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Sensor-aided NILM with Gaussian Mixture Models

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Abstract—Energy disaggregation, also known as non-intrusive load monitoring (NILM), is the process of analyzing energy consumption in a building and identifying individual appliance-level energy usage. This approach can provide valuable insights into energy consumption patterns and help reduce overall energy usage, costs, and carbon emissions. This paper proposes a new method for tackling the disaggregation problem by using data from low-cost wireless sensor networks. The proposed approach estimates appliance states using a GMM model and uses these states as features to improve energy disaggregation. The performance of the proposed method was evaluated on a real-world dataset called SmartSense deployed in our lab, and the results showed that it significantly improved the accuracy of conventional NILM disaggregation performance.

Index Terms—Energy disaggregation, NILM, GMM, Window-GRU, wireless sensor platform SmartSense

I. INTRODUCTION

The development of smart power consumption tactics is an urgent requirement for the future smart grid to adapt to the changing demands of production and lifestyle in the new era. It is also crucial for ensuring effective communication between supply and demand. An intelligent power consumption strategy significantly contributes to enhancing energy efficiency for consumers and reducing energy consumption [1], [2]. The foundation of creating an effective intelligent power consumption strategy lies in comprehending the energy consumption patterns and usage behavior of electrical devices. Energy disaggregation breaks down the total electricity usage recorded by the user’s meter into individual appliance usage, serving as a technical foundation for the creation of smart grid power consumption tactics [3].

Visual representation of household appliance energy consumption can assist users in effectively considering energy conservation. By providing insights into appliance usage, time of use, and energy consumption, these visualizations encourage consumers to be more mindful of their energy consumption habits, leading to the adoption of more energy-efficient practices. Previous research has shown that these visualizations can result in a reduction of energy consumption by as much as 15% [4]. Additionally, connecting households to a smart grid makes efficient use of household energy demand

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information [5], [6]. A smart grid is a modern grid system that collects data on power generation and consumption through a two-way communication network in connected households. This enables the exchange of power-related information and simplifies demand-side energy management.

The paper is organized as follows. In Section II, we remind the state of the art and the work environment. Section III introduces our workflow process associating wireless sensors with NILM and our new platform SmartSense. Finally, we describe and analyze preliminary results.

II. RELATED WORKS

A. Non-Intrusive Load Monitoring concept

The concept of Non-Intrusive Load Monitoring (NILM), where energy meter data from the entry point could be used to disaggregate loads, was first introduced by Hart in the 1980s [7]. With the rise of smart meters, there has been a surge in publications on the subject of NILM [8], [9]. The ultimate aim is to analyze each appliance’s state and power consumption using only a single reading of the total power usage. This is why a solved NILM problem is frequently referred to as “disaggregated” [10]. Figure 1 explains the basic NILM concept. For instance, from $t = 12$ to $t = 28$ minutes, an oven element is turned on. At $t = 17$, a stove burner is turned on. The first issue is identifying the precise moment when these appliances are turned on and off using their electrical signature, which can take the form of activation height, length, or shapes that are depicted with arrows. Estimating their power loads based on this trace is a second issue.

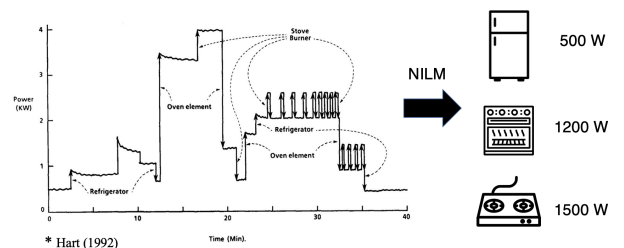


Fig. 1: Concept of typical NILM as presented in [7].

This approach employs two techniques, namely pattern recognition and event-based methods, as well as combinatorial optimization. The algorithm learns the consumption pattern of

appliances and compares it to the household meter reading in the former, whereas the latter involves learning the total consumption of appliances and comparing it to the household meter reading. These techniques have undergone extensive research and are now part of the Non-Intrusive Load Monitoring Tool-Kit (NILMTK), which is a disaggregation algorithm developed by an open-source community.

B. Non-Intrusive Load Monitoring Toolkit

Non-Intrusive Load Monitoring Toolkit or NILMTK [11] is a tool used in analysing load usage in a building. It is an open source toolkit written in Python available on Github with a big community.

Prior NILMTK published, it was almost impossible to find a way to compare literature findings and experiments in NILM. No previous standard existed in terms of experiment setup, data acquiring, data format, etc. Therefore, NILMTK was introduced to tackle these issue. It is designed to be a standard tool for NILM tasks, and to be used among researchers. With NILMTK, researchers can have some guidelines on how obtained data and predicted data to be collected, stored, compared, evaluated and even represented in the similar manner or format. Thus, the results from disaggregation can be compared and discussed on the performance of an algorithm used. NILMTK includes several features such as dataset conversion tools (to import dataset into NILMTK environment), several disaggregation algorithms and evaluation tools. The most popular metrics used in NILM field are the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE):

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T |\hat{y}_t - y_t|^2} \text{ and } MAE = \frac{1}{T} \sum_{t=1}^T |\hat{y}_t - y_t| \quad (1)$$

where \hat{y}_i represents the prediction of an appliance's energy usage at time t and y_i represents the corresponding ground truth.

