Single appliance automatic recognition: comparison of classifiers

Daniel Hernández de la Iglesia [1], Alberto López Barriuso[1]

Departamento de Informática y Automática, Universidad de Salamanca

Plaza de la Merced, s/n, 37008, Salamanca, España

{danihiglesias , albarriuso} @usal.es

Abstract. Electrical consumption measuring and recording systems which are connected to households are essential in the optimization of energy use. Non-Intrusive Load Monitoring (NILM) systems are one of the most used techniques to study the electrical consumption; these systems are based on the analysis of the load curve (the aggregated electrical consumption of the whole household). Thanks to the significant reduction of the price of sensors and sensor systems in recent years, it is possible to individually monitor each one of the devices connected to the grid. In this paper we compare different classifiers in order to know which is the most appropriate for the identification of individual appliances attending to their consumption. In this way, it will be possible to know which electrical appliance is connected to a smart plug, helping to obtain more accurate and efficient load monitoring systems.

1 Introduction

In recent years, there has been a significant increase in the price of electricity, both for households and industry around the world. In some countries of the European Union, such as France or Germany, the price of electricity has increased by more than 40% in 2015 (by comparison with previous years). In the case of Spain, according to official data from Eurostat (the statistical office of the European Union) [1] between the second half of 2008 and the same period of 2014, the cost of electricity increased by 0.081 euros / kilowatt hour, which is the almost the double of the average increase recorded in the UE (0.042 euros / kwh).

Controlling the electrical usage in both households and industry is a necessity when it comes to efficiently manage the energy costs. Monitoring the amount of electricity that is consumed by the elements that are connected to the grid, lets us establish which of them are the most energy demanding. Knowing this is essential to reduce and optimize the energy consumption.

Current electrical installations do not provide a simple way to collect the consumption data from the different devices that are connected to the grid. Therefore, the most widespread monitoring techniques are based on the analysis of the whole household consumption, that is the sum of all the individual consumptions that are produced by the connected devices. In order to obtain an estimated value of the different elements, data disaggregation techniques are used.

Most electrical consumption disaggregation methods are designed to detect switch on/off events of a single appliance. But the reality is that multiple devices can be activated or deactivated simultaneously. Therefore, disaggregation of consumption can be complicated by the simultaneous switch on/off of multiple devices. This technique is known as Non-Intrusive Appliance Load Monitoring (NIALM). One of the first approaches regarding NIALM systems was introduced in the late 1980s by George Hart at MIT[2]. Since then, the NIALM systems have evolved, improving the capacity of disaggregation and reducing their dependency to activation and deactivation events of the devices [3][4].

In recent years, the cost of technology production has fallen significantly. This has led to new phenomena such as Internet of Things (IOT) [5]. The devices and objects around us are more connected and accessible through the grid each day. There are already devices that are able to monitor the individual consumption of different appliances in real time, sending this data wirelessly. These devices are called Smart Power Plugs. Thanks to these new devices, it is easier to monitor the electrical consumption of certain devices without turning to NIALM systems. The individual consumption profile of the connected appliances can serve to improve the accuracy of NIALM systems.

In this work we show an evaluation and comparison of different classifiers in order to obtain the highest precision when identifying which electrical appliance is connected to a Smart Power Plug. A seven-month consumption data from three different appliances in the same household has been compared in this study.

The rest of the paper is organized as follows: Section 2 reviews the state of the art on appliances classification; Section 3 describes the dataset used in this work; Section 4 shows the used algorithms and a comparison of their performance and section 5 shows up the conclusions and future lines of work.

2 Background

Several studies have dealt with the classification of household appliances through their load curve. For example, authors in [6] present a system that provides a real-time appliances recognition system based in a single energy monitor -which is based in Zigbee technology- that is connected to the main electrical unit. The system generates consumption profiles for each device, recognizes the different profiles in real time using neuronal networks and is fed with additional information which is provided by the users. In [7] authors propose a new method for the classification and identification of residential appliances. This appliances classification method uses the main power consumption and the performance style as characteristics of each device. Subsequently, an appliance identification platform is designed and implemented with these characteristics.

Authors in [8] have developed a system which is able to automatically recognize home appliances according to their electrical consumption profile, that is measured in low frequency with low end sensors. This system is based on the traditional machine learning approach. The system uses the consumption profiles from a set of appliances as training data. Authors achieved a classification rate of success of 85%.

