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Abstract

This paper looks at the extraction of trends of household electrical seasonal consumption via load disaggregation. With the proviso that data for the several home devices can be embedded in a tensor, non-negative multi-way array factorization is performed in order to extract the most relevant components. First, in the decomposition step the decomposed signals are incorporated in the test signal consisting of the whole-home measured consumption. Second, the disaggregated data corresponding to each electrical device is obtained by factorizing the associated matrix through the learned model. Finally, we evaluate the performance of load disaggregation by the supervised method and study the trends along several years and across seasons. Towards this end, computational experiments were yielded using real-world data from a household electrical consumption measurements along several years. While breaking down the whole house energy consumption into appliance level gives less accurate estimates in the late years, we empirically show the adequacy of the method for handling the earlier years and the estimates of the underlying seasonal trend-cycle.

1. Introduction

Energy disaggregation of the total household electrical consumption into each appliance's demand has recently received increased attention due to

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energy efficiency concerns which gave rise to the advent of smart grids. Specific information on each home appliance plays an important role for energy-context awareness of the consumers about their behavior towards energy efficiency [1] as well as for activitymodelling either for ambient assisted living environments [2] as for response demand energy efficiency since the discrimination of electricity consumption routines for individual households may be useful for electricity service companies [3]. However, existent commercial electricity meters report only aggregated load data. Thus a tool to provide detailed information to the end-user or service utilities at virtually no cost is needed.

This study explores and evaluates the performance of a supervised single-channel source separation approach based on multi-way array (tensor) factorization for electrical source modeling regarding load disaggregation at long-term using a real dataset from an household. Multi-way arrays are a natural representation for multi-dimensional data and have been widely used in a variety of applications ranging from signal analysis neuroscience to source separation [4, 5, 6]. In a previous work, [7], we proposed a method for energy disaggregation STMF (Source Separation via Tensor and Matrix Factorization) where the data source model is obtained via non-negative factorization of a tensor composed by the collected consumption data of each electrical device for a given house (prior measurements). The learned source models are used to predict the power consumption of each device over a period of time where only the whole-home electrical consumption signal (aggregated signal) is measured. The number of active appliances in a household depends on the time of day, weekday and season as wells as on personal needs, since every person has different routine habits concerning appliances' usage. Although the electrical demand of appliances changes in accordance to consumer's behavior, user's electrical consumption is strongly related to the type of the season of the year. Hence, as STMF is a supervised method, i.e. prior data is required to train the source models, its assessment on how to achieve load disaggregation for different seasons is relevant to be explored. The performance evaluation in [7] considers a real-world dataset comprising data for several households gathered during a few months. In this work instead we look at the seasonal trends in electrical consumption analysing data from only one household over a longer period of time.

The remainder of this paper is organized as follows: Section 2 reviews recent related work. Section 3 introduces the necessary background and describes the load disaggregation problem as single-channel source separation

problem. Section 4 briefly presents the Source Separation via Tensor and Matrix Factorization (STMF) approach, further explaining how the multi-way arrays are used to define the source models and lately used to disaggregate unseen whole-home measurements. Section 5 describes the computational experiments including the dataset, the experimental setup and the performance metrics. Section 6 evaluates the STMF approach to deal with the seasonal trends on a real dataset of an anonymous real household. Section 7 concludes the paper and discusses potential extensions for future work.

2. Related Work

Non-intrusive Load Monitoring (NILM) systems [8, 9] provide the required detailed consumption by disaggregating the whole-home electrical demand signal acquired at a single point (aggregated/mixed data). A NILM method that uses a single point of power measurement requires both hardware and software components: an electricity load sensor and signal processing algorithms. As an example Figure 1 illustrates a disaggregation of the whole-home signal into the main house network circuit devices' consumption (this specific example was drawn from the data that was analysed in the following work experiment). From a complete NILM process, we are able to access the individual appliance/circuit loads for diverse end-use applications. From the beginning of NILM, it was clear that, although simple hardware was employed, complex software was needed [8], turning NILM into a very challenging problem. Most of the related research (e.g. [10, 11, 12]) followed initial Hart's framework based on appliances signatures which require: (i) acquisition of signals from the aggregate consumption of an electrical network; (ii) extraction of features of important events, such as changes in the electrical power measurements (known as steady-state changes) or characteristics; and (iii) identification of these events. These steady-state changes in signals (which can be obtained from real and reactive power reading samples for instance) are characterized by their magnitude and sign, corresponding to the turning on or off of each appliance in the network circuit. These signatures can be used to identify appliances such as heat pumps, dishwashers and refrigerators by recognizing the initial spikes in the power readings [10] or to identify the major end-uses with only the changes in the real power [13]. On the other hand, another type of electrical IDs, the transient signatures, that are composed by features extracted during the period bounded by two steady-states could provide a more accurate description of a given de-

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vice. Nevertheless, these transient signatures demand a very high-sampling rates as referred in [11]. Consequently, transients are being mainly applied to monitor loads in commercial and industrial buildings [14]. Yet the electric noise occurring in the signal when an appliance is plugged into the socket, an example of transient signature, was investigated for the identification of household devices using a specially contrived device as the sensor meter [11]. However, this signature is highly conditioned by the electrical system of the household, mostly leading to incorrect identifications wherever a device is plugged into a different socket.

Notwithstanding the significant progress that has been made in the identification of the appliances's signatures [15], recent approaches presenting diverse and interesting perspectives have appeared [16]. By reinterpreting the load disaggregation problem, Kolter et al. proposed a formulation where load disaggregation corresponds to the separation of the aggregated energy consumption into the electrical demand of each device or component circuit in the household network. The energy disaggregation problem can thus be cast into a single-channel source separation problem. In this context, approaches that learn data-adaptive representations, usually applied to source separation problems, as sparse coding and Non-negative Matrix Factorization (NMF) have been shown to be suitable to estimate the individual appliance/circuit's consumptions based solely on the whole-home electrical on-site measurements.

