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Evaluating Human Activity and Usage Patterns of Appliances with Smart Meters

Álvaro Hernández, Laura de Diego, J. Manuel Villadangos, M. Carmen Pérez, Daniel Pizarro
Electronics Department
University of Alcala
Alcalá de Henares, Spain
{alvaro.hernandez, laura.diego, mcarmen.perezr, daniel.pizarro}@uah.es

Rubén Nieto
Electronics Technology Department
Rey Juan Carlos University
Móstoles, Spain
ruben.nieto@urjc.es

Alfonso Bahillo
Computing, Electronics and Communication Technologies Department
University of Deusto
Bilbao, Spain
alfonso.bahillo@deusto.es

***Abstract*—Population ageing is becoming a key issue for most western countries, due to the challenges that it poses to the sustainability of future healthcare systems. In this context, many proposals and development are emerging trying to enhance the independent living of elderly and cognitive impaired people at their own homes. For that purpose, the massive deployment of smart meter at houses and buildings, initially focused on improving the energy management, has become a useful tool to provide the society with a variety of services and applications that can be employed for independent living. This work proposes the use of a commercial smart meter that delivers the disaggregated consumption per appliance every hour. This device has been installed on a test house during a training period of two months, in order to infer the behavior routines in the usage of the microwave. After the training, every new day can be compared to the obtained usage pattern of that appliance, in order to launch a notification when the day routine significantly differs. Similarly, since the use of the microwave is related to cooking, activities such as breakfast, lunch or dinner, may also be monitored and/or compared to a trained pattern. The proposal has been validated preliminary with experimental data coming from the aforementioned household.**

Keywords—NILM Techniques, Smart Meters, Ambient Intelligence, Independent Living

I. INTRODUCTION

Population in most western European countries is going through an ageing evolution in coming years, which will pose issues and challenges to public health care systems, while in Europe people over 50 is already 37% of the population [1]. The impact of this rising segment over 65 years on the public finances and the Gross Domestic Product (GDP) is assumed huge. In this context, cognitive impairments and disorders, many of them related to ageing, require a significant attention on behalf of society, and they are becoming an open challenge. It is expected that these disorders will imply a higher long-term care demand for elderly, thus becoming a key aspect for the sustainability of the future health systems. In this situation, most European policies are focusing on enabling elderly to live at their own homes in an independent and safe way, by providing them with new attention strategies and services at home.

On the other hand, the worldwide deployment of smart meters during the last decade has boosted the development of numerous applications, based on the measurement of power consumption provided by these meters in homes and buildings [2]. Following this deployment, non-intrusive load monitoring (NILM) has emerged as a key technique for most applications, which depend on the correct identification of the active appliances in the mains for different services, such as intelligent energy management, demand response management, etc. Apart from these applications, NILM techniques have already been employed in the context of ambient intelligence for independent living (AIIL) [3]. The identification of the appliances' usage, by determining the on/off events [4], can be analysed in order to infer the behaviour patterns of the tenants in a household. Furthermore, the usage of certain appliances are often related to the development of some Activities of Daily Living (ADL) [5] [6], which are commonly considered in the evaluation of the quality of independent living for elderly and mild-cognitive impaired.

Different technologies and methods have already been applied to ADL monitoring. In [7], a Bluetooth positioning system is used to identify daily routines by means of a Markov model. Likewise, the Holmes system presented in [8] proposes an anomaly detector for daily activities, by learning the normal, as well as complicated, behaviour of residents using clustering and semantic rules, thus reducing the number of false positives and negatives. Furthermore, in [9] it is merged data from smart meters with PIR occupancy sensors, together with temperature and humidity sensors, to detect domestic activities by applying the Dempster-Shafer Theory. A similar view is described in [10], where structural vibration is mixed with electrical load monitoring, based on Support Vector Machine (SVM) to train an ADL classifier. Finally, inertial units and sensors have also involved in activity recognition, in some cases linked to widespread smartphones and smart devices, but also providing wearable prototypes, such as in [11], where Principal Component Analysis and a neural classifier are proposed.

