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Research Article

Dealing with Demand in Electric Grids with an Adaptive Consumption Management Platform

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The control of consumption in homes and workplaces is an increasingly important aspect if we consider the growing popularity of smart cities, the increasing use of renewable energies, and the policies of the European Union on using energy in an efficient and clean way. These factors make it necessary to have a system that is capable of predicting what devices are connected to an electrical network. For demand management, the system must also be able to control the power supply to these devices. To this end, we propose the use of a multiagent system that includes agents with advanced reasoning and learning capacities. More specifically, the agents incorporate a case-based reasoning system and machine learning techniques. Besides, the multiagent system includes agents that are specialized in the management of the data acquired and the electrical devices. The aim is to adjust the consumption of electricity in networks to the electrical demand, and this will be done by acting automatically on the detected devices. The proposed system provides promising results; it is capable of predicting what devices are connected to the power grid at a high success rate. The accuracy of the system makes it possible to act according to the device preferences established in the system. This allows for adjusting the consumption to the current demand situation, without the risk of important home appliances being switched off.

1. Introduction

As De Baets et al. [1] report in their paper, European Union member countries made an agreement in October of 2014 in which they set a number of goals for 2030. These goals are related to reducing pollution and obtaining cleaner and more efficient energy. This means that the use of renewable energies should increase in the next years. However, such changes also imply certain challenges; one of them is the adjustment of electrical production to demand. That is why consumption management plays a very crucial role in electric networks and it is becoming an important facet in Smart Grids. The sources of production are very diverse and they are distributed geographically, so it is more complicated to keep an electric network in stable conditions. For these reasons, it is necessary to create a system that will allow for managing consumption automatically, adjusting the generated energy to the requirements of each moment, since the management of short-term production is not feasible. The need for an automatic consumption management system has been reflected in the variety of devices that have been proposed in recent years for the analysis of consumption in electrical networks. We live in an information age where data is highly valuable because of the knowledge that can be extracted from it. For example, a system can obtain the consumption data of a house and analyze it in order to detect behaviour patterns and identify the devices that are connected to that house's electric network. To be able to manage the data of a measurement device a multiagent system has to be implemented.

Up until now several studies addressing this topic have been published. They all focus on identifying the devices connected to an electric network by employing a range of techniques based on NonIntrusive Load Monitoring (NILM); the majority of them are improved versions of standard algorithms. While NILM techniques are used in other works, we use a variety of measuring devices in our proposal in order to extract the consumption data from each line connected to an electric network, and this simplifies the identification of electrical appliances and optimizes the system's performance.

For this reason, we propose a distributed system which will be able to connect with the different measurement systems and obtain the consumption data read by them. By analyzing and extracting important characteristics from the data provided by these measurement systems, the system will be capable of identifying the devices or appliances connected to the electric network. Simultaneously, the system will be able to act on each of the lines connected to the measuring devices.

Furthermore, the proposed system makes use of multiagent technology which provides the distributed architecture with agents who carry out different and specific tasks in the final system. The multiagent system allows creating autonomous entities that work in a coordinated way, providing features such as mobility, dynamic behaviour (the system is capable of creating agents dynamically; this feature makes it possible to modify the goals and behaviour of the system), federation of services, and high-level communication through the transparent management of message queues. This architecture makes it possible to perform different tasks in a coordinated way, improving the system's learning and adaptation capacities. There are numerous agents with different roles; one of the agents, for example, is in charge of communicating with the measuring devices and the acquirement of measurement data. There is also an agent that extracts the home appliances' activation periods from the data obtained by a different agent and another that extracts the main characteristics of activation periods. In addition, one of the agents identifies the home appliances that are connected to the gird. Finally, we have an agent who is responsible for acting on the different lines connected to the measuring systems. These agents act on smart-meter lines or smart plugs in order to interrupt the power supply to these devices; in this way demand can be managed.

The system will identify home appliances by using different supervised machine learning algorithms. To verify the proposal, the system will use several algorithms based on decision rules, decision trees, neural networks, and algorithms based on the Bayes theorem and case-based learning. These methods are tested with a dataset that has been created for the purposes of this study. In order to create the dataset, the principles of the fingerprint algorithm were followed. Fingerprint methods make use of the distances between the maximus of a sound since at these points the sound is purer. When creating the dataset, the maximus of activation periods have been used to extract some of their characteristics and to identify the different algorithms. This allows us to obtain knowledge about the behaviour of the devices. This knowledge is stored on a database in order to subsequently apply advanced reasoning and learning techniques to it.

The article is divided into the following sections. In the background section, we describe some of the studies related to this line of research. The proposed system is outlined in the architecture section. The case study section focuses on particular situations that have been considered during the research. In the results section, the system's performance will be described and analyzed. The last section draws conclusions on the different technological solutions that we had considered for our system; furthermore we discuss future lines of work related to the proposed study.

2. Background

This section is focused on literature that is related to the aims of the present research. All the related works make use of techniques based on NonIntrusive Load Monitoring, described by Hart [12] and by Zoha et al. [13]. Below, the most noteworthy works have been described.

