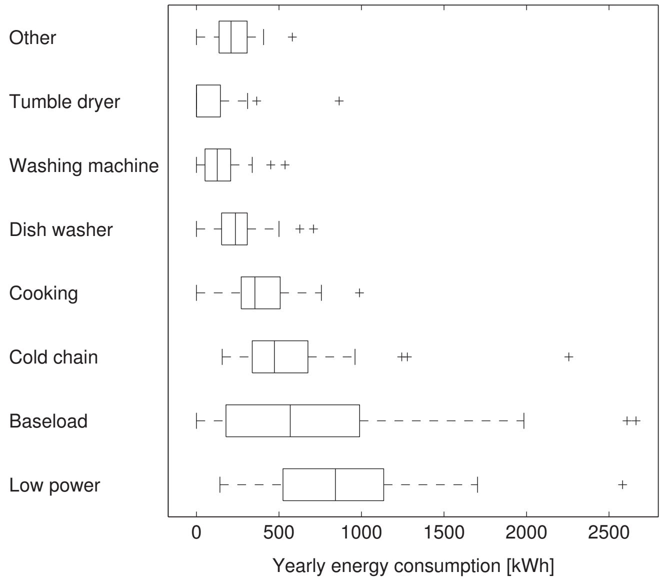

Fig. 5. Overall detection results extrapolated to a year of the fifty households through their quartiles. The horizontal whiskers indicate variability outside the upper and lower quartiles and crosses show outliers.

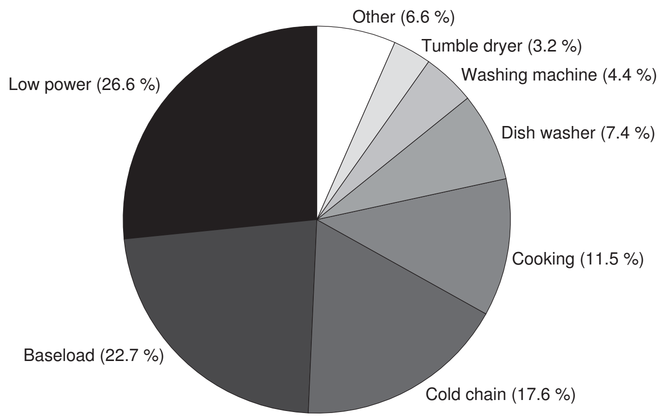

Fig. 6. Distribution of the overall detected consumed energy. The baseload and the low power appliances represent together nearly 50 % of the consumption. The high power appliances (washing machines, dish washers, and tumble dryers) only represent 15 % of the consumption.

of cycles and energy, we simulated 15 days of the electric consumption of an imaginary household including baseloads, fridges/freezers, a dish washer, a washing machine, and a tumble dryer. The cycles detection results presented in Table I show very low detection errors. The maximum error rate occurs for the first fridge/freezer and is below 2 % of false positive and false negative.

The energy detection errors presented in Table II are also very low, the highest error rate is associated with the dish washer but is below 4 %. These detection results on simulated data first show that although the detection method is very simple, it is valid and performing very well. On another hand, low error rates were to be expected as the generated data do not contain signals not related to the simulated appliances and are thus relatively easier to disaggregate compared to real data. Finally, for most appliances, the detected energy is slightly underestimated. This can be explained by the fact that some of the pairs are not associated to any detected appliances. Indeed, 4.1 kWh were not assigned to any appliance. This represents 1.8 % of the total energy. The underestimation can also be explained by the fact that the median filter applied to raw data removes the high frequencies and therefore suppresses a small portion of the energy. Moreover, the reconstruction of the active power to obtain a "square wave" can either add or remove a small amount of energy.