As for smart meters, data provided by them can be processed by NILM techniques, if necessary, to obtain the disaggregated consumption per appliance. These values may then be dedicated to the generation of warnings when a certain consumption significantly differs from the usual behaviour, or to monitor the long-term behaviour routines, compared to a known baseline. In [12] the behaviour analysis based on power consumption was already tackled, by identifying a unique signature for every person's activity and obtaining information about their health condition. The Dempster-Shafer Theory was applied in [5] to provide a daily score about

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the normality of a day, compared to a regular behaviour or pattern. Furthermore, in [13] a classifier based on SVM and on random forest allows to disaggregate the energy from three houses dedicated to training. The trained model is then used to monitor two people with dementia, obtaining information about the behaviour patterns and the modifications in routines. As mentioned before, Markov models have also often applied in this context to recognising daily activities [14]. Similarly, generalized linear mixed models were used in [15] to analyse the usage time and the hour of appliances at home in two groups, people with and without cognitive impairment, being able to develop a prediction model for impairment. A different approach is provided in [16], where a regression is applied to estimate the expected power consumption and launch alarms whether an anomalous behaviour is detected.

This work proposes the use of a commercial smart meter to obtain the global power consumption of a household, as well as the energy disaggregated by appliance. This information, and particularly the consumption from the microwave, will be analysed to extract a regular routine in its usage. After inferring these usage patterns, the microwave power consumption provided by the smart meter every hour will be compared to the previously extracted routine in order to determine if the current day presents a similarity with that reference pattern ("normality"). This comparison may be used to generate notifications and/or warnings for relatives or caregivers of the household tenants. The proposal has been experimentally validated, by installing the system in a house with mild-cognitive impaired people. The rest of the manuscript is organized as follows: Section II provides the general description of the proposal; Section III details how samples from a new day are processed, showing some preliminary experimental results; and, finally, conclusions are discussed in Section IV.

II. General Description of the Proposal

The general block diagram of the proposal can be observed in Fig. 1. A commercial Smart Meter Wibeee Box has been connected at the entrance of a household [9], where up to four mild-cognitive impaired patients live under the supervision of their specialists. Among several functionalities, this device is capable of providing the global power consumption, as well as the disaggregated values per appliance every hour. This information is uploaded to the cloud, where it can be accessed remotely for further processing. In this case, the smart meter has been installed from November 15, 2021, on. The first two months of this period, until January 15, 2022, have been dedicated to infer the usage pattern of the microwave in a training phase, whereas the rest of the days are applied to test. Note it is highly probable that not the same people have been living in the house for the whole period. A remote server is in charge of periodically accessing the energy data, inferring the usage patterns, and, then, analysing every hour how different the actual consumption of the microwave is compared to the routine inferred during the training period. Depending on that comparison, some notifications or warnings might be launched for caregivers and specialists.

Fig. 2 shows the disaggregated data provided by the smart meter, where it is possible to observe the energy from four different appliances: washing machine, oven, fridge and microwave. Since the last objective is to infer the usage patterns of these devices in order to monitor the accomplishment of some daily activities by the corresponding tenants, the fridge has been discarded hereinafter as its consumption does not imply any interaction with a person. In the same way, the oven is scarcely used in this house (only once on November 19, 2021), so it has also been discarded in this study. Only the washing machine and the microwave are

