Characterization of Energy Demand and Energy Services Using Model-Based and Data-Driven Approaches

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1 Introduction

The residential building sector is the second largest single consumer of final energy in Europe, accounting for 26% of the final energy consumption in 2018 and 16.6% of the primary energy [18], just behind the transportation sector (30%) and ahead of industry (25%) and services (15%). In terms of energy resources, natural gas accounted for 32%, electricity for 25%, renewable resources for 20%, and oil products 12%. In terms of end-uses, space heating accounted for 64%, followed by water heating 14.8%, lighting and appliances with 14%, and cooking with 6%.

In general, the energy efficiency in the residential sector can be improved by using more efficient energy equipment, by upgrading the building envelope characteristics, or by inducing changes in the consumer's behavior [5, 27]. The overall effects can be tracked by analyzing the trends of residential space heating intensity (energy consumption per floor area) as the largest end-use is usually space heating [27] or by analyzing the energy consumption historical time series and correlating it with the introduction of policy instruments like the building codes or appliance energy labels [5].

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To estimate and/or measure the impact of such actions in particular buildings or households, one should be able to develop accurate dynamic models of building's energy consumption [6]. As buildings are complex systems, the energy consumption is influenced by a combination of factors, including the age and location of the building, the household size, and the penetration of appliances and electronic devices—including the type, function, dimension, quantity, and efficiency [16]. However, two households with similar characteristics and equipment will present different energy consumption, as occupants' behavior will be different. Occupants' behavior in residential buildings can be described as the occupants' presence and the consequent use of active systems—like lighting, equipment, heating and cooling systems—and the interaction with other devices passive systems as windows and blinds that influence energy consumption. Thus, knowing the occupants' behavior is a key aspect to develop accurate models of energy consumption [26].

To describe occupant's behavior, it is necessary to perform occupancy surveys and occupants' monitoring (through sensors or direct observations), which can be time consuming and intrusive [44]. Currently, the deployment of smart meters is making the information about energy use more available [15]. In fact, EU has adopted a number of initiatives aiming to improve energy consumption awareness, including the replacement of at least 80% of electricity meters with smart meters by 2020 [17]. The smart meters data allows for a temporal assessment of the electricity use, which holds the potential to reveal insights about the electricity consumption and the behavioral and technological drivers of that consumption. In this way, the accuracy of the building's energy models can be increased, enabling the simulation of impactful measures for the improvement of the energy efficiency in the residential sector [37].

Most authors categorize energy consumption models in two classes: top-down approaches, where energy consumption is estimated by means of macroeconomic variables, like income, fuel prices, or average household floor area; and bottom-up approaches that estimate the energy consumption by synthesizing the energy consumption from the consumption of individual appliances or services [30, 43]. The first type of approaches is used when there is no specific detailed data about the households under study and therefore the energy consumption is inferred from related data, while the second is preferred when data is available. Top-down models only provide us information regarding the use of a certain type of energy in a yearly time scale and are valuable to infer general variables like total energy demand forecast [43]. However, to understand clearly the dynamics of appliances' use we need to use bottom-up models, which can be categorized into two sub-classes: engineering models, which are based on physical models of the buildings and the appliances; and statistical or data-driven models, which are based on energy consumption data.

This chapter describes the state-of-the-art methods to characterize the energy consumption and energy services in residential buildings. Firstly, a review is done spanning from model-based approaches—like building thermal simulation tools—to data-driven approaches—like Non-Intrusive Load Monitoring (NILM). This study discusses the context under which each of the approaches should be followed, such as the sampling rate of data and the available data features or even the evolution of equipment's and appliances under the new IOT setting. We also discuss the integration of these approaches, like using the model-based approaches to generate data from data-driven approaches in context with scarce data or the use of data-driven models to learn model-based models and replace them in context of real-time applications where the available computational time is low. Finally, some results are presented using two novel approaches, one based on interactive learning and another using factorial hidden Markov models, to demonstrate that it is possible to achieve reasonable demand characterization models for energy services in the residential sector.

