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Non-intrusive load disaggregation model for residential consumers with Fourier series and optimization method applied to White tariff modality in Brazil

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ABSTRACT

This paper proposes a novel approach to achieve better results for the Non-intrusive load disaggregation model for residential consumers. The proposed methodology considers two steps to face the problem. Firstly, periodical appliances are modelled by the Fourier series and extracted from the total power measured. Secondly, a Mixed Integer Linear Programming was proposed to disaggregate the remaining appliances. The paper presents results with a real case and indicates that the model can be useful for practical applications, such as the possibilty of the consumers of changing the modality of their tariff contract.

1. Introduction

Nowadays, due to the higher costs of electricity for residential consumers, the search for more efficiency in energy consumption has become mandatory. In addition, the lower cost of smart meters allows the computation of the consumer load curve and, as a consequence, helps to identify the operation cycle of home appliances throughout the day. This information could be used for shifting, if it is convenient, the home appliance's usage to periods when the energy tariffs are lower.

Appliance Load Monitoring (ALM) can be done directly, with an Intrusive Load Monitoring (ILM) or, indirectly, by a Non-intrusive Load Monitoring (NILM). Although the ILM approach is much more assertive than NILM, the number of sensors used in the first case is greater and, consequently, many projects have been dedicated to applying the NILM as an alternative to reduce electricity cost.

The NILM can be classified into two categories: transient state and steady-state analysis methods. Comparing both, the accuracy is higher in transient state methods, which requires high-frequency sampling rates (kHz to MHz). On the other hand, in the steady state approach, the power variation and low sampling rates are used as well as a longer time span to capture the cycles of operations.

The main characteristic of the transient state methods is to identify the appliances based on their transient signatures, including the transient power [1], high frequency noise [2,3], transient harmonics [4,5]), duration and waveforms of power / voltage / transient current [6,7]. In contrast, in the steady-state methods, the disaggregation process considers, mainly, the active [8–11] and reactive power variation [12], voltage and current waveforms [13,14], harmonics of steady state current and total harmonic distortion [15,16].

More recently, the methods used to address the NILM problem consider Machine Learning technique or combinatorial optimization approach. In the first case, some of the main approaches under study are based on Hidden Markov models (HMM) [1,17,18] and artificial neural networks [16,19]; while the approach based on integer programming optimization problems [20–22] belongs to the second category. One of the main challenges of using the combinatorial optimization technique is the computational burden associated with the combination of integer variables.

This paper proposes an evolution in the proposed method presented in [20], in which the optimization approach presented in this method is combined with a pre-processing procedure to identify appliances with periodical behavior, such as refrigerators or freezers. The novel procedure is based on the Fourier series model to simulate the periodic behavior. As a result, it alleviates the computational effort for the optimization problem and allows the simulation of the longer period of analysis.

In addition to that, the paper analyzes the application of such a methodology in Brazil, considering the application of the so-called White tariff [23]. In this tariff modality, the consumer can shift the energy consumption in order reduce the electricity bill. As will be seen, it seems one of the most suitable applications for the disaggregation model.

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Notation

$f_{(t,\ i)}$	calculated periodic signal of the ith appliance at time t (W).
$P_{(i,\ k)}$	nominal power of the ith appliance for the kth operation state (W).
i	index of appliance.
k	index of operation state.
t	index of time interval.
T_0	period of the signal.
T_{ON}	pulse width (pulse active time).
t_0	time to the first state variation.
T_0^{MAX}	upper bound parameter for periodical variables.
ω_0	Fourier frequency.
a_0, a_n, b_n	coefficients of Fourier series model frequencies.
n	number of harmonics.
$e_{(i,\ t)}$	error between the total power and calculated periodic signal at time t.
$e_{(i)}$	sum of the error between the total power and the calculated periodic signal of the appliance i considering the penalization.
$M_{(t)}$	penalty applied when the calculated periodic signal is bigger than the total power.
$\hat{f}_{(i,t)}$	final periodic signal of the ith appliance at time t (W).
$y_{(t)}$	household aggregate power reading at time t (W).
$\hat{y}_{(t,i)}$	calculated non-periodic signal of the ith appliance at time t (W).
$y_{(t,\ i)}$	real power signal measured from the ith appliance at time t (W).
λ_P	penalty for minimizing the difference between the reading and the calculated power.
$W_{(t,\ i,\ k)}$	weights allocated for each appliance i for the kth operation state at time t.
$\delta_{(t)}$	slack variable allocated to ghost appliance at time t.
$\theta_{(t,\ i,\ k)}$	binary variables for indicating the kth mode operation of the ith appliance at time t.
$\lambda_{(i)}$	penalty for minimizing the variation on the binary variables for the appliance ith.
λ_δ	penalty to minimize the use of ghost appliance.
λ_Δ	penalization to minimize the variation on the ghost component.
$\beta_{(t)}$	electric losses for each instant of time t.
$AP_{ON(t,\ i)}$	the matrix that indicates the ON state of the appliance i in each time t.
$\Omega^{k_{ON}}$	set of operating modes with the modes ON.
$AP_{OFF(t,\ i)}$	the matrix that indicates the OFF state of the appliance i in each time t.
I	set of non-periodic appliances with $i \in \mathbb{N}$.
J	set of appliances with periodic behavior with $i \in \mathbb{N}$.
K	set of operating modes with $k \in \mathbb{N}$.
T	set of time.
TP	true positive is when the detected appliance was actually used.
FP	false positive is when the detected appliance was not running.
FN	false negative indicates that the appliance operation was not detected.
C^{CT}	cost associated with conventional tariff modality.
E	total energy consumption.
T^{CT}	conventional tariff pricing.
C^{WT}	cost associated with White tariff modality.
E_p, E_{op}, E_i	energy consumed at peak, off-peak and intermediate time, respectively.
T_p^{WT}, T_{op}^{WT}, T_i^{WT}	time of use tariffs pricing: peak, off-peak and intermediate, respectively.