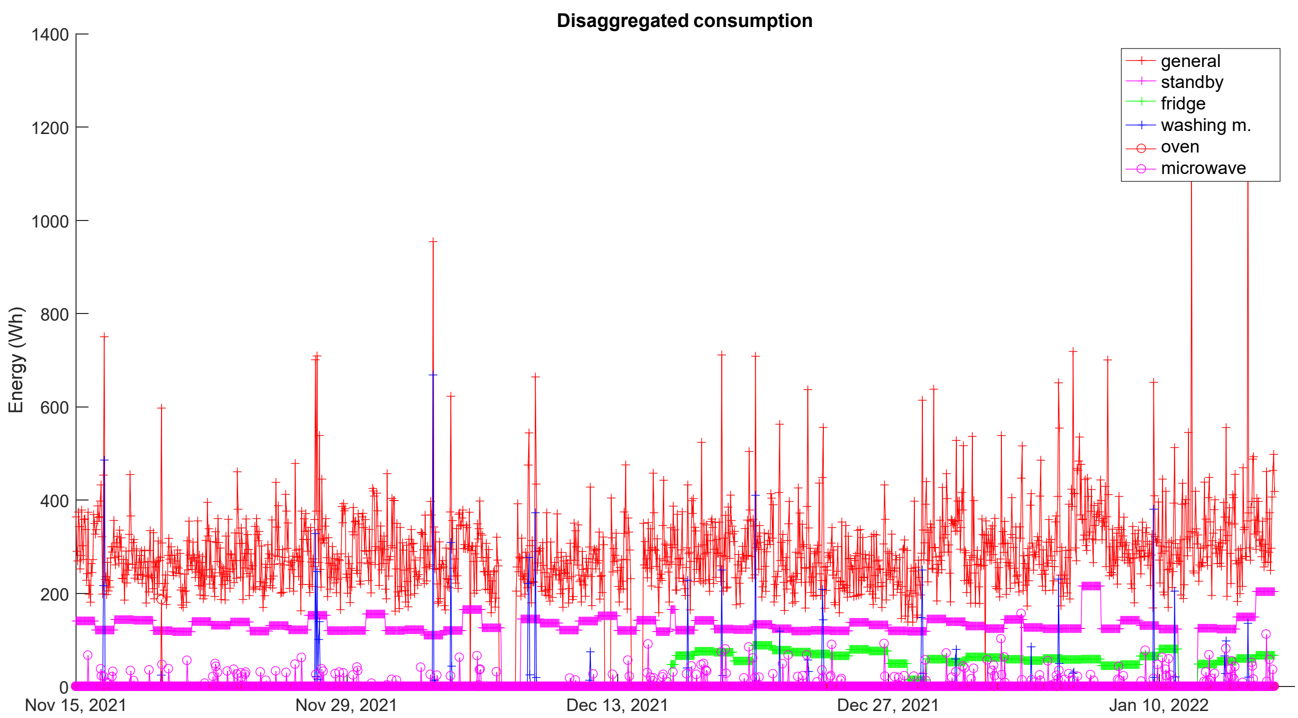

Fig. 2. Disaggregated consumptions for the household under study from November 15, 2021, until January 15, 2022.

periodically switched on and, consequently, they are suitable for further processing about their usage patterns.

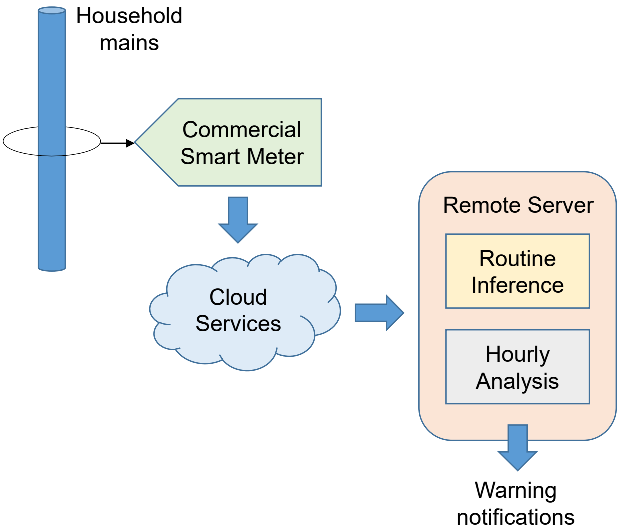

Fig. 1. General block diagrama of the proposal.