2 Engineering Models

2.1 Building Energy Simulation Models

Building Energy Simulation (BES) models are frequently used to evaluate the effect of the energy efficiency measures, since they allow to study different retrofit solutions as envelope improvement, HVAC and lighting systems improvement and operation, or occupants' behavior change [6]. They are bottom-up models.

For the past 50 years, a wide variety of building energy simulation tools have been developed and enhanced throughout the building energy simulation community [12]. These building energy simulation software have different features and various capabilities such as: general geometry modeling; definition of zonal internal loads; building envelope properties, daylight and solar radiation; infiltration, ventilation, and multi-zone airflow; renewable energy systems; electrical systems and equipment; HVAC systems; environmental emissions; economic evaluation; climate data availability, results reporting, and validation [11].

Several limitations arise related with the simulation outputs, since buildings monitoring often identifies significant gaps between the predicted and actual energy use of buildings and its thermal behavior [11]. Consequently, several techniques have been developed to support building simulation analysis, including parametric simulation, sensitivity analysis, simulation-based optimization, meta-model analysis, etc. Still, the calibration process with measurements values of building models tends to be difficult and time consuming. The amount of parameters that are uncertain and could affect the outputs of the model is normally high and difficult to identify [11].

One of the parameters that has been acknowledged to introduce more uncertainty is the occupants' behavior, as its randomness is hard to model and is influenced by multiple contextual factors [26]. Moreover, the data to support these assumptions are hard to find, as it is usually gathered through surveys, literature review, occupancy sensors and, more recently, from smart meters. To overcome this problem, typical or average profiles describing the occupants' presence are often used in energy simulations. However, the main criticism of this approach is the oversimplification, where the behavioral differences between occupants and the variability of occupants' behavior throughout the year are not considered.

2.2 Technological Models

Technological models assume that the energy consumption in a household is the sum of the use of different appliances. Therefore it requires the knowledge or assumption of what appliances exist in a household, and then the power consumption of each appliance and the time of use. These models require the existence of extensive databases of empirical data to support the description of each appliance. Often these models complete the bottom-up information with top-down information, like appliance ownership or appliance efficiency. As examples of use, we have [25] that present an approach to a bottom-up model at the energy service level, or [23] that estimate the heating, cooling, and domestic appliances' energy use for different climatic regions in Algeria.

2.3 Time-of-Use-Surveys Models

Time-of-use surveys (TUS) are surveys completed by residents, usually by keeping logbooks or diaries about the time use of activities an individual engages in during a specific time interval throughout the day. This information is extremely important to characterize the occupants' behavior and can therefore be used in building simulation models or technological models.

As examples of use of TUS, [46] analyzed the UK's time use survey 2005 to identify how social practices in the household take place in relation to the time of the day, including preparing food, washing, cleaning, washing clothes, watching TV, and using a computer. Fischer et al. [21] used the German TUS to develop a stochastic bottom-up model that generates synthetic electrical load profiles taking into consideration the seasonal occupant behavior and the correlation between the start time and the duration of an activity. More recently, [22] created models to generate a daily electricity demand profile that can be representative of a large number of Danish households using TUS.

2.4 Using Smart Meter Data to Improve Engineering Models

Electricity consumption data can provide useful information about the consumers and their habits. In fact, there has been an increasing use of smart meters data in current studies, namely to identify various types of consumers for short-term and midterm load forecasting, time-of-use (ToU) tariff design, and demand-side management (DSM) strategies [45]. Other studies focus only on the residential load characterization [42], or on inferring about the drivers behind the residential consumption, in terms of socio-economic status, appliances stocks, and dwellings characteristics [33]. Finally, electricity consumption disaggregation, appliances, lighting and plug load profiles distinction, as well as occupancy inference and inhabitants' routines are other uses of smart meter data [37]. Thus, smart meter data can be used to characterize the activities and equipment in building simulations and therefore used to calibrate and validate engineering models. This approach is particularly useful when it is necessary to extrapolate the energy consumption models for cities or regions based on the detailed monitoring of few households [24].

3 Data-Driven Models

Another approach to characterize energy demand characterization is to monitor in detail the energy consumption. Several load monitoring techniques can be implemented to determine the consumption and status of different appliances to understand the behavior of the different essential loads in the household. These techniques can be divided into two main types: Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM).