Since the electrical consumption is always a non-negative quantity, either non-negative restrictions may be imposed or specific non-negative methods can be used. In such approaches, non-negative representations of electrical consumption for each device in the network are learned, which can be enriched with information supplied by the whole-home signal, and disaggregation is then achieved for a set of unknown aggregated signals. Given that the existence of prior information about the individual consumptions required to define the representations of electrical consumption at device level is assumed, these methods are supervised. This paper emphasizes the the need and importance of this kind of approaches by empirically showing the methodology applied to a real-world dataset of a French household where on-site measurements were acquired during a fixed setup period. Without needing source models's readjustment, the method here proposed is able to yield load disaggregation forecasts for a couple of years ahead.
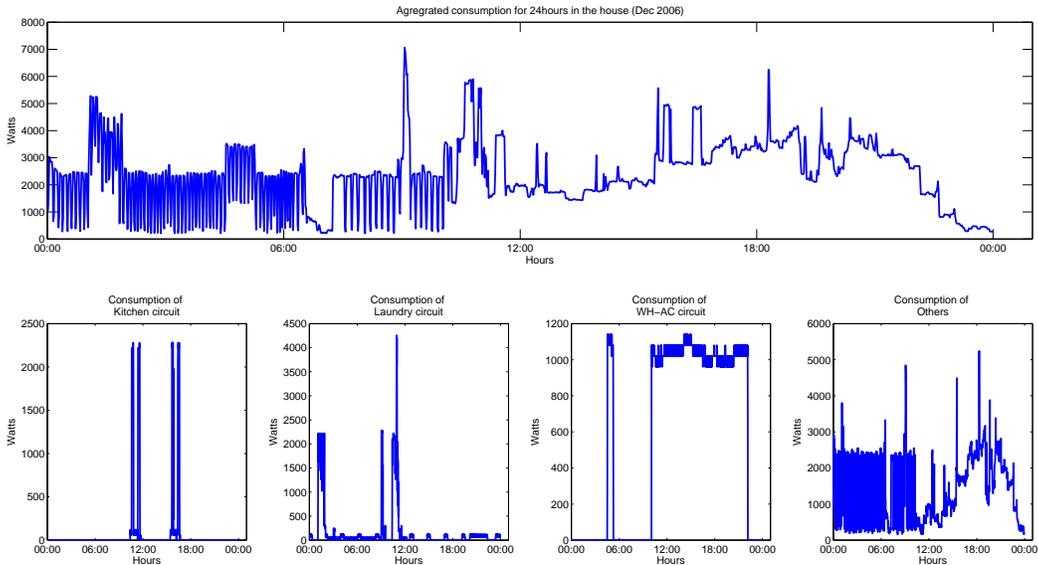
Figure 1: Total power load (top) and by appliance (bottom) for a time slice of 24hr corresponding to the electrical household consumption in December 2006.

3. Non-Intrusive Load Disaggregation

Non-Intrusive Load Disaggregation (NILM) aims to identify (or disambiguate) appliances (or groups of appliances) based in the appliance's power characteristics using only aggregated load measurements. The procedure allows to detail electrical consumption of diverse equipments which, in turn, can either be used to lead to energy savings due to potential consumer behavior change or to apply in assisted living environments. The specific information [8] is obtained through feature extraction from the acquired signal by classification based on each distinctive appliance power characteristics. Load disaggregation regarded as a classification problem is a widely studied approach in NILM related research [15, 17]. Alternatively, since the goal is to recover the electrical consumption of each device/circuit (source signals) from the aggregated signal, approaches such as signal-channel source separation are also feasible.

Formally, the disaggregation of whole-home electrical consumption into the electricity demand associated with each appliance in the network can be described as follows. Given an aggregated signal

$$\bar{x} = [\bar{x}(1), \bar{x}(2), \ldots, \bar{x}(T)]^T, \tag{1}$$

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corresponding to the aggregated electrical consumption during a period of time T we can rewrite it as the outcome of a mixing process f of sources $x_i, i = 1, \ldots, k$, *i.e.* the signals associated with the electrical consumption of each device or circuit i,

$$x_i = [x_i(1), x_i(2), \ldots, x_i(T)]^T. \tag{2}$$

In this case f is assumed as the linear mixing process thereby $\bar{x}$ is a linear combination of the x_i:

$$\bar{x}(t) = \sum_{i=1}^{k} x_i(t). \tag{3}$$

For a set of m daily observed signals, each column of $\bar{X} \in \mathbb{R}^{T \times m}$ represents the m-th aggregated consumption over the m-th day and each column of $X_i \in \mathbb{R}^{T \times m}$ the m-th daily consumption signal associated with the device i. Thus, the aggregated consumption verifies

$$\bar{X} = \sum_{i=1}^{k} X_i. \tag{4}$$

In a source separation based approach, data source models can be learned if training data is available by extracting properties of x_i. This modeling can be accomplished using matrix factorization for which a source x_i at a particular instant t is the a combination of bases, collecting the main characteristics of the source and the correspondent activations [18]. Formally, given $X_i \in \mathbb{R}^{T \times m}$ the goal is to represent X_i by a factorization $B_i A_i$, such that $B_i \in \mathbb{R}^{T \times r}$ is a matrix of r bases and $A_i \in \mathbb{R}^{r \times m}$ is an m-dimensional set of activations. The factorization $B_i A_i$ must be computed "as close" as possible of X_i. Moreover, the energy consumption is a non-negative quantity which means that not only the data but also the factor matrices are composed by non-negative elements thus needing non negative methods to keep the data meaningful. These restrictions make it evident that the use of Non-Negative Matrix Factorization (NMF) [19] is the most adequate method.