In the case of [9], authors propose a time-based classifier which firstly identifies the appliance, and then predicts the future use of the appliances which use a big amount of energy within the household. To that extent, authors propose a new set of meta-characteristics to be included. Their results have been validated with a dataset containing data from 100 houses that have been monitored during one whole year.

In [10], it is stated that the best approach in order to model the appliances classification problem is the use of bottom-up methodologies. These methodologies build the load curve from an elementary entity that could be the domestic appliance, the end-use or even the household and aggregate it at the wished modelling level. Through the study of three appliances, authors discuss about their main particularities, which are the most influential properties in the individual energy demand. Once these particularities are defined, authors apply the proposed methodology in order to identify similar curves in the consumption.

Authors of [11] use Hidden Markov models to identify different devices at the same time. The independent changes in the active power of each device are described by each Markov chain. With the active power measurements of a single Smart meter, it is required to calculate the hidden variables that define the possible states of the different appliances. In conclusion, the authors conclude that the probabilistic model allows the identification of appliances that work simultaneously.

The mentioned works have been conceptualized as NILM systems; therefore, are based on data obtained from the general consumption of the household, registered by a smart meter. This paper proposes the identification of appliances attending to their power demand profile. In this case, instead of using a single smart meter for the whole grid, single smart plugs are used individually for each appliance. In this line of work, we can find previous works such as [12] or [13].

3 Used dataset

3.1 Data acquisition

The dataset which has been used in the execution of this research was provided by the Portuguese company Virtual Power Solutions (VPS). This company offers various products that are designed to monitor the electrical consumption of both households and industrial clients.

In the scope of this work, the used devices belong to three different groups: Cloogy® Plug Power (Fig. 1 -a-) which were connected through wireless Zigbee technology to a Cloogy®Smart Hub (Fig. 1-b-), which, in turn, was connected to a central server. This central server was responsible for storing the received data. The data was collected from 05/05/2016 to 30/11/2016 in a single household, obtaining data from three different Cloogy® Plug Power, that were connected to three appliances: a fridge, a washing machine and an electric heater.

(a) (b)

Fig. 1 - Devices from VPS company. (a) Smart plug. (b) Smart Hub

3.2 Dataset

The Smart Plug sends the accumulated consumption data to the central hub every 15 minutes, providing a total of 96 records per day and appliance. Each row of the generated dataset file corresponds to the electrical consumption of one of the appliances during one day. Each row has 97 columns; the first 96 gather the electrical consumption of the appliance for each measure, while the last one establishes to which appliance does the file correspond. Since we record three different appliances consumptions, the periodicity with which consumptions are recorded in the dataset is different. In the case of the fridge, there is a quasiperiodic consumption and magnitude throughout the day. For this appliance, the user interaction does not significantly modify the consumption curve; while in the case of the other appliances -electric heater and washing machine-, user interaction does directly modify the consumption curve. The electric heater is only activated when the user activates it, and in no case its consumption provides a known frequency. It is also the case of the washing-machine. The user decides when to start it up on demand and, doing it without a predictable frequency. In addition, the washing machine can be used in different modes (more or less powerful washing modes, using hot or cold water, etc.) and with different cycles while it is being used.

During the data collection, in the case of the fridge, there were consumption measurements for every day. In contrast, for the rest of appliances, since their activation directly depend on the user actions, there were no consumption measurements for those days when the user did not use these appliances. In order to evaluate the effect of including this empty values -for those days where no activity was recorded-, two different datasets were generated. The first dataset, with raw data, including even those days with no consumption of any of the appliances, and the second one, eliminating the data of those days in which no activity was registered.

3.3 Appliances comparison

As we have introduced in the previous section, the three analyzed appliances present different usage patterns. Therefore, it was decided to perform the comparison between them since they are different in their operation and in the way that users use them.

The fridge is one of those appliances which are essential in any home. The kind of consumption of this device is characterized by being continuous along the day. As it can be appreciated in Fig. 2, the fridge has an average of 12 daily activations independently of the external factors. Weather (a higher temperature implies a higher consumption in order to keep food cold) or human intervention (opening the door or placing new food) can vary the consumption, but under normal conditions, the consumption cycle does not barely vary.