3.1 Intrusive Load Monitoring

Intrusive Load Monitoring (ILM) is a data-collection technique where measurement devices are installed at each appliance node to detect its power consumption [38] and therefore characterize in detail the household consumption. The main benefit of this technique is the accuracy of the results; however, it requires expensive and complicated installation systems [38].

The databases generated by ILM systems can be labeled in two ways: manually, which means that the appliance that is being monitored is labeled by the user; automatically, which means that the system is trained with examples from typical appliances and then recognizes the appliance that is being used. In general, manual setup ILM systems outperform automatic setup ILM systems.

3.2 Non-intrusive Load Monitoring (NILM)

Non-Intrusive Load Monitoring (NILM) technique is an alternative process, in which one single monitoring device is installed at the main distribution board at the household and an algorithm is applied to determine the energy consumption and the state of operation for each individual appliance [40]. As expected, the main advantage of NILM is the fact that only one single monitoring device is required thus lowering significantly the cost and the intrusion at the household level. The main disadvantage is the lower accuracy compared to ILM systems, in particular, those with manual labeling.

In general, any household appliance can be categorized in one of these classes [40]:

- on/off appliances, e.g., light bulbs, which have only two states: off (no consumption) and on, with a fix power demand. The duration depends on the user;
- finite-state appliances, e.g., fridges or dish-washers, which have multiple states, each one with its own power demand, and where the duration of each state is usually fixed and cyclic;
- continuously varying appliances, e.g., laptops, which have infinite states (continuous power demand) and which behavior is not cyclic;
- permanent demand appliances, e.g., routers or alarm-clocks, which are always On with a fixed power demand.

The appliances can be detected by "event-based" algorithms that detect the On/Off transitions or by "non-event-based" or "energy-based" methods that detect whether an appliance is On during the sampled duration [8].

These algorithms can use different measurements and features data, such as active and reactive power, voltage and current measurements, signal waveform and current harmonics signatures or high frequency electromagnetic interference (EMI).

The sampling rate is an important parameter in the complexity level of the disaggregation methods, as it affects not only the type of feature that can be measured but also the type of algorithm that can be used. A detailed discussion on the features and algorithms can be found in [41].

A high frequency (1 s–1 m) sample data rate allows more accuracy and detailed analysis to detect appliances loads. However, the large amount of measured data requires higher quality hardware and requires storage and processing capacity (locally or in the cloud) to run the disaggregation algorithms.

Recently the challenges in NILM approach focus in solving the disaggregation problem for the regular smart meters, which measure data at a lower frequency. The sampling rate varies between 15 min and one hour, according to the recommendation of the Energy Regulatory Authority of 2010, which states that the smart meters installed in each household must have the ability to measure the power consumption and save the actual data for at least 15-min-periods [49].

The methodologies to solve NILM problems encompass a mixture of domains. A majority of the earliest research focused on this problem from a signal processing perspective. The focus was on identifying different appliance signatures which distinguishes one appliance from another by analyzing with mathematical tools (for example, wavelet transformation) [9]. Subsequent research also considered the problem as a blind source separation task and proposed relevant techniques in that direction [32]. The details of the approaches can further be understood for the data distribution perspective.

3.2.1 NILM for High-Sapling Rate

A high-sampling rate NILM approach is generally a sampling rate of around 1 sample per second (1 Hz). In the last two decades, there has been a considerable amount of work to this effect. Each new method proposes to reduce the limitations of the previous ones both in term of signatures or applying state of the art pattern recognition techniques. The identified features are known as appliances signatures. Approaches typically consist of identifying the steady state or in some cases transient state features [51]. Subsequently, these signatures are matched with earlier learned models using a pattern recognition algorithm [9]. The drawbacks of these approaches are mainly the hardware requirement to monitor and process the information [19].

These methods do not fit well into the smart meter sampling rate, so a separate device has to be installed for training, visualization, and communication to the grid. This is a major drawback for these methods, commercially and practically speaking. The load separation at a high-sampling rate of all the appliances also raises privacy concerns as user activity can be easily detected, interpreted, and monitored [10].