A first analysis can be performed by searching for a pattern over the days of the week. This is depicted in Fig. 3, where the averaged consumption for every day of the week is provided for the training period. It is worth noting that the energy for every day is first accumulated during the corresponding 24 hours for the four considered appliances. As can be observed, in the case of the washing machine, the consumption is quite regular, although there is a certain trend to use it on Tuesdays and Saturdays. Similarly, the microwave also results in a regular behaviour, whereas the oven outstands on Fridays, since its only on-switching took place on that day. Note that the fridge consumption may be considered relatively high, although it is coming from the fact that there are actually two old fridges in the house that are integrated by the smart meter into a single measurement. A different point of view on the same data can be obtained in Fig. 4, where the energy is not accumulated on every day of the week, but plotted daily over the training period.

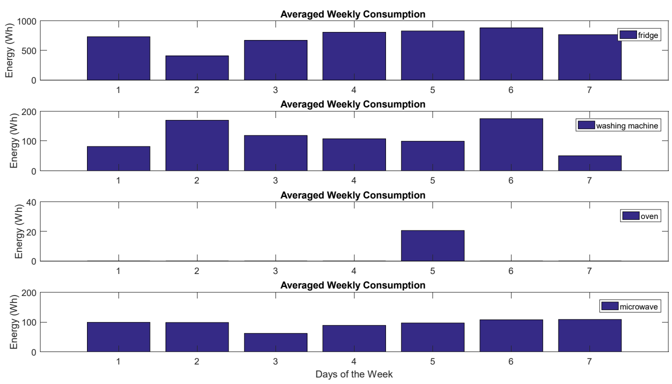

Fig. 3. Averaged consumption for every day of the week during the training period (two months).

Another analysis can be carried out, based on the 24 hours of a day. Fig. 5 shows the averaged consumption for the four appliances, according to that scheme. It is important to remark how the washing machine is mainly used in the mornings, from 9h to 11h, whereas the microwave consumption presents three peaks, clearly associated to the meals in a day: 8h for breakfast, 14h for lunch and 20h for dinner.

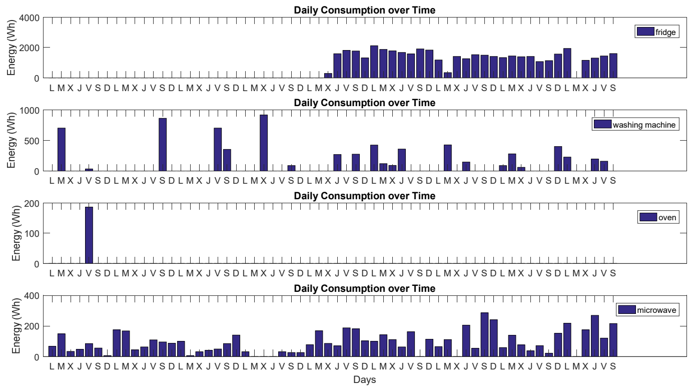

Fig. 4. Daily consumption for every day of the week over the training period.

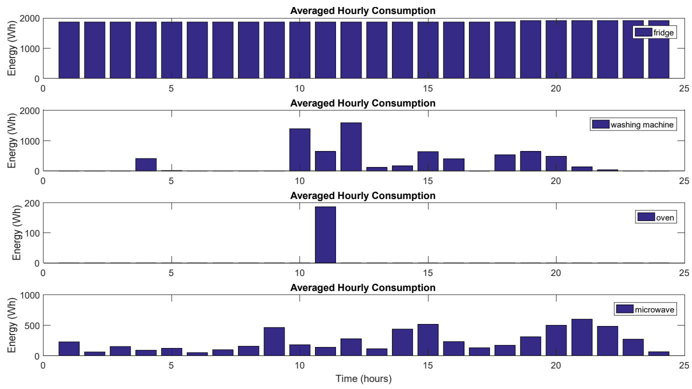

Fig. 5. Averaged hourly consumption of the appliances over the training period.

