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Test set validation for home electrical signal disaggregation

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***Abstract*—In order to enable demand response schemes for residential and industrial users, it is crucial to be able to predict and monitor each component of the total power consumption of a household or of an industrial site over time. We used the cross-validation method which is a model validation technique for assessing how the results of a statistical analysis will generalize to an independent data set. It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice. We exploit Non-Intrusive Load Monitoring (NILM) techniques in order to provide behavior patterns of the variables identified. This work presents a review Non-Intrusive Load Monitoring (NILM) techniques and describe the results of recognition patterns used for the identification of electrical devices.The proposed method has been validated on an experimental setting and using direct measurements of appliances consumption, proving that it allows achieving a high level of accuracy in load disaggregation.**

I. Introduction

The last decade has been characterized by a sharp increase in fuel prices and in energy demand. At the same time, energy consumption awareness has been raised over the impact which the greenhouse effect is having on the climate and on world economy. Furthermore, By 2020, there will be 7.5 billion on the globe and consumption will have increased by 75% (compared to 2000), equally split between developing and developed countries [1]. This means a 37.5% increase every 10 years. In Swiss,the electric consumption increased 120%in 50 years [2].

These factors have driven research of solutions for sustainability in energy production, distribution, storage, and consumption. In energy distribution, new "smart" solutions have been proposed, centered on the idea that exploiting properly data on power generation, distribution and consumption, a substantial increase in efficiency is achievable in power production and distribution.We can talk too about the objectives 3*20 in Europe : to decrease in 20% gas emissions with greenhouse effect, to reduce of 20% the energy consumption and to increase of 20% the production of renewable energy.

In 2010, the Chinese government is poised to invest more than 5.4 billion Euros in the development of Smart Grid technologies, while the United States has earmarked some 5.2 billion Euros. Meanwhile, the annual investment in Europe is estimated to be approximately 5 billion Euros [3]. At the user level, several load management and demand response techniques have been proposed, aiming at flattening the peaks of power consumption over time, and at adapting demand to variations in supply due to renewable. These strategies imply, on behalf of consumers, awareness of the amount of energy consumed by each device and of its relative impact on the total energy bill of the household. Such knowledge, besides enabling users to respond appropriately to power price variations over time, allows also identifying inefficiencies and decreasing the overall consumption, helping them to contribute to the decrease of their carbon footprint.

The techniques proposed to monitor appliance consumption, non-intrusive ones (called also NILM [4]) are of particular interest in households, since they do not require specialized, costly hardware and installation and maintenance of a sensor network. Moreover, they adapt over time in changes in households (such as changes in appliance number and type) without requiring new installations or reconfiguration of existing hardware and software. The extensive deployment of smart meters which is planned in many countries for the near future will enable a large scale deployment of NILM techniques [5]. Such deployment will make available measurements of the total active and reactive power consumed, typically sampled at low frequencies, allowing non-intrusive load monitoring without the use of additional hardware.

NILM methods have been first proposed in [6], and they are typically structured in three phases: feature extraction, events detection, and events classification. They make use of a database of electric signatures of appliances, and they are based on the measure of the total active power consumed, sampled at frequency of one Hertz. Later methods [7] [8] try to decrease the duration of the training period. Indeed, the main drawbacks of these techniques reside either in the need of a learning phase requiring intrusive measurements, and/or on the fact that they cannot detect appliances whose power consumption patterns vary drastically over time (e.g. washing machines, whose power consumption varies substantially during a washing cycle). Indeed, a fine granularity and a good accuracy in load disaggregation are crucial in order to enable useful feedback to users, to set up appropriate measures

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for changing consumption patterns, and to enable detection of anomalies and appliance malfunctioning. Many of the techniques proposed in order to overcome these drawbacks imply a substantially higher sampling frequency, and therefore expensive hardware [9] [10] [11].

