# Non-intrusive discriminant analysis of loads based on power quality data

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***Abstract*—Power quality information is useful not only to determine electricity fitness but also for another important application: load identification. One approach to identify loads is through non-intrusive load monitoring systems that estimate the nature and operation of individual appliances with measurements in a single point. In this work, load identification is addressed as a classification task by taking advantage of power quality information. Therefore, discriminant analysis of power quality characteristics are proposed, thus requiring simpler design and fitting processes than traditional techniques. In this regard, classifiers based on linear and quadratic discriminant analysis are implemented for laboratory measurements with noticeable performance.**

## I. Introduction

Power quality field analyses the deviations of the electricity service and the loads. This area is so important that the identification of disturbances and their sources might bring technical and legal implications. In general, power quality demands to measure variables such as voltage, current, power or their combinations, to determine voltage sags and swells, long duration over voltages, undervoltages, interruptions, unbalances, voltage fluctuations and harmonics, etc. Less conventional applications could be dealt through monitoring those variables. This is the case of load disaggregation systems which enquire the individual loads nature and operation, and estimate how each appliance contributes with a power $P_i$ to the total costumer power consumption $P_T$ given by (1).

$$P_T(t) = \sum_{i=1}^{n} P_i(t) \tag{1}$$

Traditionally load disaggregation used a dedicated sensor for each load, sometimes indirectly through microphones, accelerometers and video-cameras [1],[2]. However, monitoring the same variables useful for power quality analysis only in a single point has exhibited advantages in reliability, communications efforts, costs and installation times. The latter approach is called Non-Intrusive Load Monitoring (NILM). Experts in power quality have formulated the need of research about the remote identification of load transitions and characteristics to assist the utilities to take decisions about the operation of transmission and distribution system [3].

Some authors suggest the possible benefits of NILM systems to track loads that be detrimental for the power quality. Loads such as computers and other office equipment, gas discharge lighting fixtures, and adjustable-speed motor drives, etc. can draw distorted, non-sinusoidal current waveforms [4]. They are often called ”power quality offender loads” or ”critical loads” [5], [6]. Those loads interfere with other's operation and re-scheduling or other decisions might be taken to restore the quality. Thus, correlation between changes in harmonic content specific appliance operation might drive to identify these critical loads.

Steady or transient state conditions might be considered for power quality disturbances as well as for NILM. In general, steady state analysis determines individual loads by identifying the instants at which electric power measurement changed from a steady state to another one, while transient based analysis identifies the loads through a representation in the frequency domain. The pioneer works in NILM made a steady state based analysis with the real and reactive power sampled at 1 Hz [7]. Subsequent works introduced the transient based analysis, which is more suitable for identifying non-linear loads and provides details to distinguish the loads for the influence of the physical task [8]. The sampling frequency of the sensor should be higher for the transient-based than for the steady state analysis.

One of the strategies for NILM is to initially identify each appliance through classification models. Previous works include neural networks, support vector machines, among others. However, these traditional techniques are computationally intensive and their performance is deeply affected by the number of classes. Little work have considered the use of classifiers with simpler models. Therefore, this paper contributes with the use of power quality characteristics together with discriminant analysis that require simpler design and fitting processes. In this sense, classifiers based on discriminant analysis are implemented. Measurements were acquired in the laboratory and they were used to evaluate these algorithms.

The rest of this document is structured as follows. First, section II describes a system to perform load identification with the non-intrusive approach. Second, section III presents the methods for the proposed experiment and the results are stated in section IV. Finally, the conclusions wrap up this document.

## II. Non-Intrusive Load Identification Algorithms

The procedure of a NILM system begins when the total signal is acquired at a single point. Some works use general purpose sensors (current clamps, ammeters, voltmeters) with different sampling rates. Other works include smart electrical meters with the argument of the advantage of using existing infrastructure. Beyond the sensor selection, the principle is to select and mathematically characterize the load behaviour through electrical signals called *load signatures*. Afterwards, mathematical algorithms are applied to the aggregated signal to identify the appliances. These algorithms are often divided into two categories: event based and not-event based algorithms [9]. The difference is that the first does involve detection and classification of events to identify state changes in the appliances, i.e. from OFF to ON. The first approach might be carried out either as an optimization [10], [11], [12], [13], [14] or as a pattern recognition problem [1], [15], while the second is probabilistic [16], [17], [18].