3.2.2 NILM for Low Sampling Rate

At a low sampling rate (a sampling rate in the order of minutes) switching events are difficult to detect so non-event-based methods are more suited. The major issue at low sampling rate is that low energy consuming devices are difficult to be detected. However, high energy consuming appliances, such as water heater or washing machine, can still be identified with reasonable precision even at sampling rate of 15 min for example [28].

Considering the constraint of low sampling rate, the differentiation of the methods is directly dependent on the choice of algorithms. A method that partially disaggregates total household electricity usage into five load categories has been proposed at a low sampling rate in [32], where different sparse coding algorithms are compared and a Discriminative Disaggregation Sparse Coding algorithm is tested. A feature-based Support Vector Machine classifier accuracy is also mentioned but is not presented. The method of [32] is an implementation of the blind source separation problem, which aims at disaggregating mixture of sources into its individual sources. In the NILM context, the problem is undermined as there is only one mixture and a large number of sources. Another issue in using blind source separation is the assumption of no prior information about the sources. On the contrary, in this context, the sources (appliances) do have separate usage patterns which could be used. Nevertheless, blind source separation still remains a promising direction of research in this domain.

Temporal graphical models such as Hidden Markov Models also have been promisingly used in this domain as they are a classical method for sequence learning [34]. They have been successfully used in many domains, especially in speech recognition. In this context, the problem is to learn the model parameters given the set of observations as input sequence and appliances states as output. Hidden Markov Models also consider sequential patterns in consumption but in NILM problems, at a very low sampling rate it seems to have a high sensibility to training noise.

3.2.3 New Approaches Based on Machine Learning Algorithms

More recently, as in other domains, machine learning algorithms have been getting attention to solve the NILM problem [40]. Both supervised and unsupervised approaches can be used, but unsupervised methods have the advantage of not requiring a preliminary dataset to train the algorithms.

In supervised methods, the applications span from Bayesian classifiers which assume that the states of the appliances are independent although this is often not true in practice [7], to Support Vector Machine [20], Hidden Markov Models [52], or Artificial Neural Networks [47].

For unsupervised methods, most of the research is based on Hidden Markov Models, as it not required to perform event detection. This makes these algorithms suitable for low frequency samples as event detection is very difficult or not possible. In particular, Factorial Hidden Markov Model is a popular approach, as the observation for each appliance results from the output of each individual Markov model [31].

4 Case Study: Application to Residential Energy Consumption in France

In this section, we present the application of different types of methods to characterize energy demand and energy services in the residential sector using model-based and data-driven approaches for the case of France.

Between 2006 and 2008, a European project called REMODECE [13] was developed with partners from 12 EU countries that did a very detailed characterization of the electricity consumption of the residential sector in Europe. The large-scale monitoring campaign and a consumer survey around 1300 households and the study involved the collection of 6.000 questionnaires. About 11.500 single appliances were analyzed.

In the case of France, a large dataset denominated IRISE was collected, which includes the total energy consumption and particular appliances consumption in 100 households in France between 1998 and 2000. The dataset considers a broad set of electrical appliances spanning from low power-low consumption appliances such as lights to large power-large consumption appliances, such as DHW systems, HVAC systems, and wet appliances. Over the last years, this database has been used to calibrate, validate, and develop several models of the energy consumption in the residential sector in France.

After discussing the different methodological approaches to characterize the energy consumption and energy services for the residential sector, in this section we lay the foundations to discuss the applicability of each type of methods. For the engineering models, first we summarize the findings of several research papers that have been published using the IRISE dataset by type of model and then we propose a novel data-driven model to perform the characterization of energy demand, based on a new approach, the Interactive Learning [2, 3] and we compare it with standard NILM approaches for the same datasets.

4.1 Engineering Models

4.1.1 Building Energy Simulation Model

Kashif et al. [29] proposed a co-simulation environment for energy smart homes that takes into account inhabitants' dynamic and social behavior. To do that, the set-points for different controllers are adjusted using a physical building energy simulation model. To model the human behavior, the Brahms environment was used. The IRISE dataset was used to understand how inhabitants' behavior affects energy consumption. Subsequently, to model the behavior, a questionnaire was used that captured the context and the time-of-use of devices that impact the consumption.