We used the cross validation techniques to provide the behavior patterns associated to the devices tested. The goal of cross validation is to define a dataset to "test" the model in the training phase in order to limit problems like overfitting, give an insight on how the model will generalize to an independent data set. Our method requires a relatively simple setup and inexpensive, readily available hardware. In this paper, three appliances were selected to verify the model: heat pumps, freezers, and dishwasher. We have a verification around 94% with the decision tree algorithm.
We chose these appliances because there power can be sifted for a predetermined time. The peak consumption can be move 15-minute for the cold and one hour for the heat pumps without major impact on the users comfort. We remove in a first time the detection of washing machine and dryer : their usage are planned in the Swiss building and used practically every time.There are one washing machine and one dryer for ten apartments in a Swiss building.

The paper is organized as follows. In Section II we present our cross validation method and detail the algorithm for load disaggregation. In Section III we describe the setting used for the test and in Section IV we present the results of the different algorithms. Finally we conclude and discuss future directions of research in Section V.

II. Verification Method

In this section, we describe the data required for our method and the prediction model to classify the started devices in use the global power curve.
There are at least three techniques of crossed validation: test set validation, k-fold cross-validation and leave-one-out cross validation.In this paper, we used the test set validation. We partitioning the sample of size n into training dataset and a testing set. The model is built on the training set and validated on the testing set. The error is estimated by calculating a test, a measure or a score of performance of the model on the testing set.
In our case, we define a contingency matrix representing the possible outcomes of the classification. We interpret this matrix like a good or bad prediction for each algorithms and for each devices.
Our method requires data for every second for the active power and reactive power for each phase. This allows us to understand the dependency of the target variable to the input vectors. The target variable are the difference between two active power points and in a second part,the difference between two reactive power points.

Feature extraction: We have in inputs three values every second for voltage, three for amperage, three for active and reactive power, three for the power factor and the accumulated active energy and a time reference for the global load curve. We have too in inputs the active power and the time reference for the different devices connected inside the house. We use edge detector method , which consists on detecting variations of active and reactive power with regards to a predefined threshold [6]. The different work on this subject and our analysis working enable to know the different characteristics to describe a device [10], [9] [11].
We begin by filtering the interferences that we must identify on the global diagrams as well as on individual connected appliances diagrams.To reduce the effects of noise and transients on the measured data, we apply a median filter of size 60 to the time series of measured values.We have empirically determined the optimal size of the filter via a set of tests, by attempting to balance the elimination of spurious load level variations and the performance of the event detection algorithm, in terms of average number of undetected events.
We use a median filter on each entry signal to remove high frequencies. This is used on the global load curve for each phase and on the different devices' signals. The threshold used depends mainly on the type of device that we want to detect.If the objective is to detect all devices, the active threshold must be the finest possible, but the variations detected can lead to errors corresponding to residual noise.
We have now a list of variations of active and reactive powers variations by phases which represent the different devices connected in the test house. A time level recognition is realized to group the potential vectors (deltaP / deltaQ) for the three observed devices.

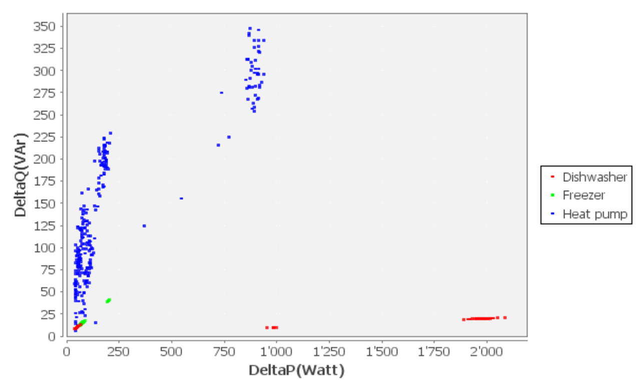

Fig. 1. Active and Reactive power vectors detected on phase 1 for three devices, (Dishwasher,Freezer and Heat pump),11 February 2013 - 17 February 2013

Predictors: We use a random sampling of all active/reactive power vectors for the partitioning: the input table is split into two partitions,train and test data. To estimate the training data, we use three known classification algorithms : k- Nearest Neighbor(KNN) [14], Support Vector Machine (SVM) [15], and a decision tree [16]. The nearest neighbor algorithm derives the class labels or the numeric target values of new input objects from the most similar training examples, where similarity is measured by distance in the feature space. The prediction is computed by a majority vote of the nearest neighbors or by averaging their numeric target values.

