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Non-intrusive load monitoring for appliance status determination using feed-forward neural network

Abstract. *Energy efficiency regulations and initiatives have been implemented as part of proactive actions to address the energy crisis that has arisen due to the increasing demand and depletion of resources. A load monitoring system is used to provide real-time data for appropriate feedbacks towards electricity savings. It can also be used to evaluate the effectiveness of the implementation of an energy management scheme. However, monitoring all individual appliances by installing an energy meter for each appliance will incur high installation and maintenance costs. Therefore, this work aims to determine the status of individual appliances from an aggregated measurement using non-intrusive load monitoring (NILM) based on a feed-forward neural network. The establishment of a NILM model has for main processes, including, data acquisition, pre-processing, training and performance evaluation. In the pre-processing, a new approach using threshold is introduced to identify the status of appliances based on their power consumption readings. The performance of the proposed approach is then evaluated and compared with the traditional logistic regression technique in terms of accuracy. The results show that the NILM using a feed-forward neural network outperformed the traditional logistic regression by 5.78%. Moreover, the proposed approach with threshold helped to improve the accuracy further by 19.1% as compared to the same learning algorithm without considering the threshold. Consequently, the overall performance is improved by almost 25% as compared to the logistic regression as presented in the previous work. Hence, it clearly shows that the status of individual appliances can be determined from measurements at the main meter using NILM based on a feed-forward neural network with high accuracy.*

Streszczenie. *Regulacje i inicjatywy dotyczące efektywności energetycznej zostały wdrożone w ramach proaktywnych działań mających na celu zaradzenie kryzysowi energetycznemu, który powstał z powodu rosnącego popytu i wyczerpywania się zasobów. System monitorowania obciążenia służy do dostarczania danych w czasie rzeczywistym w celu uzyskania odpowiednich informacji zwrotnych dotyczących oszczędności energii elektrycznej. Można go również wykorzystać do oceny skuteczności wdrożenia systemu zarządzania energią. Jednak monitorowanie wszystkich poszczególnych urządzeń poprzez zainstalowanie licznika energii dla każdego urządzenia będzie wiązało się z wysokimi kosztami instalacji i konserwacji. Dlatego celem niniejszej pracy jest określenie stanu poszczególnych urządzeń na podstawie zagregowanego pomiaru przy użyciu nieinwazyjnego monitorowania obciążenia (NILM) w oparciu o sieć neuronową ze sprzężeniem do przodu. Ustanowienie modelu NILM obejmuje główne procesy, w tym akwizycję danych, wstępne przetwarzanie, szkolenie i ocenę wydajności. W przetwarzaniu wstępnym wprowadza się nowe podejście wykorzystujące próg do identyfikacji stanu urządzeń na podstawie ich odczytów zużycia energii. Wydajność proponowanego podejścia jest następnie oceniana i porównywana z tradycyjną techniką regresji logistycznej pod względem dokładności. Wyniki pokazują, że NILM wykorzystujący sieć neuronową ze sprzężeniem do przodu przewyższał tradycyjną regresję logistyczną o 5,78%. Co więcej, zaproponowane podejście z progiem pomogło jeszcze bardziej poprawić dokładność o 19,1% w porównaniu z tym samym algorytmem uczenia bez uwzględnienia progu. W rezultacie ogólna wydajność jest poprawiona o prawie 25% w porównaniu do regresji logistycznej przedstawionej w poprzedniej pracy. Stąd wyraźnie widać, że stan poszczególnych urządzeń można określić na podstawie pomiarów na głównym liczniku za pomocą NILM w oparciu o sieć neuronową ze sprzężeniem do przodu z dużą dokładnością.* ***(Nieinwazyjne monitorowanie obciążenia w celu określenia stanu urządzenia za pomocą sieci neuronowej ze sprzężeniem do przodu)***

Keywords: Demand-side management, Feed-forward neural network, Non-intrusive load monitoring
Słowa kluczowe: nieinwazyjny monitoring obciążeń, sieć neuronowa