In the year 2014, Belley et al. [2] had already used a smart meter to obtain a house's consumption data. The authors made use of the activation periods of appliances that were in the house. In this study, the authors used the equality between the cases stored in the database and the appliances they analyzed. This methodology entails a high computational cost due to the process of comparing an element with each of the instances stored in the database. In [3] the same authors proposed an improved version of their system using the same algorithm for the identification of devices; however, in the new proposal the system was capable of identifying erratic behaviours related to possible cognitive problems experienced by the users.

Other authors like Lin et al. [4] proposed a new strategy for NILM systems. They suggested that devices should be identified using quadratic programming rules. The results of this research proved that this methodology is effective. The work of De Baets et al. [1] proposed two new algorithms applied to NILM techniques for the identification of devices in electronic networks. The two new methods were as follows: a modified version of the chi-squared goodness-of-fit test and an event detection method based on cepstrum smoothing. Besides, the authors explained that both methods can be optimized using surrogate-based optimization.

Other lines of research focus on improving NILM techniques. The researchers Tang et al. [5] suggested that the state of the building must be taken into account; it can be either occupied or unoccupied. Thus, a system that is capable of considering these two situations will not operate when there are no people in the building. On the contrary, when the building is occupied the system will decide to identify the connected devices in the household. This methodology allows for improving the accuracy of classifiers and reducing computational costs at times when the building is not occupied.

The study conducted by Brown et al. [6] also considers the state of the building. In this work, ultrawideband radar technology was used to determine whether a building is occupied or not. This was done by comparing its results with the data that the system receives from the power monitoring system. Apart from establishing the state of the building, this technique also detects the devices connected to the grid. In addition, this methodology examines the users' behaviour.

The research conducted by Liang et al. in [7] is focused on the construction of a new platform that would provide a better understanding of electrical consumption patterns and that would successfully identify the devices connected to the electrical network. For this purpose, the different activation periods of the devices were analyzed and a number of mathematical programming and pattern recognition techniques were applied to unbundle the load.

A similar task is tackled in the study presented by Lee et al. [8]. In this case, the article leverages already existing methods for measuring and representing the characteristics of electricity consumption. Moreover, the article considers signal processing as a method of identifying the devices connected to the network by means of disaggregation and filtering techniques.

There are also researches that focus on slightly different aspects, such as electrical demand forecasts for a few days ahead. Examples of works that address this issue are Chen et al. [9] and Chen and Tan [10]. In the first work, daily demand is predicted for each hour using a hybrid clustering algorithm. The second one fulfils the same function but it uses a hybrid algorithm based on support vector regression. Both techniques render great results.

Finally, it is important to list an open source tool that implements several NILM techniques. This tool is called NILMTK (NonIntrusive Load Monitoring ToolKit). It has been developed by Batra et al. [11]. This tool is designed to employ several techniques and shows the results rendered by each of them. It also includes public datasets.

The studies presented above make use of NILM techniques or use a new method to identify the devices connected to an electric network. However, none of them consider the use of smart devices which will be present in our future homes and buildings, and these can measure the consumption of home appliances. In our article, we also propose a new method for the identification of electronic appliances connected to the grid. This new technique makes use of a combination of characteristics of the fingerprint algorithm and NILM techniques. Hence, this proposal sets forth a new methodology for the analysis of data that allows for identifying the devices connected to electric networks. In conclusion, this section summarizes the novel aspects of the work and the main contributions of the work: (a) a management platform that allows for adapting consumption in a network. (b) The identification of household appliances using NILM techniques and their integration with fingerprint algorithm principles. (c) The use of smart meters and relevant communication protocols for obtaining consumption data and switch household appliances on/off in order to adapt consumption. In order to clearly show the features of this proposal, we include a comparison between the proposal and the state of the art (Table 1).

3. Proposed Architecture

The adaptive consumption management system for satisfying demand in electrical networks has to work with different measuring devices in order to read information from them and act accordingly. Information is extracted for the purpose of processing and extracting the knowledge contained in it. The system needs this knowledge in order to identify the household appliances connected to the electric network.

The system works according to the principles of NILM techniques. The NonIntrusive Load Monitoring or NILM systems use a technique that disintegrates the data extracted from meters. Meters are located outside of homes; this is where the name nonintrusive comes form. So, according to a definition proposed by Hart [12], the consumption of a network is composed of the consumption of all the devices connected to it; therefore the goal is to identify as many devices as possible.

In mathematical terms, we could say that, in an instant of time t, the energy is consumed by all the devices n_i, connected to an electric network N in the instant t, as formulated by Zoha et al. [13]:

$$N(t) = n_1(t) + n_2(t) + \cdots + n_n(t). \quad (1)$$

The appliances that are connected to a network are identified by their activation period. Usually, every device has a singular activation period that makes it distinguishable from the rest. So, it can be said that these activation periods are like a signature or a fingerprint; a similar idea is proposed in the work of Haitsma and Kalker [14].

However, we should stress that not all devices behave in the same way; as explained by Kaustav in [15] this makes their identification and distinction easier. Some groups of appliances have a more continuous performance in time than others. Other devices can only have two possible states—on or off. Some appliances, such as a microwave, have a more variable behaviour; this is related to their program or the role they are performing. However, there are also many appliances that have almost infinite behavioural patterns; this depends on the role they perform and on a specific moment in time, such as an LED printer.

Commonly, systems based on NILM techniques can be divided into three successive stages, consisting of three modules: a data acquisition module, a feature extraction module, and finally a learning module. The NILM process is illustrated in Figure 1.

