

# Single Appliance Automatic Recognition: Comparison of Classifiers

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**Abstract.** Measuring and recording systems for the consumption of electrical energy which are connected to households, are essential in the optimization of energy use. Non-Intrusive Load Monitoring (NILM) is one of the most used techniques in the study of electrical consumption; these systems are based on the analysis of the load curve (the aggregated electrical consumption of the whole household). Thanks to a significant reduction in 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 find out which is the most appropriate for the identification of individual appliances attending to their consumption. In this way, we will 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 (in comparison to 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 second half of 2014, the cost of electricity increased by 0.081 euros/kWh, which is the almost the double of the average increase recorded in the EU (0.042 euros/kWh). Controlling the electrical usage in both households and industry is a necessity if we want to manage energy costs efficiently. Monitoring the amount of electricity that is consumed by the elements connected to the grid, lets us establish which of them is the most energy demanding. Knowing this is essential for the reduction and optimization of 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 for the different elements, data disaggregation techniques are used. For this reason, creating a system that allows for the automatic detection and classification of household appliances is important for analyzing energy consumption.

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. Classifiers based on different algorithms such as fuzzy logic, probabilistic models or neural networks have been used. To perform the tests, real consumption data has been used by installing smart plugs, which are connected to a central node through ZigBee. This central node retrieves the consumption data of all the devices. In this study, we gathered consumption data for seven months, from three different appliances in the same household.

The rest of the paper is organized as follows: Sect. 2 reviews the state of the art on appliance classification; Sect. 3 describes the dataset used in this work; Sect. 4 shows the used algorithms and a comparison of their performance and Sect. 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 real-time appliance recognition, based on a single energy monitor –using Zigbee technology– which 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 the 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 success rate of 85%.

In the case of [9], authors propose a time-based classifier which first identifies the appliances, and then predicts the future use of those 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 such as a domestic appliance, the end-use or even the household and aggregate it at the desired modelling level. Through the study of three appliances, authors discuss 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 for the identification of appliances that work simultaneously.

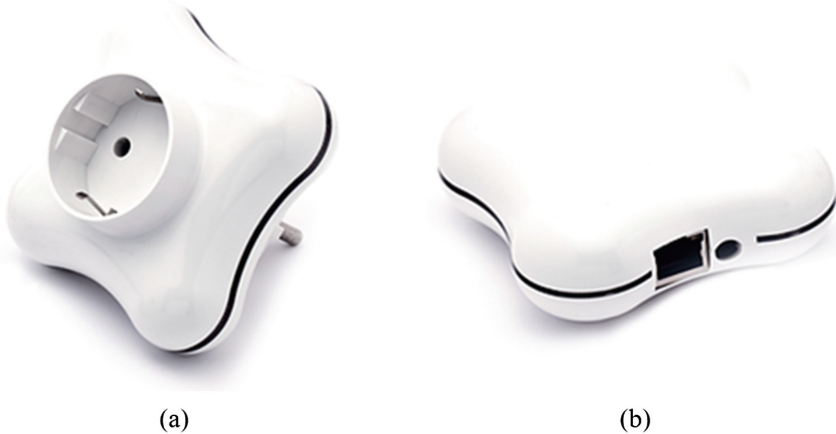
The mentioned works have been conceptualized as NILM systems; therefore, they are based on data obtained from the general consumption of the household, registered by a smart meter. This paper proposes the identification of appliances attending to their power demand profile. In this case, instead of using a single smart meter for the whole grid, single smart plugs are used individually for each appliance. The use of this kind of devices allows to create the consumption fingerprint of the appliances, so it can later be used to automatically recognize them with no user interaction. Similar topics are dealt with in previous works such as [12] or [13].

### 3 Used Dataset

#### 3.1 Data Acquisition

The dataset which has been used when carrying out 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 study, the used devices belong to three different groups: Cloogy® Plug Power (Fig. 1a) which were connected through wireless Zigbee technology to a Cloogy® Smart Hub (Fig. 1b), 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.



**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 min, 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 appliance 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, 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 consumption frequency cannot be known, the same goes for the washing-machine. The user decides when to switch it on and, does 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.), it also goes through different cycles while being used.

During data collection, in the case of the fridge, consumption measurements were made every day. In contrast to the rest of appliances, since their activation directly

depends on the user, there were no consumption measurements for those days when the user did not use these appliances. In order to evaluate the effect of including empty values -for those days where no activity was recorded-, two different datasets were generated. The first dataset contained raw data, including those days with no consumption measurements from any of the appliances, and the second dataset which eliminated empty values, including only the days where activity was registered.

