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Exploring the Performance of Non-negative Multi-way Factorization for Household Electrical Seasonal Consumption Disaggregation

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Abstract— **The performance of household electrical seasonal consumption disaggregation is explored in this paper. Firstly, given a tensor composed by the data for the several devices in the house, non-negative tensor factorization is performed in order to extract the most relevant components. Secondly, the outcome is embedded in the test step, where only the whole-home measured consumption is available. Lastly, the disaggregated data by device is obtained by factorizing the associated matrix regarding the learned model. This source separation approach thus requires prior data, needed to learn the source models. Nevertheless, the consumer behaviors vary along time particularly from season to season, and hence also the electrical consumption. Consequently, the assessment of performance at long-term and across different times of the year is essential. We evaluate the performance of load disaggregation by this supervised method 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. The analysis of the computational results illustrates the adequacy of the method for handling the shifts between seasons.**

I. Introduction

ENERGY DISAGGREGATION of the total household electrical consumption into each appliance's demand has recently received renewed interest boosted mainly by the increasing energy efficiency concerns and by the emerging of smart grids. Appliance-specific information plays an important role not only for raising awareness of the consumers about their behavior towards energy efficiency [1] but also for activity-modeling in ambient assisted living environments [2]. However, existent electricity meters only report aggregated load data. Thus a tool to provide detailed information without incurring in further costs and invasive submetering is needed.

Non-intrusive Load Monitoring (NILM) systems [3], [4] provide the required detailed consumption by acquiring the whole-home electrical demand signal at a single point (aggregated/mixed data) and breaking it up into the individual appliance/circuit signals in the electrical network employing simple hardware but complex software [3] turning NILM into a very challenging problem. Load disaggregation is the essence of a NILM system. Related research [5], [6], [7] has followed the initial Hart's framework based on appliances signatures, requiring the (i) acquisition of signals from the aggregate consumption of an electrical network; (ii) extraction of features of important events, as changes in the electrical power measurements from one nearly constant value (steady-state) to another, and/or characteristics; and (iii) identification of these events. These steady-state changes in signals (real and reactive power for instance), characterized by their magnitude and sign, correspond to the turning on or turning off of an appliance in the network. These are the so-called steady-state signatures, explored to characterize appliances as heat pumps, dishwashers and refrigerators using the analysis of the initial spikes in the power [5] or to identify the major end-uses using only the changes in the real power [8]. On the other hand, the transient signatures composed by features extracted during the period bounded by two steady-states could provide a more accurate description of a given device. Nevertheless, the transient signatures demand high-sampling rates as described as basic requirements in [6]. Consequently, transients were mainly applied to monitor loads in commercial and industrial buildings [9]. Still, the electric noise occurring in the signal when an appliance is plugged in the socket, an example of transient signature, was explored for the identification of household devices [6]. However, and as remarked by the authors, this signature is conditioned by the electrical system of the household and so, an incorrect identification may occur when plugging a device to a different socket.

Despite appliances signatures and associated classification/identification techniques have been receiving plenty attention of researchers [10], other approaches have been explored like the ones derived from the reinterpretation of the load disaggregation problem proposed in [11]. Bearing in mind that load disaggregation corresponds to the separation of the whole-home energy consumption (aggregated consumption) into the individual electrical demand of each device/circuit in the household network, energy disaggregation can be though as 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), are suitable to estimate the individual appliance consumptions based on the whole-home electrical consumption measurements. Since the electrical consumption is always a nonnegative quantity, non-negative restrictions are usually imposed. In such approaches, non-negative representations of electrical consumption for each device in the network are

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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. Since 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 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 the load disaggregation at long-term in a given house. 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 [12], [13], [14] and a particular application to energy disaggregation is proposed in [15]. In the approach therein proposed - Source Separation via Tensor and Matrix Factorization (STMF) - the data source model results from the 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 thus 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. Notwithstanding, the electrical consumption and usage of appliances vary in accordance to consumer behaviors which are deeply related with the seasons of the year. Hence, as STMF is a supervised method, *i.e.* prior data acquired at a certain point in time is required to train the source models, the evaluation of the performance of load disaggregation for different seasons using the STMF arises as a relevant question to be explored. However, the performance evaluation detailed in [15] considers a real-world dataset comprising data for several households gathered during only a few months. This paper aims at performance evaluation of the method under consideration on a context similar to the real-world: appliance-detailed measurements are acquired only during a setup period and thereafter during several years no source models readjustment exists. In order to evaluate the performance of the STMF under different periods of the year, in this work a computational experience was outlined using real-world data comprising measurements for several years in a given house.

