Low frequency-based energy disaggregation using sliding windows and deep learning

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Abstract. The issue of controlling energy use is becoming extremely important. People's behavior is one of the most important elements influencing electric energy usage in the residential sector, one of the most significant energy consumers globally. The building's energy usage could be reduced by using feedback programs. Non-Intrusive Load Monitoring (NILM) approaches have emerged as one of the most viable options for energy disaggregation. This paper presents a deep learning algorithm using Long Short-Term Memory (LSTM) models for energy disaggregation. It employs low-frequency sampling power data collected in a private house. The aggregated active and reactive powers are used as inputs in a sliding window. The obtained results show that the proposed approach gives high performances in term of recognizing the devices' operating states and predicting the energy consumed by each device.

1 Introduction

The issue of controlling energy use is becoming extremely important. Indeed, global energy consumption impacts greenhouse gas emissions and, therefore on climate change [1]. One of the most significant energy users in the world is the residential sector [2]. In the US, for example, the residential sector consumes about 40% of primary energy [3]. According to [4], residential energy consumption contributed to 25.71% of the EU's total energy consumption in 2016, making it the second-largest consumer after the transport sector. Moreover, the global population is increasing, which means that energy consumption will rise in the following years [5]. This requires energy conservation policies.

People's behavior is one of the most important elements influencing energy usage in the residential sector [6]. According to research on feedback programs about specific appliances consumption reported in [7], the building's energy usage could be reduced by more than 12%. Meanwhile, Home Energy Management Systems (HEMS) are now more essential to counteract the upward trend in electrical energy use [8]. The development of HEMS systems requires the monitoring of several existing appliances in a house [8]. There are two basic ways to appliance load monitoring. On one side, the intrusive methods require installing one or more sensors in each appliance of interest. However, due to its intrusive character, which includes some privacy concerns, the difficulty associated with the deployment of several sensors, and its high cost, non-intrusive methods are favored [8]. On the other side, non-intrusive methods aim to estimate specific appliance consumption from the aggregate overall consumption captured by a smart meter at the building's entry. Non-Intrusive Load Monitoring (NILM) approaches have emerged as one of the most viable options for energy disaggregation. They allow for the separation of individual usage for specific appliances while preserving users' privacy and frequently utilizing already-installed smart meters [8].

Many NILM algorithms have been presented in the literature, and they may be classified into high frequency (in the range of kHz) sampling rate approaches [9] and low frequency (1Hz or less) sampling rate approaches [10–12]. The sampling rate refers to the rate at which the meter collects data. However, the high-frequency approach is not a practical alternative because of drawbacks, including its challenge in data transmission and data storage and its cost both in terms of hardware and software [13]. Hence, low-frequency techniques have been the focus of research because they can be easily measured by the existing smart meters without any additional equipment.

Despite the numerous works proposed in the literature about NILM, disaggregation of all types of appliances is far from addressed. The different devices can be divided into four groups [14]. The first category consists of two states (ON-OFF) devices such as a toaster (type I); the

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second group is made up of multi-state devices like a washing machine (type II), the third group consists of continuously variable consumer appliances such as dimmers (type III) and finally group 4 is made up of permanent consumer appliance such as alarms (type IV). Furthermore, owing to their simple architecture, most of the NILM algorithms existing in the literature work well for type I devices. The disaggregation of type II to type IV devices is still a challenging and open problem. Thus, it is essential to develop methods capable of disaggregating all types of devices with high prediction accuracy [15]. Deep learning algorithms might be a good fit for enhancing the accuracy and efficiency of energy disaggregation algorithms [11]. A discussion about the current deep learning work in NILM will be presented in Section 2.