In terms of the overall machine learning system, note that $\bar{X}$ and X_i are solely available for training and a set of m' different aggregated signals, $\bar{X}' \in \mathbb{R}^{T \times m'}$ are used at the test step. At this point, we want to decompose $\bar{X}'$ into $X_i', i = 1, \ldots, k$, i.e. into the signals associated with each device (or group of devices).
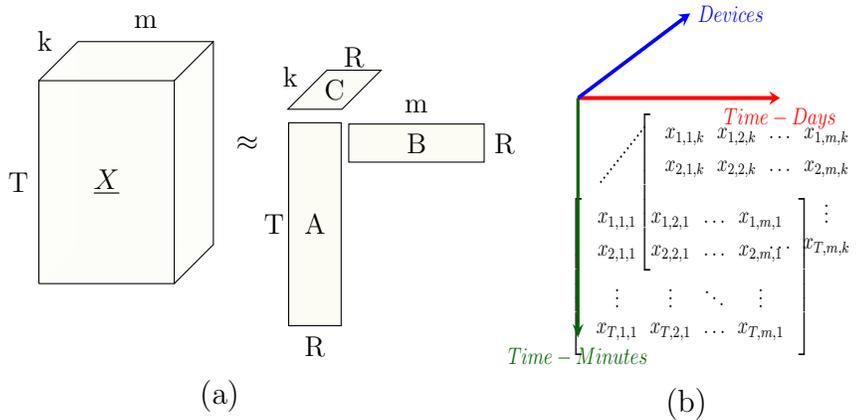
4. Energy Disaggregation via Tensor and Matrix Factorizations

A tensor $\underline{Y} \in \mathbb{R}^{I_1 \times I_2 \times \dots \times I_n}$ is a multi-way array also known as N-way tensor where N corresponds to the number of involved dimensions, and each element $(i_1, i_2, \dots, i_N)$ is denoted by $y_{i_1,i_2,\dots,i_N}$. Analogously to columns and rows of matrices, one-dimensional and two-dimensional sections of tensors can be defined. The one-dimensional sets are obtained by fixing every tensor index excluding one. Likewise two-dimensional slices result from fixing every tensor index except two of them. A particular example of the latter for a 3-order tensor is the frontal slice $Y_{:,:,i_3}$.

The idea and the respective illustration of using multi-way arrays and associated non-negative factorization for load disaggregation was proposed in [7]. In order to integrate all the important and dependent energetic features for circuit/appliance load disaggregation, we define a 3-order tensor $\underline{X} \in \mathbb{R}^{T \times m \times k}$ by considering that each frontal slice of the tensor is a matrix X_i representing the electrical consumption of device i during m days using T samples a day (see Figure 4).

This multi-dimensional representation allows for the exploration across the three different domains (T-minutes of a day, days sampling and devices) and therefore the models resulting from the factorization of $\underline{X}$ still incorporate this information. Recalling that electrical consumption is a non-negative quantity and, as explained in [7], this approach uses the PARAFAC method with non-negativity constraints to, given $R \in \mathbb{N}$, decompose $\underline{X}$ into factors

$A \in \mathbb{R}_+^{T \times R}$, $B \in \mathbb{R}_+^{m \times R}$ and $C \in \mathbb{R}_+^{k \times R}$, (corresponding the each one of the dimensions as represented in Figure 2) such that

$$\underline{X} \approx \sum_{l=1}^{R} a_l \circ b_l \circ c_l, \tag{5}$$

where $a_l \in \mathbb{R}_+^T$, $b_l \in \mathbb{R}_+^m$, $c_l \in \mathbb{R}_+^k$ for $l = 1, \dots, R$, and $\circ$ represents the outer product.

Then the i-th frontal slice of $\underline{X}$ can be approximated by

$$\tilde{X}_i = A D_i B^T, \tag{6}$$

where D_i is a diagonal matrix based on the i-th row of C. The columns of $\tilde{X}_i$ correspond to the reconstructed consumption signals for the appliance i. As a consequence, note that

$$\bar{X} \equiv \sum_{i=1}^{k} X_i \approx \sum_{i=1}^{k} \tilde{X}_i = \sum_{i=1}^{k} \left(A D_i B^T \right) = A \left(\sum_{i=1}^{k} D_i \right) B^T, \tag{7}$$

since $\bar{X} \equiv \sum_{i=1}^{k} X_i$ and $X_i \approx \tilde{X}_i$.

To achieve the separation of m' aggregated signals previously unseen, $\bar{X}' \in \mathbb{R}_+^{T \times m'}$, into the consumption of each device $\hat{X}'_1, \dots, \hat{X}'_k \in \mathbb{R}_+^{T \times m'}$, we need to decompose it accordingly. Since $\bar{X}'$ is the only measured consumption at this point, non-negative matrix factorization techniques are the most suitable. Non-negative matrices $W \in \mathbb{R}_+^{T \times R}$ and $H \in \mathbb{R}_+^{R \times m'}$ are computed in order to minimize the reconstruction error between WH and $\bar{X}'$. Usually, this error is quantified by the Euclidean distance or alternatively by the divergence of $\bar{X}'$ from WH as proposed by Lee and Seung [19].

The non-negative factorization of $\bar{X}'$ must include the model learned in the previous steps, in particular, contains the characteristics associated with the time and device domains, i.e., matrices A and C and the correspondent matrices $D_i, i = 1, \dots, k$ to achieve $\hat{X}'_i, i = 1, \dots, k$. Thereby, the factorisation of the new signal matrix must be computed such that

$$\bar{X}' \approx \tilde{W} \left(\sum_{i=1}^{k} D_i \right) \tilde{H}, \tag{8}$$

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where $\tilde{W}$ and $\tilde{H}$ are, respectively, initialized as matrix A and as a random matrix with positive values. The associated optimization problem then consists in solving

$$\min E'\left(\tilde{W}, \tilde{H}\right) = \min \left\| \bar{X}' - \tilde{W} \left(\sum_{i=1}^{k} D_i\right) \tilde{H} \right\|^2 , \quad (9)$$

with respect to $\tilde{W}$ and $\tilde{H}$, subject to $\tilde{W}, \tilde{H} \geq 0$. Note that this is a difficult optimization problem since it is not convex for both $\tilde{W}$ and $\tilde{H}$. One possible strategy is that of using an alternated optimization method: while optimizing over $\tilde{W}$, the factor $\left(\sum_{i=1}^{k} D_i\right) \tilde{H}$ remains fixed and repeat by fixing the other matrix in turns. Considering Equations 7 and 8 both $\tilde{W}$ and A comprise time-domain information and the same observation can be made for $\tilde{H}$ and B^T. To keep $\tilde{W}$ and $\tilde{H}$ similar to A and B^T in terms of sparseness, constraints were added to the problem and non-negative matrix factorization updates presented in [20] were used to solve the problem. The Source Separation via Tensor and Matrix Factorization (STMF) approach is summarized in Algorithm 1.

