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Non-Intrusive Load Monitoring (NILM) Using a LSTM With Socio-Economic Parameters

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ABSTRACT

Nonintrusive load monitoring (NILM) deconstructs aggregated electrical usage data into individual appliances. The dissemination of disaggregated data to customers raises consumer awareness and encourages them to save power, lowering CO2 emissions to the environment. The performance of NILM systems has increased dramatically thanks to recent disaggregation methods. However, the capacity of these algorithms to generalize to various dwellings as well as the disaggregation of multi-state appliances remain significant obstacles. In this paper, we propose an energy disaggregation approach by using socio-economic parameters. The suggested approach helps in creating more accurate load profiles, which improves the accuracy and helps in better detection of the appliances. The proposed model outperforms state-of-the-art NILM techniques on the PRECON dataset. The mean absolute error reduces by 5% - 10% on average across all appliances compared to the state-of-the-art. Thus, improving the detection of the target appliance in the aggregate measurement.

Keywords: NILM, LSTM, advanced energy technologies, energy conservation in buildings, energy systems for power generation, environment, and climate change

1. INTRODUCTION

NILM, or load disaggregation, is a technique for determining the operational status (on/off) and accurate power consumption of individual electrical loads using just the aggregated consumption as input. Due to advances in the field of machine learning and deep learning algorithms, this idea was initially suggested by Hart in 1992 [1], but it has been refined substantially over the previous decade. Many disaggregation methods are utilized in the residential sector and in industry sector [2], [3], As a non-intrusive mechanism, the strategies apply the least amount of intrusion and have minimal impact on consumer privacy, because measurements are taken from a single source (aggregated load) and there is no need to deploy additional equipment.

Having access to appliance-specific data instead of whole-house measurements has a variety of advantages for both consumers and energy companies. Consumers, for example, may better understand their energy usage since they can see which appliances use the most energy. As a result, individuals will be better prepared to make energy-related decisions. Most of the customers are unaware of how much energy they use or their appliances environmental effects. Therefore, Increased awareness may result in more reasonable appliance usage. Consumers may choose to use less of their high energy-consumption equipment and, in some situations, replace the inefficient appliances or use CO2-emitting appliances more efficiently.

Furthermore, according to the International Energy Agency's (IEA) "Net Zero by 2050" study, the energy sector accounts for three-quarters of global greenhouse gas emissions [4]. Furthermore, as global energy demand grows faster than supply, existing power grid systems face major problems in terms of efficiency and dependability. The restructuring of electrical infrastructure is crucial on the way to zero CO2 emissions by 2050. The combination of increased computing power and unique modeling and simulation capabilities allows for a seamless transition from traditional grids to the smart grid age [5]. Smart grids are expected to integrate assets such as Distributed Energy Resources (DERs), Electric Vehicles (EVs), and Energy Storage Systems (ESSs), as well as intelligent services, to unlock the flexibility potential that will allow for more efficient 2 Copyright © 2020 ICAE energy generation, distribution, and consumption. Nonintrusive load monitoring (NILM) is a service that helps achieve this goal by evaluating the consumption of individual appliances in a facility.

2. RELATED WORK

For many years, Deep Neural Networks (DNN) techniques have been used to disaggregate energy [6], [7]. These state-based methods are mostly utilized for low-frequency (less than 1 Hz) monitoring, which needs less expensive gear. Recurrent neural networks [6]-based methods, such as LSTM [8], [7], or Gated Recurrent

Unit [9], have mostly been proposed because they are ideally suited for 1D time-series data. The authors of [10] present a Bayesian optimized bidirectional LSTM model for NILM that extends the RNN.

High-frequency data has more load features than low-frequency data. The harmonic approach was improved in [11] and [12]. [11] employed total harmonic distortion rate, power, and current harmonics as characteristics to construct similarity scores to achieve load detection. [12] proposed a method based on lower odd-numbered harmonics and a bagging decision tree (FFT BDT), which included two processes: obtaining magnitude and phase at lower odd-numbered harmonics and recognizing loads using a bagging decision tree. For NILM, a voltage-current (V–I) image-based technique has been developed. [13]. The reconstructed picture of a V-I trajectory was employed as input data for a convolutional neural network (CNN) to categorize appliances, especially resistive appliances, in the study. When compared to the other two approaches on the PLAID and IDOUC datasets, the proposed approach performs extremely well. [14] suggested a non-intrusive load detection system based on a two-stream convolutional neural network with current time-frequency feature fusion. To extract the time domain and frequency domain characteristics, a time series image coding approach was devised first. The load detection performance was then improved by using a two-stream neural network integrating a gated recurrent unit (GRU) and a 2D-CNN. Finally, PLAID and IDOUC datasets were used to test it.