The rest of this paper is organized as follows: next section introduces the necessary background, describing the load disaggregation as single-channel source separation problem. Section III presents the approach under consideration (STMF), explaining how the multi-way arrays are used to define the source models and lately used to disaggregate unseen whole-home measurements. The experimental setup designed to explore the STMF performance under different seasons of the year is detailed in Section IV followed by the results, performance assessment and correspondent discussion. Lastly, conclusions and directions of future work are given.

II. Non-intrusive Load Disaggregation as a Single-source Separation Problem

The load disaggregation casted in a NILM system corresponds to the inference of appliance-detailed electrical consumption information, over a period of time, provided only measurements gathered at a single point of an electrical network, *e.g.* the power panel. The influential work [3] proposes the use of feature extraction techniques and classification methods considering distinctive characteristics defined to represent each appliance in the network in order to achieved the appliance-detailed information. The load disaggregation thought as a classification problem is as widely studied approach in NILM research [10]. Alternatively, since the goal is to recover the electrical consumption of each device/circuit (source signals) that composes the aggregated signal (aggregated signal), signal-channel source separation approaches are also feasible to solve the load disaggregation problem.

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

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

corresponding to the whole-home electrical consumption during a period of time T we intend to 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 [16]. Formally, given $X_i \in \mathbb{R}^{T\times m}$ the goal is to represent X_i by a factorization B_iA_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. This corresponds to compute B_iA_i as close as possible of X_i. Restrictions as non-negativity can be added leading to Non-Negative Matrix Factorization (NMF) [17]. In fact, as the

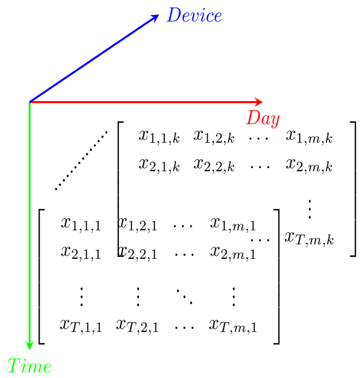

Fig. 1. Three-way tensor $\underline{X}$ in the STMF approach.

energy consumption is a non-negative quantity, all the data and factor matrices are composed by non-negative elements, then suitable approaches require non-negativity restrictions.

Note that $\bar{X}$ and X_i are solely available for training while only a set of m' aggregated signals, $\bar{X}' \in \mathbb{R}^{T\times m'}$, are accessible at the test step. We want to decompose $\bar{X}'$ into $X_i', i = 1, \ldots, k$, the signals associated with each device.

III. Energy Disaggregation via Tensor and Matrix Factorizations

A tensor is a multi-way array also known as N-way tensor where N corresponds to the number of involved dimensions, and each element $(i_1, i_2, \ldots, i_N)$ is denoted by $y_{i_1,i_2,\ldots,i_N}$. 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 of using multi-way arrays and associated non-negative factorization for load disaggregation was proposed in [15] and is formalized in this paper. For energy disaggregation a 3-order tensor $\underline{X} \in \mathbb{R}^{T\times m\times k}$ is defined considering that each frontal slice is the matrix X_i representing the electrical consumption of device i during m days with T samples by day (Fig. 1). This multi-dimensional representation would allow for the exploration across the three different domains (time, day and device) and therefore the data source models resulting from the factorization of $\underline{X}$ could incorporated this information. For that purpose, decomposition methods as Tucker's or its extensively studied case the PARAFAC method (also known as CANDECOMP or canonical polyadic) can be employed [18], [12], [13], [19]. Recalling that electrical consumption is a non-negative quantity, the approach uses the PARAFAC with non-negativity constraints to decompose $\underline{X}$ into factors $A \in \mathbb{R}_+^{T\times R}$, $B \in \mathbb{R}_+^{m\times R}$ and $C \in \mathbb{R}_+^{k\times R}$, given $R \in \mathbb{N}$, 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 $l = 1, \ldots, R$, and $\circ$ represents the vector outer product. Then the i-th frontal slice of $\underline{X}$ can be approximated by

$$\tilde{X}_i = AD_iB^T, \tag{6}$$

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

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

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 $\hat{X}_1', \ldots, \hat{X}_k' \in \mathbb{R}_+^{T\times m'}$, 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 [17].