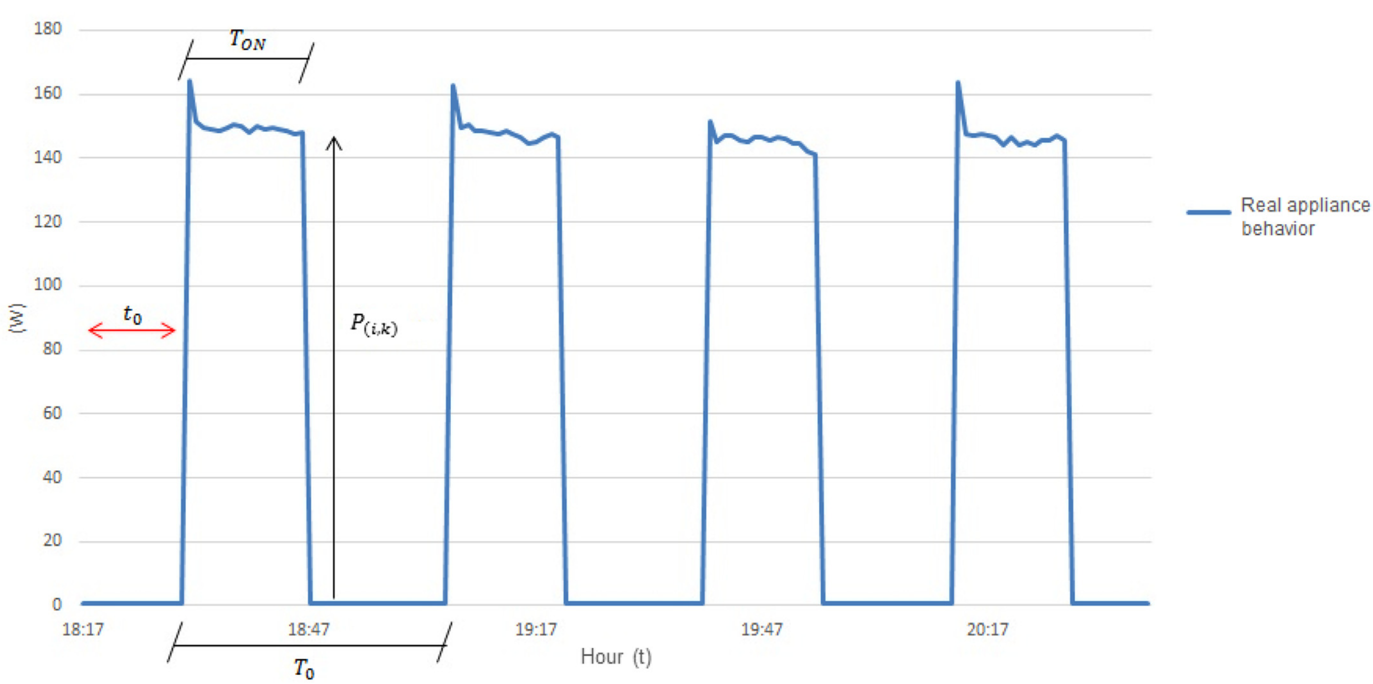

Fig. 1. Energy consumption for a typical refrigerator.

To achieve the objectives, the rest of the article is organized as follows: Section 2 presents a proposed methodology with the disaggregation of periodical appliances and the optimization model for non-periodical appliances; Section 3 presents a study case with the organization of the data set from [24] and the disaggregation results followed by the study case that analyses the saving for a consumer under the possibility of migration to the White tariff used in Brazil; Section 4 presents the conclusion of the paper.

2. Proposed methodology

Home appliances have different standards of operation, defining their signatures. Based on this information, the different types of appliances can be described as follows:

- Type I: The appliance has only two states (on or off);
- Type II: The appliance has multiple and finite states of operation;
- Type III: The appliance has continuous variation, with no fixed number of states;
- Type IV: Single state constants.

Most of the appliances are Type I, such as lights, refrigerator or TV. The refrigerator, specifically, has a periodical behavior. Here, the proposed methodology divides the home appliances into two categories: periodical, with energy consumption relatively well-defined in cycles, and non-periodical, without a well-defined standard of consumption such as lights, TV or air conditioner.

The methodology proposes, firstly, the disaggregation of the periodical appliances with the Fourier series [25] and, secondly, based on this information, the disaggregation of non-periodical appliances by the optimization model inspired in [20]. In the next subsection, each step of the proposed approach is presented.

2.1. Disaggregation of periodical appliances

To reproduce the signature of periodical-appliance, the power function for the appliance i at the time t can be described as follows:

$$f_{(t,i)} = \begin{cases} P_{(i,k)}, & t_0 \le t \le T_{ON} \\ 0, & T_{ON} < t \le T_0 \end{cases} \tag{1}$$

To illustrate, Fig. 1 shows the standard of energy consumption for a typical refrigerator.