Plessis et al. [36] proposed also a co-simulation environment using an Agent-Based Modeling (ABM) to simulate occupant behavior and a building energy simulation model that uses hybrid and differential algebraic equations to perform the dynamic thermal modeling. The "Mozart" house was modeled as it is one of the most representative houses in the French residential building stock (medium size detached house of $100\,\mathrm{m}^2$ of living surface area and an air volume of $252.15\,\mathrm{m}^3$). The FMI standard for co-simulation was used to couple the SMACH occupant behavior simulator and a building energy model built with the BuildSysPro Modelica library. Again, the IRISE dataset was used to describe the occupants' behavior.

From these examples, we can conclude that the use of building energy simulation models is mostly adequate to forecast the thermal behavior of a household given a set of different control parameters (e.g. switch on the heating or cooling system, increase the set-point temperature, close the blinds or open the windows), which has a significant impact in the energy demand of a household.

4.1.2 Technological Models

Almeida and Fonseca [1] describe the detailed monitoring campaign done under the REMODECE project and, based on that analysis, propose a technological model that describes the average energy consumption in the residential sector in Europe. From the data, they extracted the average power consumption for different appliances and the average time of use. They concluded that at the time, the electronic loads were a key contributor to the power demand and that there was a wide range of performance levels in the models available in the market. They also looked into detail into the patterns of residential lighting use, in which an increasing penetration of CFLs was being partly compensated by an increasing penetration of halogen lighting. Residential air conditioning was growing fast and was already a major contributor to summer peak demand in Mediterranean countries, as shown by the summer load curves from very hot days. Finally, based on the technological models, they were able to evaluate the potential energy savings from improving the efficiency of different appliances.

From this example, we can conclude that technological models are useful to estimate the impact of energy efficiency measures based on the replacement of appliances with low efficiencies.

4.1.3 Time-of-Use Survey Model

De Lauretis et al. [14] try to correlate the average energy and expenditure intensities of time uses of the total population as well as of income, household-composition and housing-type subgroups. To do that, they use a time-of-use survey done in France from 2009 to 2010. They find out that income is an obvious driver of energy and expenditure intensities but is revealed to influence time use as well. Household composition and housing type are also associated with substantial variations in activity patterns and in the energy and expenditure intensities of activities, even within a given income group. In conclusion, they underline the importance of household disaggregation in household energy analyses, to properly account for such disparities.

Robinson et al. [39] have proposed a structure for a new multi-agent simulation system in which occupants' presence, activity, behavior, comfort, and investments are each simulated in a coherent way using time-of-use surveys and bottom-up technological models. They suggest that this forms a robust basis for future simulations at the range of scales, from the building to the urban and beyond, with which we wish to examine occupants' impacts on sustainability and test strategies for ameliorating these impacts.

From these examples, we can conclude that time-of-use surveys are important source of information to describe the activities in the residential sector and therefore can replace detailed monitoring campaigns or questionnaires to characterize the activities in a household. Together with a technological model of the appliances that are used during each type of activity, it is possible to build a detailed disaggregated model of energy consumption.

4.2 *Data-Driven Models*

4.2.1 Intrusive Load Monitoring

The IRISE dataset was built using an Intrusive Load Monitoring approach [1, 13].

Basu et al. [8] perform a detail analysis for all the 100 households and conclude that they can be clustered in 4 main classes depending on the average load, average deferable load, area, and number of occupants.

Here, we chose to include houses with both Water Heating and Electric Heating Appliances. From the available dataset, 3 houses have been chosen: 28, 38, and 78. These houses also have other appliances with high power, such as the “Electric Cooker” or “Micro Wave Oven” that during the identification process might introduce uncertainty. Compared to the work of [8], house 28 would fall in the cluster "2," 38 would fall in cluster "1," and 78 in cluster "3."

Table 1 summarizes the main indicators regarding the consumption in each household. We can see that the houses present different profiles: house 38 has high consumption, distributed throughout the day. Houses 28 and 78 have low consumption and the consumption patterns more concentrated in specific periods (dawn for 28 and evenings and dawns for 78).