5. Computational Experiments

This section describes the dataset, the experimental setup and the performance metrics used in the study.

5.1. Individual Household Electric Power Consumption Dataset

The Individual Household Electric Power Consumption Dataset (IHEPCD) is an energy consumption dataset available at the UCI Machine Learning Repository [21] that reports data measured in a real environment. The aggregated and circuit/device specific electricity minute-averaged consumption measurements were gathered during 47 months between December 2006 and November 2010. For defining the training set we decided to use only the measurements made in the household during the period of 15 days in December 2006. The remainder data, the daily signals for the years 2007, 2008, 2009 and 2010 (1425 daily signals) were then considered to be the test set. Figure 3 ilustrates the average daily consumption of electricity for each year in the dataset with the exception of the training set data. With respect to seasonality, we decided to take a binary perspective on it. The months of

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Algorithm 1 The STMF algorithm [7]

Data: $X_i \in \mathbb{R}_+^{T \times m}, i = 1, \ldots, k,\ \bar{X} \in \mathbb{R}_+^{T \times m},\ \bar{X}' \in \mathbb{R}_+^{T \times m'},\ R \in \mathbb{N}, \epsilon \in \mathbb{R}_+$

Result: $\hat{X}_i' \in \mathbb{R}_+^{T \times m'}, i = 1, \ldots, k$

1 Let $\underline{X} \leftarrow \text{Tensor}(X_i, i = 1, \ldots, k)$
2 Use the non-negative PARAFAC model $\underline{X}$ and compute A, B and C
3 Let $D_i, i = 1, \ldots, k$ be the diagonal matrix based on the i-th row of C
4 Initialize $\tilde{H}$ with random positive values
5 $\tilde{W} \leftarrow A$
6 $v_0 \leftarrow \left\| \bar{X}' - \tilde{W} \left(\sum_{i=1}^{k} D_i \right) \tilde{H} \right\|$
7 $j \leftarrow 0$
8 **repeat**
9 $\quad W \leftarrow \tilde{W} \left(\sum_{i=1}^{k} D_i \right)$
10 $\quad \tilde{H} \leftarrow argmin_{\tilde{H} \geq 0} \left\| \bar{X}' - W\tilde{H} \right\|$
11 $\quad H \leftarrow \left(\sum_{i=1}^{k} D_i \right) \tilde{H}$
12 $\quad \tilde{W} \leftarrow argmin_{\tilde{W} \geq 0} \left\| \bar{X}' - \tilde{W}H \right\|$
13 $\quad v_j = \left\| \bar{X}' - \tilde{W} \left(\sum_{i=1}^{k} D_i \right) \tilde{H} \right\|$
14 $\quad j \leftarrow j + 1$
15 **until** $|v_j - v_{j-1}| < \epsilon$;
16 Predict $\hat{X}_i' = \tilde{W} D_i \tilde{H}$

May, June, July, August, and September show an average daily demand lower than 1.1kW across all the years in analysis. Therefore, we considered this period to represent the Summer season while the Winter season comprises the remaining months.

5.2. Experimental Setup

Three main circuits, for which the highest consuming appliances have been identified, were monitored and discriminated as: the Kitchen circuit; the Laundry circuit; and the WH-AC circuit. A fourth specification, which we called Others, corresponds to the active power consumed in the household by
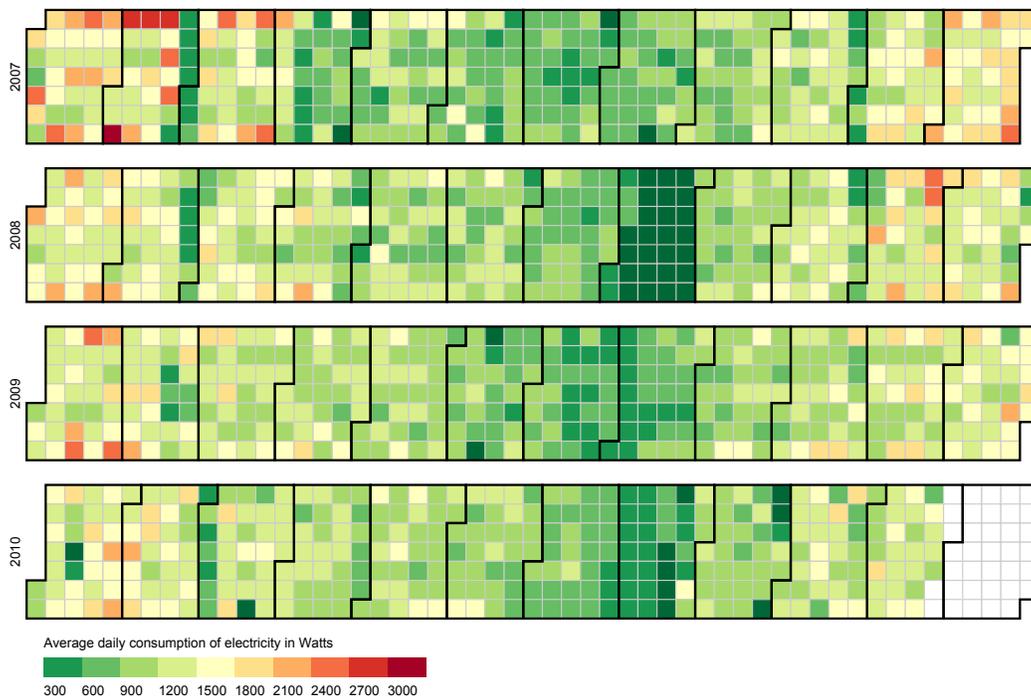
Figure 3: Average daily consumption of electricity along the years 2007 to 2010 for the dataset in analysis. Each column represents the week of the month while the rows correspond to the day of the week (the first row corresponds to Sunday).

electrical devices that were not sub-measured. The complete characterisation of the three main sub-metered circuits is:

(i) Kitchen circuit - containing mainly a dishwasher, an oven and a microwave without the hot plates since these are gas powered;

(ii) Laundry circuit - laundry room, containing a washing-machine, a tumble-drier, a refrigerator and a light;

(iii) WH-AC circuit - electric water-heater and an air-conditioner;

(iv) Others - remnant active power consumed.