The number k of neighbors to be taken into account is a parameter of the algorithm.The best choice of which depends on the data and the prediction task. The kNN node allows setting the number of neighbors to be considered and if the distance should be used to weigh in on those neighbors. The kNN is very sensitive to the chosen distance function so we should make sure to normalize the data and use the exact same normalization procedure for both the training and test data.This can be achieved by using the normalizer function and Normalizer (Apply) function , which copies the settings from the first node. We then feed those two data tables into the K Nearest Neighbor node which adds a column with the predicted class to the test data.

Support vector machine algorithms have not been around as long as neural networks but in the meantime, many implementations of support vector machines (SVM) have shown up in commercial and open software packages. Our analysis consists of two steps, one learning the SVM model offering the choice of a few well known kernels and the second one allowing to apply the model to a second data set. The native SVM implementation currently offers three different kernels functions: a polynomial, hyper tangent and RBF kernel. In contrast to e.g. decision trees, kernel functions (or at least the settings of their respective parameters) are rather sensitive to the normalization of the input data. For instance, the sigma parameter of the RBF kernels controls the width of the basis functions in relation to the Euclidean Distance of the input vectors to the support vectors. Hence it is critical to adjust this parameter accordingly.

When constructing decision trees in data mining software, a number of options are available. We need to first and foremost select the target attribute (it has to be a nominal attribute). After that,we can choose between two different ways to compute the information gain (Gini index and Gain ratio) and if a pruning of the tree is to be performed (The data mining software offers to either skip pruning or performs a minimum description length (MDL) [16] based pruning). Noteworthy is the last option number threads, which allows to control how many threads the software can use to execute the learning method in parallel on, e.g. a multi core machine. Once the node is run, we can display the resulting decision tree. In order to evaluate the decision by scored, we define a contingency matrix representing the possible outcomes of the classification, namely the true positives , the True Negatives.

III. Experimental Setting

In this section, we describe how our information system collects data, how the parameters are used in our analysis software and how the data set for prediction model.

Information System: We use the Schneider Electric system to collect active and reactive power by phase on the global electric meter [17]. This smart meter is the PowerLogic Series 800 PM810 of the Schneider Electrical Company [18]. As outputs, we have the amperage, voltage, active and reactive power and energy consumed with in a one second interval per phase. We use the same device to collect data from the principal Heat pump. We also have amperage, voltage, active and reactive power per second for each phase for the heat pump 1.
The different devices of houses are connected using the Geroco smart plugs. This smart meter collects the amperage, voltage, the active power and timestamps. The protocol of communication used is a Zigbee [20]. This enables piloting after a processing step in order to define activation and disactivation of one or many devices. An integrated pre-programmable code enables the recognition of variations of active and reactive powers on the global load curve for each device. The data travels through a modbus communication.These datas are stored on mini-pc in csv files and to send on server in HES SO at Sion. We use the open source data analysis software KNIME [20] to connect the database and process the data. At this point, we have one year of data (November 2012- November 2013) for the global charge charts and the devices connected. 10houses are today connected.

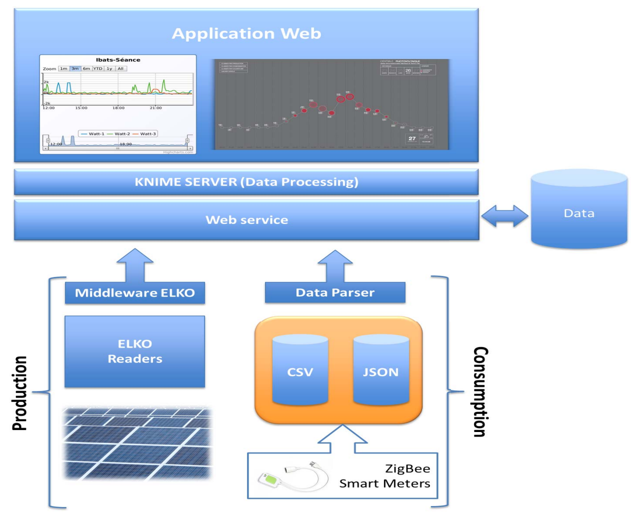

Fig. 2. I-BAT information system architecture based No-SQL databases

Data set: We chose a traditional Swiss house in a mountainous area. The different devices are by phases :