Introduction

In the age of technology, electrical appliances have been widely used to ease human life. However, the excessive use of electrical equipment will result in high electricity consumption and inevitably lead to high electricity bills. According to the United States Energy Information Administration [1], energy consumption is expected to increase by nearly 50% between 2010 and 2050. However, the peaks occur only at a certain period in daily consumption. Therefore, a collection of strategies and policies called demand side management (DSM) should be carried out to balance energy usage during the day [2]. DSM is an important feature in a smart grid because it can effectively promote and mobilize users' enthusiasm to adjust or move their power consumption based on demand response signals such as dynamic pricing, time of use pricing, and inclining block rates [3]. However, information regarding the daily power consumption is usually not accessible from the existing monitoring system because the limitations of the traditional electromechanical meters which is a key challenge in implementing the DSM program [4]. Fortunately, in the era of big data, all information can be easily accessed subject to the adequate installation of monitoring devices. Availability of the information will help consumers to change their lifestyle and become frugal in their daily use of electricity. Consumers normally respond after noticing that their electricity consumption is high and take appropriate actions to reduce their usage for possible savings in the electricity bill.

The simplest way to monitor the power consumption in a building is by installing an energy meter at each piece of electrical equipment. However, this approach will incur high installation cost considering quite a number of electrical appliances, especially in a big residential building. The installation of an individual meter at each appliance will also increase the maintenance cost. A similar issue can be observed in power grids where a minimum number of monitoring devices are used for monitoring the power quality events to reduce the installation costs [5, 6]. Thus, an alternative approach is needed to determine individual appliance usage without installing an energy meter at each appliance. Unlike applications in power grids, one energy meter is enough to perform the monitoring. This technique is called non-intrusive load monitoring (NILM). The basic goal of NILM is to measure the aggregate load of a residence using a single energy meter installed in the properties' main meter [7]. This goal can be achieved by identifying the appliance's features from measurements at the main meter through signal processing techniques, such as S and TT transforms [8]. Unfortunately, such analytical techniques are complicated, require a high sampling rate of data, and are unable to adapt to various features of power consumption. Therefore, machine learning is a good alternative for application in the existing low sampling rate of smart meters. Machine learning can learn and improve automatically from experience without being explicitly programmed [9].

Several types of machine learning have been used in the literature and they can be classified into two groups, namely, supervised and unsupervised machine learning [10]. The supervised learning technique needs to be taught first or go through a training process before it can be used. This type of machine learning algorithm can be categorized further into neural network, classification, regression, and deep learning [11]. Based on the review, each supervised algorithm can be trained and used to classify the individual power consumptions of electrical appliances. Meanwhile, the unsupervised learning technique does not require a training process before it can be used which is important advantage because only minimal effort is needed and it helps to minimize the disruption of the steps required to build a database [12]. One of unsupervised machine learning used for NILM applications is the clustering algorithm. Nevertheless, the unsupervised machine learning algorithms incur higher costs in understanding the patterns especially in terms of human intervention because of the unclear correlation between the data and performance metric. Therefore, supervised learning techniques are usually preferred because they ease the training process and give clarity to the data for analysis [13]. Thus, this work focuses on the supervised learning technique to determine the status of electrical appliances from the main meter.

Supervised learning techniques have attracted considerable attention in recent years, particularly in their applications to address the NILM problem. In [14], a decision tree algorithm within the group of classification was used to predict the status of appliances either "on" or "off" from the extracted transient signals. Le et al. [14] incorporated the decision tree and a deep learning model, specifically long short-time memory (LSTM), to improve the accuracy in determining the status of appliances. Yuan et al. [15] proposed an optimized support vector regression, which is an important branch of support vector machines (SVM), to identify the operating appliances from the aggregated low-frequency measurement data. In a later work in [16], logistic regression is proposed where individual logistic models are trained and used for each appliance to ensure better accuracy in determining the switched "on" or "off" appliances. A convolutional neural network algorithm is applied for the NILM model in [17] to reduce the computational time where double processing for detection and classification of events can be avoided. Recently [18] suggested the use of an improved k-nearest neighbors algorithm together with a local power histogramming (LPH) descriptor for higher accuracy in solving the NILM problem. The LPH descriptor is used to extract individual appliance consumptions to better discriminate features between the appliances. Although the aforementioned studies cover a wide range of supervised learning techniques, the performance of a feed-forward neural network using an appropriate identification of the switched "on" appliances remains unclear.