(i) *Data Acquisition*. In this stage, the system obtains the data that allow identifying the different behaviours in an electric network; a meter system is used for this purpose.

(ii) *Feature Extraction*. In this module, the system extracts the connected devices and differentiates between active and inactive devices. That is, it is capable of detecting and extracting the activation periods of household appliances. Diverse techniques are used to extract activation periods; one of them is event-based extraction. These so-called events are the on/off transactions of the different devices. On the contrary, extraction that is not based on events uses sample times to determine whether an appliance is active.

(iii) *System Learning*. This stage consists of training and learning. Learning can be supervised or unsupervised. The systems with supervised learning need a labelled dataset in order to learn and identify devices correctly. Moreover, these systems can also be identified as on-line or off-line systems.

Consequently, to achieve the aim of this work, the system is operated by the different agents. Agents carry out all the subprocesses in the global system. The agents that form part of the system can be divided into two large groups, as shown in Figure 2. These two groups are environmental agents and processing agents.

Table 1: Comparison between the proposal and previous work.

	Belley et al. [2]	Belley et al. [3]	Lin et al. [4]	De Baets et al. [1]	Tang et al. [5]	Brown et al. [6]	Liang et al. [7]	Lee et al. [8]	Chen et al. [9]	Chen and Tan [10]	Batra et al. [11]	Our proposal
Use NILM techniques								X			X	X
New method	X		X	X			X		X	X		X
Improve a method		X										
Consider the state of the building					X	X						
Consumption prediction									X	X		
Toolkit											X	
Uses smart devices												X
Adaptive consumption												X

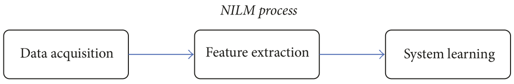

FIGURE 1: NILM process.

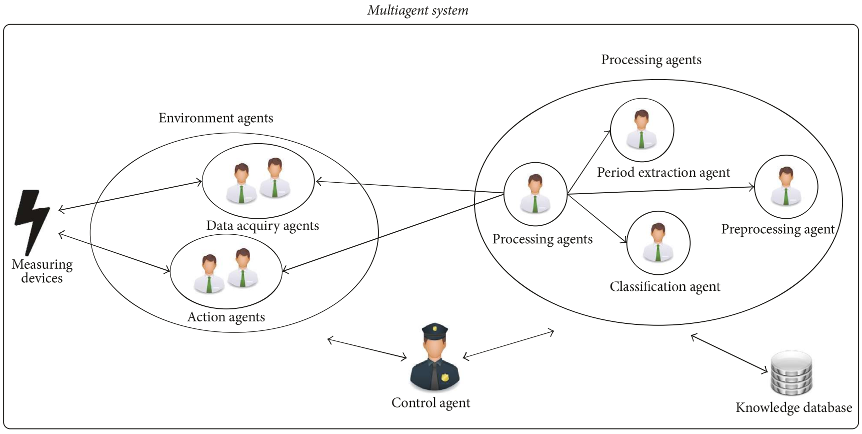

FIGURE 2: Proposed multiagent system architecture.

(i) *Environmental Agents.* These agents communicate with the measuring systems that are connected to the global system. Their task is to obtain data and work with the measuring system. The agents that acquire data have to communicate with the meters through the required protocols, in order to obtain them, whereas the agents acting on the meters are responsible for turning on/off the different lines of the measuring devices. By acting on the smart meter and the smart plug it is possible to manage demand according to requirements. For efficient demand management, it is necessary to identify the connected devices beforehand. This identification is done in the processing agents organization. In order to determine the order of priority in which these devices have to be switched off, the agent has a prioritized list of how important a device is for daily use and it proceeds to the interruption of supply according to these preferences, until the demand is adjusted.

(ii) *Processing Agents.* They are in charge of the internal processing of information. They carry out a number of actions, such as the pretreatment of data. They are responsible for all the important actions in the system. The processing agent controls the rest of the agents in the same group. The period extraction agent extracts activation periods from the raw data it receives. This agent will extract the consumption values of every activation period, in a way that there are as many groups with consumption values as there are activation periods. These activation periods are detected when the consumption changes in a considerable way. In Figure 3 we can see the agent will extract four activation periods. The preprocessing agent is in charge of extracting the necessary information for identifying the appliances. The extracted features are outlined below.

(a) Mean (m): this characteristic indicates the mean of the consumption values for each activation period; therefore it is the arithmetic mean of consumption of a device in its activation periods:

$$m = \frac{\sum_{t=0}^{n} w(t)}{n}, \tag{2}$$

where $w(t)$ is the set of consumption values in the instant of time t and n indicates the total time instants that compound the activation period.

(b) Maximum (m_x): this value indicates the device's highest consumption value during the activation period:

$$m_x = \max W, \tag{3}$$

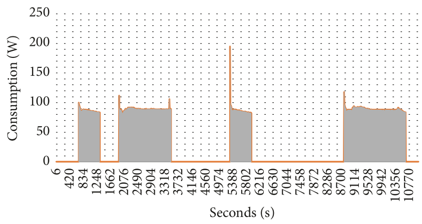

FIGURE 3: Line connected to a fridge.

where W is the set of consumption values of the activation period.