The dataset comprises the aggregated active power and the household global reactive power, both measured in kW, the household global minute-averaged current intensity (A), and the active energy for the three main circuits of the house measured in Wh. However, there data missing representing 1.25% of the total of the signals. For the computational experiment, using only active consumption measures, a preprocessing phase was carried

out. First, data was transformed accordingly so as to represent the active power in Watts. Second, for treating the missing data, a single imputation of a period of zero-consumption was assumed. Third, the active power consumed by electrical devices that was not sub-metered was calculated. The latter comprises the fourth group in analysis (Others) as referred above. In addition, the signals were normalized using the aggregated time series norm to preserve the relative importance of each group. The measurements corresponding to the period of 15 days in December 2006 comprise the training set. In Figure 1 we illustrate the total power load and the load by each appliance for a time slice of 24hr corresponding to the electrical household consumption in December 2006 after completing the preprocessing mentioned above.

For the purpose of this work, we studied the performance of the STMF method for forecasting seasonal electrical energy consumption in the household used in the IHEPCD dataset. The STMF was implemented using MAT-LAB and the N-way Toolbox [22]. The source models were obtained through the load disaggregation procedure over the training data. For testing, the data was partitioned into years and, for each, the aggregated signals were separated based on the model learned. The maximum number of iterations was set to 1000 and the error threshold ϵ to 0.00001 (see Algorithm 1).

5.3. Performance Metrics

Within NILM context the performance is usually assessed according to the specific method designed to solve the problem. If the load disaggregation is solved as a classification problem metrics such as accuracy, precision and recall are well-suited [17]. On the other hand, since our the approach is that of to solve load disaggregation as a single channel source separation problem, other performance metrics are required. One of the most useful ones is to measure the performance of the STMF in terms of the disaggregation error $\sum_{i=1}^{k} \frac{1}{2} \left\| X_i - \hat{X}_i \right\|_F^2$ where X_i is the matrix of measured signals for equipment i, $\hat{X}_i$ is its predicted version and $\|\bullet\|_F$ is the Frobenius norm. Clearly, this metric provides a global measure of the distance between the prediction and the measured consumption [16]. However, and because the disaggregation error is not normalised, we have also resort to use another metric, the root-mean-square error (RMSE), which measures the difference between the predicted values and the truly observed amount. The RMSE is directly interpretable in terms of measurement units and so is a better measure of goodness of fit than a correlation coefficient. The RMSE was computed regarding (i)

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an overview of the error concerning the m days in study ($d = 1, \ldots, m$ for training and $d = 1, \ldots, m'$ for test) and (ii) a detailed error assessment by appliance. For the former, the RMSE associated to both the aggregated signal $\bar{X}$ and its predicted version $\hat{\bar{X}}$, was calculated by $RMSE(\bar{X}, \hat{\bar{X}}) = \sqrt{sum_{t=1}^{T} \sum_{d=1}^{m} \left(\bar{X} - \hat{\bar{X}} \right)^2 / T * m}$. For the latter, the RMSE corresponding to each device i between the measured signal X_i and its predicted version $\hat{X}_i, i = 1, \ldots, k$, the same formula with the necessary adjustments was used. Additionally, we calculated the percentage of electrical energy associated with the load demand of each device by $\% X_i = \frac{\sum_{t=1}^{T} \sum_{d=1}^{m} X_i}{\sum_{t=1}^{T} \sum_{d=1}^{m} \bar{X}} \times 100\%$. In this way, it was possible to compose the electricity consumption profiles and thus to evaluate the STMF performance both in the long-term (i.e., across the years from 2007 - 2010) and in the seasonal trends (i.e., across Winter and Summer).

6. Results and Discussion

We begin by noticing that the STMF requires the previous setup of R, the number of bases for the tensor decomposition. Therefore, the impact of the variation of the number R on the disaggregation performance of the method was studied. Figure 4 presents the results of the RMSE mean value for all the yearly data under analysis. As it can be observed, the number of bases for achieving the best value decomposition is $R = 30$. Thus, the parameter R was set 30 since it yielded the best performance in regard of the major metric considered in this work.

In the following, representative results using the metrics described are presented. The STMF performance analysis is focused in three distinct directions: observable trends across the years, season changes and performance for each circuit. Firstly, an effectiveness analysis relating to the disaggregation error and the overall RMSE of both seasons is presented. Secondly, the RMSE associated with each main sub-metered circuit for assessment of the estimated consumption is estimated. Finally, the consumption profiles in terms of percentage of load of energy are examined.