The non-negative factorization of $\bar{X}'$ should include in their calculation the previously learned model, in particular, the characteristics associated with the time and device domains *i.e.* matrices A and C and the correspondent matrices $D_i, i = 1, \ldots, k$ to achieve $\hat{X}_i', i = 1, \ldots, k$. Thereby, $\tilde{W}$ and $\tilde{H}$ should be computed such that

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

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

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

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 W and H. The strategy is to optimize over one matrix while the other is fixed. While optimizing over $\tilde{W}$, the factor $\left(\sum_{i=1}^{k} D_i\right)\tilde{H}$ remains fixed and while optimizing over $\tilde{H}$, the factor $\tilde{W}\left(\sum_{i=1}^{k} D_i\right)$ remains fixed. Considering Equations 7 and 8, both $\tilde{W}$ and A comprise time-domain information and a similar observation can be drawn between $\tilde{H}$ and B^T. Thereby, 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. The described Source Separation via Tensor and Matrix Factorization (STMF) approach is summarized in Algorithm 1.

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

`/* Training: */`

Set $\underline{\mathrm{X}}$ as a tensor such frontal slices are $X_i, i = 1, \ldots, k$;

Compute the PARAFAC model with non-negativity restrictions associated to $\underline{X}$: A, B and C;

Set $D_i, i = 1, \ldots, k$ as a diagonal matrix based on the i-th row of C;

`/* Test: */`

Initialize $\tilde{H}$ with random positive values;

Set $\tilde{W} \leftarrow A$;

Set $v_0 \leftarrow \left\| \bar{X}' - \tilde{W} \left(\sum_{i=1}^{k} D_i \right) \tilde{H} \right\|$;

Set number of iterations $j = 0$;

repeat

Set $W \leftarrow \tilde{W} \left(\sum_{i=1}^{k} D_i \right)$;

$\tilde{H} \leftarrow argmin_{\tilde{H} \geq 0} \left\| \bar{X}' - W\tilde{H} \right\|$;

Set $H \leftarrow \left(\sum_{i=1}^{k} D_i \right) \tilde{H}$;

$\tilde{W} \leftarrow argmin_{\tilde{W} \geq 0} \left\| \bar{X}' - \tilde{W}H \right\|$;

$v_j = \left\| \bar{X}' - \tilde{W} \left(\sum_{i=1}^{k} D_i \right) \tilde{H} \right\|$;

$j + +$;

until $|v_j - v_{j-1}| < \epsilon$;

Predict $\hat{X}_i' = \tilde{W} D_i \tilde{H}$

Algorithm 1: The STMF algorithm [15].

IV. Computational Experiments

A. Individual Household Electric Power Consumption Dataset

The Individual Household Electric Power Consumption Dataset (IHEPCD), an energy consumption dataset freely available at the UCI Machine Learning Repository [21] that reports data measured in real environment, is the base of this computational experience. The aggregated and circuit/device specific electricity minute-averaged consumption measurements made for one household were gathered during 47 months between December 2006 and November 2010 and stored in this database. Three individual circuits labeled with its category of appliance were monitored:

- kitchen, containing mainly a dishwasher, an oven and a microwave without the hot plates since these are gas powered (Kitchen circuit);
- laundry room, containing a washing-machine, a tumble-drier, a refrigerator and a light (Laundry circuit);
- electric water-heater and an air-conditioner (WH-AC circuit).

The dataset is composed by the aggregated active power and the household global reactive power, both measured in kiloWatt, by the household global minute-averaged current intensity, measured in ampere, and by the active energy for the three main circuits of the house measured in Watt-Hour. Additionally, missing data exists, representing 1,25% of the total measurements. In the context of this computational experiment, we are interested in the active aggregated consumption and on the sub-circuits signals, therefore a preprocessing phase composed by three tasks was carried out. First, data was transformed accordingly to represent the active power into Watts. Second, the missing data was assumed as a period of zero-consumption and, third, the active power consumed every minute (in Watts) in the household by electrical equipment not measured in sub-circuits was computed comprising the fourth group in analysis (hereinafter called of Others). In addition, the signals were normalized using the aggregated time series norm to preserve the relative importance of each group.