The Fourier series can be used to describe the behavior of such appliances for a longer period as well as to generate a square wave. To do this, consider the Fourier series can be described as follows:

$$\begin{aligned} f_{(t,i)} &\cong \frac{a_0}{2} + \sum_{n=1}^{\infty}\left[a_n.\ \cos\left(\frac{2\pi}{T_0}nt\right) + b_n.\ \operatorname{sen}\left(\frac{2\pi}{T_0}nt\right)\right] \\ &= \frac{a_0}{2} + \sum_{n=1}^{\infty}[a_n.\ \cos(\omega_0 nt) + b_n.\ \operatorname{sen}(\omega_0 nt)],\ \forall\ t \in T \end{aligned} \tag{2}$$

Combining (1) and (2), the coefficients of the Fourier series can be computed by:

$$a_0 = \frac{2}{T_0}\int_0^{T_0} f_{(t,i)}\,dt = \frac{2}{T_0}T_{ON}P_{(i,k)} \tag{3}$$

$$a_n = \frac{2}{T_0}\int_0^{T_0} f_{(t,i)}\cos(\omega_0 nt)\,dt = \frac{2}{T_0}P_{(i,k)}\frac{\operatorname{sen}(\omega_0 nT_{ON})}{n\omega_0} \tag{4}$$

$$b_n = \frac{2}{T_0}\int_0^{T_0} f_{(t,i)}\operatorname{sen}(\omega_0 nt)\,dt = \frac{2}{T_0}P_{(i,k)}\frac{1-\cos(\omega_0 nT_{ON})}{n\omega_0} \tag{5}$$

To determine the variables t_0, T_{ON} and T_0 for each appliance, the proposed approach combines different values to identify the best set to minimize the difference between the energy measured at the home's entrance and the function associated with the appliance. Those **variables are limited by** T_0^{MAX}**,** which represents the upper bound and is an input for the proposed model. The procedure to analyses each set of parameters can be described as follows:

1. Compute the error for each set (t_0, T_{ON} and T_0) in each time interval over the period of analysis:

$$e_{(i,t)} = |y_{(t)} - f_{(t,i)}|,\ \forall\ t \in T,\ i \in J \tag{6}$$

2. Apply a penalty when the power of the appliance is greater than the total power:

$$e_{(t,i)} = \begin{cases} e_{(t,i)}, & if\ f_{(t,i)} \le y_{(t)} \\ e_{(t,i)} + M_{(t)}, & otherwise \end{cases},\ \forall\ t \in T,\ i \in J \tag{7}$$

3. Sum the error for the period of analysis

$$e_{(i)} = \sum_t e_{(i,t)},\ \forall\ t \in T,\ i \in J \tag{8}$$

The signature of the appliance i is determined by the set of parameters t_0, T_{ON} and T_0 associated with the lower value of $e_{(i)}$. Finally, to avoid the power of the appliance being greater than the total power of the house in each time t, the values of the $f_{(t,\ i)}$ function are adjusted by $\hat{f}_{(t,i)}$ as follows:

$$\hat{f}_{(t,i)} = \begin{cases} f_{(t,i)}, & if\ f_{(t,i)} \le y_{(t)} \\ 0, & otherwise \end{cases},\ \forall\ t \in T \tag{9}$$

As can be inferred, the proposed approach can be generalized for more than one appliance.

2.2. Disaggregation of non-periodical appliances

The results obtained in the aforementioned subsection can be used as an input to disaggregate the remaining appliances. To do this, this paper proposes an optimization which takes into account the power measured at the entrance of the house and some information associated with the appliances in this house, such as the rated power and some indications of its usage during the day. The optimization model can be described as a MILP (Mixed Integer Linear Programming) because it considers integer (binary) variables to identify the appliance and real variables to compute the losses and the ghost loads. The ghost loads can be associated with the appliances which are not indicated in the model or unforeseen variations of the appliance. The model was inspired by [20] and it is presented as follows:

$$\min_{\theta_{(t,i,k)},\delta_{(t)},\beta_{(t)}} \begin{Bmatrix} \lambda_P \sum_{t\in T} |y_{(t)} - [\sum_{i\in J}\hat{f}_{(t,i)}] - \sum_{i\in I}\hat{y}_{(t,i)} - \beta_{(t)} - \delta_{(t)}| + \\ \sum_{t\in T}\sum_{i\in I}\sum_{k\in K} W_{(t,i,k)}\theta_{(t,i,k)} + \\ \sum_{t=2}^{T}\sum_{i\in I}\sum_{k\in K}\lambda_{(i)}|\theta_{(t,i,k)} + \theta_{(t-1,i,k)}| + \\ \lambda_\delta \sum_{t\in T}\delta_{(t)} + \lambda_\Delta \sum_{t=2}^{T}|\delta_{(t)} + \delta_{(t-1)}| \end{Bmatrix} \tag{10}$$

s.t.