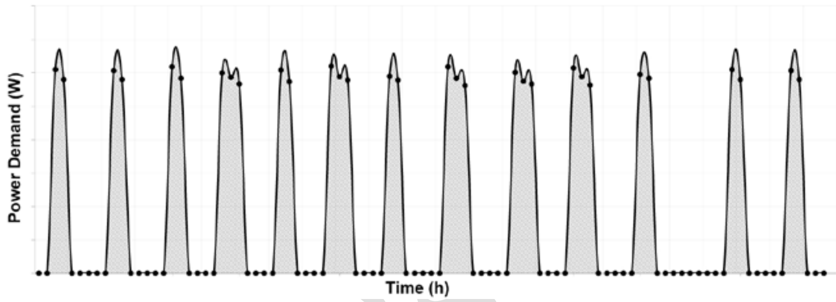

Fig. 2 - Daily consumption of a fridge

On the other hand, the washing machine does not present a periodical consumption, and it exclusively depends on the user actions for the generating consumption. In some households, turning on events happen in the same time zones, but it always will depend on the family's habits. In any case, it is not a predictable or periodic consumption. In addition, current washing machines can be programmed with different functions, such as an intense washing or the use of high temperature water (which means an increase in energy consumption). Fig. 3 shows a consumption chart of the energy consumption of a washing machine during 24 hours. As it can be observed, the appliance has been connected three different times, and for each of this periods, the load curves are somewhat different.

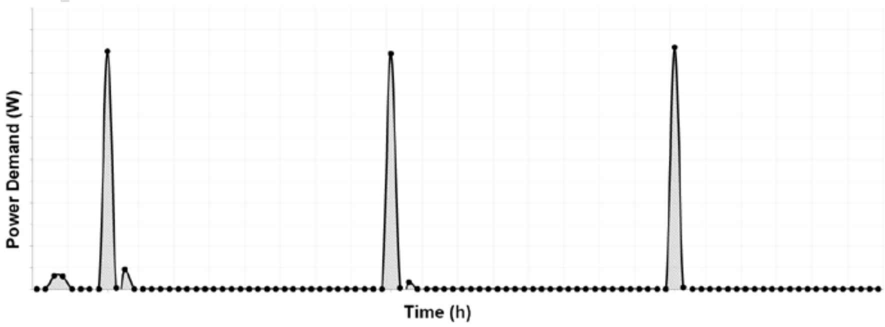

Fig. 3 - Daily consumption of a washing machine

We finally analyze the electric heater, which as well as the washing machine is user-dependent. It is a difficult appliance to be temporally classified. Its use varies depending on the outside temperature, the season of the year and the intensity with which it is used. In figure Fig. 4 we can see the consumption produced by this appliance during a 24-hour period. In this figure, it is possible to observe how the electric heater has been connected five times. Four of this connections present a similar consumption pattern, while one of them shows a substantially higher demand of energy.

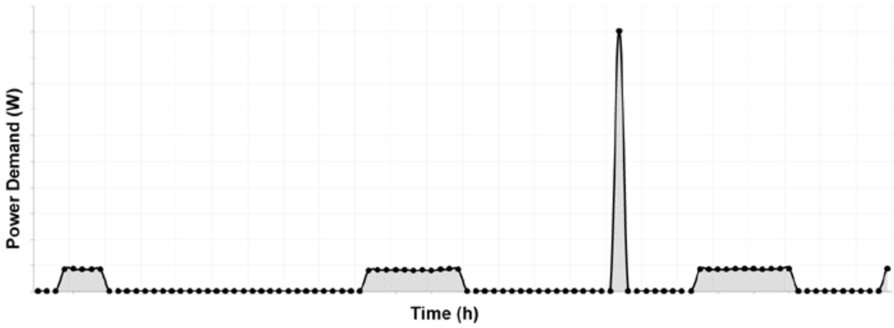

Fig. 4 - Daily consumption of an electric heater

4 Experiments, comparision and results

In this section we analyze the results of the used algorithms. We have followed several steps: firstly, we have applied the classification methods with each pair of appliances (fridge and washing machine, fridge and electric heater and washing machine and electric heater), and we have finally applied those methods facing the three appliances at the same time. The used algorithms are presented below:

- **Bayesian Network**
- **Naive Bayes**
- **Random forest**
- **Random tree**
- **REPtree**
- **DecisionStump**
- **HoeffdingTree**
- **J48**
- **Logistic model tree**
- **GradientBoost**

In order to validate the performance of the classifiers, we analyze different **Cohen's kappa coefficient**, which is a statistic that measures inter-rater agreement for qualitative (categorical) items. It is usually thought to be a more robust measure than simple percent agreement calculation, since κ considers the possibility of the agreement occurring by chance. ***Table 1*** shows evaluation the of Kappa coefficient:

Evaluation of Kappa coefficient	
K value	**Level of agreement**
<0.20	None
0.21-0.39	Minimal
0.40-0.59	Weak
0.60-0.79	Moderate
0.80-0.90	Strong
Above 0.90	Almost perfect

Table 1 - Evaluation of Lappa coefficient

At the time of the validation of the results, on the one hand a cross validation of 10 iterations was performed and, on the other hand, a division of data with 66% of data for training and 33% of data for testing.