For the purpose of this study, the evaluation of the STMF performance over the different seasons of the year, the post-processed dataset was divided in training and test subsets. For the design of this experiment we considered that the equipment in the household was only sub-metered once, corresponding to the period of 15 days in December 2006. These measurements comprise, thus, the training set. The remainder data, the daily signals for the years 2007, 2008, 2009 and 2010 (1425 daily signals) were then considered as test set. From Fig. 2, that represents the average daily consumption of electricity for each year in the dataset, we can distinguish months for which the electrical demand was lower. In fact, for May, June, July, August and September, the average monthly demand was lower than 1100 Watts across all the years in analysis, then in this work they correspond to the Summer season while the Winter period consists of the remaining months. Besides the lower global electrical usage for the Summer, a change in the electrical consumption associated to each circuit also occurs, for instance the average electricity consumed by the air conditioner circuit was 129W lower in the Summer of 2010 than in the Winter months.

B. Experimental Setup

For this experiment, the data comprising the IHEPCD dataset was divided into training and test sets. Training was performed with the data from 2006 (15 days from December) and the disaggregation was performed using its outcome: the source models. For test, the data was divided yearly, and for each year in study the aggregated signals were separated based on the model learned using data from 2006. The maximum number of iterations was set to 1000 and the error threshold ϵ to 0.00001 (see Algorithm 1). The proposed method requests the setup of the number of bases being used for the tensor decomposition (R). The influence of the number of bases used, R, on the STMF performance was investigated in [15]. For this setting we considered several possible values, and in the following we report the results associated to $R = 30$ which was the value with best performance considering the indicators next described. MATLAB and the N-way Toolbox [22] were used for the STMF implementation.