(c) Minimum (m_n): this feature indicates the minimum consumption value in the activation period of an appliance:

$$m_n = \min W, \tag{4}$$

where W is the set of consumption values of the activation period.

(d) First step (s_1): this value indicates the difference between the first value of the activation period ($w(0)$) and the maximum value (m_x). This "leap" is taken into account:

$$s_1 = m_x - w(0). \tag{5}$$

(e) Second step (s_2): in this case, the value represents the difference between the maximum value of consumption (m_x) and the last value of the period ($w(n)$), so that the second "leap" is also taken into account:

$$s_2 = m_x - w(n). \tag{6}$$

(f) Time (T): it refers to the time during which the device has been active, that is, switched on:

$$T = t(n) - t(0), \tag{7}$$

where $t(n)$ is the final instant of the activation period and $t(0)$ is the initial instant.

The classification agent is in charge of determining what kind of devices it is dealing with. This agent is able to predict what kind of a device exhibits the determined features. In this case, to identify the appliance, case-based reasoning is applied. There are several algorithms that agents can execute (some of them are defined in [16–20]); the process that is followed to determine which of them renders better results will be described in the Results.

Once we obtain a model that is capable of identifying home appliances with a certain level of accuracy, this model will be included in the case-based reasoning system. Every one of those cases will contain all of the features explained before. So, the cases will have the following structure:

$$C = \{m, m_x, m_n, s_1, s_2, T, class\}. \tag{8}$$

The nomenclature of a case is composed of the following values: mean, maximum, minimum, first step, second step, time, and the tag *class* which refers to the device that is represented by the characteristics of C. Thus, the CBR (case-based reasoning) will go through a phase in which it will recover the composed model. The CBR also has a reutilization phase where the recovered model will be used to classify new cases. If the model correctly classifies a new case in the review stage, we move on to the learning stage in which the new case is added to the database. If the user decides it has been incorrectly classified, the model is reconstructed taking into account the new instance added to the database.

(i) Control agent: it is in charge of monitoring the rest of the agents in the system that are found in any of the groups described previously.

The agents from different groups communicate with each other in order to achieve a common goal in the system. This communication between agents is illustrated in Figure 2.

As explained before, the accuracy of several machine learning methods in the identification of appliances was tested. These methods are data mining algorithms based on decision rules, decision trees, case-based learning, neural networks, and the Bayes theorem.

These algorithms can be combined with the fingerprint algorithm for the identification of home appliances. The fingerprint algorithm is used to identify music/songs by their sound wave. Wang [21] and Haitsma and Kalker [14] talk about this in their works. This technique is based on the calculation of hidden Markov models; however the main idea of this technique is the use of distances between the maxims of a sound, since at these points the sound is purer and there is less ambient noise. By finding maximum values and calculating the distances between them, the algorithm can compare these values with the ones stored in a database in order to identify a song; the system then provides the user with an answer containing all the information on the predicted song.

In this way, the relative sound wave maximums allow the algorithm to form a single fingerprint that would be contrasted with those stored in the system database. This algorithm can therefore be used to identify the appliances that are connected to a network once the periods of activation of the consumption network are extracted. The idea is quite similar; the maximums of these activation periods are used to identify the device. However, there is a possibility that difficulties occur in the extraction of relative maxims that contain information; this is because some devices have a continuous or constant activation. Other devices have a variable performance which is what makes them less predictable than others. All this suggests that the task of collating those "fingerprints" with records in the database would be complicated. We therefore have to study and analyze whether using the fingerprint algorithm is practical for this study.

4. Case Studies

For the case study consumption data from different buildings and different users and therefore from different lines of several electric networks were obtained.

Nowadays, there is a great variety of tools that allow measuring the amount of consumed energy in a particular electric network or by a specific appliance that is connected to that network.

Before the study of these technologies, it is important to clarify how they will be integrated in the intelligent system. The first aspect to consider is that this measuring system must offer information in real time; that is to say, the proposed system must be able to communicate with the measuring devices using some kind of protocol that establishes a connection between them. This will allow the intelligent system to communicate with the measuring system, extract information from it, and send it at specific moments.

The intelligent system must be able to manage the information it receives, and this information must regard the consumption of the electric grid or on the consumption of a particular electronic device. This is very important since the extraction of information is necessary for identifying the connected electronic device(s).

Another important feature that this intelligent system must possess is the ability to turn on/off the different devices connected to an electrical grid. Considering the total amount of consumption in a network, at times it may be advisable to turn off devices that are not being used but that continue to consume electricity. That is, the intelligent system must be able to act on the devices using the required communication protocol.

The following measuring and/or actuator devices make communication with the system possible thanks to specialized agents developed for each of them.

(i) *Smart Meter.* Intelligent meters or smart meters are used to measure consumption levels in a home, but in a more detailed and precise way than a traditional electric meter. In addition, these types of counters are capable of communicating the data that they read through some type of a protocol (usually a standard protocol) and in this way consumption can be monitored at all times. If necessary they can interrupt the power supply from a number of lines without interrupting electricity provided by the rest of the lines. This feature allows for the automatic management of demand, suited to the energy needs.

In this study, the German-made "EMH LZQJ XC" smart meter has been used. This device is manufactured by the "EMH metering" company. This smart meter has all of the functions that have been described in the previous paragraph and for this reason it can easily be integrated with any intelligent system. In Figure 4, we can see one particular model.