Traditional CNN's extract characteristics by just feeding data in one way. These networks are unable to capture data that varies over time, such as time-series data. Recurrent neural networks (RNN) and LSTM [16] were offered as solutions to this problem. The LSTM, which records time-series patterns through two states in each cell, is the most widely used recurrent model today.

3. METHODOLOGY

A typical system-level NILM setup refers to one time calibration period to learn appliance signatures and store them in a database. Once the system learns these signatures it can identify the appliances based on those signatures whenever the switching event takes place [17]. These typical systems only use appliance signatures to train the model. In our approach we use socio-economic parameters with the appliance signatures so this NILM setup can correctly identify those appliances based on those parameters, which can be seen in the results section that this NILM setup reduces the loss errors for correct appliance detection.

In our methodology, we focus on different scenarios where test houses are held out during the training process, for each scenario we used the PRECON data. In the first scenario, we held out 5 houses and trained the modal on another house without using socio-economic parameters and calculated the average mean absolute errors. In the second scenario we again held the same 5 houses and trained the modal on the same other house but this time we used the socio-economic parameters by attaching them before the training so our modal could train based on these weights. In another scenario we also used 20% of the data of each house for training the modal and then validated using the rest of the data, we named it “results on seen data and unseen data”.

We trained the proposed model through supervised learning. We used the optimizer 'Adam' with loss function 'Root Mean Square' with a dropout rate initialized at 0.3. The model contains six groups of layers with dimensions input, 64, 128, and 256 respectively with a dense layer attached at the end with this stacked LSTM architecture as shown in Fig 1 and Table I.

TABLE I
NUMBER OF HIDDEN NEURONS AND OUTPUT SHAPE OF LSTM BLOCK

Name	Output Shape	# Of Param.
LSTM layer	64	22,528
LSTM layer	128	98,816
LSTM layer	256	394,240
Dense	1	257

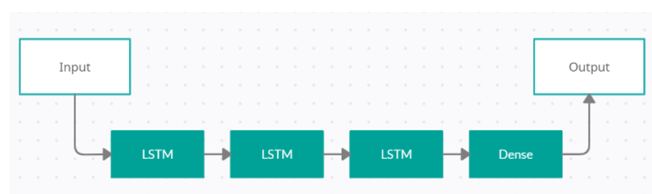

Fig. 1. Stacked LSTM Architecture

Regardless of the appliance type all the hyperparameters are fixed and all the experiments are run on a maximum of 100 epochs using the batch size 60.

4. EXPERIMENTS

In this section, we discuss the experiments and present comparisons with state-of-the-art methods with and without socio-economic parameters to validate the effectiveness of our approach.

4.1 Dataset

The PRECON dataset is used for our experiments, this reference dataset is a set of 42 houses. Each house data was collected over the course of one year using smart meters. Aside from power usage statistics, various home attributes are also recorded in this dataset. Some of these attributes are summarized as. Total number of people living in the house, their age groups, property area of the house etc. Other than this, all the other important electrical loads of the house are also recorded which include the number of LED lights, fans, washing machines, electric iron, tube-lights, electric heaters, water pumps, refrigerators, electronic devices, and water dispensers etc.

4.2 Training Set and Test Set

The house 4 in the PRECON dataset is used as the train set. It contains Total Usage (Usage_kW), Air Conditioner in bedroom (AC_BR_kW), kitchen (Kitchen_kW), Air Conditioner in lounge room (AC_LR_kW), Air Conditioner in master bedroom (AC_MBR_kW) as shown in Table II.

TABLE II
OVERVIEW OF HOUSE 4 in PRECON DATASET

	Usage	AC_DR	Kitchen	…	AC_BR
2019-03-10 11:05:00	1.3084	0.008	0.5134	…	0.0268
2019-03-10 11:06:00	1.4813	0.009	0.5088	…	0.0268
	…	…	…	…	…
2019-03-10 11:07:00	1.7421	0.008	0.5021	…	0.0270

With this data a metadata file is given which contains other attributes of the houses. The other attributes of house 4 are shown in Table III.