- Phase 1: Dishwasher, electric ovens, induction plates, heat pump1, heat pump 2, fridge, microwave ovens, light, Modem, kettle, coffee machine,overhead projector;
- Phase 2: Two freezer, light, heat pump 1, induction plates, electric ovens;
- Phase 3: A washing machine, a dryer, light, heat pump 1, induction plates, electric ovens;

This region benefits of a warm and dry climate (approximately 2 500 hours of sunlight a year) and the house has a production of renewable electricity by photovoltaic panels. Furthermore,the two heat pumps and the dishwasher are today piloted.These devices are activated automatically at 12 am in priority one. The goal of this piloting for the consumer is to decrease the invoice of electricity. The cost of electricity is low the night between 9pm and 6 am. If we have a significant classification, the prediction enable to pilot the heat with the heat pump, the cold with the freezer and refrigerator and the dishwasher. For our test, we chose a random week in the winter season to study the activation of two heat pumps(11 February 2013 and the 17 February 2013) which corresponds to 7 cycles for the dishwasher, 19 cycles for the heat pump and 146 cycles for the freezer.

Feature extraction: We tested two threshold for the active and reactive power to 50W/15VAR and 40W/5VAR to study the impact of transitional effects on electrical signals. If we use a median filter with a size of 60 and an edge detector of 40W/5VAR, we detect all variations for the three devices (heat pump, refrigerator/freezer, dishwasher). The active threshold, 40Watt or 50 Watt, is sufficient to detect a dishwasher, a freezer or a heat pump on/off jumps. But the reactive power threshold is too high to detect a fridge or freezer. That is why we used a 40W and 5VAR threshold in our methodology. The devices not detected with this active power threshold are the modem and the computers.

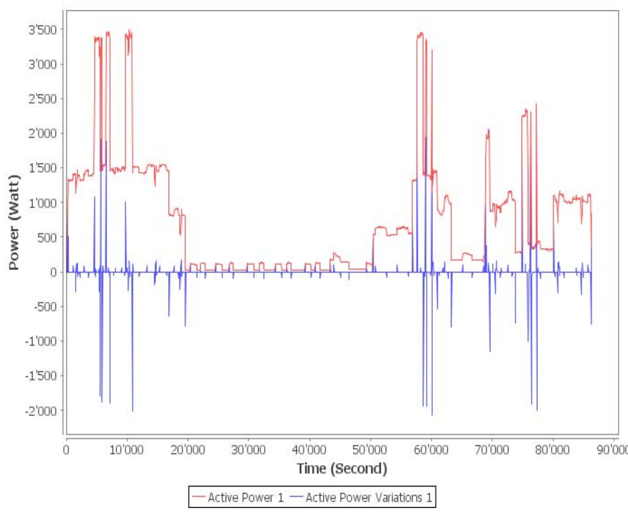

Fig. 3. Active power variations on phase 1, 15 February 2013

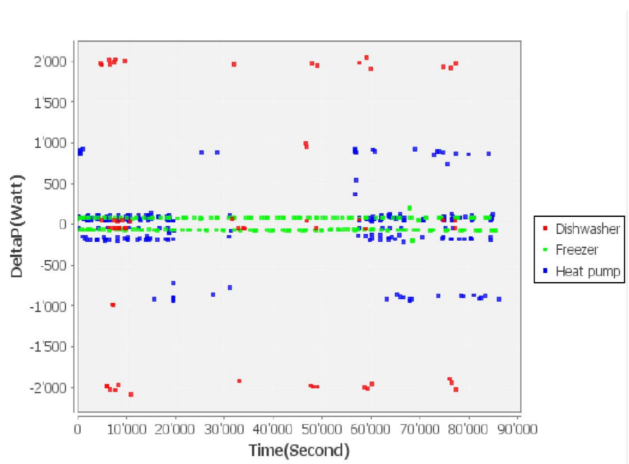

Fig. 4. Active power variations on phase 1 for the three studied devices, 15 February 2013

Predictors: The training set vectors are normalized by Min-Max Normalization Method. The model of normalization is applied for the test set. The three values normalized are the time reference, active power and reactive power.For the kNN, we fix k = 3 and we chose the weight neighbors by distance.