This model, in particular, communicates through a protocol that uses "TCP/IP" type connections. So, the information stored and managed by this meter can be accessed remotely. It is common for these meters to use standard communication protocols, and specifically the presented model uses the IEC 62056 protocol. Moreover, this smart-meter model has already been installed in many homes in Germany.

Figure 4: Smart-meter LZQJ XC.

(ii) *Smart Plugs.* Smart plugs can be plugged into a standard wall socket and the consumption of any electronic device that is plugged into it can be controlled. Figure 5 shows an example of a smart plug.

These devices allow controlling consumption remotely and in real time. We can operate these devices either through the official developer applications or through third-party APIs that allow establishing a connection with smart plugs.

In this way, smart plugs allow users to obtain consumption data remotely and in real time. It is essential for the intelligent system proposed in this article to be provided with the necessary information. It also allows acting on the devices connected to them, allowing the intelligent system to switch them off or on when necessary or convenient.

With these devices, the necessary information can be extracted and consumption data can be obtained for different electrical devices. To carry out this study ten different home appliances have been used; we have extracted sufficient samples from them to form a dataset. This dataset has been used to test supervised machine learning algorithms and helped us create a classification model that will enable us to identify the behaviour of future appliances. The following devices have been selected to validate the proposed system: a refrigerator, a water pump, a television, a dishwasher, an electric gas heater, a washing machine, a kettle, a freezer, a microwave, and an LED printer. Figure 6 shows an example of the distribution of different devices in a house.

The activation periods of some of these appliances are illustrated on the graphs found in the appendix, where it can be seen that in all cases the appliances have waveform characteristics. Once the characteristics of each activation period are extracted, the identification of devices is, a priori, performed easily. However, given that the behaviour of some of the appliances varies depending on their use over time, identifying them may be more complicated.

Figure 5: Edimax smart plug.

5. Results

This section will analyze the function of the agent organizations illustrated in Figure 2. Furthermore, it will examine the architecture's capability to acquire data from the devices and manage demand. Also, it will evaluate the performance of the processing organization in identifying devices connected to smart plugs. This automatic identification performed by the processing organization is necessary due to the dynamic variations in smart plugs.

The first step is the monitoring and control of the actuators. Firstly, in order to obtain consumption data, we must communicate with the different measurement systems that provide it. To do this, it is necessary to establish a connection with the meters through the specific protocols belonging to each of the meters. In Figure 7, you can see an example of how communication is established with the smart meter to obtain real-time information on energy consumption. Figure 8 shows a fragment of the response to the request for real-time consumption data. The real-time consumption information is located in row seven. Relevant data is then extracted from this information and it is used by the system.

The system uses the same communication protocol to manage the smart meter (Figure 7), thus communication allows for both, the acquirement of data and its management. This scheme is followed in order to reduce energy consumption whenever this is necessary, by acting on the different lines.

The second step is the evaluation of the processing organization. This organization includes the Automatic Device Identification System which uses an algorithm to classify different measuring devices. To choose the most accurate classifier, several supervised machine learning algorithms have been tested and their performance was compared. The following classifiers were used: RIPPER algorithm, PART, C4.5, RandomForest, RandomTree, REPTree, k-NN, KStart, Bayesian networks, and neural networks. These algorithms are provided by the machine learning library Weka. Different databases were used when comparing the algorithms, each database varied in the number of classes and each had one hundred instances per class. Tests have been performed with datasets of four, seven, and ten classes, respectively. Each of the classes is associated with a type of appliance, so that the instances belonging to the same class belong to different models of the same appliance. In order to evaluate the functioning of the identification system, the classifiers were included in the case-based reasoning system's reuse stage and the performance of each of them was analyzed in order to assess the effectiveness of the fingerprint algorithm in the detection of household appliances. After verifying the different algorithms and their classification accuracy, the final system makes use of a dataset of ten classes and one thousand instances, one hundred for each of the classes.

The created dataset has the same characteristics as those described in the architecture section. At the time of tests and experiments, this dataset will help to determine which algorithms offer better results and are the most suitable for the device identification system in a power grid.

In this part of the article we are going to describe the process that we followed to verify and create the final model. Initially a dataset was created, and it contained a total of 400 instances divided among four classes, each containing 100 instances. Therefore, the four classes in the dataset are balanced and represent four different appliances: a refrigerator, a water pump, a television, and a dishwasher. Tests were performed with this dataset, using the 10-fold cross validation method with each of the algorithms mentioned above.

Table 2 shows the results of the tests that were performed on the dataset.

As we can observe, all the proposed algorithms, with the exception of neural networks, offer excellent results. Moreover, the algorithms that work best are the algorithms whose behaviour is based on decision rules: rule algorithms and tree algorithms.

From these results, we can infer that all algorithms render very good results, but we wanted to see how these algorithms would behave if they had to identify more classes. So, three more appliances were introduced to the dataset: a washing machine, a kettle, and a gas heater. For each of these devices 100 new instances were introduced.