4.2.2 Non-intrusive Load Monitoring

The IRISE dataset was already used to develop Non-Intrusive Load Monitoring approaches, as describes in [8]. That work proposes a generic methodology using temporal sequence classification algorithms, based on an innovative time series distance-based approach that uses k-nearest classifier using different distance metrics (Euclidean, dynamic time warping, and temporal correlation), with 10% training and 90% testing. The results are compared with a standard NILM application based on the hidden Markov model (HMM) algorithm, using precision, recall, and F-measure, commonly used in information theory studies [48], but the proposed approach outperformed the HMM.

Table 1 Energy consumption of the houses in the dataset

House	28	38	78
Total yearly consumption (kWh)	8943	14031	8264
Average hourly consumption (kWh)	1.02	1.60	0.94
Standard deviation of hourly consumption (kWh)	1.27	1.97	1.22
Hourly peak (kW)	6.9	4.6	7.9
Water heater	16.71%	15.57%	67.19%
Electric heating	58.31%	52.25%	1.72%
Clothes drier	0.74%	2.14%	4.48%

The results for the k-nearest approach using the dataset with 10 min resolution to detect the ON event are described in Table 2. Notice that these results are not specific for houses 28,38, and 78, but for houses in the same cluster.

For this work, we asked the company WATT-IS to run the results for the chosen houses [50]. This algorithm combines the traditional NILM techniques based on "event detection"—which explores heuristics derived from the power demand, power variation, and total energy consumed for each event from different appliances—and unsupervised machine learning techniques (as there is no labeled data), like clustering to identify similar events and feature selection, to identify the most relevant data attributes. The algorithm is totally unsupervised.

The results for the NILM using the dataset with 10 min resolution are described in Table 3. We cannot directly compare these results with the ones in [8]—as those ones are for different houses within a cluster that presents similar characteristics, so the relative weight of the appliances and even the use of the appliances is different. Still we can see that the F-score is lower than the k-nearest supervised approach from [8], which demonstrates that at this sample rate, the water-heater loads, electric heating, and clothes drier, the signals can be mixed.

Finally, we also applied an algorithm based on Factorial Hidden Markov Model from [35], which was based on [31].

Table 2 Results for NILM approached based on k-nearest classifier from [8]: 10 min

House	Appliance	F-score
Cluster 2 (28) On	Water heater	94%
	Electric heating	n.a.
	Clothes drier	n.a
Cluster 1 (38) On	Water heater	91%
	Electric heating	n.a.
	Clothes drier	n.a.
Cluster 3 (78) On	Water heater	91%
	Electric heating	n.a.
	Clothes drier	39%

Table 3 Results for NILM: 10 min

House	Appliance	Precision	Recall	F-score
28 On	Water heater	32%	40%	36%
	Electric heating	66%	68%	67%
	Clothes drier	n.a.	n.a	n.a.
38 On	Water heater	66%	45%	54%
	Electric Heating	33%	75%	45%
	Clothes drier	n.a.	n.a	n.a.
78 On	Water heater	45%	31%	37%
	Electric heating	13%	1%	2%
	Clothes drier	n.a.	n.a	n.a.

Table 4 Results for factorial hidden Markov models: 10 min

House	Appliance	Precision	Recall	F-score
28 On	Water heater	93%	65%	75%
	Electric heating	80%	72%	75%
	Clothes drier	n.a.	n.a	n.a.
38 On	Water heater	91%	67%	77%
	Electric heating	55%	68%	60%
	Clothes drier	n.a.	n.a	n.a.
78 On	Water heater	93%	62%	74%
	Electric heating	n.a.	n.a.	n.a.
	Clothes drier	n.a.	n.a	n.a.

The results are described in Table 4. The results show that for water heater and electric heating, the algorithm presents higher performance and is comparable to the supervised approach presented in [8].

