Residential Appliance Identification and Future Usage Prediction from Smart Meter

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Residential Appliance Identification and Future Usage Prediction from Smart Meter

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***Abstract*—Energy management for residential homes and/or offices requires both identification and prediction of the future usages or service requests of different appliances present in the buildings. The aim of this work is to identify residential appliances from aggregate reading at the smart meter and to predict their states in order to minimize their energy consumption. For this purpose, our work is divided in two distinct modules: *Appliance identification* and *future usage prediction*. Both identification and prediction are based on multi-label learners which takes inter-appliance co-relation into account. The first part of the paper concerns the identification of electrical appliance usages from the smart meter monitoring. The main objective is to be able to identify individual loads from the aggregate power consumption in a non-intrusive manner. In this work, high energy consuming appliances are identified at 1-hour sampling rate using novel set of meta-features for this domain. The second part of the paper concerns future usage prediction. A comparison of algorithms for future appliance usage prediction using identification and direct consumption reading is presented. This work is based on a real residential dataset, called IRISE: 100 houses monitored every 10 minutes to one hour during one year (including weather informations).**

***Index Terms*—Non-intrusive load monitoring, Multi-label classifier, Appliance usage prediction, Energy Management, Datamining, Smart Homes, Smart Grids.**

I. Introduction

There are currently two main ways to deal with the worldwide growing energy consumption. The first, to globally increase energy production capabilities. The second, to head toward a more efficient energy consumption. Considering this last scenario, we chose to focus on one of the highest energy consuming sectors : residential buildings. In the near future, the main issue for civil engineering is the thermal insulation of buildings. But in the long term, issues concern *local integration of renewable energy* and *smarter buildings* connected to *smarter grids* [1]. A relevant knowledge of appliances consumption in buildings is needed for control or monitoring, the issue being to properly define "relevant knowledge". Monitoring and control of appliances consumption has two different purposes whose business model is still in development. First, from a *user* point of view, having informations on appliances level usage can lead to reduced cost through a reduction of the consumption of energy or possible ancillary services (unbalancing requests, load shading or energy price variations, etc.). Second, from a *smart grid* point of view the control of more loads represent more stability for the grid, i.e. more flexibility and reliability (reduce peak demand by eliminating electricity use, or by shifting it to non-peak times, etc.). These services represent elementary bricks of an energy management system whose privacy limits has still to be defined. They are based firstly on load identification and secondly on prediction of load energy consumption. Fig. 1 shows the different actors in a *smart residential building* or *smart home*.

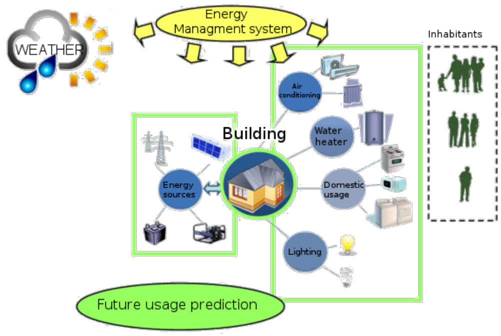

Fig. 1. Potential actors in a smart residential building

A. Load identification

The primary approach of load separation is based on identifying the state transitions of appliances which in most cases is done by the ON/OFF transition identification.

The pioneering work in load separation proposed methods to identify individual appliances from their ON/OFF transitions [2]. Appliances transitions result in corresponding changes in the overall power consumption monitored at the power meter. In the last two decades there have been sizable amount of work to this effect [3], [4]. 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. These identified features are called appliances signatures [5].

The drawbacks of these approaches are mainly hardware requirement due to high sampling rates and the impracticality of the process being totally non-intrusive. The load separation at high sampling rate of all the appliances also raise privacy concerns [6] as user activity can be easily detected and monitored.

However, high energy consuming appliances, such as water heater or washing machine, can be identified with reasonable precision even at sampling rate of 15 minutes [7]. A method partially disaggregating total household electricity use into five load categories was also proposed based on a discriminative sparse coding for energy disaggregation at low sampling rate [8], [9].

B. Prediction of energy consumption

The anticipation of problematic situations from the context of energy management requires also prediction capabilities. Even if it is easier to predict overall consumption, it is important to be able to predict the usage of each appliance because, regarding dynamic demand side management, it is also important to evaluate how much energy can be saved thanks to specific requests to the customers like unbalancing requests, load shading or energy price variations.