Again, we submitted the algorithms to a series of tests with the objective of seeing with what precision they classified the seven appliances. After validating the different models shown in Table 2, we could see that the algorithms that provided the best outcomes were those based on rules. Specifically, the RandomForest algorithm offered the best results and its validation is shown in Table 2, although this time with lower success rate, which is logical since the number of classes and instances has increased. However, if we look at the results of neural networks, their success rate has increased considerably in the second case, from around 0.89 to about 0.925. The improvement in the performance of this algorithm can be caused by a greater number of instances and classes and this leads the weights and the bias assigned to each of the simple neurons to adjust better to the characteristics of the problem. Furthermore, we decided to check if by adding three more appliances—a freezer, a microwave, and an LED printer—the neural network would exhibit further improvement. We also wanted to check if the accuracy of the rest of the classifiers

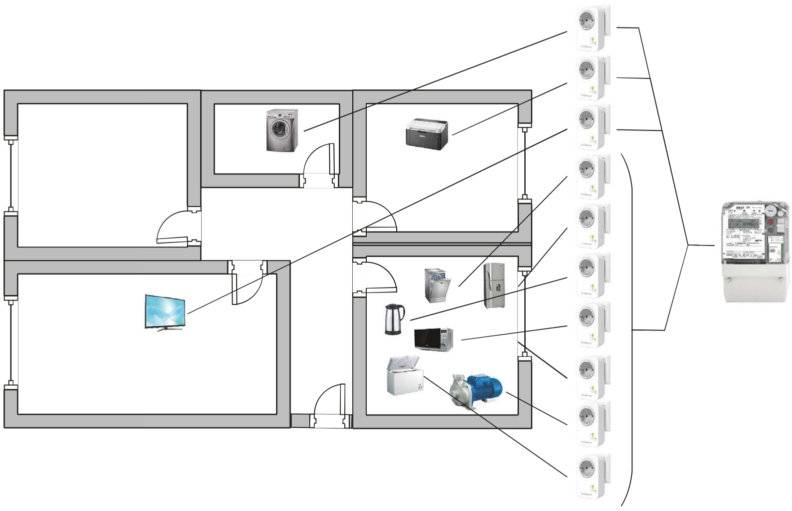

Figure 6: Distribution of the smart meter and smart plug in a house.

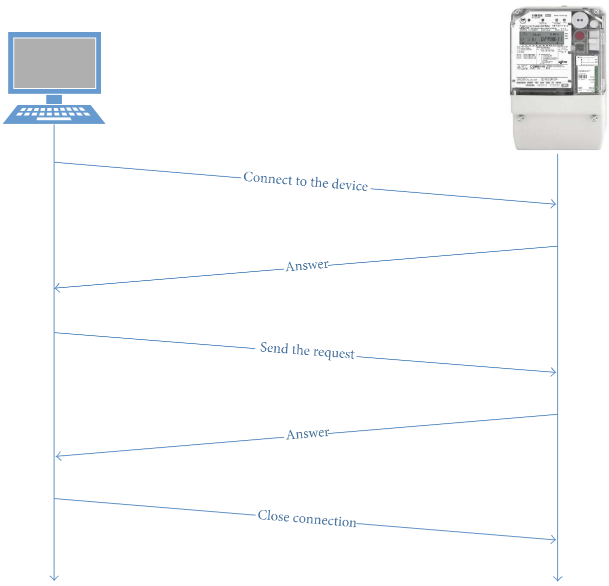

Figure 7: Smart-meter communication sequence.

Table 2: Datasets results.

Algorithm	Four classes' dataset		Seven classes' dataset		Ten classes' dataset	
	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa
RIPPER	0.9775	0.97	0.967143	0.9617	0.928	0.92
PART	0.9875	0.9833	0.975714	0.9717	0.959	0.9544
C4.5	0.9875	0.9833	0.974286	0.97	0.958	0.9533
RandomForest	0.9925	0.99	0.987143	0.985	0.98	0.9778
RandomTree	0.975	0.9667	0.977143	0.9733	0.96	0.9556
REPTree	0.99	0.9867	0.978571	0.975	0.945	0.9389
k-NN	0.97	0.96	0.967143	0.9617	0.952	0.9467
kStart	0.9575	0.9633	0.972857	0.9683	0.966	0.9622
Bayesian networks	0.9575	0.9434	0.94	0.93	0.927	0.9189
Neural networks	0.8875	0.85	0.924286	0.9117	0.853	0.8367