A pattern recognition approach is implemented in this solution. The aim is to compute some features from stationary voltages and current signals in order to identify loads, i.e. only electric variables are regarded. The system has the following stages as shown in Fig. 1:

- Measurements: Signals are taken repeatedly to build a training dataset. Each measurement is recorded as a .mat file to be processed offline in Matlab. Voltage and branch currents are measured for every setup.
- Feature extraction: Features from time and Fourier domain are computed to distinguish one appliance from another. They are extracted from the electrical signals (current and voltage) some time after a switching.
- Classification: A supervised learning is carried out to classify the events. According to previous tests, the unsupervised learning methods work better for visualization or abstraction than for obtaining accurate classification. Cross-validation is used to test the algorithms. Consequently, some models are created.

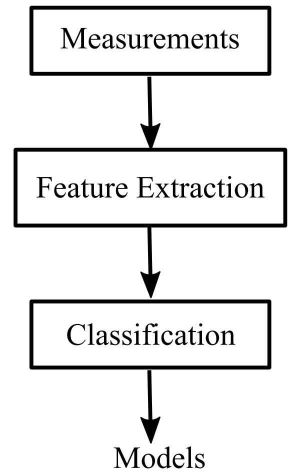



Fig. 1: Block Diagram of NILM Systems

## III. Methods

### A. Measurement Framework

Measurements were taken in the laboratory as shown in Fig. 2. A power source emulates the voltage supply of Colombian utilities at 120V/60 Hz, with a variation in the voltage according to the allowed values in the regulation between 108 and 126V. A sinusoidal voltage is set to supply the load. Voltage and current measurements are obtained through a data acquisition system of several channels with simultaneous sampling at 50 kHz. This system comprises a set of data acquisition cards connected to a chassis to allow the power and the communication with the computer. Both the data acquisition system and the power source are controlled by a computer. The load includes residential appliances that are usually present in conventional Colombian households. More details about these appliances are displayed in Table I.

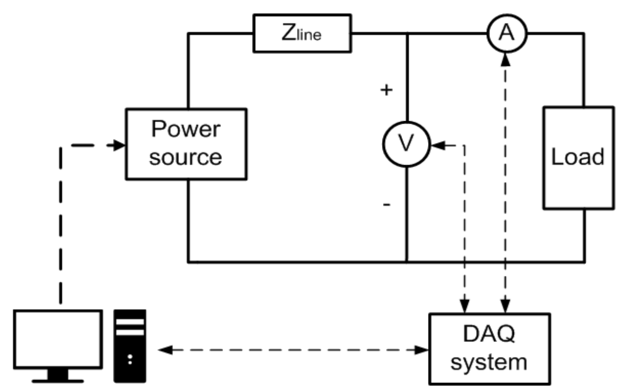



Fig. 2: Measurement setup. DAQ stands for data acquisition system.

Once the measurements are taken, they are processed offline to derive the power characteristics of loads and to test the algorithms.

### B. Load signatures

Data from every appliance are considered as one class. Load signatures from power and current are computed and they work as features to build classification models. The features for this study are:

TABLE I: Equipment under test

| Appliance | Rated Power [W] | State |
|---|---|---|
| CFL | 9 | ON |
| CFL | 20 | ON |
| LED lamp | 7 | ON |
| Incandescent Bulb | 75 | ON |
| Halogen Lamp | 50 | ON |
| Halogen Lamp | 70 | ON |
| Fan | 48 | High speed |
| Blender | 600 | Low<br>High |
| Refrigerator | 1,15 kWh /24h | ON (Compressor working) |
| Sandwich maker | 750 | ON |
| Hair Dryer | 1875 | Low<br>High |
| Iron | 1200 | ON at a given mode |
| Cellphone Charger | | ON (During charging) |
| TV | 90 | Video mode |
| Laptop | 40 | ON (No programs running) |
| Desktop PC | 250 | ON (No programs running) |
| Monitor | 180 | ON (No bright changes) |

- RMS value of current $(I)$
- Harmonic component of current $(I_H)$
- Active Power $(P)$
- Fundamental reactive power $(Q)$
- Fundamental power factor $(PF_1)$
- Total harmonic distortion of the current $(THD_i)$

They are basically computed from steady state signals, this is, an integer number of cycles is captured and processed, when an appliance is individually connected. The results can be useful in this scenario of individual operation or when an appliance switching ON is detected once other appliances were previously operating too.

### *C. Classification Method*

The appliance identification is addressed as a classification problem where the measurements are used to create models to separate one appliance from others and test them. Thus, a mapping $y_i = F(x_i, \theta)$ is achieved between the inputs $x_i$ and the class labels $y_i$ which represent classes or categories (appliances for this work), where $\theta$ represents some parameters and $F$ the model. Once the model is trained using labeled instances, it is used to assign a label to an unknown instance. Classifiers based on discriminant analysis are implemented in this work whose theoretical bases are explained as follows.