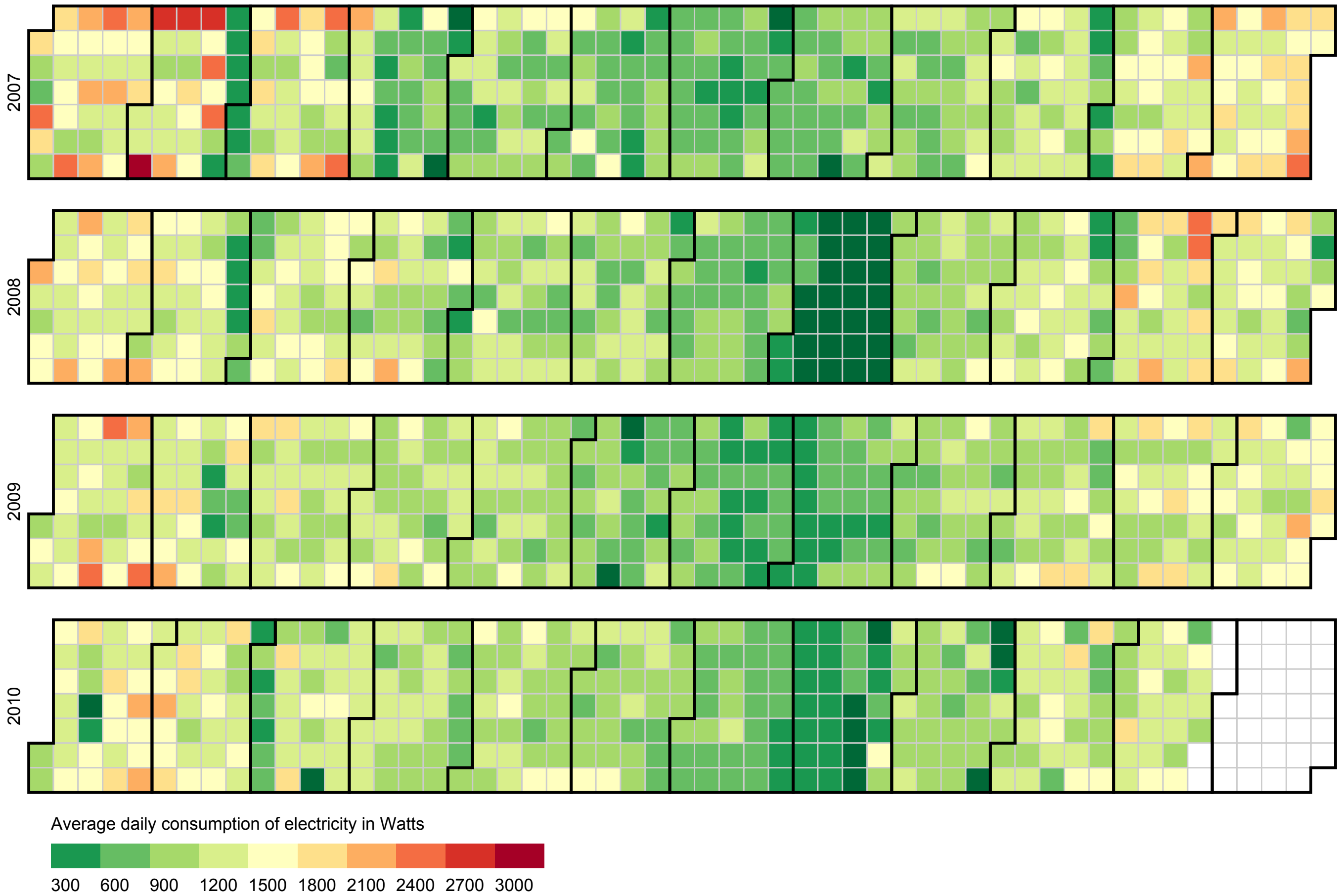

Fig. 2. Average daily consumption of electricity along the years 2007 to 2010 for the dataset in analysis from January (leftmost) to December (rightmost). Each square represents a day: columns represent the week of the month while rows correspond to the day of the week (the first row corresponds to Sunday).

C. Performance Indicators

In the NILM context the performance is assessed according to the designed solution. If the load disaggregation was solved as a classification problem, metrics as accuracy, precision and recall are suitable [23]. On the other hand, when the problem is seen as a source separation challenge other performance indicators are required. In this work, the performance of the STMF was measured in terms of the disaggregation error

$$\sum_{i=1}^{k} \frac{1}{2} \left\| X_i - \hat{X}_i \right\|_F^2 \tag{10}$$

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, thus providing a global measure of the distance between the prediction and the measured consumption [11]. Notwithstanding, the disaggregation error is a no normalized, global performance indicator. Thus, the root-mean-square errors (RMSE), a measure between the predicted values and the truly observed amount, were also considered. The RMSE was computed regarding (i) 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 analysis, the RMSE associated to the aggregated signal $\bar{X}$ and its predicted version $\hat{\bar{X}}$,

$$RMSE(\bar{X}, \hat{\bar{X}}) = \sqrt{\frac{\sum_{t=1}^{T} \sum_{d=1}^{m} \left(\bar{X} - \hat{\bar{X}}\right)^2}{T * m}}, \tag{11}$$

was computed. For the latter, the RMSE corresponding to each device i between the measured signal X_i and its predicted version $\hat{X}_i, i = 1, \ldots, k$ was also computed by Equation 11 with the appropriated adjustments. Additionally, the percentage of electrical energy associated with the demand of each device composing the electricity consumption profiles were also considered to evaluate the STMF performance at long-term and between the two defined seasons.

D. Results and Discussion

The STMF performance evaluation with regard to each year and associated seasons in the IHEPCD dataset is based on the average results of 30 runs. First, a global effectiveness analysis is presented concerning the disaggregation error and the RMSE achieved for the estimated aggregated signal (overall RMSE) of both seasons. Second, a more detailed RMSE assessment of the estimated consumption associated with each appliance is performed. Finally, the consumption profiles are also analyzed.

TABLE I

AVERAGE DISAGGREGATION ERROR AND AVERAGE OVERALL RMSE FOR THE STMF APPROACH.