The energy savings depend on appliances : some can be unbalanced, some can be postponed and some cannot be touched. These load controls need at least anticipation (prediction) and reaction. Considering these elementary bricks of algorithm, Fig. 2 proposes a synoptic of a three layer energy management system [10].

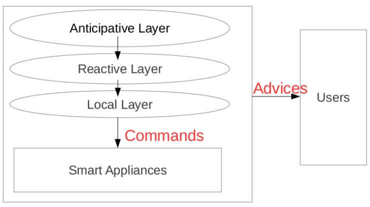

Fig. 2. A three layer architecture for energy management of residential houses

The problem of appliance usage prediction through consumption data is new. Short term load forecasting (STLF) at the grid level has been studied for some time but at the appliance level, these techniques are yet to be tested. Though STLF uses regressive approaches whereas the proposed approach is based on classification but the strategies used in the domain of energy load prediction led to the choice of inputs to the classifier.

In [11], [12] a generic learning approach to the appliance future usage prediction is proposed which also formalized a way to represent domain knowledge. In [13] a multi-label classification based approach is proposed which is capable of taking inter-appliance dependence into account.

C. Context of the work

In 2010, the French distribution system operator "Electricité Réseau Distribution de France", ERDF, launched an Automated Metering Management (AMM) project that aims to implement 300 000 smart meters in France. The smart meters present however a low sampling rate of 30 minutes [14]. This low rate of sampling considerably reduces the hardware complexity of the process, especially considering that most of the high energy consuming appliances have low frequency of usage, typically once a day. In fact, method proven to be effective with a high sampling rate may not be as effective in that case due to the difficulty to detect events based on less information.

The objective of this work is to propose a *generic learning system* able to help the *smart meter* to increase visibility of different appliances present in the house and also make predictions for their future usage based on the limitation of a 30 minutes sampling rate. This work is validated for a sampling period of 1-hour.

This paper proposes related contributions in two fields. Firstly, novel set of meta-features are proposed in addition to previous work [15] to identify high energy consuming appliances present in the house. Secondly, the identification results are used as inputs for a prediction system in an online manner with the model proposed in [13]. In figure 3 the total work flow is shown.

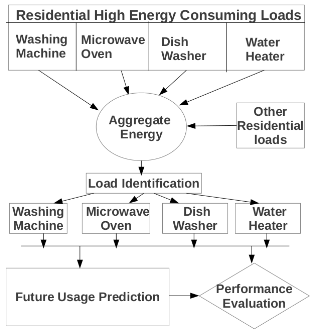

Fig. 3. Identification and prediction work-flow

In the following sub-sections, the dataset is introduced, the concept of temporal sliding window, meta-features and multi-label classification are introduced and their relevance in the domain is emphasized. The generated meta-features for load identification are discussed followed by the results. Lastly, future appliance usage prediction is discussed followed by the comparison of results with and without load identification at the smart meter.

II. Dataset

The IRISE database is obtained from Residential Monitoring to Decrease Energy Use and Carbon Emissions in Europe (REMODECE) which is a European database on residential consumption, including Central and Eastern European Countries, as well as new European Countries (Bulgaria and Romania). This database store the characterization of residential electricity consumption by end-user and by country.

As part of the REMODECE dataset, The IRISE dataset deals only with houses in France, grouping the energy consumption of 100 houses. In each database concerning one house, information is recorded every 10 minutes and 1-hour for each appliance in the house and for a year. This information represents the energy consumed by each appliance, its date and its time. At 1-hour sampling rate is included the weather and humidity informations.

The major appliances present in the house are washing machine, microwave oven, water heater, dish washer and chest freezer. The identification of chest freezer is ignored because the appliance is always consuming.

10 percent of the dataset is used in sequence to train the model for identification and 90 percent is used for testing. The future usage prediction receives as input the results of the identified state (ON/OFF). The predictor model is then rebuild online for every instance once enough historical data is available for pruning.

III. Temporal classifier

A. Temporal sliding window

Temporal data mining encompasses time series analysis both in form of type of data and scope. Temporal data can be time series or events and include among others topics such as classification [12], [16].