This paper presents an artificial neural network application that uses a feed-forward neural network to determine the status of appliances from the aggregated power consumption. A new status identification is introduced in this work to provide more suitable data for training purposes. This paper is organized as follows: the development of a feed-forward neural network in the NILM application is explained in the subsequent section. The effectiveness of the proposed technique is evaluated and discussed in the results and discussion section. Finally, conclusions are drawn in the last section.

Feed-Forward Neural Network Application

Artificial neural networks (ANN) have been used to forecast electrical load demand since the 1990s [19]. ANN has been widely used in the field of engineering optimization because of its excellent capabilities in non-linear mapping, generalization, and self-learning. Electricity demand is highly non-linear, and ANN is a good method for its application because it does not require an explicit model. Therefore, ANN has replaced traditional methods in various applications due to its better performance [20]. The most utilized ANN architecture for electric load forecasting is the back-propagation network [21].

The learning process involves two stages when using the back-propagation algorithm as shown in Fig. 1. In the first stage, the input information is sent in a forward direction where the input information will go to the hidden layer and then to the output layer. This stage is called forward propagation. In the second stage, the information is sent in a backward direction for corrective measures and is called back-propagation. If the output layer differs from the desired output, the difference or error will be calculated and propagated back to the hidden layer for possible weight modification in each neuron for possible error reductions. A feed-forward neural network is the simplest type of back-propagation and is used to create a multi-layer network in this work.

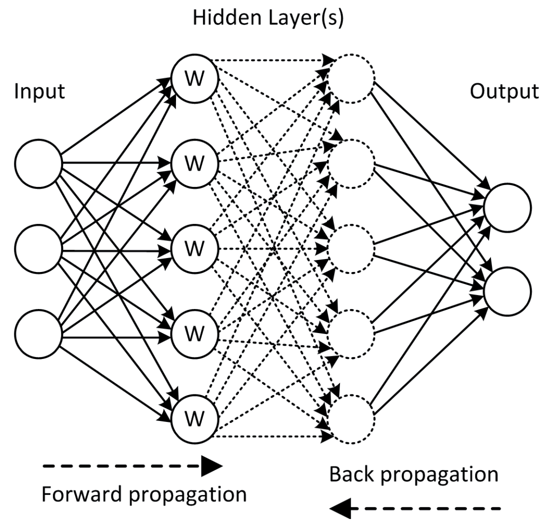

Fig. 1. A general structure of ANN

Fig. 2 shows an application of the feed-forward neural network for NILM to determine the status of electrical appliances. The explanation for each process in the flowchart is given in the following sub-sections.

Data acquisition

Dataset of a household power consumption is obtained from [22]. It describes the electricity consumption of individual appliances over four years starting from 16 December 2006 to 26 September 2010. The consumptions are recorded for every minute. However, the value of global active power (kW) from the main meter is not equivalent to the total active power of the three available sub-meters (W) installed at the appliances. In other words, the measured active power at the main meter contains other electrical appliances that are not being monitored. Therefore, this process involves re-calculation of the global active power to ensure that the global active power is equal to the total active power of the three sub-meters as follows:

$$P = \sum_{i=1}^{N} P_i \tag{1}$$

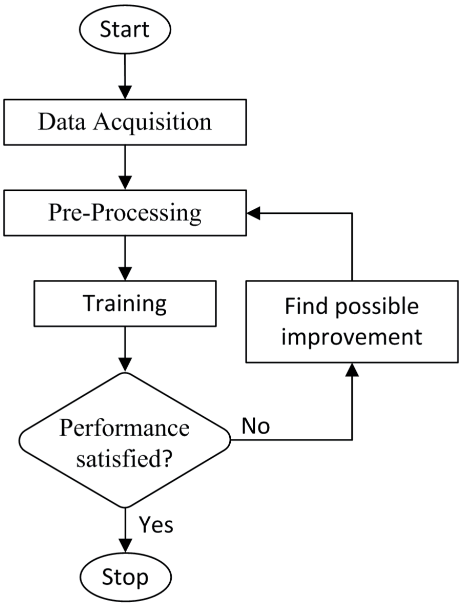

Fig. 2. A flowchart of NILM model development

where P is the new global active power, P_i represents the active power of the i-th sub-meter and N is the total number of sub-meters. Because the value of global active power (kW) is recalculated, the parameters of global reactive power (kVAR) and global intensity (I) should also be recalculated by keeping the power factor unchanged and this is mainly to provide suitable ground truth for performance comparison purposes.