$$\hat{y}_{(t,i)} = \sum_{k\in K} P_{(i,k)}\theta_{(t,i,k)},\quad \forall\ t \in T, i \in I \tag{11}$$

$$\sum_{k\in K}\theta_{(t,i,k)} = 1,\quad \forall\ t \in T, i \in I \tag{12}$$

$$\sum_{k\ \in\ \Omega^{k}ON}\theta_{(t,i,k)} \ge AP_{ON\,(t,i)},\quad \forall\ t \in T, i \in I \tag{13}$$

$$\theta_{(t,i,1)} \ge AP_{OFF\,(t,i)},\quad \forall\ t \in T, i \in I \tag{14}$$

$$1.5\%\ y_{(t)} \le \beta_{(t)} \le 2.5\%\ y_{(t)},\quad \forall\ t \in T \tag{15}$$

$$\theta_{(t,i,k)} \in \{0, 1\},\quad \forall\ t \in T, i \in I,\ k \in K \tag{16}$$

$$\delta_{(t)} \in \mathbb{R},\quad \forall\ t \in T \tag{17}$$

The first part of the expression (10) aims to minimize the absolute value of the difference between the power measured at the entrance of the house and the disaggregated power for periodical and non-periodical appliances, as well as the losses and ghost appliances at time t.

The second part of the expression (10) uses the W matrix to give more weight to some appliances in a specific period of time. The lower $W_{(t,\ i,\ k)}$ value, the greater the probability of the operation mode k for the appliance i at the time t to be active is.

The third part of the expression (10) penalizes the frequent states' variations since it is not a normal situation for most appliances. Finally, the fourth and fifth part of the expression (9) minimizes the use of ghost appliance as well as their frequent variation over time.

The constraint (11) represents the power associated with the operation of the appliance i at time t. The constraint (12) establishes that the appliance should be active in only one state. The constraint (13) is used to activate the appliances that have a well-known behavior. Due to the higher power consumed by some appliances or its periodical behavior, they can be identified in a pre-processing step. With the same idea, these appliances can be deactivated, when their working power is greater than the system power. Then, the constraint (14) can be used for that.

The constraint (15) bounds the losses of the system between 1.5% and 2.5% of the total load. This constraint is based on the information provided in [26], which indicates these limits for residential losses in Brazil. The constraints (16) and (17) define that the variables θ and δ are binary and real, respectively.

At the end of the optimization process, the λ and W parameters are adjusted according to the usage frequency of each appliance. A similar approach was applied in [20]. Fig. 2 illustrates the flowchart that summarizes the proposed methodology.

To deal with the absolute values presented in the objective function (10), consider x as a variable, or a function, in which we need to compute $|x|$. The problem can be modelled by assuming that $L \le x \le U$ and $x = x^+ - x^-$. Then, if $L \ge 0$, $|x| = (x^+ - x^-)$. On the other hand, if $U \le 0$, so $|x| = -(x^+ - x^-)$. Then, $x^+ - x^-$ should be applied in the objective function and with two additional constraints being incorporated in the problem as follows:

$$0 \le x^+ \le U$$
$$0 \le x^- \le |L| \tag{18}$$

2.3. Metrics of evaluation

The metrics used to assess the results of the proposed model aims to identify the precision (PR), sensitivity (SE) and F-Measure (F_M), which is the harmonic mean between precision and sensitivity, as defined by [27]. The metrics can be computed by the following expressions:

$$PR = TP/(TP + FP) \tag{19}$$

$$SE = TP/(TP + FN) \tag{20}$$

$$F_M = 2^* \frac{PR^*SE}{PR + SE}. \tag{21}$$

The Net Error in assigned Power (NEP), as used in [28], allows us to analyze the net error power of each appliance over a period of time as follows:

$$NEP_i = \frac{\sum_{t=1}^{T} |\hat{y}_{(t,i)} - y_{(t,i)}|}{\sum_{t}^{T} y_{(t,i)}} \tag{22}$$

On the other hand, to analyze the energy disaggregation by the proposed approach, we can compute the NEE (Net Error in assigned Energy) of each appliance over a period of time by:

$$NEE_i = \frac{|(\sum_{t=1}^{T} \hat{y}_{(t,i)} - \sum_{t=1}^{T} y_{(t,i)})|}{\sum_{t=1}^{T} y_{(t,i)}} \tag{23}$$