The classifier system both for load identification and future usage prediction is based on temporal classification of standard propositional machine learning algorithms. In order to model the time dependency it creates copies of the target field that are shifted in time and generate the sub-sequences. Instances containing these sub-sequences and the current target value are presented as standard propositional instances to the underlying classifying algorithm. This process effectively removes the time dependency in the original target since this is captured by the shifted attributes which is essentially a sliding window.

The first step is to input enough historical data to "populate" this sliding window and hence create a single test instance that can start the closed loop classifying process for the future time steps (*priming*). So, the priming data typically just needs to be filled with enough historical instances to complete the window.

Once the classifier produces a prediction for the next time step, this classified value moves into the sliding window as the most recent value of the target and the oldest value in the window falls out. Another test instance is then created from the history window and then the next time step is classified. This is also known in the literature as "closed loop" forecasting. Once the classifier is trained, it only needs to be primed each time for classifying future instances.

B. Meta-features

Knowledge extraction of a specific representation of a problem is a technique of attribute construction applied whenever there is some kind of underlying substructure to the training instances and there is some way to extract these substructures. In temporal classification domains, these substructures are in the form of sub-events, like periodicity in data. These substructures become synthetic features, which are then fed to a propositional learner and are called *meta-features* [17].

The issue is to convert raw data into a target concept that can be understood by established machine learning techniques. There are three broad approaches in this domain :

1) Algorithms which deal specifically with temporal classification for example factorial hidden Markov models and sparse coding [9], [18], [19].
2) Relational learning based techniques, like recursive neural networks.
3) Problem representation in a way that it can be understood by propositional concept learners [17], [20].

The work presented in this paper is based on the third approach. The definition of the meta-features is one of the key point to increasing the relevance of the identification and prediction techniques. Indeed, depending on the application of the algorithms, the choice of the meta-features will lead to a better inclusion of representative physical quantities. In our case, the meta-features will be clearly linked to time and energy (values and variations).

The concept also allows the inclusion of background knowledge and domain knowledge for temporal classification. The output of the learner can then be converted back to a readable form (from the human point of view) that is described in terms of decision tree for example.

In this work, *meta-features* are defined depending on their usage (identification or prediction) and techniques of meta-feature generation in the temporal domain framework are used [9].

C. Multi-label classifiers

For multi-label classification learners [21], [22], the problem of load identification is not a simple case of temporal classification as there is a possibility to take into account co-relations between appliances whenever they exist.The classification learner approximates a function mapping a vector into labels rather than a scalar output by looking at input-output examples of this function. There are two broad approaches in handling multi-label classification algorithms. One is by way of problem transformation where a multi-label problem is transformed into one or more single-label problems. Another is to modify an existing single-label algorithm directly for the purpose of multi-label classification [22]. Given a data-set of labelled instances, classification algorithms seek relations that will correctly predict the class of future unlabelled instances. The learner is built during the training phase based on the attributes values and class labels. Subsequently the class labels are predicted during the testing phase for every instance based on the known attribute values. In our case, the labels classes represent appliances states. Only two possible states for appliances are considered : ON or OFF. The two different multi-label transformation used in this paper are presented below.

1) Binary Relevance, BR: is a method of problem transformation that learns separately single-label binary models for each classes of label [21]. It transforms the original data into single-label data-sets that contain all the features of the original data-set. The BR algorithm will extract as much new tables as there are labels, each one of them grouping all attributes and only one label.

2) Label Powerset, LP: considers each different set of labels that exists in the multi-label data-set as a single-label [21]. Unlike the BR classifier, the LP algorithms learns using only one single classifier consisting of the number of classes power the number of labels in the original multi-label problem. The primary advantage of using this transformation is that it can take into account inter-appliance correlation if it exists. The primary drawback is the computational expense.

D. Evaluation Measure

In order to compare different classifiers and test different meta-features, we need tools for qualifying the results of identification or prediction. The data associated with high energy consuming appliances is generally sparse, so a simple *accuracy measurement* does not give enough information on the performance of a classifier. Indeed, even a classifier which predicts no consumption at all can present a high accuracy score if appliances are most of the time shut down. A typical example is the washing machine.

For that reason, the confidence of the predictions is monitored in our work with tools commonly used in information theory [21], [22].