Based on these hourly usage patterns, hereinafter, it is intended to apply the hourly consumption profile from the microwave to estimate how probable the microwave is to be switched on for every hour of a day, as well as to obtain a cumulative percentage function for that activation. This is represented in Fig. 6, and it is the basis of the proposed generation of warnings, according to the microwave usage. The samples from the training period are used to obtain this percentage profile, which can be used later to analyze every new day, depending on the activation of the microwave. Its daily cumulative percentage increases over time, as can be observed in Fig. 6. A warning can be launched whether the microwave has not been used yet at a certain hour of a day and the accumulated percentage in Fig. 6 is over a value t_h at that hour. This means that, during a new day, while the hours pass by, the cumulative percentage increases until reaching the threshold t_h at a certain hour. At this moment, if the microwave has not been employed yet, then the day is not considered so similar to the reference profile and the corresponding notification is issued at that instant (and not necessarily by the end of the day). Likewise, this approach can be extended to shorter periods than a day: for example, it can be considered independently for the breakfast interval, the lunch or the dinner, in order to evaluate how similar a particular meal is, compared to the average behavior. It is worth mentioning that, since the microwave is related to cooking, only this activity has been considered here, but other appliances might be employed to monitor other activities of daily living.

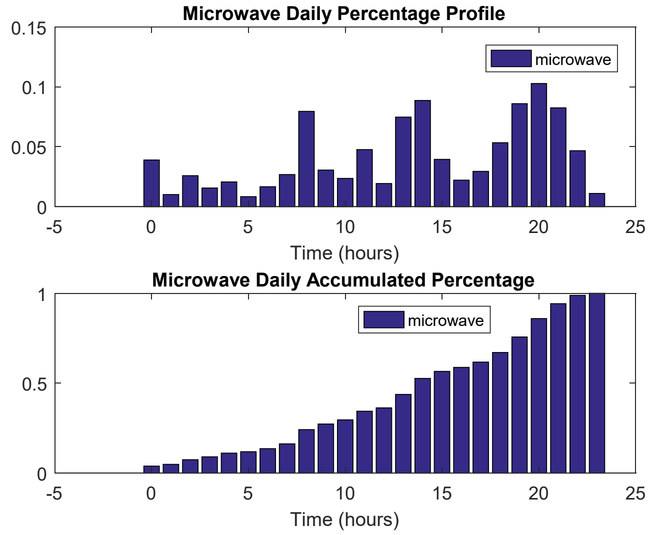

Fig. 6. Microwave daily percentage profile and accumulated percentage.

III. Experimental Results

For the validation of the proposal, the week after the training period from the same household, shown in Fig. 7, has been dedicated to analyse every day and launch the corresponding warnings if necessary.

Taking into account these test data and the microwave profile in Fig. 6, Fig. 8 shows the resulting warning generation for those dates (blue circles), assuming a threshold t_h=0.4 from now on. It is possible to observe that the microwave usage seems normal for the first days, while the last two days the house remains empty (validation ground-truth), what is detected by the system in both cases. Note that the blue warning circles do not correspond to the left axis scale in the graphs, since they are just on/off values.

The test data have also been processed for some particular range of hours, associated to the breakfast (6h-11h), the lunch (12h-16h) and the diner (18h-23h). Figs. 9, 10 and 11 depict the corresponding results for these meals, respectively, where the blue circles are still the warnings generated. In all the cases, the last two days launch the warnings since the house is empty and without activity. With regard to the breakfast, it is possible to observe how the three first days of the test week are not considered regular, mainly because the activation of the microwave takes place too late in the morning. As for the lunch, the first day generates a warning since the microwave is not switched on during this meal. Finally, the warning is launched twice for the dinner, due to the fact that the microwave was used later than expected, according to the reference usage pattern derived from the training period. Note that the value fixed for the threshold t_h may be adjusted, as a tradeoff between the sensitivity in the warning generation and the flexibility to consider a certain usage as normal compared to the pattern.