Pre-processing

This stage involves the preparation of suitable data for training and learning using the feed-forward neural network. Parameters such as time, global active power (P), global reactive power (Q), voltage (V), and global intensity (I) from the obtained dataset are used as input parameters. The selection of time as an input is to provide information on a potential correlation between usage of appliances and time. In some cases, certain appliances, such as electric lamps are most likely not used during the daytime. Therefore, considering the parameter as input is important. The rest are electrical parameters that provide information on the electrical behavior of used appliances and are useful in distinguishing between different types of appliances. Active and reactive powers are the most common input parameters in the ANN application for the on or off detection of appliances [23]. Output parameters can be determined from the active power of all sub-meters. The parameter will directly show the operation status of the appliances. This stage can be divided into the preparation of the 1) input and 2) target data.

In the preparation of the input data, a more appropriate range of data should be used to avoid unfair treatment that could affect the performance of the feed-forward neural network. As mentioned earlier in the previous sub-section, the global active power should be recalculated to tally with the total active power of all three sub-meters. After recalculation, the range of global active power can be observed between 0 and 134 W. Meanwhile, the voltage for example varies between 223 and 255 V. In this case, 1 V deviation of the voltage is not equal to 1 W deviation of the global active power because of their operating ranges are different. To address this issue, a standardization process is carried out to normalize the input data within a certain range. It can be achieved using the following expression:

(2) $$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where the symbol x_{new} is represents the current data, x refers to the original data, x_{min} is the minimum value of the data and x_{max} is the maximum value of the data. All input data are standardized in a range of [0,1].

In the preparation of target data, the active power consumption at each sub-meter needs to be converted into binary because this work aims to determine the status of appliances either "on" (bit "1") or "off" (bit "0"). The conversion can be done by checking the value of the active power at the i-th sub-meter, P_i. The appliance i is considered "on" whenever the P_i shows a reading or otherwise, "off" as expressed in the following equation [16]:

(3) $$Y_i = \begin{cases} 1, & \text{if } P_i > 0 \\ 0, & \text{otherwise} \end{cases}$$

In this work, a modification was made to the target data representation. A threshold, α, is introduced to the formulation to tackle the issue with appliances at standby mode. During the standby mode, small power consumptions are observed and they are unstable because of disturbances. Therefore, the threshold is applied to allow some tolerance for the disturbances and avoid false representation of the appliance status. The proposed approach can be expressed as follow:

(4) $$Y_i = \begin{cases} 1, & \text{if } P_i > \alpha \\ 0, & \text{otherwise} \end{cases}$$

The proposed approach using the threshold is carried out after the performance evaluation in Fig. 2 to further improve the suggested approach in [16].

Training

All the datasets are divided randomly into two parts where 85% for training and 15% for testing. It is important to note that the selection for training data is carried out randomly to establish a more generalized NILM model to determine the status of appliances. This work uses the newff function in MATLAB to create the feed-forward neural network. A general syntax `net = newff(P,S,TF,BTF)` is used to set the training parameters of NILM model, `net`, using the feed-forward neural network. `P` is a matrix that contains lower and upper bound values of input. In this case, the size of matrix `P` is 5×2 because five input parameters are considered, namely, time, global active power (P), global reactive power (Q), voltage (V), and global intensity (I) as explained earlier. `S` is a vector that contains the number of neurons in the hidden and output layers where only one hidden layer is considered and is set to 5 neurons. `TF` is a transfer function setting of the i-th layer. In this work, the hyperbolic tangent sigmoid transfer function or `tansig` is used for hidden layers and the linear transfer function or `purelin` is used for the output layer. `BTF` is a back-propagation network training algorithm setting and Levenberg-Marquardt back-propagation or `trainlm` is used in this work. Table 1 summarizes the parameter settings to train the NILM model using the feed-forward neural network. Then, a syntax `net = train(net,I,T)` is used to execute the training procedure based on input training data, `I`, and target data, `T`, to establish the NILM model, `net`.