B. *Real households*

The cycles detection results presented in Table III show very encouraging error rates. The detection of fridges/freezers generated a maximum of false positives and negatives for household 2 (H2), but the accumulated error rate remains just below 10 %. The detection of the dish washer was most problematic with household 5 (H5) with an accumulated error rate of about 13 %. The washing machine was the most difficult appliance to detect, with a maximum accumulated error rate for household 4 (H4). This could be explained by the different possible settings of a washing machine (40, 60, or 95 degrees, special programs, spin speeds, etc.), generating largely varying electrical signatures of a given washing machine. In particular the part of the electrical signature associated with water heating will be very different between low and high temperature washing cycles. Only 2 households included a tumble dryer and the maximum error rate remains below 10 %, which is acceptable for our application. Finally, the cooking detection (both lunch and dinner) performed very well with no errors at all for 3 households and a maximum error rate for household 5 (H5) just below 11 %.

As already mentioned, we do not have access to true values of the energy consumed since the EcoWizz plugs didn't systematically provide a reliable recording and manual estimation of the energy would only be very approximate. However, energy detection results presented in Table IV are in accordance with our expectations and more importantly consistent with the expectations of the households inhabitants. Even if the validity of the disaggregation algorithms is presented in this article through the results of only five households, they were applied and verified on the whole set of fifty households. The results were consistent with our experience of the field and confirmed by the inhabitants during feedback meetings. To enhance the evaluation of the detection technique, it would be useful to extend the analysis to more households, as the variety of appliances used by households is really extended. Finally, the detailed detection results presented for five households show that although the detection method is not perfect, it is performing well. The main advantage of this technique is its simplicity and its low computational requirements. Indeed, after the evaluation of the parameters of each appliance, the whole detection can be performed on a standard office computer in less than one minute. This is a key issue for al future application in real-time remote feedback systems.

C. Overall consumption

Figure 5 shows the overall detection results extrapolated to a year of the fifty households through their quartiles and Figure 6 presents the distribution of the appliances according to their average electricity consumption. The main contributor (26.6 %) is the low power appliances (below 250 W) mainly including lighting and electronics. The second contributor is the baseload (22.7 %). Together, these first two categories represent almost 50 % of the consumption and also show large variances. This means that these two categories include a large variety of appliances, but also that the inhabitants behavior has a strong impact on their importance. The high potential of consumption reduction of these two categories has been confirmed during feedback meetings with the inhabitants. Indeed, it is relatively easy to point out which appliances contribute to the baseload (modems/routers, media boxes, circulation pumps for domestic hot water, stand-bys, etc.) and the impact of some of them can be reduced simply using multi-socket plugs or timers. Similarly, although the electricity consumption related to consumer electronics is growing, its impact can be reduced or at least controlled by behavioral adaptation (turn off the TV when nobody is watching it, etc.). The impact of lighting can also easily be reduced through similar behavioral adaptation and/or by replacing old technologies like halogen lamps with newer consuming much less energy such as saving bulbs or LEDs. According to a Swiss Agency for Efficient Energy Use (SAFE) distribution mentioned in a 2012 World Wide Fund for Nature communication [16], the low power category represents nearly 40 % of the electricity consumption, which is consistent with our results considering that the baseload contains part of the electronics consumption through devices permanently on and stand-bys.

The next two categories are cold chain appliances (fridges and freezers, representing almost 18 % of the consumption) and cooking (almost 12 %). Our study on fifty households suggest that over 75 % of the total electricity consumption is explained by these first four categories. The yearly consumption of the high power appliances (washing machines, tumble dryers, and dish washers) is relatively low with low variance. This suggests that these appliances are used in a similar way in all households. Even if there are significant differences between our results and the SAFE distribution (in particular with the tumble dryers, 12 % in the SAFE distribution), both distributions are relatively similar. This is another evidence of the validity of the proposed disaggregation technique. Finally, the average total yearly household electricity consumption is about 3’680 kWh. This is consistent with the SAFE analysis estimating that consumption between 3’000 and 4’000 kWh for a standard Swiss household not using electric power for heating and domestic hot water. The standard deviation is very high (2’027 kWh). This can easily be explained by the highly variable consumption behaviors of the fifty measured households, spanning from people that already tracked and analyzed thoroughly their electric consumption to reduce it to more carefree people. It should be however noted that all households were all volunteers for this study and showed a great interest in their electricity consumption and advice to reduce it.