TABLE III
METADATA OVERVIEW OF HOUSE 4 in PRECON DATASET

Attributes	Value
Property Area sqft.	5445.01
Number of people Living	7
Total number of Rooms	7
Number of Electric Heaters	0
Number of UPS	2
Number of Fans	10
Number of Refrigerators	3
…	…
Number of Water Pumps	1

To create the train and test sets we treated our static features as fixed temporal data and made a temporal dimension for each of our selected socio-economic parameter and appended them with our house 4 data. This dataset is then used to train the modal. After the model training is completed, the data from the remaining houses in the PRECON dataset is used to test the model's performance and versatility.

5. RESULTS

In this section, we conduct extensive experiments and make comparisons. We conducted experiments on 2 appliances kitchen and air conditioner on 5 different houses with socio-economic parameters and without socio-economic parameters. We have divided our results into following 3 sections for comparisons.

5.1 Without socio-economic parameters

Table IV shows our results without parameters and the training set is only based on total usage of the house. The Model is trained on House 1 and other houses are used as test sets. Table V shows mean absolute error for the same trained model.

TABLE IV
MEAN SQUARE ERROR WITHOUT SOCIO-ECONOMIC PARAMETERS

	Kitchen	Air Conditioner
House 1	0.0373	0.0447
House 2	0.0171	0.1198
House 3	0.0088	0.1185
House 4	0.0274	0.2303
House 5	0.0322	0.0774

TABLE V
MEAN ABSOLUTE ERROR WITHOUT SOCIO-ECONOMIC PARAMETERS

	Kitchen	Air Conditioner
House 1	0.1636	0.1143
House 2	0.0947	0.1259
House 3	0.0562	0.2547
House 4	0.0931	0.2360
House 5	0.1170	0.1392

5.2 With socio-economic unseen parameters

We trained the model using socio-economic parameters with the total usage of the house and used completely unseen houses as test sets. The model gave better results if the model was trained on some of the same parameters of the same house. Table VI and Table VII shows our mean square error and mean absolute errors with socio-parameters. The Model is trained on House 1 and House 1 parameters other houses are used as test sets.

TABLE VI
MEAN SQUARE ERROR WITH SOCIO-ECONOMIC PARAMETERS (UNSEEN DATA)

	Kitchen	Air Conditioner
House 1	0.0309	0.0435
House 2	0.2531	0.1673
House 3	0.0600	0.0884
House 4	0.0382	0.2867
House 5	0.2720	0.0864

TABLE VII
MEAN ABSOLUTE ERROR WITH SOCIO-ECONOMIC PARAMETERS (UNSEEN DATA)

	Kitchen	Air Conditioner
House 1	0.1441	0.1174
House 2	0.4750	0.3440
House 3	0.2244	0.2726
House 4	0.1312	0.3242
House 5	0.4491	0.2383

5.3 With socio-economic seen parameters

We created a new train set which is trained on 20% of the parameters of each 5 house. This model gave the best results the mean square error and mean absolute error were less then both previous models. Table VIII and Table IX shows the mean square error and mean absolute error of the model which is trained using socio-economic parameters and where 20% of the data is used in the training set.

TABLE VIII
MEAN SQUARE ERROR WITH SOCIO-ECONOMIC PARAMETERS (SEEN DATA)

	Kitchen	Air Conditioner
House 1	0.0335	0.0435
House 2	0.0078	0.0020
House 3	0.0018	0.0662
House 4	0.0354	0.0079
House 5	0.0372	0.0010

TABLE IX
MEAN ABSOLUTE ERROR WITH SOCIO-ECONOMIC PARAMETERS (SEEN DATA)

	Kitchen	Air Conditioner
House 1	0.1517	0.1174
House 2	0.0600	0.0205
House 3	0.0183	0.1879
House 4	0.1149	0.0278
House 5	0.1335	0.0174

6. COMPARISONS

In this section, we will compare our results of our models which were trained with and without socio-economic parameters.

Table X shows mean square error of all three models for kitchen data set. It can be seen from the results that the model trained by using the socio-economic parameters reduced the mean square error and improved the model in prediction of the appliance. House 1,2 and 3 shows the effectiveness of socio-economic parameters on the Model trained with these

TABLE X
COMPARISON OF MEAN SQUARE ERROR OF ALL THREE MODELS ON KITCHEN

	Without parameters	With parameters unseen data	With parameters seen data
House 1	0.0373	0.0309	0.0335
House 2	0.0171	0.2531	0.0078
House 3	0.0088	0.0600	0.0018
House 4	0.0274	0.0382	0.0354
House 5	0.0322	0.2720	0.0372

TABLE XI
COMPARISON OF MEAN SQUARE ERROR OF ALL THREE MODELS ON AIR CONDITIONER

	Without parameters	With parameters unseen data	With parameters seen data
House 1	0.0447	0.0435	0.0435
House 2	0.1198	0.1673	0.0020
House 3	0.1185	0.0884	0.0662
House 4	0.2303	0.2867	0.0079
House 5	0.0774	0.0864	0.0010

parameters. The loss relatively decreased as compared to the model which was trained without these parameters.