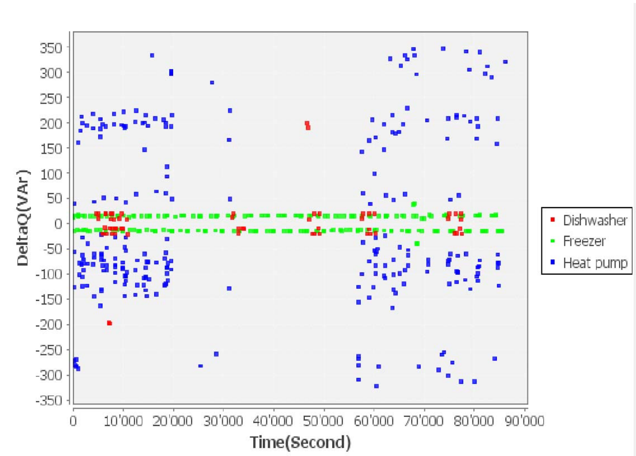

Fig. 5. Reactive power variations detected on phase 1 for the three studied devices, 15 February 2013

For the DCT, the pattern finding increase the DCT performance because three data are analyzed by split of the tree so we don't use a post pruning method like "Minimal Description Length" (MDL). The quality measures for split calculation used is the gini index. We unchecked the split value by average compute. For the SVM, we use a RBF kernel .

We realized two tests in order to evaluate the training set. For the test 1, we evaluate the behavior pattern, the active power events in first time and the active and reactive power in a second time. We used for this part a training set of 60 percent and a test set of 40 percent.For the test 2, we used the active and reactive power and we check the result in function of the part of training. We used a training set of 60% and 70 %.

IV. Classification results

In this section, we discuss of our results of the cross validation method. InWe think that the devices studied was very different devices but this three devices, a freezer, a dishwasher and a heat pump are a same state : the functioning of the pump.

In our case, a freezer has one state but the dishwasher and the heat pump have many states. These two devices are one or many pumps. The functioning of these pumps are the same: the event on are followed by an event off. We can consider that these events are in the same class.

We checking if the active and reactive power variations enable the identification a class of devices or a state of a device. However, the power (active and reactive) of these pumps depends of the installations of the house, the type of function (for example,there are several ways of functioning the dishwasher). In our case the pumps of the dishwasher and the heat pump are more powerful than that of the freezer. Furthermore, the variations of the reactive power of the pumps of the heat pump are more powerful than those of the refrigerator and dishwasher. The different algorithms can separate these significant variations, but the difficulty is to separate the different pumps.

Our results are suitable if we used the active power and reactive power. The difference is of 20% between the test with the active power and the test with the active and reactive

3-NN	SVM	DCT
75.7 ±2.6	69.1.8 ±2	82.1 ±2.7

TABLE I. AVERAGE RESULTS BY ALGORITHMS WITH ACTIVE POWER DATA SET FOR A WEEK

3-NN	SVM	DCT
94.4 ±1.8	92.4 ±1.4	96.3 ±1.1

TABLE II. AVERAGE RESULTS BY ALGORITHMS WITH REACTIVE AND ACTIVE POWER DATA SET FOR A WEEK

Devices	3-NN	SVM	DCT
Heat pump	99.8 ±0.1	94.4 ±1.2	97.1 ±1.5
Dishwasher	91.5 ±1.4	58.1 ±1.8	90.9 ±2.5
Freezer	89.4 ±2.1	100 ±2.2	96.9 ±2.6