*1) Discriminant analysis classifier:* This technique was introduced by R. Fisher. Two types of discriminant analysis classifiers can be implemented: linear (LDA) or quadratic (QDA). During the training, discriminant functions are computed for each class, and then they are employed to establish decision boundaries and regions for each class [19]. The difference between linear and the quadratic classifiers lies in the shape of the separation boundaries between regions of the classes. These boundaries are straight lines for LDA classifiers, and conic sections (ellipses, hyperbolas, or parabolas) for QDA classifiers. The input space is split into a set of regions bounded by decision boundaries. The assumption is that each class generates data with a Gaussian mixture distribution and all the distributions are different. Then this technique fits a multivariate normal density to each class. Likelihood ratios are considered to assign the instances to the classes.

Discriminant analysis classification belongs to the family of generative algorithms which model the distribution of the observed variables. Two types of models can be built. For the linear method, the model considers that the means of each class vary, while for the quadratic method, not only the means but also the covariances of each class vary. So the mean and covariance parameters of each class should be estimated. The procedure to build the models comprises the following steps [20]:

1) Compute the mean of each class
$$\mu_i = \frac{1}{n_i} \sum_{i=1}^{n_i} x_i, x_i \in y_i \tag{2}$$
for $i = 1, ..., c$, where $c$ is the number of classes and $n_i$ is the number of instances of the class $y_i$.
2) Compute the a priori probability of each class
$$P(y_i) = \frac{n_i}{N}, \tag{3}$$
where N is the number of instances that conform the input data.
3) Calculate the covariance matrix for each class
$$C_i = \sum_{x \in y_i} (x - \mu_i)(x - \mu_i)^T, \tag{4}$$
for $i = 1, ..., c$. The resulting matrix is symmetric. Determine the discrimination function $f_i$, for $i = 1, ..., c$, i.e. for all the classes.

The decision boundary between two classes is the difference between the two discriminant functions. Once the models are built, they can be used to predict the class of an unknown instance according to the next steps [20]:

1) Evaluate the discriminant functions of all the classes at the instance to be predicted.
2) Select the discriminant function $f_k$ with the highest value or score for that point or instance, i.e. $f_k > f_i$, for $i = 1, ..., c, k \neq i$. If the scores of any two discriminant functions are equal, thus the unknown instance is on the boundary between both classes.
3) Assign the class label $y_k$ to the unknown instance.

*2) Evaluation criteria:* A stratified 10-fold cross validation is implemented to prevent overfitting. Cross validation is a suitable practice that ensures classifier stability and bring a more accurate estimation of the classifier carried out. In this process, the dataset is divided into 10 folds. Then every fold is tested once, thus taking advantage of the complete set.

The metric for evaluation criteria is the classification accuracy. This is computed as the ratio of number of correct predictions to the total number of input samples, thus:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad (5)$$

In addition, confusion matrices are used to show the complete model performance. They has two dimensions: the actual and the predicted classes. Their diagonal entries are the true positives, i.e. the cases that are assigned to the correct class, while the off diagonal entries represent the cases where classes are confused. In turn, classification accuracies can be computed from this matrix as the ratio of the main diagonal entries over the total matrix entries.

## IV. Results

Table II depicts the performance of the classifiers with the complete set of features mentioned in Section III. In order to explore the performance with subsets of features, a forward feature selection is performed. This process does not evaluate evaluate all possible combinations of the features unlike the brute force strategy.

TABLE II: Classifier performance with the complete set of features

| Classifier | Classification rates |
|---|---|
| Linear | 93,67% |
| Quadratic | 100% |

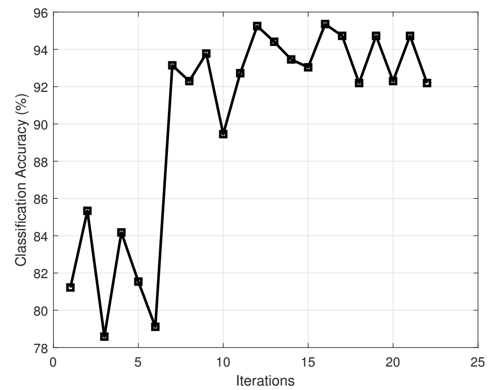
Forward feature selection involves the following steps:

1) Evaluate the performance of subsets that comprise only one feature and find the best subset $bestF1$.
2) Evaluate subsets that comprise two features: $bestF1$ and another one. Find the best subset $bestF2$.
3) Evaluate subsets that comprise three features: the features in $bestF2$ and another one. Find the best subset $bestF3$.