Figure 5 presents the average disaggregation error and the RMSE computed over 30 runs with respect to each assigned season and corresponding year as well as the overall yearly metrics performance. In general, the disaggregation of Winter signals shows a higher disaggregation error than for Summer. It is interesting to notice this particular occurrence since the source

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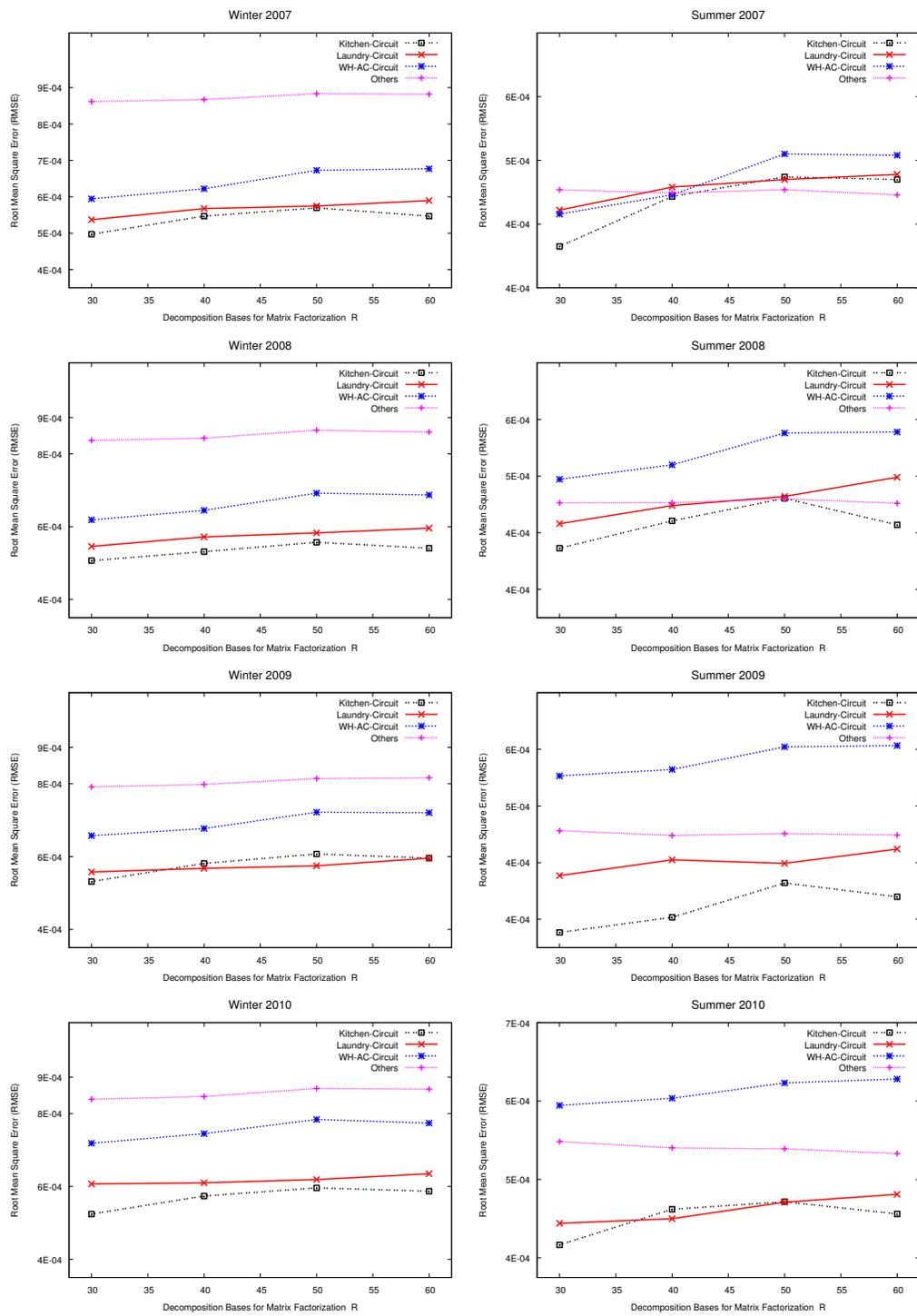
Figure 4: RMSE for R number of basis decomposition discriminated season and circuit from years 2007 and 2010.

models are derived from a training signal consisting of 15 days of Winter loads. In fact, the error resulting from the estimation of cold season loads, although being small, corresponds to more than half of the values associated with Summer. Note also that the computed performance measure is a global assessment and, in this experiment, the Winter test set comprises seven months while the Summer consists of five months in each year. Thereby, the number of entries in the error matrix for each appliances' circuit associated with Winter is clearly larger than for Summer. As a consequence, if these are non-zero entries then they must necessarily influence the error values. With regard on how accurate the disaggregate estimates are Figure 5also
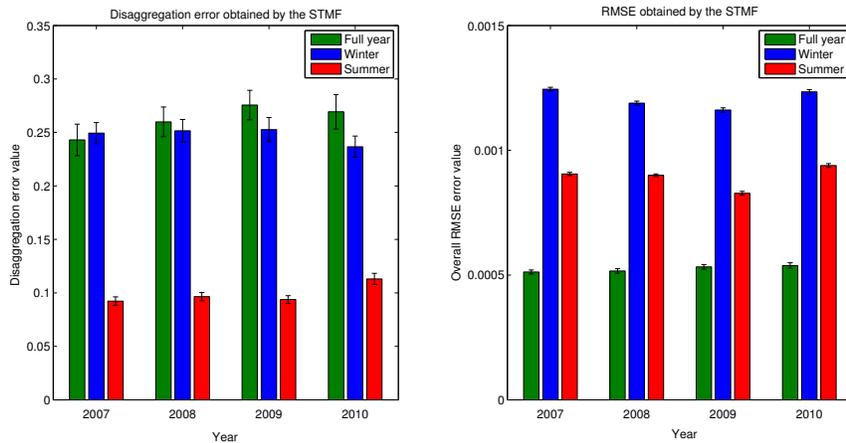
Figure 5: Mean Disaggregation Error and RMSE for the STMF results by year, season, all the overall yearly metrics.

reports the overall yearly RMSE. It is noticeable that virtually no variation on the RMSE values associated with the estimated total power consumption was observed for the Winter season across all the years. A similar remark can be drawn for the results achieved for the hot season. The relative error between both seasons is at most of 0.0003, i.e., the error for Winter is 33% higher than for the Summer, which reinforces the fact that the aggregated estimated consumption for Summer days is more accurate than for Winter.