### 3.3 Appliances Comparison

As mentioned in the previous section, the three analyzed appliances present different usage patterns. Therefore, it was decided to perform the comparison between them since they operate differently and users use them in different ways.

The fridge is one of those appliances which are essential in every home. The consumption type of this device is characterized as being continuous along the day. As can be seen 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 barely varies.

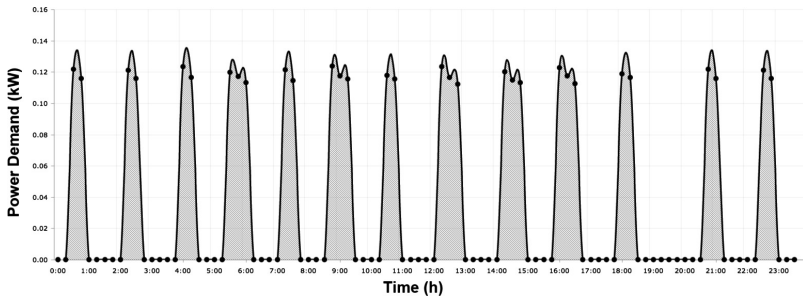
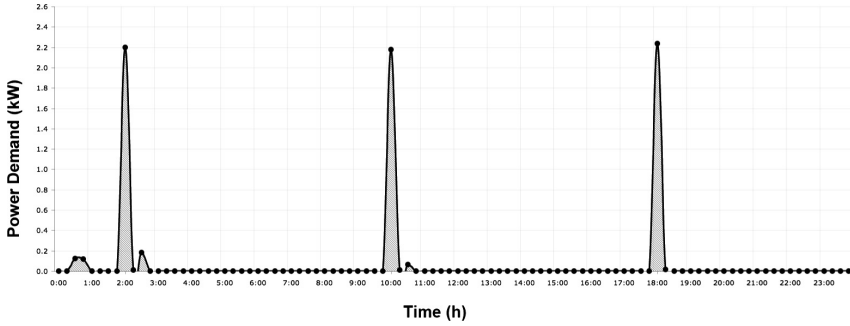


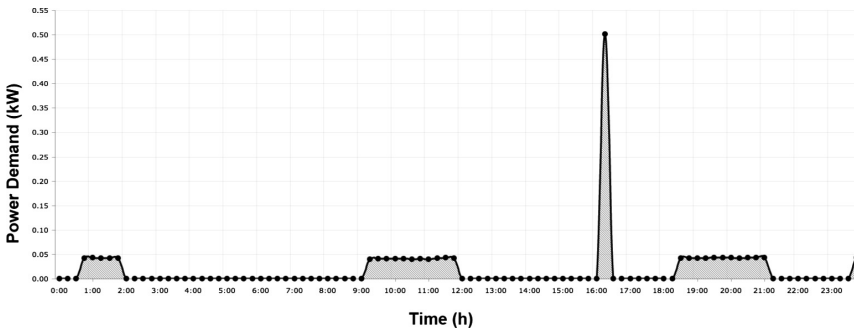
Fig. 2. Daily consumption of a fridge

In contrast, the consumption of a washing machine is not continuous and exclusively depends on the user actions that generate consumption. In some households, the switching on of an appliance happens more or less at the same times, however, this will always 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 intensive wash or a high temperature wash (which means an increase in energy consumption). Figure 3 shows a consumption chart of the energy consumption of a washing machine during 24 h. As it can be observed, the appliance has been connected at 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 Fig. 4 we can see the consumption produced by this appliance during a 24-hour period. In this figure, we can observe how the electric heater has been connected five times. Four of these 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, Comparisons 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 then applied those methods classifying the three appliances at the same time. The used algorithms were: bayesian network, naivebayes, random forest, random tree, REPTree, decision stump, hoeffding tree, J48, logistic model tree and gradient boost.

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  $\kappa$  considers the possibility of the agreement occurring by chance. Table 1 shows evaluation the of Kappa coefficient:

**Table 1.** Evaluation 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

During the validation of results, on the one hand a 10 fold-cross validation iteration was performed and, on the other hand, a division of data with 66% of data for training and 33% of data for testing.

In 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 (Tables 2 and 3).