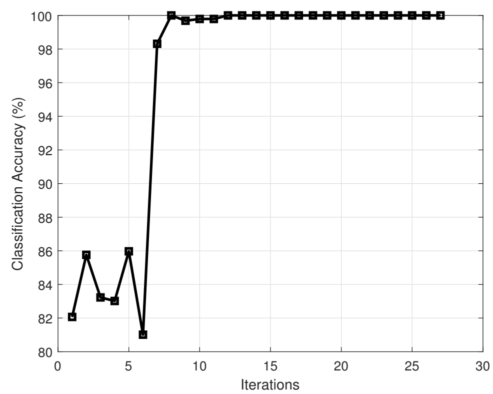
And so on until completing $bestFn$ where $n$ is the length of the complete input feature vector. The most promising feature vector is the one with the best performance in all the steps. The progress of the forward feature selection algorithm is presented in Fig. 3. Several local maxima are observed, then it is recommended to complete all the steps to avoid to pick a local instead of a global maximum. An abrupt change is visualized for both classifiers in the $7th$ iteration which corresponds to beginning of the evaluation of feature vectors of length two.

Feature vectors with the lowest misclassification rates and shortest lengths are selected. In the case of quadratic classifiers, the performance obtained with the complete set of features is 100%, but the resulting feature vector is shorter, then the feature selection is still useful. Feature vectors resulting from the feature selection are presented in Table III for linear and quadratic classifiers. Tables II and III indicate that feature selection improved the performance of linear classifiers in 1.58% and the length of the feature vector for all the classifiers.

Figure 4 shows the confusion matrices for the classifiers. The diagonal cells represent the instances where appliances are correctly identified and the off-diagonals cells indicate misclassifications. The darker the cells, the higher the numbers of correct or incorrect identifications. None misclassification is found for the quadratic classifier, while linear classifier predicts the cellphone charger as it were the led lamp and the other way around, and it confuses slightly the incandescent bulb with the TV. This is explained by the similarity of the power consumption of theses appliances.




(a) Linear classifier




(b) Quadratic classifier

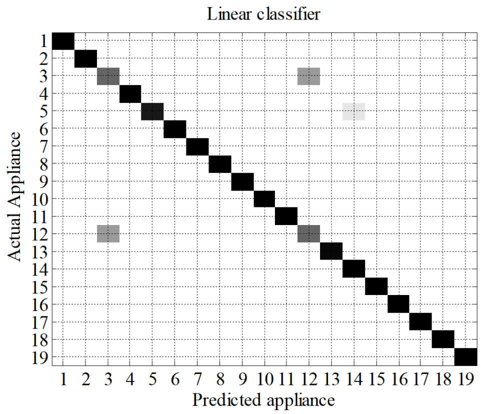
Fig. 3: Feature selection iterations

TABLE III: Classifier performance with the subsets obtained with the forward feature selection.

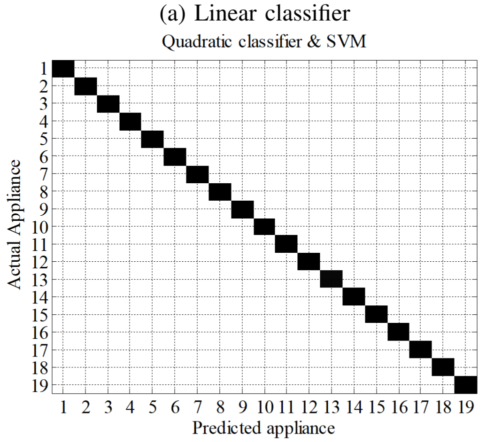
| Classifier | Feature Vector | Accuracy | Elapsed Time [s] |
|---|---|---|---|
| Linear | $[I, I_H, Q]$ | 95.25 % | 0.0807 |
| Quadratic | $[I, I_H]$ | 100% | 0.0626 |
| | $[I_H, PF_1]$ | | 0.0601 |
| | $[I, THD_i]$ | | 0.0600 |
| | $[I_H, THD_i]$ | | 0.0604 |

## V. Conclusion

Power quality information is used together with discriminant analysis for load identification. Here a classification task was achieved with discriminant analysis classifiers, thus distinguishing the operation of appliances in steady state.




(a) Linear classifier




(b) Quadratic classifier

Fig. 4: Confusion matrices.

Linear and quadratic discriminant analysis classifiers were implemented. These classifiers yielded noticeable performance, with the advantage of a quite reduced training and fitting times.

For future works the study of distorted environments is suggested. Power quality is a more mature field than Non-Intrusive Load Monitoring (NILM), so retrieving the experiences in power quality is promising to give support to the research in NILM, specially the techniques and knowledge for disturbances recognition.

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