Precision : Represents the fraction of the positives states (ON) of the appliances correctly predicted.

Recall : Represents the ratio between the predicted positives states (ON) of the appliances and the total number of correct positives states of the appliances.

Accuracy : Is defined as the percentage of cases where the predicted energy state (ON or OFF) is correct for an appliance.

Among all monitoring tools, *precision* and *recall* are well suited because they present information about the *correctness* of the prediction system. *Accuracy* is also a measurement which gives an information about how well the overall prediction system is working.

IV. Load Identification

A. Synoptic

The synoptic of the load-identification proposed in this work is shown Fig. 4.

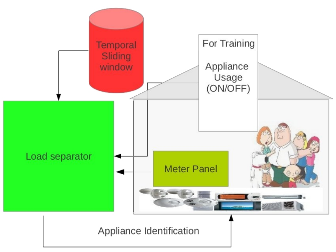

Fig. 4. Synoptic of load identification

In this section, the detailed implementation of the load identification is discussed. A stepwise outline of the load identification implementation is shown below.

1) The aggregate energy readings from the IRISE dataset (Sec. II) at the sampling rate of 1 hour rate are generated.
2) Subsequence is generated using temporal sliding window (Sec. III-A) with a window size of 10 units (the unit being the sampling rate of the dataset).
3) Meta-features (Sec. III-B) for the subsequence are generated.
4) The Multi-label classifier (Sec. III-C) with the generated features as input and high energy appliances as output classes is trained for 10 percent of the dataset.
5) The model is evaluated (Sec. III-D) on the other 90 percent of the dataset.

The identification uses a specific set of meta-features which takes into account the different characteristics of appliances (loads) such as time of use, duration of use, trend of loads, sequence of loads, spike in loads and co-relation among appliances. In order to monitor and evaluate the variation of these meta-features, they are translated in more mathematical expressions bellow. In addition, some of the generated meta-features are summed up Fig. 5.

- Hour of the day,
- local maximum and minimum in the sliding window,
- Distance from current state to local max. and min.,
- energy change from current state,
- gradient and laplacian at each time interval,
- mean and standard deviation within the event window.

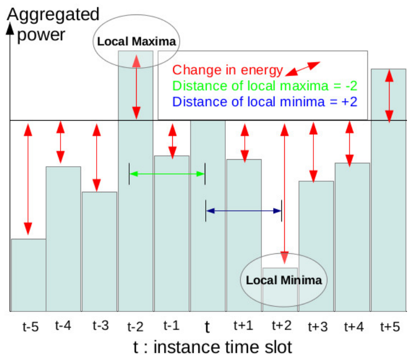

Fig. 5. Different meta-features concerning the aggregated power measurements in a sliding window

B. Identification Results

The results obtained by the previously described steps of load-identification is presented in Table I. These are identification results for a 1-hour sampling rate on one of the 100 houses present in the IRISE dataset. The identification results are subsequently used as input for the future appliance usage prediction.

The results indicate that water heater and washing machine are identified with higher performance than other high energy consuming appliances in the house. These two loads are interesting for deferring and therefore it is favourable to propose an algorithm presenting good efficiency to identify them. Though not presented in this work, the appliance identification based on algorithms which take into account inter-appliance dependence performs in general better than without.

TABLE I
RESULTS OF APPLIANCE IDENTIFICATION

Appliance	Algorithm	Accuracy	Precision	Recall
Washing Machine	LP	95.62	72.80	57.85
Microwave Oven	LP	95.65	14.75	2.88
Water Heater	LP	97.81	89.54	92.80
Dish Washer	LP	97.91	11.90	9.43

V. APPLIANCE USAGE PREDICTION

Real-time demand response can be complemented if the future usage of deferrable load can be predicted with reasonable accuracy. The proposed model tries to take into account all the possible informations based on identified appliance state, time of the event and meteorological information. This work uses the learning model presented in [13]. The input to the learner is the identified appliance state presented in section IV-B along with meteorological information.

A stepwise outline of the future usage prediction implementation is shown bellow.

1) The identified states (ON/OFF) from the load identification results at 1-hour sampling are obtained.
2) Subsequence is generated using temporal sliding window with a window size of 24 units.
3) Features for the subsequence are generated.
4) The Multi-label classifier with the generated features as input and high energy appliances as output classes is trained and tested iteratively.
5) The model is learned iteratively and is tested in an online learning procedure.