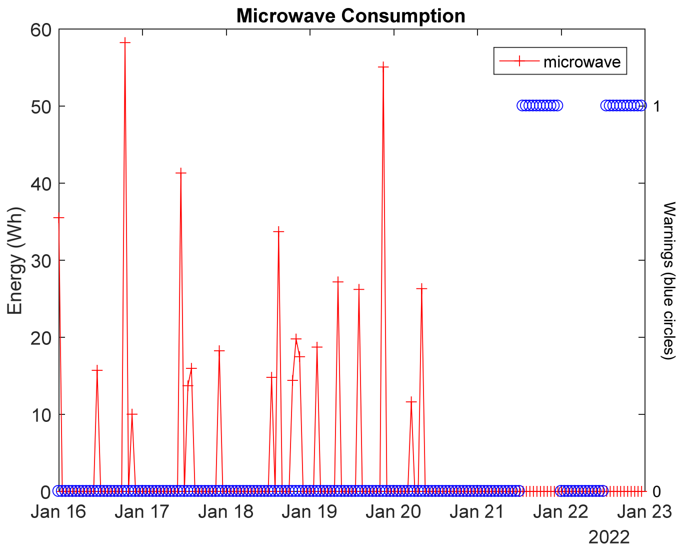

Fig. 8. Microwave consumption for the test period (red crosses) and the corresponding launched warnings (blue circles).

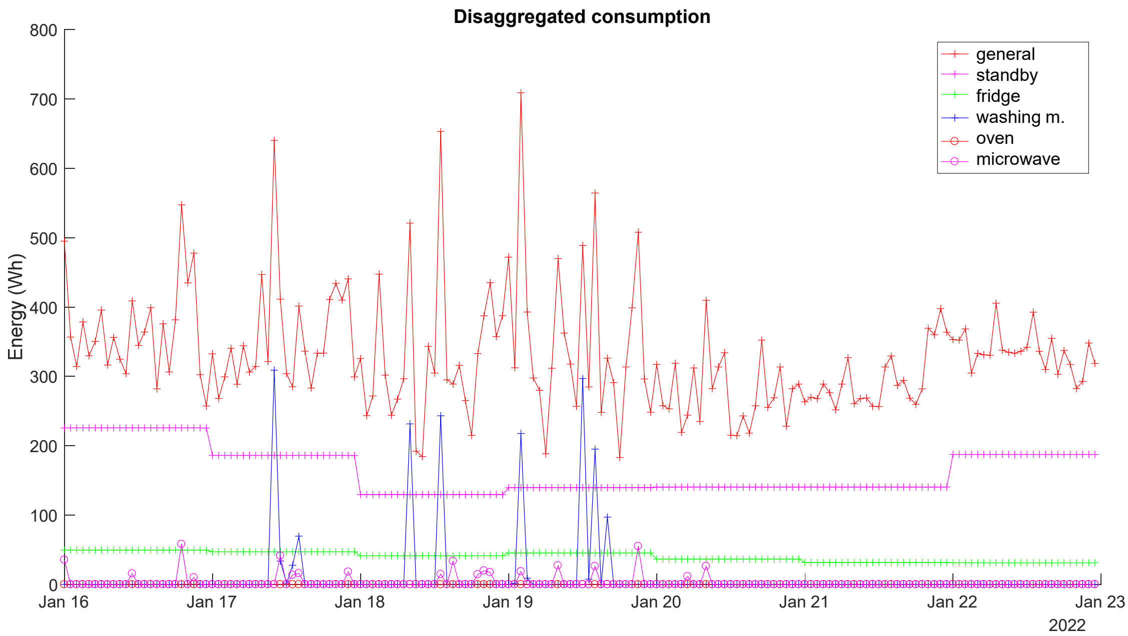

Fig. 7. Disaggregated consumptions for the household under test from January 16, 2022, until January 22, 2022.

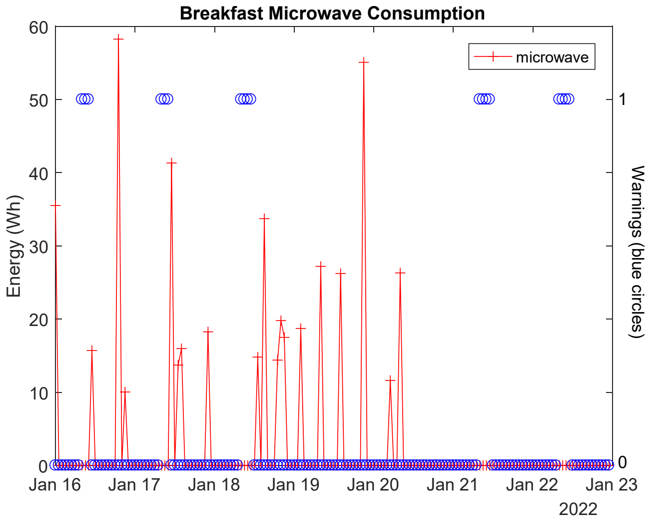

Fig. 9. Microwave consumption for the test period (red crosses) and the corresponding launched warnings (blue circles) during the breakfast interval (6h-11h).