House	Disaggregation Error Winter	Disaggregation Error Summer	RMSE Winter	RMSE Summer
2007	0.2494 ± 0.0099	0.0923 ± 0.0040	$1.25 \times 10^{-3} \pm 7.71 \times 10^{-6}$	$9.05 \times 10^{-4} \pm 6.45 \times 10^{-6}$
2008	0.2516 ± 0.0105	0.0965 ± 0.0038	$1.19 \times 10^{-3} \pm 7.99 \times 10^{-6}$	$9.00 \times 10^{-4} \pm 5.37 \times 10^{-6}$
2009	0.2527 ± 0.0113	0.0937 ± 0.0036	$1.16 \times 10^{-3} \pm 8.67 \times 10^{-6}$	$8.28 \times 10^{-4} \pm 7.69 \times 10^{-6}$
2010	0.2366 ± 0.0100	0.1131 ± 0.0052	$1.23 \times 10^{-3} \pm 9.11 \times 10^{-6}$	$9.39 \times 10^{-4} \pm 7.76 \times 10^{-6}$

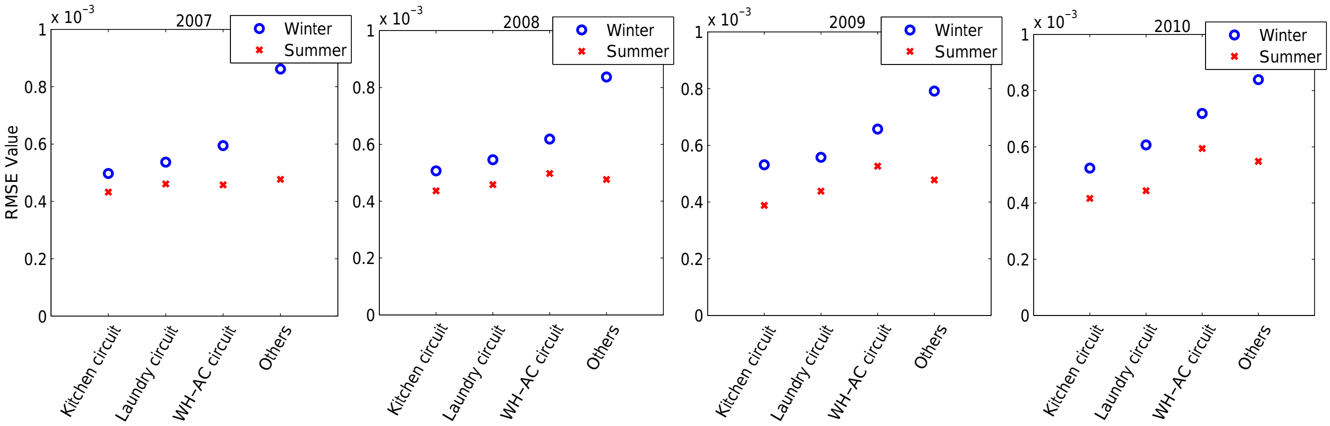

Fig. 3. Average value of RMSE for each appliance across the four years and for the seasons considered.

Table I presents the average disaggregation error and the overall RMSE of 30 runs with respect to each defined season of the years. In general, and despite the fact that the source models derived from a training with 15 days of winter loads, the disaggregation of signals from Winter lead to a higher disaggregation error than for the Summer. In fact, the error resulting from the estimation of cold season loads is more than half of the value associated with the Summer. Note that this performance indicator, computed in accordance with Equation 10, is a global assessment, and in this experiment the Summer consists of five months while the Winter test set is composed by seven months for each year. Thereby, the number of entries in error matrix for each appliance associated with Winter is clearly larger than for the Summer and in fact if these are non-zero entries necessarily influence the error values.

Another perspective on how accurate was the accomplished disaggregation is reported by the overall RMSE also presented in Table I. In this case, no variation on the RMSE associated with the estimated total consumption was observed for the Winter across the years. A similar remark can be drawn for the results achieved for the hot season. The error between both seasons is mostly of 0.0003, *i.e.* the error for Winter is 33% more than in the Summer. Once again, despite that source models are being learned from data associated with Winter days, the whole-home estimated consumption, which in fact is the optimization problem being solved in the test phase yet including the learned models (see Equation 9), on Summer days was more accurate in terms of RMSE than for the Winter. However, the load disaggregation problem regards the separation of the signal and the estimation of the individual loads and thus a more detailed analysis is required to evaluate the disaggregation performance.