This paper presents a deep learning-based algorithm using Long Short-Term Memory (LSTM) models. It employs low-frequency sampling rate power data collected in a private house. The aggregated active and reactive powers are used as inputs in a sliding window. The goal is to classify the states of the devices in the first instance to detect the ON and OFF states of the appliances. Then the model predicts the power consumption of each specific device in the house. The results show that this approach makes it possible to achieve high performance in recognition of the devices' operating states and the prediction of the energy consumed by each device. The rest of the work is structured as follows: Section 2 presents the related works, and the proposed method is described in section 3. The dataset used, the evaluations metrics, and the results are illustrated in section 4, and finally, the conclusion and outlooks are drawn in section 5.

2 Related works

George Hart introduced NILM in 1992 to monitor devices that switch ON and OFF independently in an electrical circuit [16]. Hart's research showed that devices exhibit unique power consumption signatures, and that ON/OFF events were sufficient to detect the operation of certain devices. The approach works effectively for high-consumption devices, particularly type I. Nevertheless, devices of type II through IV, on the other hand, are complicated to recognize. Consequently, several works on NILM have been proposed in the literature. Indeed, Hidden Markov models and their variants have been widely applied to NILM [17]. However, generalization and scalability issues have been noted for HMM-based approaches, limiting their real-world usefulness. Their performance is limited to an accurate prediction of device real power consumption, particularly for type II to type IV appliances [15].

Machine learning and deep learning approaches have attracted researchers' interest in recent years to address the NILM problem. Hence, both supervised and unsupervised approaches such as support vector machines, k-nearest neighbors [18], Decision Trees [19], k-means, Artificial neural networks (ANN) [20], convolutional neural networks (CNN), LSTM [15] and deep learning [11,21] have been proposed.

The authors of [11] introduced three deep neural network architectures for energy disaggregation. CNN, Bidirectional LSTM, and denoising autoencoder. In their approaches, NILM was considered as a regression problem. They used aggregate active power as input. The models were evaluated using the UKDALE public dataset, where the suggested models outperformed combinatorial optimization and FHMM state-of-the-art models.

The authors of [19] suggested a transient signal event identification strategy based on decision trees and long-term memory models. The transient signal was obtained using a low frequency active power signal. They demonstrated that integrating the transient signal with the input signals enhances the efficiency of the algorithm.

The authors of [22] developed a fully convolutional neural network-based multi-label classification technique. A features space is used to classify the states of the devices, which is improved by a temporal pooling module. The power is estimated by considering a constant average value when the device is detected ON. They demonstrated that the proposed technique was accurate in detecting device activation.

A method based on a post-processing algorithm was proposed in [15]. In the proposed approach, a number of the most influential electrical features were combined to form a multi-feature input for the model. They used a bidirectional LSTM combined with a convolutional layer. They obtained good performances on the UKDALE and ECO public datasets.

Unlike most literature on NILM works, which use either a single point of aggregate time series of the main active power to estimate the power consumption of the appliance at that sample [11], or a sliding window of a single aggregate variable, especially active power [20], in our case, we propose a sliding window containing two variables (active and reactive powers) as inputs to our model to predict the operating state of each device and its power consumption using LSTM algorithm. The proposed LSTM model will be detailed in Section 3.

3 Proposed method

The main objective of NILM is to estimate the energy consumption of each individual device using the aggregated data of the overall consumption of the house. The problem can be formulated as follow: giving a sequence of aggregated readings from a smart meter of the house $X = \{x_1, x_2, \ldots, x_T\}$ where T is the length of the sequence, the goal is to estimate the sequence of specific power consumption $y^{(i)} = \{y_1^{(i)}, y_2^{(i)}, \ldots, y_T^{(i)}\}$ of each device from X where i is the known number of devices.

$$X(t) = \sum_{i=1}^{M} y^{i}(t) + e(t) \qquad (1)$$

where e(t) denotes the noise.

LSTM is a deep recurrent neural network that uses a feed-forward variation to process sequential data and deal with vanishing gradient issues [15]. The input layer simply creates a sequence of vectors for the following L layers. Each recurring layer is made up of N units which transfer an input sequence to an output sequence. The last recurring layer L is preceded by a feed-forward output layer made up of N (L + 1) units. The static nonlinear mapping at each instant t is given by Eq. 2. The description of the model can be found in [23].

$$y(t) = \sigma^{(L+1)} (W^{(L+1)} X^{(L)}(t) + b^{(L+1)}) \tag{2}$$

where σ is the activation function, W is the weight and b represent the bias.