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F.F(00000000)
0.0.0(05439342)
0.0.9(1EMH0005439342)
0.9.1(0111147)
0.9.2(0170320)
1.2.1(000.188*kW)
1.2.2(000.000*kW)
1.2.3(000.000*kW)
1.6.1(0.102*kW)(0170314103000)
1.6.2(0.000*kW)(0000000000000)
1.6.3(0.000*kW)(0000000000000)
1.8.0(00016.722*kWh)
1.8.1(00016.722*kWh)
```

Figure 8: Smart-meter response.

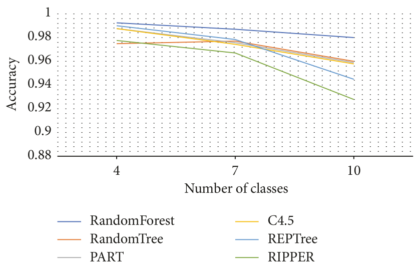

Figure 9: Results of rule-based classifiers in different test.

continued to decline as new appliances were introduced to the dataset. The results of this validation are shown in Table 2.

Interestingly, what we observe in Table 2 is that the accuracy of neural networks lowers significantly with three more classes. The performance of the other algorithms also decreased but to a lesser extent. For the third time, the algorithms that have the greatest accuracy are those that formulate decision rules, specifically RandomForest, which has an accuracy of 98%.

Good results are rendered by techniques that use decision rules and decision trees. We can therefore infer that this kind of algorithms performs well when determining what electronic devices are connected to an electrical network. For this reason, the graph in Figure 9 compares them on the basis of each of the experiments in which they had been tested.

From the graph, we can conclude that all these techniques have very similar behaviour; when the number of instances and classes increases the precision of the classifiers decreases. However, the RandomTree algorithm is an exception because its accuracy increased in the second test, which contained seven classes. Although RandomForest gave outstanding results, it is clear that all the rule-based classifiers performed very well and can be used to predict what devices are connected to an electrical network.

This statement could be confirmed with an ROC analysis. Various techniques can be used to carry out this analysis: the area under the ROC curve or the distance to the point (false positive rate, sensitivity) of each classifier to the point $(0, 1)$; this technique is explained by Fawcett [22]. The second technique has been selected because it allows distinguishing the different classifiers better. In Figure 10, the points of each classifier were represented in a two-dimensional space.

Table 3: ROC analysis of the best algorithms.

Algorithm	Distance to point (0, 1)	Area under the ROC curve
RIPPER	0.0724	0.98
PART	0.0413	0.987
C4.5	0.0423	0.984
RandomForest	0.02	0.998
RandomTree	0.0402	0.978
REPTree	0.0553	0.988

At first sight, the results we see here for the tested algorithms are the same that we saw in the previous plots and tables. However, they are nearer to the point $(0, 1)$. To verify this, we illustrate the results in Table 3, with the distance of each of the points, as shown in the graph in Figure 10, as well as the area under the ROC curve of each algorithm.

In these types of analyses, the distance is closest to 0 and the area under the ROC curve is the closest to 1. In cases where a classifier has these values, it could be considered

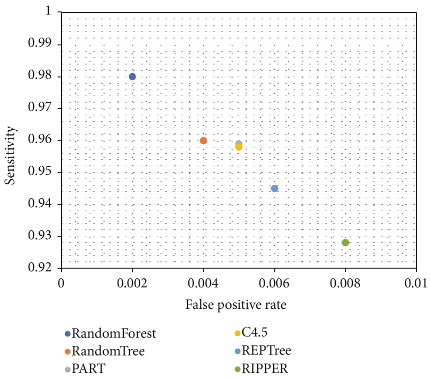

Figure 10: Rank positions (false positive rate, sensitivity) of classifiers.

Table 4: Attribute selection results.

Attribute	Info gain	Correlation
Mean	2.565	0.261
Maximum	2.333	0.248
Minimum	1.005	0.198
First step	2.21	0.289
Second step	2.197	0.289
Time	1.889	0.178

the most suitable classifier for that problem. In the analyzed algorithms, the two values obtained are very close to the objective values, so it can be said that the methods employed are very well coupled to the problem that arises.

However, there is no doubt that the success of these classifiers in the conducted experiments is largely due to the great quality of the dataset. The performance of instances and especially the selection of attributes from the dataset cause the difference in results when executing the machine learning algorithms, as we can see in the tables and the previous plot. For this reason, it would be worthwhile if we made an attribute selection with different techniques, in order to see which of these characteristics are more important when classifying a new instance.

To carry out these studies two different techniques have been used—the info gain and the correlation of attributes in connection with the class. Table 4 and Figure 11 show a comparison of the two techniques mentioned before. The results of these analyses have been normalized with the variable scaling formula, in order to make a clearer comparison between the results of the two techniques.