D. Algorithm performance

Most NIALM studies use their own dataset recorded from different types of appliances in various environment (workbench, households, public buildings, etc.) using different measuring units. These varying recording conditions have a strong impact on the available features (phases, low frequency signatures (e.g., active and reactive power), high frequency signatures (e.g., harmonics, Fourier transforms, wavelet transforms), etc.) and the data accuracy. The performance of a disaggregation algorithm is directly dependent of these elements. In consequence, comparing the performance of reported NIALM algorithms is very difficult if not impossible. The development of publicly available datasets like the REDD database [17] or the BLUED database [18] would help researchers in the development and evaluation of disaggregation algorithms. Another aspect making the comparison very complicated is the fact that most studies report the performance of their system using different accuracy metrics. Common measures of accuracy include fraction of correctly recognized events, fraction of total energy explained, classification accuracy, difference in estimated and true power draw, etc. Zeifman and Roth [4] proposed the use of ROC curve [19] for benchmarking of NIALM algorithms, but there’s no agreement upon what accuracy metrics should be used.

In their survey, Zoha et al. [20] compare the most commonly used learning algorithms for load disaggregation (support vector machine, bayesian learning, hidden markov model, neural networks, k-nearest neighbors and optimization). The reported accuracies vary between 60 and 99 %. Based on the results of Table I and Table III, the accuracy of the presented method could be calculated as the ratio of the correct predictions (true positives and true negatives) and the total number of classified samples. In this case the accuracy would systematically be very high (over 95 %) due to the large number of true negatives. This is therefore probably not the best way to evaluate the accuracy. To illustrate this, let’s consider the following example: a totally biased algorithm detects none of the 20 cycles of a washing machine out of 500 events. This is clearly a bad clissifier. However, the accuracy, calculated as the ratio of the correct predictions and the total number of classified samples would be 480/500 = 96 %! A better way to evaluate the accuracy is the fraction of correctly recognized events. In this case the accuracy is over 95 % for the simulated household and varies between 70 % and 90 % for the real households. This is a more realistic way to compute the accuracy of the system. Finally, another interesting way to calculate the accuracy would be the fraction of the correctly explained energy. In this case the accuracy is again over 95 % for the simulated household but is not possible to compute for the real households as we don’t have references values for the energy.

More generally on this topic, the main goal of this study was not to develop a new and better performing disaggregation algorithm. The goal was to design a real world NIALM system to provide consumers with personalized advice about their electricity consumption. The detection algorithm, although simple, performs sufficiently well for this application, thank to the good quality of the recorded data together with an efficient initial data processing algorithm.

V. Conclusion

This paper shows a field application of NIALM techniques to provide consumers with personalized advice about their electricity consumption and how to possibly reduce it. The detection algorithms, although simple, performed sufficiently well for this application. Moreover, they could be directly embedded in a real-time product, thanks to their low complexity and thus low computational requirements. The proposed solution was successfully tested on 50 households measured during about one month. The feasibility of this solution and the interest of the consumers for such an analysis was also demonstrated. As a result, a new pilot of 200 households is already in plan in collaboration with local DSO (Distribution System Operators).

The next step will also aim at improving the disaggregation algorithms and adapt them to both lower resolution and precision data that could be recorded by simpler systems like pulse counters for electricity meters. Simpler recording solutions are required for a wider study. Pulse counters can be installed by anyone whereas the measuring unit presented in this paper required the intervention of an electrician. In the near-future, smart-meters should also provide access to electricity consumption data measured with a typical frequency of 1 Hz and a precision of a few Watts.

Last but not least, a consequent development work remains to be done in the field of the interaction with the consumers. NIALM techniques provide the consumer with information to better understand what counts for the main parts of his electricity invoice. This information is however not sufficient. The key issue is to provide the consumer with concrete advices on how to reduce the consumption of the different appliances. These concrete advice might not be obvious to find and/or implement. Developing automated and personalized systems comparing the consumer's appliances consumption with reference values and showing predicted electricity bills reduction should help taking the most efficient actions. Special attention should finally be given to the baseload consumption as this category can count for up to 58 % of the total consumption in our pilot study, and means to reduce it have been relatively easy to find out during feedback meetings with the consumers.

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