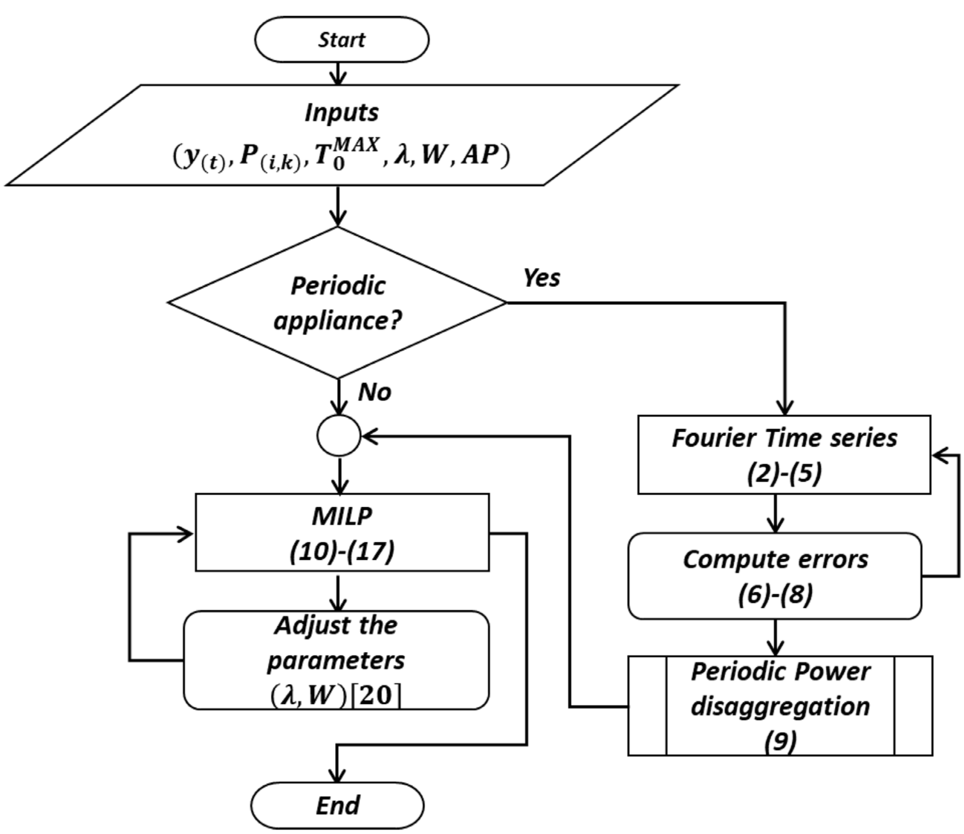

Fig. 2. Flowchart of the proposed methodology.

3. Case study

The case study was conducted with the data set called REDD – Reference Energy Disaggregation Dataset, presented in [24]. The data set contains the reading of energy consumption from 6 residences located in Boston, and it was collected in the summer of 2011. The proposed model was used to disaggregate the energy of the appliances, and the metrics presented in the last section were used to compare the results of the proposed model and the data set. Finally, the results of the disaggregation were used to evaluate the viability of the consumer migrating to the White tariff in Brazil for residential consumers.

3.1. Dataset (REDD)

The REDD provides the total consumption for two electrical phases, as well as the consumption disaggregated with a higher frequency (15 kHz samples) and a lower frequency (samples of 1 Hz for aggregate measurement in a single circuit and 0.5 Hz for devices individually or grouped into categories) presented in csv files. In this study, data from "House 2" was used, which contains a total of 20 channels (or measurements), in which 2 are the measurements from the electrical phases, to measure the total electrical consumption, and the rest of them (18 channels) are the measurements for each individual circuit in the house [24].

According to [24], Lighting and Kitchen Outlets were aggregated in three different channels labeled with the main information of those circuits. Because the data of this paper is only based on the data provided by [24], we followed the same rule of aggregation. As observed in [29], some appliances can be neglected from the analysis due to their low energy consumption (less than 0.1% in total consumption), such as an electric heater, an oven and electric stove. In addition to that, to reduce the computational burden of the proposed model, we converted the time interval to 1 data per minute. A similar procedure was performed in [28] and [29].

Table 1 presents the different states of operation for each appliance, or the (a) group of them, extracted from REDD dataset [24].

3.2. Case study for the disaggregation model

The proposed methodology can be divided into two parts. In the first part, programmed in MATLAB [30], the Fourier series was used to identify periodic home appliances from (1) to (9). The proposed approach considers the total active power sampled in minutes.

In the second part the MILP from (10) to (17), implemented in XPRESS [31], was used for non-periodic home appliances due to its performance for this kind of problems [32]. The software uses a branch and bound technique with cutting planes approach [33]. However, it is essential to highlight that any other software that has a built-in MILP function could be used. The simulations were performed in an Intel Core i7 processor with 8 GB of RAM. The total processing time for 24 hours of analysis was 40 minutes, considering both mathematical models. Finally, for this specific simulation one periodical and eleven non-periodical appliances were used.

The first step starts with the analysis of periodic signals for the disaggregation of periodical appliances, which is the case of the Refrigerator in this example. In Fig. 3A), cropping of the disaggregation of the refrigerator is presented. As it can be observed in some intervals, the power of the appliance is greater than the total power consumption, which is not coherent. Here, the pre-processing step is needed to fit the data from the first step to the optimization model. To do this, the incoherent interval was removed from the disaggregation process. Fig. 3B) presents the same interval of the disaggregation of the Refrigerator taking this step into account.

In addition to the pre-processing of the refrigerator, some appliances were continuously working, such as the standby of the Microwave, with a fixed consumption of 4.4 W. For cases like this, the matrix $AP_{ON(t,\ i)}$ was used to increase the accuracy of the results and reduce the computational burden of the optimization model. On the other hand, the Bathroom represents the group of appliances with the highest power in the house. Based on this information, for each time when the total power is lower than the active state of the Bathroom, it is possible to guarantee that the group of the appliance is inactive (OFF). Here, the $AP_{OFF(t,\ i)}$ matrix was used for these time intervals improving the accuracy of the results and reducing the computational effort of the optimization model. Fig. 4 visually presents the results of the disaggregation.

Although the disaggregation process seems appropriated by visualizing Fig. 4, the best way to analyze the results is by using the metrics presented in the subsection C. Table 2 presents the real and simulated energy disaggregation and the results of these metrics, in percentage. More details of the power disaggregated can be found in the dataset in [34].

Since the best results are associated with lower *NEP* and greater F_M values, we can conclude that, in general, the disaggregation results are, in some ways, accurate. The worst disaggregation results are associated with the Lightings, which can indicate volatility of their usage and, consequently, the difficulty of capturing it.