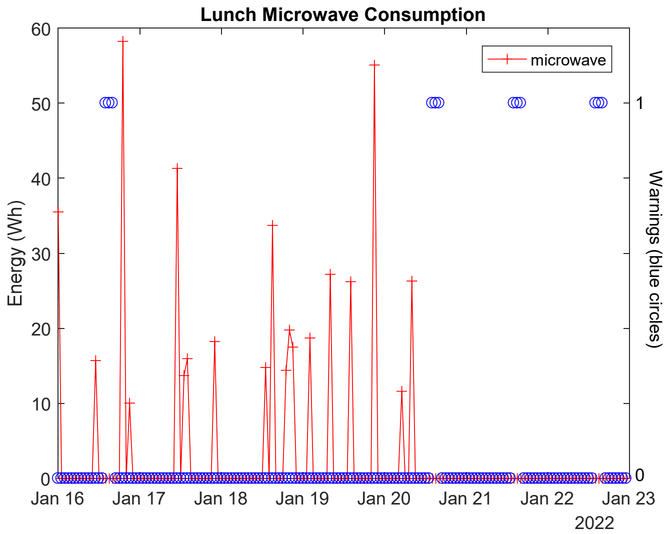

Fig. 10. Microwave consumption for the test period (red crosses) and the corresponding launched warnings (blue circles) during the lunch interval (12h-16h).

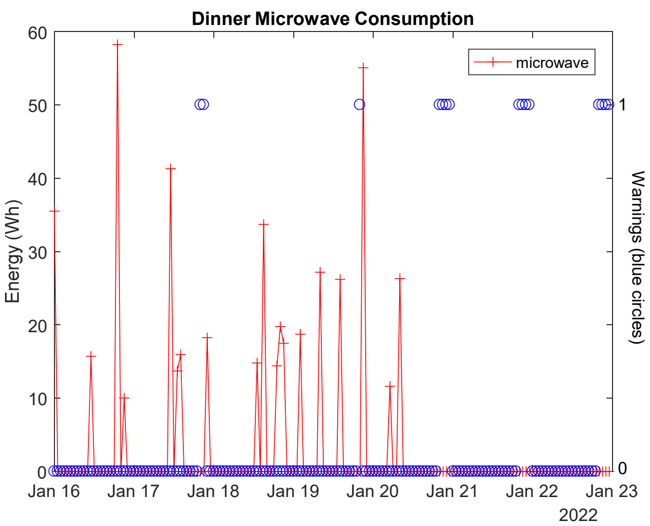

Fig. 11. Microwave consumption for the test period (red crosses) and the corresponding launched warnings (blue circles) during the dinner interval (18h-23h).

IV. Conclusions

This work has presented the employment of a commercial smart meter in order to obtain the power consumption of a household, disaggregated per appliances. These disaggregated data can be used during a training period to infer the usage patterns for the most relevant appliances, where the microwave has been particularly considered here. In this way, a profile of the microwave usage during a day has been obtained as a reference, so every new day can be analysed by comparing the activation of this appliance with that reference. Not only the day can be monitored from a general point of view, but also some activities related to the microwave use, such as breakfast, lunch or dinner, can be monitored during their corresponding time intervals. As a consequence, the proposal can launch warnings whether the actual usage of the microwave significantly differs from the baseline. The proposal has been validated preliminarily, by installing the system in a household occupied by mild-cognitive impaired patients. Future works will deal with longer periods, where annotated variations in health conditions and behaviour routines can be processed to fully validate the proposal.

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