Fig. 3 presents the average values of RMSE for each appliance across the four years in the test set. The observed trend for the overall performance indicators previously presented is also noticed in the RMSE values for the four groups in study, across the four years in test: the values are lower for the Summer days than those for Winter. In fact, the difference between both seasons is of remark for the group "Others", across all the four years, for which the RMSE in Winter of 2007 is 80% higher than for the Summer of the same year. Nevertheless, this difference decreases in the year 2010, for which the RMSE associated with the Winter of the group "Others" is 53% higher than the correspondent value in Summer. Indeed, this mitigation of the distance between the errors of both seasons is due to the increase of the Summer RMSE values from 2007 to 2010, across all the appliances. Note that the RMSE of appliances for the Summer of 2007 was very close to 0.0004, while for the Summer of 2010 this value increased to 0.0006 and 0.0005 regarding the "WH-AC circuit" and the group "Others", respectively. Additionally, the RMSE of the former circuit increased by 20% from the Winter of 2007 to 2010. Since the source models were learned regarding data from 2006, this increment in the RMSE value may result from a change of behaviors in

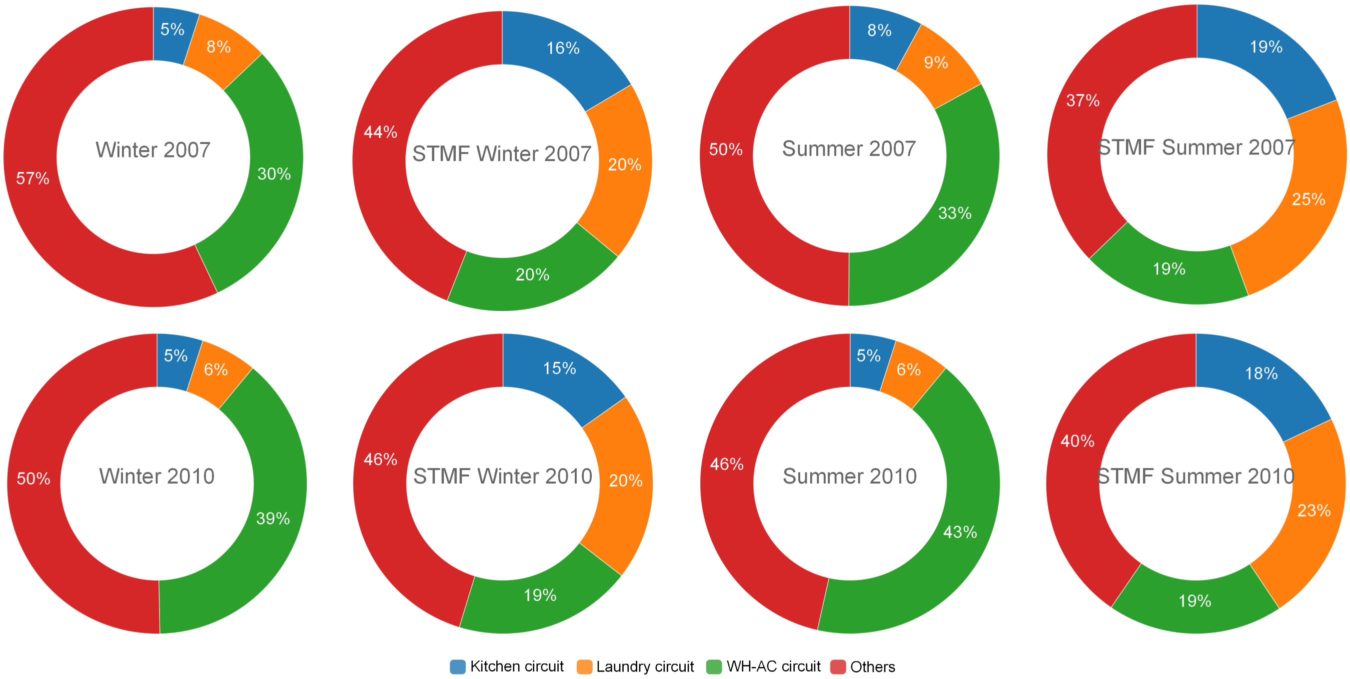

Fig. 4. Measured and predicted electrical consumption by STMF for years 2007 and 2010 by season and appliance.

terms of the usage of the appliances in this circuit. Actually, as it can be observed in Fig. 4, the electricity consumption of this circuit represented 30% of the total electrical usage in Winter of 2007 which increased 9% for the year 2010.