The result associated with the refrigerator could be improved if the defrosting process could be modeled. This process occurs a few times during the day, consuming a great amount of energy and, consequently, increasing the disaggregation error. We can conclude that if the defrosting process could be controlled by users, the disaggregation process could be significantly improved. For the rest of the appliances, the method indicated that the model is quite accurate. Observing the *NEE* for 24-hours of analysis, we can infer that the longer is the period of study, the better the results will be.

Finally, to provide a general view of the disaggregation process, Fig. 5 shows the energy disaggregation of the appliances compared with the total energy for a period of seven hours randomly chosen to be presented.

3.3. White tariff

The White tariff is a new modality of contract for low voltage consumers in Brazil. According to the law associated with this contract [35], eligible consumers must have an annual energy consumption of 250 kWh or above. In 2020, most of the low voltage consumers, with some specific exceptions, will be eligible for this new modality.

Specifically, the main difference between the White and the Conventional Tariff is the tariff periods over the day. In the Conventional Tariff, there is only one value of the tariff, whereas, in the White Tariff, there are three different values for peak, off-peak, and intermediate time.

Table 1
Data set of appliances from REDD.

Appliance	$P(W)$			
	$k=1$	$k=2$	$k=3$	$k=4$
Refrigerator	0	-	7	220
Dishwasher	0	240	414	1130
Washer dryer 1	0	-	2800	3000
Washer dryer 2	0	-	-	600
Bathroom	0	-	-	1650
Kitchen 1	0	-	25	33
Kitchen 2	0	27	75	126
Kitchen 3	0	-	-	1115
Lighting 1	0	40	82	120
Lighting 2	0	65	95	270
Lighting 3	0	35	70	120
Microwave	0	4.44	1400	1600
Others	0	-	-	Variable

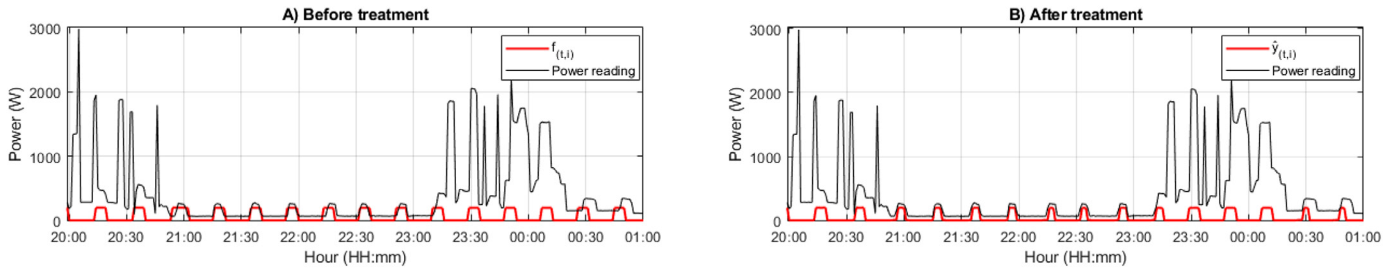

Fig. 3. (A) Disaggregation for the periodical-appliance; (B) Disaggregation for the periodical-appliance with data treatment described in (9).