As previously stated, the optimization problem which is solved in the test phase includes the learned source models from the Winter training data (see Equation 9). The load disaggregation takes a single channel source separation approach of the aggregated signal. To proceed with a throughout
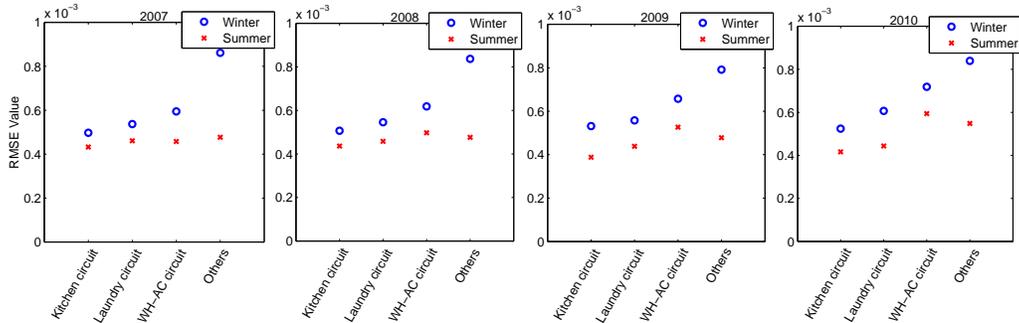
Figure 6: Mean RMSE for each major circuit across the years and seasons: other perspective.

analysis of the disaggregation estimates provided by the method, the circuits' performance must also be analysed.

In Figure 6 the mean RMSE for the forecast of each main circuit across the four years is presented. The previous observation of higher precision estimates for Summer when compared to Winter seasons remains valid, as it should be expected. However, a closer look into these differences points out that this trend is more evident in the group "Others", where the RMSE in Winter of 2007 is 80% higher than for the corresponding Summer. Although decreasing in 2010 it keeps the observed trend as it turns out to be still 53% higher.

Note that there is an increase in RMSE values from Summer 2007 to 2010 across all the appliances' groups. Note that the RMSE values for the Summer of 2007 was approximately 0.4×10^{-3} while for 2010 it increased to 0.6×10^{-3} and 0.5×10^{-3} regarding the "WH-AC circuit" and the group "Others", respectively. We may also observe that for the former circuit the RMSE values increased by 20% from the Winter of 2007 to 2010. Since the source models were learned regarding data from Winter 2006, this increase in the RMSE value may well be a direct result from a change of behaviors in active appliances usage that could not be foreseen by the models. Indeed, as it can be observed in Figure 7, the measured electricity consumption of the WH-AC circuit corresponds to 30% of the total electrical usage in Winter 2007, which increases by 9% in 2010.

The energy profiles for 2007 and 2010 provided by the STMF as well as the ground truth or measured consumption for each season are compared in

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Figure 7. The information of the profiles of the the ground truth illustrates that groups "WH-AC circuit" and "Others" represent a predominant slice of the loads $[30\%; 43\%]$ and $[46\%; 57\%]$, respectively. The remaining groups represent a lower percentage of the consumption ($< 10\%$ each). With regard to the profiles of the estimated consumption by the Source Separation via Tensor and Matrix Factorization (STMF) method it can be observed that the "WH-AC circuit" and the "Others" estimated usage is always lower than the actual consumption. Moreover, the "Kitchen circuit" and the "Laundry circuit" estimated usage is 10% higher than the ground truth while the estimated usage of "Others" obtained for 2010 was the most accurate.
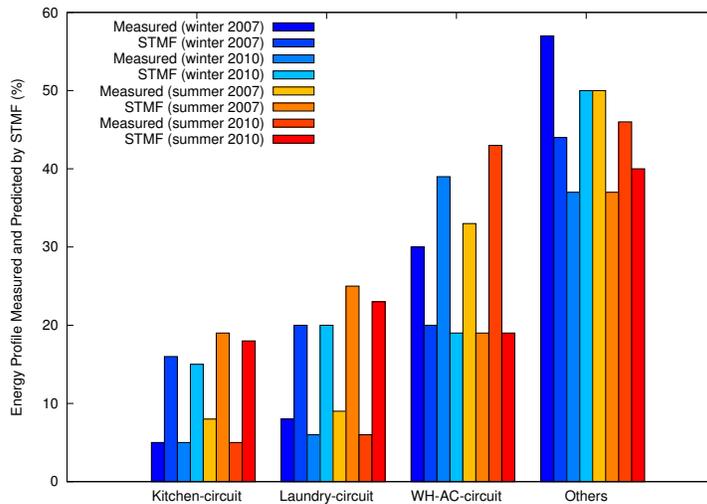
Figure 7: Measured and predicted electrical consumption by STMF for years 2007 and 2010 by season and appliance's circuit.

Towards a more detailed view of the seasonal changes presented by the method we observed that from the Winter 2007 to the Summer 2007, the ground truth trends for the several groups were successfully followed by STMF estimates, excepting group "WH-AC". Meanwhile, from Winter 2010 to Summer 2010, the trends of the ground truth were favourably tracked by the STMF estimates for the group "Others". In addition, from Summer 2007 to 2010 the method STMF originated good estimates of the "Kitchen circuit" and "Laundry circuit", following the ground truth trends.

These results are in line with the RMSE by appliance presented in Figure 6. As explained the whole-home electrical consumption for each year

was disaggregated on the basis of part of 2006 Winter demand loads. In the test phase sources may be misrepresented by the model downgrading in some cases the STMF performance. Nevertheless, the observed failures in predictions might also be due to personal variances of habits towards active appliances' usage across the years.

7. Conclusion

Energy efficiency is a concern of modern societies for environmental and economic reasons. Electricity represents a considerable segment of the energy consumed in the residential sector, which is growing in importance. In order to cut their energy bills households need to identify actions able to bring the most savings. This can be achieved providing to the consumer detailed appliance load information so that misuses can be easily identified. Such information could be computed by breaking down the electrical energy measure at a single global point, usually the electrical network entrance of the household, into the loads of the several devices. This problem, known as electrical energy disaggregation, can be cast into a non-intrusive load monitoring system if only the aggregated electrical consumption signal is sampled without any plug level sensors.