**Table 2.** Algorithms performance with 10 fold cross-validation

	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
Random forest	0.6903	0.7867	0.4828	1	1
Random tree	0.5384	0.6807	0.3802	0.9097	0.8063
REPtrree	0.4292	0.6807	0	0.8339	0.7253
Decision stump	0.2909	0.3973	0	0.5594	0.559
Hoeffding tree	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
Gradient boost	0.46744	0.78263	0.11372	0.96988	0.88862

**Table 3.** Algorithms performance with percentage split (66%)

	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
Random forest	0.6208	0.7812	0.4696	1	1
Random tree	0.4495	0.6023	0.3581	1	0.6964
REPtree	0.4417	0.6393	0	0.9091	0.7829
Decision stump	0.3187	0.2996	0	0.5594	0.5036
Hoeffding tree	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
Gradient boost	0.4045	0.7637	0.323170	1	0.93499

## 5 Conclusions and Future Lines of Work

In the view of the results, we can conclude that all the classifiers have been more accurate when classifying the fridge than 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.

Whereas, the worst results have been obtained when classifying the washing machine against the electric heater, as 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 levels of agreement.

Based on these results, we realized that it would be impossible to classify the appliances which may have periods of no electrical consumption along the day, because it is not possible to classify them, this no-value data is just noise for the



classifiers, making their performance significantly lower. We proceeded 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 applied the classifiers once again (to all the three appliances together), and the results improved significantly.

In order to improve the obtained results, we plan to follow this research line, making additional investigation: although some of the algorithms have shown a good performance when 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, the extraction of new variables from the dataset is necessary, including: (i) 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, (ii) others: maximum and minimum temperatures, day of the month, day of the week, month.

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## References

1. Home - Eurostat. <http://ec.europa.eu/eurostat>. Accessed 12 Jan 2017
2. Hart, G.W.: Nonintrusive appliance load monitoring. *Proc. IEEE* **80**(12), 1870–1891 (1992)
3. Najmeddine, H., Drissi, K.E.K., Pasquier, C., Faure, C., Kerroum, K., Diop, A., Jouannet, T., Michou, M.: State of art on load monitoring methods. In: 2008 IEEE 2nd International Power and Energy Conference, pp. 1256–1258 (2008)
4. Kong, S., Kim, Y., Ko, R., Joo, S.-K.: Home appliance load disaggregation using cepstrum-smoothing-based method. *IEEE Trans. Consum. Electron.* **61**(1), 24–30 (2015)
5. Atzori, L., Iera, A., Morabito, G.: The Internet of Things: a survey. *Comput. Netw.* **54**(15), 2787–2805 (2010)
6. Ruzzelli, A.G., Nicolas, C., Schoofs, A., O'Hare, G.M.P.: Real-time recognition and profiling of appliances through a single electricity sensor. In: 2010 7th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON), pp. 1–9 (2010)
7. Wang, Z., Zheng, G.: Residential appliances identification and monitoring by a nonintrusive method. *IEEE Trans. Smart Grid* **3**(1), 80–92 (2012)
8. Zufferey, D., Gisler, C., Khaled, O.A., Hennebert, J.: Machine learning approaches for electric appliance classification. In: 2012 11th International Conference on Information Science, Signal Processing and their Applications (ISSPA), pp. 740–745 (2012)
9. Basu, K., Debusschere, V., Bacha, S.: Residential appliance identification and future usage prediction from smart meter. In: IECON 2013—39th Annual Conference of the IEEE Industrial Electronics Society, pp. 4994–4999 (2013)

10. Grandjean, A., Binet, G., Bieret, J., Adnot, J.: A functional analysis of electrical load curve modelling for some households specific electricity end-uses. In: 6th International Conference on Energy Efficiency in Domestic Appliances and Lighting (EEDAL 2011), p. 24 (2011)
11. Lukaszewski, R., Liszewski, K., Winiński, W.: Methods of electrical appliances identification in systems monitoring electrical energy consumption. In: 2013 IEEE 7th International Conference on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS), pp. 10–14 (2013)
12. Ridi, A., Gisler, C., Hennebert, J.: Automatic identification of electrical appliances using smart plugs. In: 2013 8th International Workshop on Systems, Signal Processing and their Applications (WoSSPA), pp. 301–305 (2013)
13. Barker, S., Musthag, M., Irwin, D., Shenoy, P.: Non-intrusive load identification for smart outlets. In: 2014 IEEE International Conference on Smart Grid Communications (SmartGridComm), pp. 548–553 (2014)