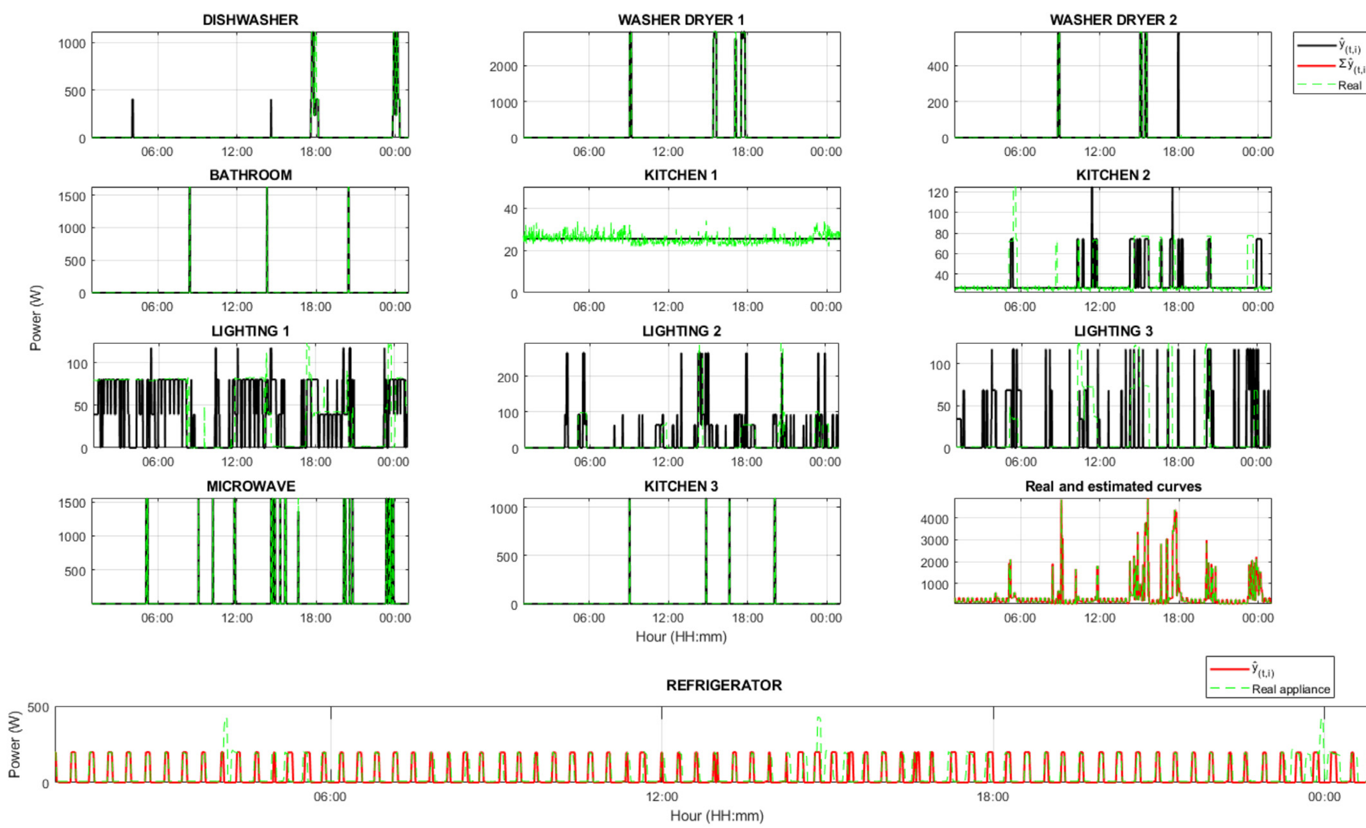

Fig. 4. Comparison between disaggregated and real power signal of each appliance from REDD dataset.

Table 2
Metrics used to assess the disaggregation model, computed in percentage.

Appliance	Real Energy (Wh)	Simulated Energy (Wh)	*PR* (%)	*SE* (%)	F_M (%)	*NEP* (%)	*NEE* (%)
Refrigerator	1409.2	1363.3	82	79	80	39	*3*
Dishwasher	782.5	724.2	86	90	88	17	*7*
Washer dryer 1	2247.8	2206.2	89	100	94	14	*2*
Washer dryer 2	237.4	261.9	100	100	100	2	*10*
Bathroom	240.4	239.4	100	100	100	0	*0*
Kitchen 1	606.0	611.9	100	99	99	7	*1*
Kitchen 2	801.8	768.9	94	91	93	25	*4*
Kitchen 3	221.1	206.0	100	100	100	7	*7*
Lighting 1	1087.5	971.8	73	63	68	48	*11*
Lighting 2	369.8	522.4	21	28	24	146	*41*
Lighting 3	383.8	340.6	9	9	9	148	*11*
Microwave	1240.8	1225.5	100	100	100	2	*1*
Others + Losses	156.2	416.4	-	-	-	-	-
Total	9784.3	9858.5	-	-	-	-	-

Mathematically, the cost associated with Conventional and White tariff can be expressed, respectively, as follows:

$$C^{CT} = E*T^{CT} \quad (24)$$

$$C^{WT} = E_p*T_p^{WT} + E_{op}*T_{op}^{WT} + E_i*T_i^{WT} \quad (25)$$

In order to compare both modalities, the sum of the energy consumed at peak, off-peak and intermediate times for the White tariff

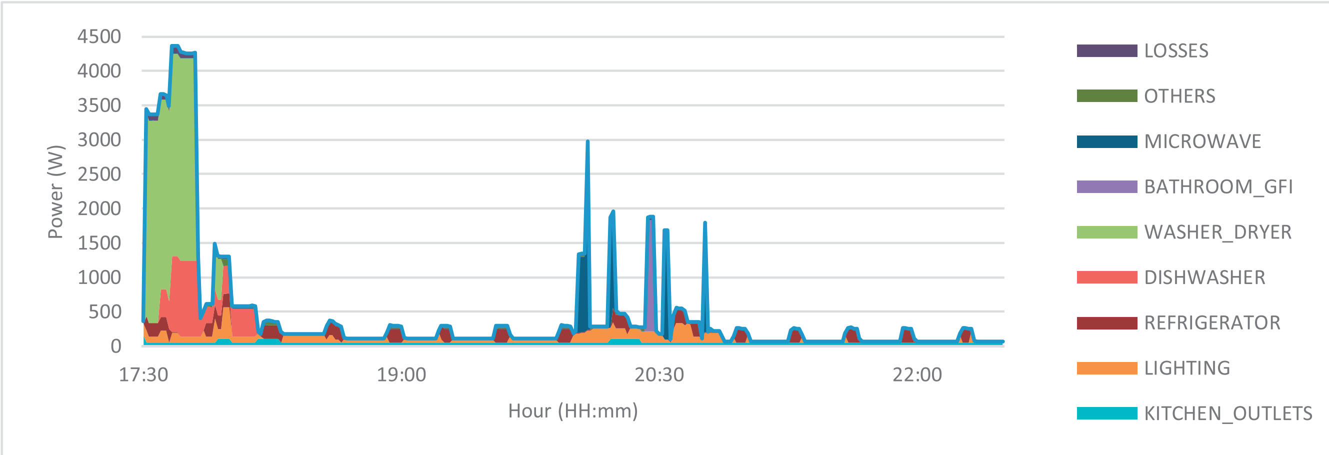

Fig. 5. Comparison between disaggregated and real power signal of each appliance from REDD dataset.

Table 3
Tariff for both modalities from a specific utility and for a consumer.