In Fig. 4, the energy profiles for 2007 and 2010 associated with the results of STMF in addition to the ground truth for each season are presented. Regarding the percentages of the measured consumption, it is clear that the group "Others", the electricity not measured in any of the monitored circuits, represents a predominant slice of usage: it ranges in $[46\%, 57\%]$. Moreover, the "WH-AC circuit" is also responsible for a substantial part of electrical consumption, from 30% to 43% of the total demand in study. Thereby, the remaining groups have a relative low importance ($< 10\%$ each) in the whole-home consumption. The accomplished disaggregation performance in terms of the assigned consumption to each circuit may be a reflection of this imbalance between the weight of each group in study, leading to the allocation of a higher usage to the smaller groups than the energy actual consumed. In fact, in what concerns the "Kitchen circuit" the STMF considered a consumption of around $10\% \pm 1\%$ more than the ground truth and for the Summer of 2010 it was 13% higher. Similar observations can be drawn for the "Laundry circuit". On the other hand, the demand associated to the "WH-AC circuit" and to the group "Others" by the STMF was always smaller than its actual consumption. Although, regarding the latter group, the distance between the estimated and the measured percentage in 2010 was smaller than for the remaining circuits. In regard to the changes between seasons, the consumption estimated by the STMF for the Summer of 2007 followed the changes occurred in the weight of each group in the total electrical usage, *i.e.* whenever a group increased its importance in the total electrical consumption the estimated electricity also increased, with exception of the "WH-AC circuit". Nevertheless, no similar changes between the Winter of 2010 and the Summer nor between 2007 and 2010 for both seasons were observed. The exceptions are the groups 'Kitchen circuit" and "Laundry circuit" for which the importance in the total consumption decreased from the Summer of 2007 to 2010, both the ground truth and the estimated consumption by the STMF. These results are in line with the RMSE by appliance and with the observed increment for the Summer of 2010 presented in Fig. 3. Recall that the whole-home electrical consumption for each year was disaggregated based on source models learned using 2006 Winter loads. A change of usage habits and behaviors between the years may have occurred and then the sources would be misrepresented by the model leading to a deterioration of the STMF performance. This degradation occurs as the consumption being disaggregated is temporally distant from the measurements used to learn the source models. The inclusion of additional information, as the average daily temperature, should be explored in order to improve the appliance usage estimations. Further investigation on the seasonal effect could highlight additional improvements to the proposed approach.

V. Conclusion

Energy efficiency is a concern of modern societies for environmental and financial reasons. Electricity represents a substantial slice of the energy consumed in our households, thereby energy efficiency requires a necessary readjustment in the electricity consumed by the appliances. This can be achieved providing the consumer with detailed consumption by appliance so misuses can be easily identified. Such information could be computed by separating the measured electrical energy 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 casted in a non-intrusive load monitoring system if only the aggregated electrical consumption signal is sampled and no additional sensors are used to gather information about the consumption of particular appliances. The usual approaches rely on electrical appliances signatures and classification methods rather, in this paper, the load disaggregation is interpreted as a source separation problem.

The single-channel source separation approach explored 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 used to predict the consumption of appliances connected to the electrical network in study over a period of time, provided only measurements of the whole-home consumption. Nevertheless, the usage of appliances vary, in particular from season to season, thus also the electrical consumption. Since the approach in study is supervised, *i.e.* based on prior information for learning the source models, a pertinent study consists in the evaluation of its performance across the seasons.

This paper presented a study regarding this performance assessment. Towards this end, a computational experiment was designed considering real-world data for a given house. The source models were learned from 15 days of the 2006 Winter, and whole-home electrical consumption for each year from 2007 to 2010 was disaggregated. A comprehensive performance assessment of the method across the seasons and years was presented regarding global and overall performance indicators. Moreover, appliance-level evaluation was also performed. The outcome results of this real-world dataset demonstrate that for the former years the changes occurring between seasons are capably handled by the method. The performance indicators achieved very similar values for both Winter and Summer. Notwithstanding, as years go by a degradation on the method performance occurs in both RMSE and amount of electrical energy assigned. Additionally, the amount of electricity consumed by each circuit in study regarding the total usage is quite imbalanced: two circuits together represent less than 18% of the total demand while the remaining is associated with only other two groups. This appeared to affect negatively the disaggregation performance, leading to a high level of misassigned electricity usage. Future work will focus on exploring the seasonal effect in more detail by using training sets of different seasons for different experiments, exploring the weight of each group/circuit in the total and additional information, as the daily temperature, to improve the usage estimation.

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