As a conclusion, NILM approaches can be used to disaggregate the use of the appliances, especially the ones that present a significant weight in the overall consumption. The approach presented in [8] appears to capture fairly well the water heater, but is uses a training set. The NILM proposed by WATT-IS, which does not use any labeled training data, is able to capture fairly well the appliances if the relative weight in the consumption is high, as it is the case of electric heating in houses 28 and 38 and Water heating in house 78. The NILM using Factorial Hidden Markov Model performs well, except if the relative weight in the consumption is small, like the electric heater in house 78. Overall, even with low resolution data, NILM models can be used to obtain detailed disaggregated data without resorting to ILM, in order to supply information of occupants' behavior for other models, like building simulation models or technological models.

4.3 A New Approach to Develop Data-Driven Models: Interactive Learning

In this work the deployment of Interactive Learning (IL) is used to disaggregate the appliances consumption. IL is a supervised learning methodology that involves the exchange of information with the user to collect a training dataset related to a specific context [2]. One of the advantages of IL is that useful feedback can be obtained from the end-user and increase their awareness of energy systems. This algorithm, proposed by Amayri et al. [2], has been successfully applied to estimate the occupancy in office rooms, using different sensors and avoiding the use of cameras [3]. Besides, the concept of interactive learning allows us to evaluate and improve the quality of the database [4].

In Interactive Learning, each data point is a list of features coming from sensors, which is called an "ask." In our case, the features correspond to the list of features which include the current and the previous total electricity consumption data, the hour of the day and the derivative of electricity consumption. The data point may include a label provided by the feedback of the user regarding the use of a certain appliance. The main problem in interactive learning is to determine when a candidate "ask" should be considered for collecting occupant feedback, considering the existing database. The density of the neighborhood, average error estimation, the weight of each class, and the score of the spread of the data (Qscore), are used to define the valuable time to interact with the end users. In [3, 4], the IL approach is enhanced to define the right time to question occupants when relevant, by limiting the number of interactions and maximizing the information gain. The classifier construction is part of the method, so the IL will determine what is the expected state of the appliance at the next instant.

In this work, the algorithm of IL is used as a multi-label classification model (i.e., three appliance states, on/off). The interactivity depends mainly on the methodology used to define when it is necessary to ask occupants information about the state of the appliances. It does so by limiting the number of interactions and maximizing the information's usefulness about the disaggregated appliances.

The first step for the validation is to apply IL approach with the spread rate concept [4] on IRISE case study. At this step, Human Machine Interface (HMI) interaction with end users in the IRIS houses is simulated, using as the answers of the "asks" the data labels obtained from the power consumption sensors which are connected to each appliance. Naive Bayes classifier has been applied with the interactive learning process.

In Table 5 we present the number of "asks" over 18 days and Table 6 presents the results.

Comparing IL to the NILM results, we can see that in general, the IL method outperforms the NILM for the Water Heater and Electric Heating, especially for the houses where the performance of NILM was lower (water heater On in house 38 and Electric Heating ON in house 78). Further, IL presents the advantage of identifying the clothes drier, although the accuracy of the ON detection is low (around 30%). This is due the fact that the weight of this type of appliance in the total consumption

Table 5 Number of asks each day: 10 min for one appliance

Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Number of *asks* with 100 % replies (28)	18	3	0	0	0	1	0	0	2	1	0	0	2	1	0	1	0	0
Number of *asks* with 100% replies (38)	16	3	0	0	0	0	0	2	1	0	0	2	0	0	1	0	0	0
Number of *asks* with 100% replies (78)	20	0	1	2	0	0	0	0	0	1	0	0	0	0	1	0	0	0

Table 6 Results for Interactive learning: 10 min

House	Appliance	Precision	Recall	F-score
28 On	Water heater	85%	76%	81%
	Electric heating	50%	34%	66%
	Clothes drier	24%	33%	37%
38 On	Water heater	54%	33%	30%
	Electric heating	77%	64%	70%
	Clothes drier	35%	10%	14%
78 On	Water heater	90%	89%	87%
	Electric heating	99%	99%	99%
	Clothes drier	25%	70%	41%

is small, so there are not a lot of data to perform well the classification, compared to the other appliances.

5 Discussion and Conclusions

In this section, we summarize the findings regarding the use of the different types of approaches that can be used to characterize the energy demand and energy services in the residential sector.