TABLE III. RESULTS BY ALGORITHMS AND BY DEVICES WITH REACTIVE AND ACTIVE POWER DATA SET FOR A WEEK,60% TRAINING SET;40% TESTING SET

power. For the KNN,we have 2039 events correct classified (significant variations of active and reactive power) and 121 wrong classified. 179 events of the Dishwasher are correct classified on 210. Only two variations are classified with the heat pump and 29 events with the freezer.For the freezer, 843 events are correct classified, the error is the same between the wrong events classified for the dishwasher and heat pump. For the heat pump, only two variations are wrong classified with the freezer.
For the DT, we have 2100 events correct classified and 60 wrong classified. 22 events of the Dishwasher are correct classified on 210. Only two variations are classified with the heat pump and 13 events with the freezer.For the freezer, 852 events are correct classified, the error is the same between the wrong events classified for the dishwasher and heat pump. For the heat pump, 1026 events are correct classified. We have 20 events wrong classified with the dishwasher and 3 with the freezer.
For the SVM, we have 2002 events correct classified and 158 wrong classified. The correct classified of the different devices is perfect for the freezer.140 events of the Dishwasher are correct classified. Only two variations are classified with the heat pump and 13 events with the freezer.For the heat pump, 1009 events are correct classified. We have 54 events wrong classified with the freezer and 0 with the dishwasher.

The algorithm which obtains the accuracy with highest 96.3% is the decision tree.The SVM is very interesting to classify a freezer. Under these circumstances, we can conclude that the performed methods are suitable and that the active and reactive power are the pattern which described the different devices. Moreover, the composed signature can be an accurate description for each of the appliances in the data set. Nevertheless, the small number of electrical appliances might be a limitation that should be further considered.

V. CONCLUSIONS

We propose a cross validation method which uses active and reactive power to differentiate three devices : a heat pump, a dishwasher and a freezer. We have more than 96% percent of recognition on the studied devices with the Decision Tree algorithm. The results are encouraging and the active and reactive power are the pattern which described the different devices. In a future work, we want associate an energetic analysis with an electrical analysis in order to predict and pilot the two heat pumps. Furthermore, in a smart grid or microgrid system, on of the objectives is to increase the auto-consumption. In our test house, the devices are started the night but the production of electricity is summit the daytime, the hours depends of the seasons. In our case,the sunrise at 8am and sunset at 6 pm, the peak of production may be between 12am and 2pm. In general, we have no presence the day in the house when the solar production is present.If we chose a random day in the data set, we notice the two heat pumps and the dishwasher, which are present during 8 hours in the day.The maximum total flexible energy is 3.4 KWh when the two heat pumps and the dishwasher are started. In decentralized electrical production, such as in a microgrid, this potential of flexible energy is important. In your case, it's the heat pump 1 presents on the three phases which consume most energy with 1.6KWh. Next, it's the heat pump 2 and the dishwasher. The cold (freezer and fridge) are small consumptions around 40Wh.

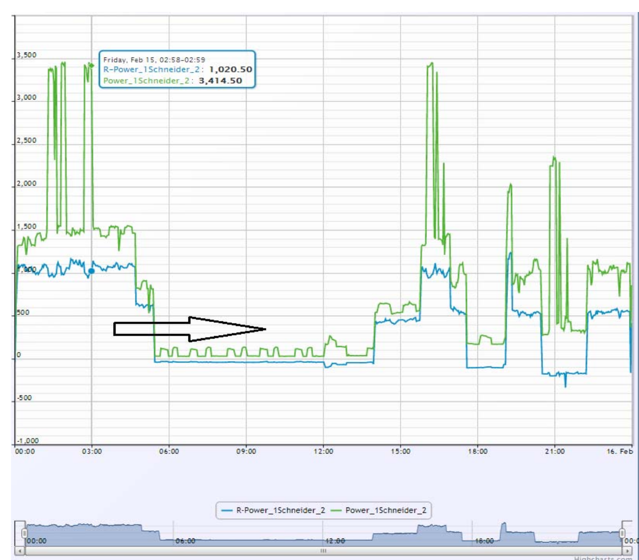

Fig. 6. Active and Reactive power by phases for the 15 February 2013 in use the schneider2 smart meter

Hours	Flexible energy	Detected Devices
00-01	2.8	Heat pump 1,2 + Cold
01-02	3.4	Heat pump 1,2 + dish-washer + Cold
02-03	3.7	Heat pump 1,2 + dish-washer + Cold
03-04	1.6	Heat pump 1,2 + Cold
04-05	1.2	Heat pump 1 + Cold

TABLE IV. TOTAL FLEXIBLE ENERGY IN KWH BETWEEN 12.PM AND 5.AM FOR THE 15 FEBRUARY 2013

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