Table 1. Training parameter settings of feed-forward neural network

Item	Layer		
	Input	Hidden	Output
Number of neurons (size)	5	5	3
Range of data	[0,1]	-	binary
Transfer function	-	`tansig`	`purelin`
Training algorithm		`trainlm`	

Performance evaluation

At this stage, the selected testing data are used to evaluate the performance of the established NILM model, `net`, from the previous stage. A syntax, `Y = round(sim(net,X))`, is used to determine the status of appliances from the testing input data, `X`, and the performance of the NILM model based on accuracy can be evaluated. The accuracy is calculated by comparing the predicted data and the target testing data as follows:

$$\text{(5)} \qquad \text{Accuracy} = \frac{TN + TP}{TN + FP + TP + FN} \times 100\%$$

where TN refers to the number of the successfully predicted bit "0", TP refers to the number of the successfully predicted bit "1", FP refers to the number of the unsuccessfully predicted bit "1" and FN refers to the number of the unsuccessfully predicted bit "0". In other words, accuracy is the percentage of successful predictions over the total number of testing data. Therefore, this formulation will be used to calculate the overall accuracy where the prediction is considered successful only if all combinations are correct. Any potential improvement is investigated in this process until satisfactory performance is achieved.

Results and Discussion

The simulation is carried out within a MATLAB environment using a PC with a 2.50 GHZ processor and 8 GB RAM. The traditional target data preparation without threshold is also carried out for fair comparison between logistic regression as in [16] and the proposed feed-forward neural network. Table 2 shows the training performance of NILM using a feed-forward neural network between the proposed threshold and the traditional without threshold approaches. Training execution of both approaches is stopped when it reaches maximum iteration (1000) but the proposed approach requires slightly less computational time. The performance of both approaches in terms of mean square error (MSE) and Mu (training multiplier) are almost the same. However, significant differences can be observed in terms of gradient where the proposed threshold approach is higher than the traditional approach. This finding indicates that a more accurate model may be obtained if the training process is extended. Fig. 3 shows an example of the training convergence characteristic for the approach without threshold. A similar pattern can be observed for the approach with a threshold.

Table 2. Training performance of feed-forward neural network

Item	Without threshold	With threshold
Epoch (iteration)	1000	1000
Elapsed time (minute)	51.93	47.83
Mean square error	0.0145	0.0144
Gradient ($\times 10^{-5}$)	3.30	11.4
Mu ($\times 10^{-11}$)	1.00	1.00

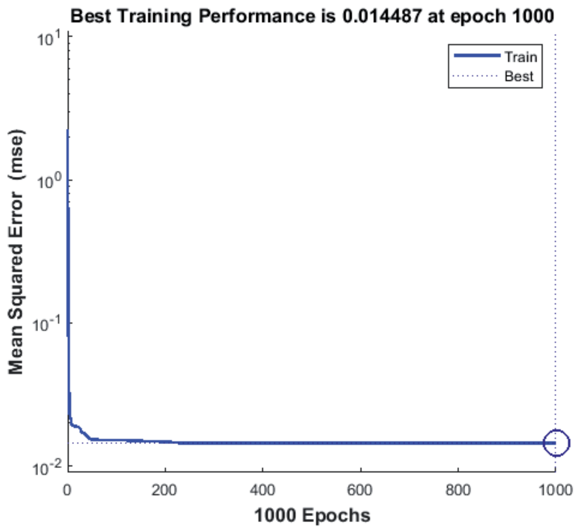

Fig. 3. A training convergence of NILM without threshold

Performance of machine learning

As mentioned earlier, the case study without threshold is used to showcase the performance of the proposed feed-forward neural network as compared with the logistic regression as suggested in [16]. Table 3 shows the performance comparison between the logistic regression and the proposed feed-forward neural network in terms of accuracy. Accuracy for individual sub-meters is calculated based on equation (5). The results show the feed-forward neural network outperformed the logistic regression for sub-meter 1 but was not for sub-meters 2 and 3. Nevertheless, the overall accuracy indicates that the feed-forward neural network has better performance than the logistic regression. The overall accuracy is more important in highlighting the effectiveness of the classification technique where the technique should be treated as fail even if only one bit of the combination is predicted wrong because all combinations of appliance operations will determine the total power consumption at the main meter. In this case, the NILM technique using the feed-forward neural network showed a more than 5% improvement of overall accuracy as compared to the logistic regression.