Our LSTM design was finished after adjusting several hyperparameters. The same architecture is used for both classification and regression models. The output layer's parameters are adjusted depending on whether we want to classify the device's state (sigmoid as activation and Binary cross entropy as loss function) or estimate the target device's power sequence (linear as activation and mean square error as loss function). The following is the whole architecture with optimal hyperparameter values:

1. Input shape (length defined by the appliance data)
2. LSTM layer (number of hidden units = 32, activation = PReLU ())
3. Dropout layer with dropout = 0.3
4. LSTM layer (number of hidden units = 64, activation = PReLU ())
5. Dropout layer with dropout = 0.3
6. LSTM layer (number of hidden units = 128, activation = PReLU ())
7. Dropout layer with dropout = 0.3
8. Fully connected dense layer (number of units = 1024, activation =PReLU ())
9. Fully connected dense layer (number of units = 1)

4 Results

The LSTM model is first trained to classify each device's operating states and determine whether the device is on or off. Then a second LSTM regression model is trained to estimate the power consumption of each device. One model is trained for each target appliance.

4.1 Dataset

A dataset was collected in a private house to evaluate our approach as part of a real-life scenario in Algarve, Portugal. Measurements of several variables, including aggregate active and reactive powers, were collected over several months in a low-frequency sampling interval of every second (1 Hz). For a description of the house and the acquired variables, please see [24]. This paper is particularly interested in the data of three devices (refrigerator, washing machine, and electric heating water), which are popular devices for testing NILM algorithms. The breakers for these three devices have been monitored for several months using wibee meters (https://wibeee.com/) via the Modbus interface (www.modbus.org). The individual appliance power consumption is monitored using smart plugs. It is assumed that an appliance is considered ON when its power consumption exceeds a certain threshold. After pre-processing the data, we considered data from October 2020 and March 2021 and split it into training (80%) and testing set (20%). Training and testing periods for each appliance are presented in Table 1.

Table 1. Training and testing period.

Appliance	Training	Testing
Washing machine	from 01/03/21 to 21/03/21	from 22/03/21 to 28/03/21
Electric water heating	from 01/03/21 to 21/03/21	from 22/03/21 to 28/03/21
Fridge	from 01/10/20 to 21/10/20	from 22/10/20 to 28/10/20

4.2 Evaluation metrics

The model is evaluated using both energy estimation and classification metrics. In the latter group we have the F1_score, the precision, the recall, while in the former the mean absolute error (MAE), the signal aggregate error (SAE), and estimation accuracy (EA) metrics are used. They are described in Table 2 [15,25].

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$F1 = 2 \times \frac{precision \times recall}{precision + recall} \tag{5}$$

$$MAE = \frac{\sum_1^N |y-p|}{N} \tag{6}$$

$$SAE = \frac{|\hat{E}-E|}{E} \tag{7}$$

$$EA = 1 - \frac{\sum_1^N |y-p|}{2 * \sum_1^N y} \tag{8}$$

where N is the number of values representing the load data, y is the ground truth values, p is the predicted values. E is total ground truth energy for each device, $\hat{E}$ is total estimated energy, TP is the number of true positives, FP is the number of false positives, TN is the number of true negatives, and FN the number of false negatives.

The model was trained using three weeks of data. The input was a sliding window of aggregate active and reactive powers (window size =20). The output for the classification model is the ON/OFF label of the device, and the output of the second regression model is the sequence of target device power consumption. The results in the test dataset (the last seven days) are presented in Table 2 and Table 3.

Table 2. Classification results.

Appliance	F1	Precision	Recall
Electric water heating	0.9986	0.9994	0.9977
Fridge	0.9971	0.9976	0.9967
Washing machine	0.9740	0.9787	0.9693

Table 3. Estimation accuracy results.