Modality	Period	R$/kWh[a]
White tariff	Peak	1.14742
	Intermediate	0.76401
	Off-peak	0.55166
Conventional	-	0.62565

[a] US$ 1 ~ R$ 3.81 according to [37]

Table 4
Consumption and cost of each period and for each modality.

Modality	Energy (kWh)	Cost (R$)
White tariff	2.1755	6.77
	0.3712	
	7.2376	
Conventional	9.784	6.12

should be equal to the total energy consumed for the Conventional Tariff. Because the results provided by the *NEE* seem suitable for longer period of analysis, the proposed approach will be used for the White tariff in the Brazilian context. In the next subsection, the results of the disaggregation model will be combined with the modalities of tariffs available in Brazil to support the decision of the consumer analyzed.

3.4. combining the disaggregation model with the white tariff

The Tariffs in Brazil are regulated by the National Agency of Electrical Engineering [35] considering the cost associated with the utilities. From LIGHT [36], the utility of Rio de Janeiro, the values of tariffs, in the local currency, are presented in Table 3.

As it can be observed, the advantage of migrating to the White tariff should be defined by the amount of energy that can be shifted from peak to intermediate or to off-peak times. By using the data from REDD, presented in the previous section for a specific consumer, the disaggregation of the energy in each period of consumption is presented in Table 4.

Without the disaggregation model proposed in this paper, the consumer can only compute the level of displacement of appliances migrating to the White Tariff. As an example, Fig. 6 presents the level of displacement from peak to off-peak to makes it worthwhile to migrate from Conventional to the White Tariff. On the other hand, considering only the case of Intermediate to off-peak, there is no advantage in migrating.

For the case of displacement from peak to off-peak, 50% of the total energy in this period should be shifted. For the study case, it means that Dishwasher and Washer dryers, both with flexibility, should be shifted to off-peak times. These appliances represent 55% of the energy consumed at peak times. This is the level of shifting to achieve the breakeven to change the contract. This analysis is only possible with the disaggregation model and it indicates that the effort for this consumer

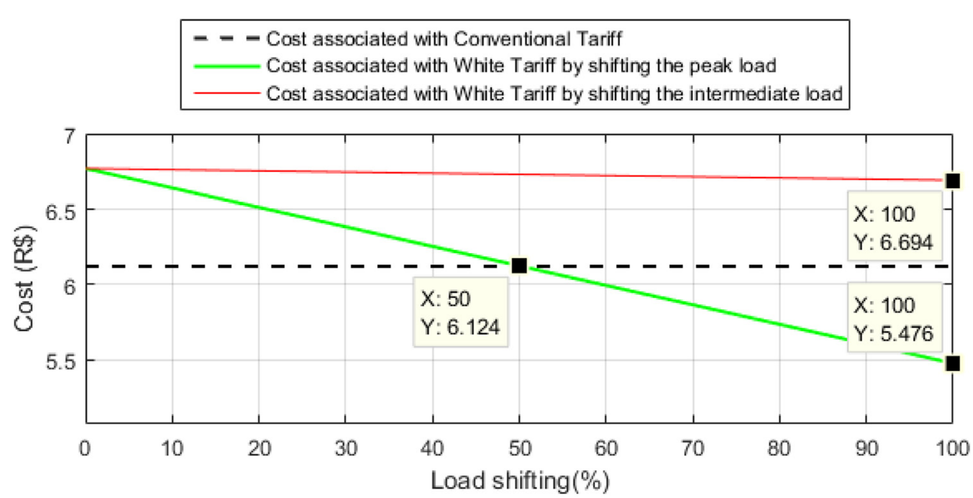

Fig. 6. Comparison with Conventional and White tariff considering load displacement.

to obtain a small saving seems to be almost useless.

4. Conclusion

In this paper, a novel disaggregation methodology for home appliances for residential consumers was proposed taking into account periodical and non-periodical appliances as well as a suitable real application for the proposed approach. Appliances such as refrigerators, and freezers among others can be modeled by the Fourier series as a pre-processing step, reducing the computational burden and increasing the accuracy of the model. On the other hand, a Mixed Integer Optimization model can be used to disaggregate the remaining appliances.

The proposed approach can be applied for any home appliance or a set of them, once the number of devices, type (periodic or non-periodic), and power nameplate are informed. In addition to that, the more information of the consumption pattern is available, the more accurate the disaggregation will be.

One of the main applications for the proposed approach is to identify the loss of comfort of consumers when they decide to migrate to the other modality of tariff contract. In the specific case of this paper, the Conventional and White Tariffs applied in Brazil were compared and we identified that the effort to achieve the breakeven would be significant. Besides the proposed application, the model can be useful for the regulator to adjust the rates of the utilities, providing more or fewer incentives aligned with the estimation of the consumers' usage. For future research, a more comprehensive application could be done, involving analysis with many consumers to reduce the loss of comfort taking advantage of the flexibility of each one and, at the same time, decreasing power and energy at peak times.

Conflict of Interest and Authorship Conformation Form

Please check the following as appropriate:

- ○ All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.
- ○ This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.

CRediT authorship contribution statement

Delberis A. Lima: Conceptualization, Methodology, Validation, Formal analysis, Writing - review & editing, Supervision. **Marilia Z.C. Oliveira:** Software, Investigation, Data curation, Visualization. **Estiven O. Zuluaga:** Software, Investigation, Data curation.

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