Table 3. Accuracy comparison using different machine learning

Sub-meter	Accuracy	
	Logistic regression	Feed-forward neural network
1	83.99%	91.93%
2	86.40%	84.86%
3	89.19%	87.12%
Overall	70.51%	76.29%

Performance of data preparation

The conversion of target data is modified to improve the performance in determining the status of appliances from measurement at the main meter. A threshold value is used to decide whether the respective appliance is "on" or "off" based on the installed sub-meter readings. The approach without threshold refers to the decision for the "on" appliances is made when the corresponding sub-meter shows reading (active power is higher than zero) as expressed in equation (3). Meanwhile, the appliances are considered "on" when their active power is higher than 5 W ($\alpha = 5$) in the approach with threshold using the expression in (5). Fig. 4 shows a comparison of appliance status determination between approaches without and with threshold. The data are based on the recorded power readings from sub-meter 2 on 17th December 2006 at 9:15 AM that last for 4 hours (240 minutes) as an example to showcase the advantages of the threshold. It is clearly shown that the approach with threshold considers the appliance is "on" only when the power readings go higher than 5 W. This helps to avoid the false representation of appliance status due to small fluctuations in the power readings as illustrated by the without threshold approach. As a result, a more accurate model can be obtained after considering some tolerance as illustrated by the approach with the threshold.

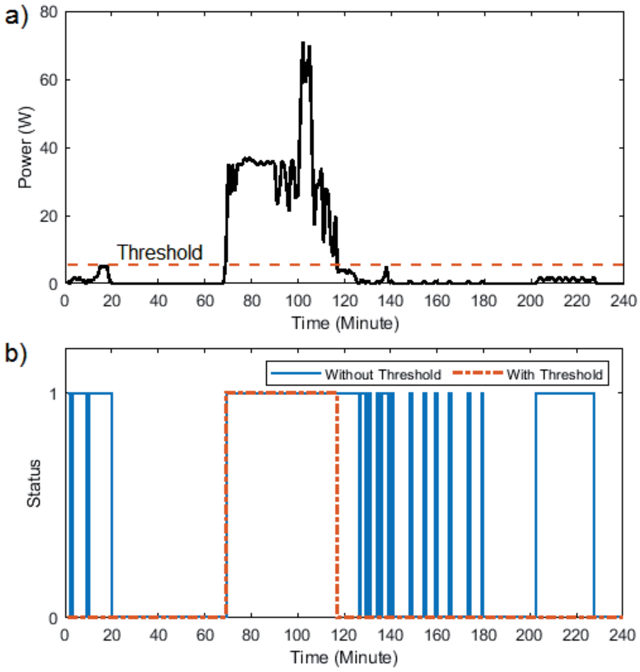

Fig. 4. Example of appliance statuses using different approaches

Table 4 tabulates the accuracy comparison between the target data preparation using approach without and with threshold based on the feed-forward neural network. The results in the table show that the accuracy of each sub-meter using the approach with threshold improved by 4.78%, 11.59% and 10.03% for sub-meters 1, 2, and 3, respectively. All individual accuracies are outperformed the NILM model in [16]. The results also show that tremendous improvement can be achieved in the the overall accuracy after applying the proposed data preparation approach with a threshold as compared to that without a threshold. More than 19% overall accuracy improvement can be observed after introducing the threshold, which indicates that the proposed approach with the threshold was able to successfully filtered the noises and disturbances to produce more trustworthy training data. The overall accuracy in this work also showed almost a 25% improvement as compared to the findings in [16]. Thus, the proposed approach in this work is shown to be more reliable than that in the previous work.

Table 4. Accuracy of different data preparation approach

Sub-meter	Accuracy	
	Without threshold	With threshold
1	91.93%	96.71%
2	84.86%	96.45%
3	87.12%	97.15%
Overall	76.29%	95.39%

Conclusion

This work proposes an NILM model to determine the status of appliances by using a feed-forward neural network. A new approach to identify the status of appliances is also introduced in the process of data preparation. In terms of machine learning performance, the NILM model using the feed-forward neural network exhibited a more than 5% improvement of overall accuracy from the previous logistic regression technique. More than 19% overall accuracy improvement can be achieved from the previous feed-forward neural network after introducing the threshold. Thus, almost 25% can be achieved from the overall accuracy as compared to the previous logistic regression technique. The status determination of appliances in this work can contribute to providing a more reliable NILM system that can be used to disaggregate the power consumption from measurements at the main meter.

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