Appliance	MAE (W)	SAE	EA
Electric water heating	37	0.00169	0.9986
Fridge	1.75	0.0105	0.9834
Washing machine	2.27	0.0054	0.9380

The results show that the proposed LSTM models obtain a very high performance both in terms of classification and prediction of the power consumption of each device. The direct comparison with the work of the literature is not achievable because of the ambiguity on the evaluation's metrics, which depend on the context and the data used for each experiment. However, as an indication, Table 4 shows the comparison of our approach to the work of state-of-the-art. The proposed approach gives better performance in terms of f1 score compared to the work of [11] and [15] where only active power was used.

Table 4. Font styles for a reference to a journal article.

Method	Electric Water Heating	Fridge	Washing Machine
LSTM (this paper)	**0.9986**	**0.9971**	**0.9740**
LSTM [11]	-	0.6900	0.0900
Bi-LSTM [15]	-	0.9970	0.7950

Figure 1 shows the comparison between the estimated active power and the ground truth active power of washing machine, fridge, and electric water heater as well as the aggregated active and reactive powers consumption. As it can be seen, they show a good agreement between the predicted power and the real power (see Fig. 1).

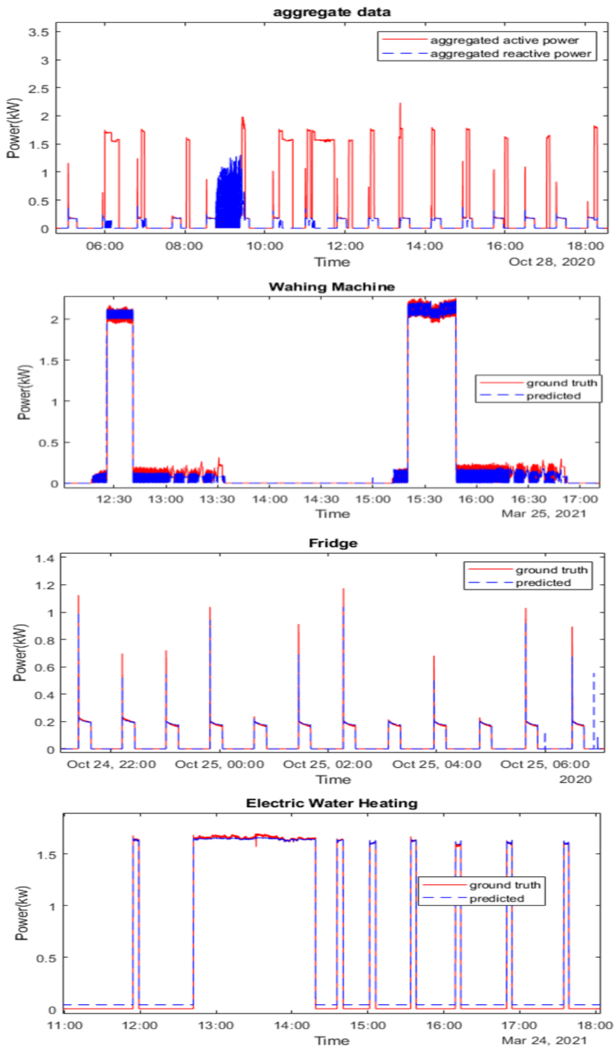

Fig. 1. Results of disaggregation: predicted versus ground truth.

5 Conclusion

This paper presented a deep learning-based algorithm using LSTM models. It is based on low-frequency sampling rate data collected in a private home. The aggregated active and reactive powers are used as inputs in a sliding window. The model was trained to classify the states of the devices first to detect the ON and OFF states. Then, a second model was trained to estimate the power consumption of each specific appliance in the house. The results showed that this approach can achieve high performance in recognizing devices' operating states and predicting the energy consumed by each device. Our future work will be devoted to the comparative analysis of other NILM methods.

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