As can be seen in Figure 11, in the two techniques the most important characteristics that have to be considered in an algorithms' classification of instance are the mean, the maximum value, the first step, and the second one. The minimum value and time are less important than the other attributes in the classifiers' classification task; however, they are the main reason for which the accuracy of the tested techniques is so high.

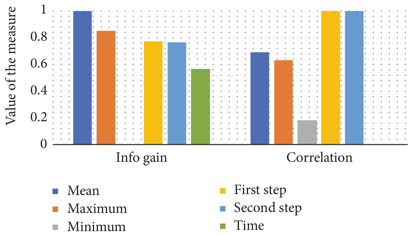

Figure 11: Results of attribute selection with normalized results.

6. Conclusions

This work presented the developed adaptive consumption management system, capable of identifying devices connected to an electrical network. In cases where the production of energy is scarce or when excessive energy is being consumed, the user can choose to disconnect some of the devices that are not necessary, in homes, offices, and so forth.

The proposed system has a multiagent architecture, where different types of agents are in charge of carrying out different functions in the process. The agent system also includes the use of case-based reasoning systems.

Different techniques and methods have been studied in order to consider the possibility of implementing them in the proposed system. Above all, we examined the different machine learning techniques that were the most appropriate for the type of problem presented in this work. Specifically, the Results demonstrates that there is a variety of algorithms that offers a more satisfactory behaviour, and for this reason any of these techniques could be used in the proposed system.

Moreover, the work studied the performance of existing devices developed for measuring electrical networks, as well as the home appliances connected to the network itself. The system presented in this work has been developed to act and communicate with two types of devices—smart meters and smart plugs. Thus, the system can obtain data from each of them.

Accordingly, the objectives set forth in the Proposed Architecture have been achieved. The designed platform adapts the consumption of electricity in the networks by interacting with intelligent devices. The purpose of the proposed method is the extraction of knowledge from the electrical network, which allows us to obtain a network's consumption data. It employs NILM techniques to identify the connected household appliances. Subsequently, a method based on the principles of the fingerprint algorithm is used to form a dataset with the identified devices. This dataset allows obtaining excellent results in adapting the electrical

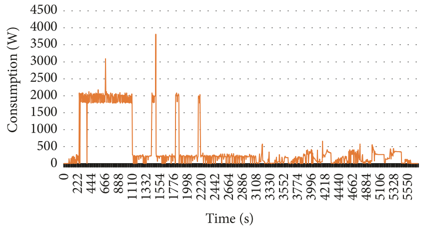

FIGURE 12: Washing machine activation period.

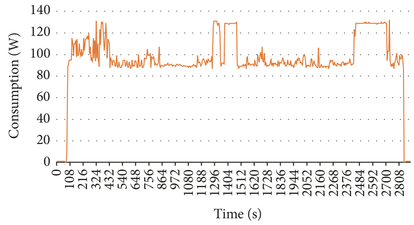

FIGURE 14: TV activation period.

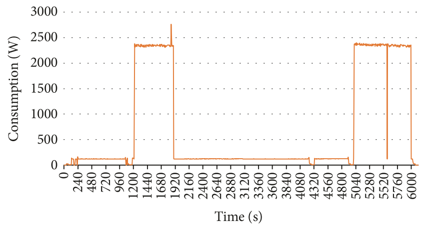

FIGURE 13: Dishwasher activation period.

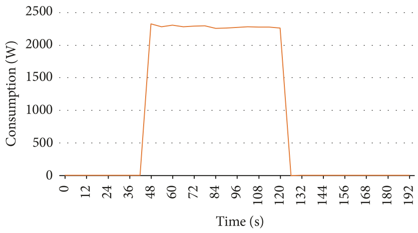

FIGURE 15: Kettle activation period.

consumption of the devices. Thus, the proposed platform uses a new method that leverages modern technologies for the control of the consumption in the network.

Making our system more effective is an important goal for the coming years. Therefore, future lines of research will include improving the system by adding more devices and appliances to it. This would allow identifying new devices and make the system more complete. The more the appliances in the system's database are, the more robust the system will be.

In addition, a new technique could be added for extracting the activation periods of the devices connected to the network. Some techniques allow withdrawing activation periods, as proposed by Serrà and Arcos [23]. Thus, the effectiveness of this type of techniques for the extraction of patterns in time series could also be verified in a future work.

Security is another aspect that certainly should be considered. The communications established between meters and the system connected to them could be provided with security. The reason for which this improvement is crucial is that transmitted information can be considered important and the privacy of users' data must be guaranteed in intelligent systems.

Appendix

In this appendix we introduce the activation periods of the different devices used in the study (see Figures 12–21).

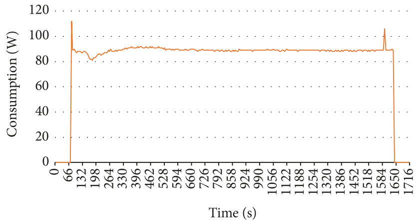

FIGURE 16: Fridge activation period.

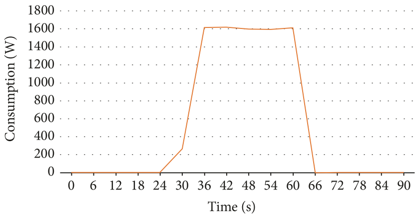

FIGURE 17: Microwave activation period.

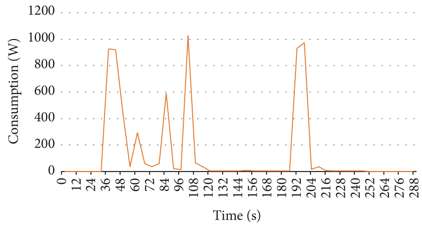

FIGURE 18: LED printer activation period.

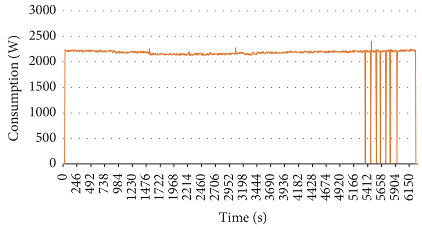

FIGURE 19: Electrical boiler activation period.

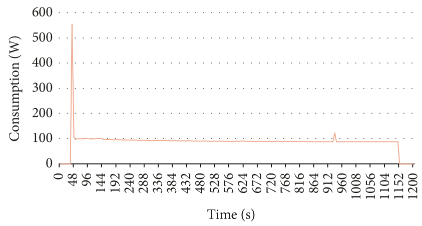

FIGURE 20: Freezer activation period.

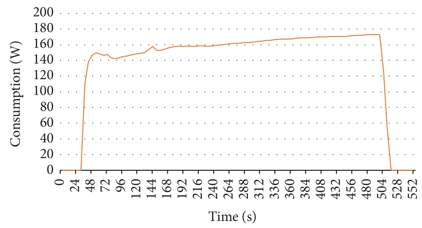

FIGURE 21: Water pump activation period.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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