Fig. 6 describes the principle of the proposed model. At every sampled time instance it is predicted if an appliance will start at the following hour or not. This idea will be extended to more than one hour in future works. In the following subsections the feature space and the results are discussed.

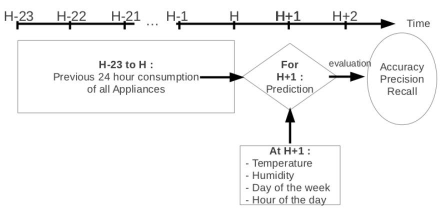

Fig. 6. Proposed method at a given time instance [13]

A. Generated Features

The inputs to the model can be categorized thereby :

- The identified state (ON/OFF) of each appliance at each hour for the previous 24 hours.
- The time of event and meteorological information.

The inputs to the system are shown in Fig. 6 for a given time instance (hour H). At each time instance the system predicts the coming hour and then the window is shifted one hour to the right for the next prediction.

The identified state at each hour for the previous 24 hours of all appliances is taken into account as input, so that any sequential inter-appliance relation can be learned.

This methodology results in a high amount of data which is processed subsequently at the prediction stage. The previous hour appliance states are sequential and this information is known only after the availability of previous events, for example, it is only possible to predict Hour *H+1* if we have all the needed informations about Hour *H*.

On the other hand the time of event and meteorological information (temperature and humidity) are available for future time instances and it is relatively independent of the current time. Furthermore, the time of event is expressed as two periodic variable :

- Hour of the day,
- day of the week.

This way to consider the time allows to take into account the periodic nature of human behavior.

B. Appliance Usage Prediction Result

The future usage prediction based on iterative learning approach is proposed taking into account identified state, time of event and meteorological information. The prediction architecture is presented Fig. 6. In this work, the future appliance usage when the individual consumption load are known are compared with the appliance usage after it has been identified at the smart-meter, i.e. based on the previous identification as discussed in Sec. IV-B. Results using LP algorithm which takes inter-appliance co-relation and BR algorithm are shown in Table II.

The results in Table II indicates the appliances which can be identified with high accuracy and precision can also be better predicted for future usage. In our case the water heater can be predicted with higher accuracy because it was identified with high precision. As only high energy consuming appliances are used for prediction, the inter-appliance dependence is not reflected in the results. So both the algorithms give similar performances. But the results in [13] show strong indication of inter-appliance dependence. The fact that some appliances have high accuracy but low precision and recall (sometimes zero) is due to the dataset being highly sparse and it being representative of only the ON class. Indeed, most of the high energy appliances are OFF most of the time.

VI. CONCLUSION

The availability of fine grained data and the advent of smart-meter infrastructure have increased the need for better monitoring of different energy consuming appliances in residential buildings. A real time temporal classifier is proposed to first identify and then predict the future usage of high energy consuming appliances in the house. A novel set of meta-features are formalized and proposed for the same purpose.

The results have been validated for a dataset of 100 houses monitored over 1-year and a result for 1-house is presented.

TABLE II
RESULTS OF APPLIANCE USAGE PREDICTION

Appliance	Algorithm	Based on identification (Smart Meter)			no previous identification (direct connection)		
		Accuracy	Precision	Recall	Accuracy	Precision	Recall
Washing Machine	LP	95.11	66.66	18.66	96.58	90.74	64.42
	BR	95.13	60.51	28.22	96.61	90.00	65.57
Microwave Oven	LP	88.22	13.33	1.41	90.47	32.83	2.75
	BR	88.27	0	0	90.40	35.92	4.62
Water Heater	LP	95.71	83.42	81.68	98.73	96.29	93.29
	BR	95.96	86.16	80.33	98.73	96.29	93.29
Dish Washer	LP	95.94	0	0	98.96	83.67	33.60
	BR	95.94	0	0	99.00	86.00	35.24

The results suggest that certain high consuming appliances can be identified and predicted even at a low sampling rate of 1-hour. This result is important in the context of energy management and specifically designed for better non-intrusive monitoring of loads and future usage prediction of deferrable loads.

VII. ACKNOWLEDGEMENT

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