The single-channel source separation approach exploited in this work is a supervised method based on the use of multi-way arrays and correspondent decomposition methods for solving the load disaggregation problem. Source models are learned and then applied to predict the consumption of appliances. Nevertheless, the usage of appliances vary, in particular from season to season and so does the electrical consumption. Since the approach in study is supervised, i.e. based on prior information for learning the source models, the rationale behind this study consists in evaluating the method capability to handle both seasonal and long-term trends in power demand. Towards this end a computational experiment was designed using real-world data from a French household. The source models were learned employing only 15 days from the 2006 Winter and the whole-home electrical consumption from 2007 to 2010 was yearly disaggregated. A comprehensive performance assessment of the method across the seasons and years was presented by applying overall performance metrics. Moreover, major groups appliance-level evaluation was also performed. The outcome results uphold seasonal forecasting trend patterns which demonstrate the adequacy of the method. Notwithstanding,

the long-term trends in electrical energy demand have shown to be affected by the disaggregation performance in the late years.

Future work will focus on improving the optimization method by studying different metrics for the non-negative tensor factorization procedure when applied to electrical energy disaggregation. Another line of work is to explore the seasonal effect in more detail by using several training sets with distinct weights associated to each group of appliances.

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References

[1] S. Karjalainen, Consumer preferences for feedback on household electricity consumption, Energy and Buildings 43 (2-3) (2011) 458–467, ISSN 0378-7788.

[2] S. Rahimi, A. D. C. Chan, R. A. Goubran, Nonintrusive load monitoring of electrical devices in health smart homes, in: Proc. of the IEEE Intl. Conf. on Instrumentation and Measurement Technology, 2313–2316, 2012.

[3] J. Abreu, F. Pereira, P. Ferrão, Using pattern recognition to identify habitual behavior in residential electricity consumption, Energy and Buildings 49 (2012) 479–487.

[4] T. G. Kolda, B. W. Bader, Tensor Decompositions and Applications, SIAM Review 51 (3) (2009) 455–500.

[5] A. Cichocki, R. Zdunek, A. H. Phan, S. Amari, Nonnegative Matrix and Tensor Factorizations: Applications to Exploratory Multi-way Data Analysis and Blind Source Separation, John Wiley & Sons, Ltd, ISBN 9780470747278, 2009.

[6] D. Fitzgerald, M. Cranitch, E. Coyle, Non-negative tensor factorisation for sound source separation, in: Proc. of the Irish Signals and Systems Conf., 2005.

[7] M. Figueiredo, B. Ribeiro, A. de Almeida, Electrical Signal Source Separation Via Nonnegative Tensor Factorization Using On Site Measurements in a Smart Home, IEEE Transactions on Instrumentation and Measurement 63 (2) (2014) 364–373, ISSN 0018-9456, doi:\bibinfo{doi}{10.1109/TIM.2013.2278596}.

[8] G. W. Hart, Nonintrusive Appliance Load Monitoring, Proc. of the IEEE 80 (1992) 1870–1891.

[9] F. Sultanem, Using appliance signatures for monitoring residential loads at meter panel level, in: IEEE Trans. on Power Delivery, vol. 6, 1380–1385, 1991.

[10] A. Cole, A. Albicki, Algorithm for non-intrusive identification of residential appliances, in: Proc. of the IEEE Intl. Symposium on Circuits and Systems, 338–341, 1998.

[11] S. N. Patel, T. Robertson, J. A. Kientz, M. S. Reynolds, G. D. Abowd, At the flick of a switch: detecting and classifying unique electrical events on the residential power line, in: Proc. of the Intl. Conf. on Ubiquitous Computing, 271–288, 2007.

[12] M. Figueiredo, A. De Almeida, B. Ribeiro, Home electrical signal disaggregation for non-intrusive load monitoring (NILM) systems, Neurocomputing 96 (2012) 66–73, ISSN 0925-2312, doi:\bibinfo{doi}{10.1016/j.neucom.2011.10.037}.

[13] M. Marceau, R. Zmeureanu, Nonintrusive load disaggregation computer program to estimate the energy consumption of major end uses in residential buildings, Energy Conversion and Management 41 (13) (2000) 1389–1403.

[14] S. B. Leeb, J. L. Kirtley Jr, A Multiscale Transient Event Detector for Nonintrusive Load Monitoring, in: Proc. of the IEEE Intl. Conf. on Industrial Electronics, Control and Instrumentation, 354–359, 1993.

[15] M. Zeifman, K. Roth, Nonintrusive appliance load monitoring: Review and outlook, IEEE Transactions on Consumer Electronics 57 (1) (2011) 76–84.

[16] J. Zico Kolter, S. Batra, A. Ng, Energy Disaggregation via Discriminative Sparse Coding, in: J. L. et al. (Ed.), Advances in Neural Information Process. Systems, vol. 23, 1153–1161, 2010.

[17] A. Zoha, A. Gluhak, M. Imran, S. Rajasegarar, Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey, Sensors 12 (2012) 16838–16866.

[18] M. Schmidt, Single-channel source separation using non-negative matrix factorization, Ph.D. thesis, Tech. Univ. of Denmark, 2008.

[19] D. D. Lee, H. S. Seung, Algorithms for Non-negative Matrix Factorization, in: In Advances in Neural Information Process. Systems, vol. 13, 556–562, 2001.

[20] P. O. Hoyer, Non-negative matrix factorization with sparseness constraints, Journal of Machine Learning Res. 5 (2004) 1457–1469.

[21] K. Bache, M. Lichman, UCI Machine Learning Repository, URL `http://archive.ics.uci.edu/ml`, 2013.

[22] C. A. Andersson, R. Bro, The N-way Toolbox for MATLAB, Chemometrics and Intelligent Laboratory Systems 52 (1) (2000) 1–4.