Table XI shows mean square errors on air-conditioner appliance. The model trained using the socio-economic parameters the mean square and mean absolute errors reduced drastically for all the five houses showing the effectiveness of using socio-economic parameters. visualization.

Fig. 3 and Fig.4 shows some graph visualization of true value and predicted value by the system of houses 2 and 4. The blue line shows the actual values of the appliance, and the red line shows the predicted values. The graphs show the data of two random days from the whole year.

7. CONCLUSION

The idea of NILM appears to have a prominent position as a future smart energy grid service, allowing users to gain control over their energy usage through enhanced awareness. The breakdown of energy use at the appliance level might also aid in the detection of abnormalities in equipment that are malfunctioning.

This paper has proposed a non-intrusive load monitoring technique using socio-economic parameters on a LSTM Algorithm and verified its effectiveness through PRECON dataset. Compared with the traditional techniques the mentioned approach of using socio-economic parameters with the house data reduces the losses of LSTM algorithm and showed better results in the detection of the appliance.

In future work we would like to see the effectiveness of socio-economic parameters on other algorithms other than LSTM such as decision trees etc. We would also like to design a multi-headed network for this technique using time series data separately and socio-economic parameters as separate model and then concatenating both the outputs in the last layer. We believe this model can give even better results than our current disaggregation solutions.

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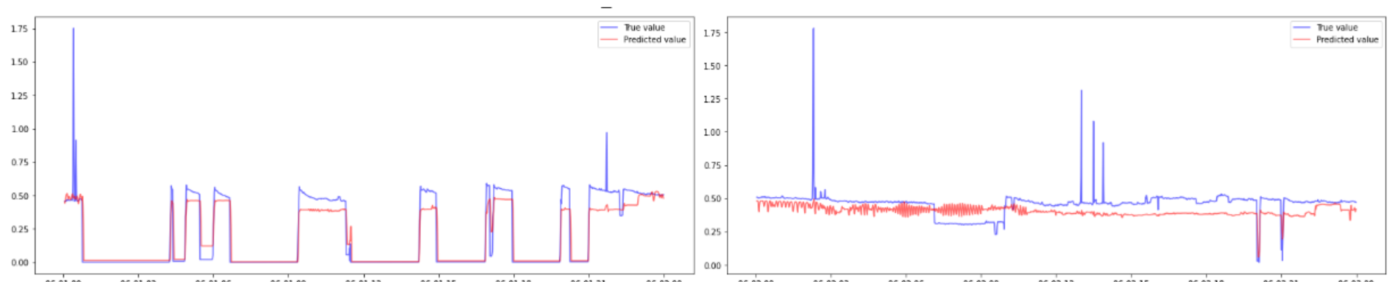

Fig. 3. Real and Predicted values of house 4 for kitchen

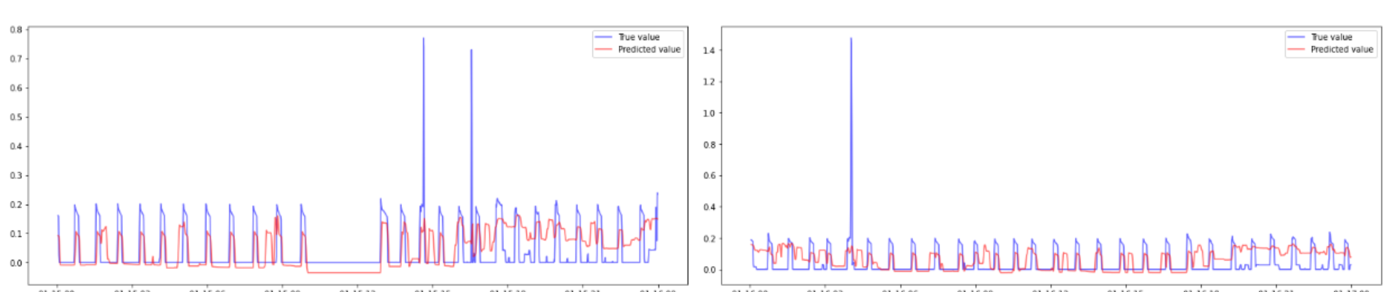

Fig. 4. Real and Predicted values of house 2 for kitchen

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