As a summary, we present the kappa statistic for each algorithm and dataset. This is a representative statistic, since it represents the level of agreement of the classifier.

	All Data	All Data (no empty data)	Washing machine and electric heater	Fridge and electric heater	Fridge and Washing machine
Bayes Net	0.4924	0.7703	0	1	1
Naive Bayes	0.5744	0.5479	0.2949	0.9404	0.6623
RandomForest	0.6903	0.7867	0.4828	1	1
RandomTree	0.5384	0.6807	0.3802	0.9097	0.8063
REPtree	0.4292	0.6807	0	0.8339	0.7253
DecisionStump	0.2909	0.3973	0	0.5594	0.559
HoeffdingTree	0.4313	0	0	0.9399	0.5134
J48	0.5078	0.6077	0	0.9549	0.8802
Lmt	0.4241	0.5799	0	0.9399	0.7253
GradientBoost	0.46744	0.78263	0.11372	0.96988	0.88862

Table 2 - Algorighms performance with cross-validation -folds 10-

	All Data	All Data (no empty data)	Washing machine and electric heater	Fridge and electric heater	Fridge and Washing machine
Bayes Net	0.2971	0.7573	0	1	1
Naive Bayes	0.6058	0.5747	0.3296	0.9539	0.6057
RandomForest	0.6208	0.7812	0.4696	1	1

RandomTree	0.4495	0.6023	0.3581	1	0.6964
REPtree	0.4417	0.6393	0	0.9091	0.7829
DecisionStump	0.3187	0.2996	0	0.5594	0.5036
HoeffdingTree	0.4127	0.2996	0	0.9109	0.4068
J48	0.4417	0.6004	0	0.8643	0.6395
Lmt	0.3459	0.5609	0	0.9552	0.7829
GradientBoost	0.4045	0.7637	0.323170	1	0.93499

Table 3 - Algorighms performance with percentaje split (66%)

5 Conclusions and future lines of work

In the view of the results, we can conclude that in general terms, all the classifiers have been more accurate when classifying the fridge facing any other appliance as expected a priori, since the load curve of the fridge is more representative than the other appliances in the dataset, since it is continuously working and it has a more or less periodical consumption, while the other appliances are turned on by the householder, and the consumption fingerprint is not as representative as the fridge one. When classifying the fridge individually against the electric heater and the washing machine, we can say that all the algorithms have shown a better performance in the case of the electric heater, since the kappa statistic values denote a strong level of agreement. In the case of the washing machine, the classifiers performance has been slightly worse, but still reaching a moderate level of agreement.

In the other hand, we have obtained the wort results when classifying the washing machine against the electric heater, since the kappa statistic points out the minimal or poor level of agreement of the majority of algorithms.

When we have faced the classification of all the appliances together, the results were not as good as we could expect, and the different performances oscillate in the different algorithms, obtaining a range of the kappa statistic results that vary from minimal to moderate level of agreements.

In face of this results, we realized that two of the appliances may not have electrical consumptions along one day, so it would be impossible to classify this appliances during this period, so this data is just noise for the classifiers, making their performance to significantly be reduced. We proceed to omit the data of the washing machine and the electric heater, for those days where there was no electrical consumption. After removing this data, we proceeded to apply the classifiers one again (facing all the three appliances together), and the results improved significantly.

In order to improve the obtained results, we have planned to follow this research line, making additional investigation: although some of the algorithms have shown a good performance classifying the appliances, the input data is still very time-dependent, that is to say that the specific moment of the day when an appliance is used, establishes to a large extent the proper classification of the appliance. So, in order to improve the performance of the algorithms, a new extended version of the dataset has been planned, including:

- Extracted from consumption data:
  - Maximum value
  - Total consumption
  - Mean
  - Variance
  - Standard deviation
  - Interquartile Range
  - Number of activation periods (number of times when an appliance has been working along the day)
  - Average duration of the activation periods
  - Total duration of the activation periods
- Others:
  - Maximum and minimum temperatures
  - Day of the month
  - Day of the week
  - Month

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