The choice of the approach to use regarding the model is based on two dimensions: the objective of the study and the available data. Firstly, engineering models like building energy simulation models or technological models have to be used to estimate the energy service demand (heating and cooling needs, water heating, lighting, cooking), which are extremely difficult to obtain from data-driven models, as these are complex to measure directly. Consequently, if the objective of study is to develop an energy management system or evaluate the impact of energy management strategies, whether it refers to changing the set-points of appliances or the replacement of the appliances, it is necessary to resort to an engineering model. No data-driven model "per se" will be able to provide conclusive answers regarding the changes in consumption caused by changes in the operation of the appliances.

In any case, engineering models require in general the modeler to consider several assumptions, like, for example, the occupant's behavior in terms of schedules or set-points. In this case, time-of-use surveys provide this information, as they describe the type of activity and eventually details about the use. On its own, TUS cannot be used to characterize the energy consumption, only if coupled with an engineering model.

Finally, data-driven models can only be implemented directly to characterize energy consumption, as this is the variable which is usually measured. In case of ILM approaches, the details of the demand characterization (for example, when each appliance is operating) depends directly on the monitoring system. However, in most cases, only aggregated measurements and with low resolution are available.

In that case, NIML approaches can disaggregate information. The challenge for NILM approaches is that the data being monitored is in general low resolution data, without labeling. The comparison between three different NILM approaches shows some differences between the algorithms, but in general for this low resolution, these algorithms are able to capture the operation of the appliances that are relevant in the overall consumption (water heaters, heating systems). Even the detection of large white appliances presents a significant challenge if no labeled data is used.

To solve this challenge, we propose here the use of Interactive Learning, which is a learning method that can label data directly with the user feedback in case the available data is not enough to perform the classification. As shown in the results, after a first initial set of questions on the first days, the need to ask the user for additional information is sparse. It presents the advantages of NILM (only using aggregated data) with the advantages of ILM, which is the access to labeled data. In this way, we find IL a very promising approach to disaggregate total energy data, even for low resolution data and with the additional capability of disaggregating the use in other appliances.

The disaggregation provided by NILM models, even if the accuracy it is not very high, can replace to a certain extent the Time-of-use-surveys, as often specific activities are related to the use of specific appliances. This is the case of an electric oven (used when people are cooking) or a TV. However, this is not necessarily true for heating systems (they can operate while people are cooking, watching TV or sleeping) or water heaters with storage tanks (they can heat the water before people take their shower or when they are not at home). Again, the use of an approach like IL is less invasive than performing a detailed questionnaire regarding the use of appliances.

Finally, to characterize the energy services, it is necessary to couple the data-driven model with a technological model or energy simulation model. Take as an example the hot water service. Measuring water heating consumption without measuring the water temperature or the water consumption requires a technological model to infer the service from the data. The same applies for heating needs. Even with the temperature of the room, it is necessary to know the area of the heated space, the type of equipment to estimate the service.

From the examples described, we see that most of the works that perform detailed energy demand characterizations often use co-simulation frameworks, integrating different types of models. Thus, we believe that in the current context of large-scale deployment of smart meters in the residential sector, it becomes feasible to characterize in detail the energy consumption and energy services in the residential sector.

With the aggregated electricity consumption data, and using NILM or Interactive Learning, it is possible to disaggregated energy consumption, replacing ILM approaches. From multiples households disaggregated data it is possible to build appliances databases and generate technological models from it. This allows to identify households with poor performance equipment or inadequate uses of equipment (e.g., water heaters operating during the day and not taking advantage of lower tariffs in the evening). From disaggregate data from multiple households in the same location, e.g., neighborhood, it is possible to infer the parameters about the houses for energy simulation models. Take the example of several households that use the air-conditioning in the same building. By comparing the use of it, we can estimate infiltration or envelop losses using energy simulation models. And with good calibrated simulation models, it is possible to design smart energy management systems that learn the behavior of the user, learn the characteristics of the equipment and the buildings and optimize the energy system by minimizing consumption while providing the correct comfort level of energy service.

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