In fact, many public datasets are available for researchers to work on. Datasets in NILM contain both main power meter reading and an appliance power reading. The sampling rates of the dataset are typically in the range of 1 second to several seconds, but some datasets may also provide a higher sampling rate like 16kHz [12]. Popular NILM datasets such as REDD [13], BLUED [14] and UKDALE [12] are the most used by researchers to evaluate their algorithms since they are integrated in NILMTK. Moreover, NILMTK provides several deep learning models for energy disaggregation such as WindowGRU which will be used in our experiments.

C. WindowGRU

The Windowed Gated Recurrent Unit (WindowGRU) is a novel Recurrent Neural Network (RNN) architecture that is designed to capture long-term dependencies in sequence data. The algorithm introduces a window-based processing technique that selectively focuses on relevant past information while suppressing irrelevant information. The WindowGRU algorithm showed its effectiveness on various sequence modeling tasks, and show that it outperforms traditional GRU

models and other state-of-the-art approaches. Added to that, the WindowGRU algorithm has the potential to improve the performance of RNNs in various sequence modeling tasks that involve long-term dependencies.

The architecture in detail is the following:

- 1) Input is windowed with length optimised to the appliance
- 2) 1D Convolution with 16 filters, 4 kernels and linear activation
- 3) Bidirectional GRU with 64 units, tanh activation and 0.5 dropout rate
- 4) Bidirectional GRU with 128 units, tanh activation and 0.5 dropout rate
- 5) Fully connected with size of 128, tanh activation and 0.5 dropout rate
- 6) Fully connected with size of 128, tanh activation and 0.5 dropout rate

III. SEMI-INTRUSIVE LOAD MONITORING

A. SmartSense dataset

Using environmental sensing and diverse information can help overcome challenges faced by current NILM techniques [15]. However, this can increase complexity. Hence, a more efficient approach could be to merge supplementary data with the overall power consumption of the building for load monitoring. Furthermore, the increasing number of intelligent sensors integrated into buildings for different purposes has made it more feasible to acquire this information without additional setup, which may explain the recent emphasis on this method.

The dataset used in this study is called SmartSense, which serves as a research platform that employs a sensor network designed for multiple data acquisition purposes. More than 120 nodes are deployed inside our lab and each node within the network comprises fifteen sensors that collect a diverse range of information (see Figure 2), including:

- Video sensors (Video-Graphic-Array (VGA), Infra-Red (IR) cameras) and audio sensors (4 microphones in tetrahedron authorizing localization);
- Radio sensors (2.4 GHz, Sub-GHz, and Ultra-Wide-Band) to sense the radio-frequency band occupancy and to estimate positions;
- Air quality sensors (temperature, humidity, carbon dioxide concentration, air pressure, etc.);
- Light sensors (Ultraviolet and Red-Green-Blue-White);
- Distance sensor (Laser telemeter).

Additionally, SmartSense platform contains a record of power consumption in each floor in our lab as a classical NILM (figure 3):

- global power consumption recorded by an EcoCompteur with a frequency of 7Hz;
- individual power consumption of various electrical appliances recorded by a ZigBee meter with a frequency of 100mHz.

A summary of SmartSense features is shown in Table I.

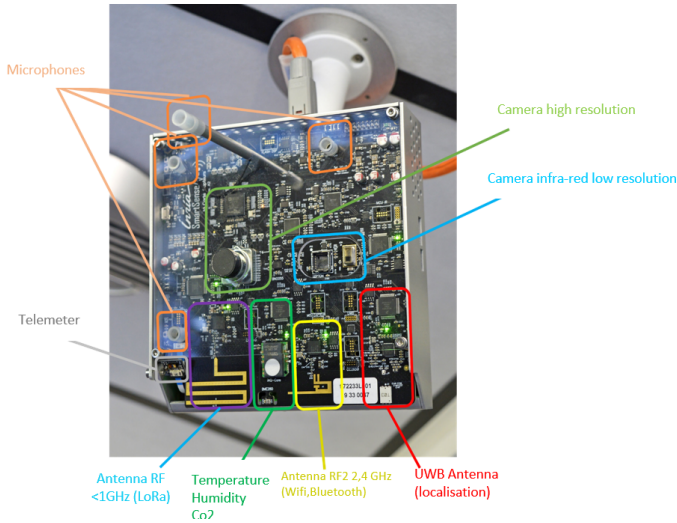


Fig. 2: Different sensors in one node.



(a) EcoCompteur Legrand module (b) ZigBee Cleode meter

Fig. 3: Hardware devices used to collect power consumption data for SmartSense data

This paper proposes a Semi-Intrusive Load Monitoring architecture (SILM) that uses power consumptions and wireless sensors data to detect individual power consumption of devices from aggregated power data as shown in Figure 4a.

In fact, the SILM architecture is composed mainly of 2 parts:

- The first part called the features extraction phase intends to extract a useful information from sensors data and then feed them to the input of the next step;
- The second part called the disaggregation phase in which the standard NILM workflow is kept. It entails three main phases, including data preprocessing, disaggregation, and performance evaluation.

The aim of our work is to find a good way in exploiting sensors data and extracting a useful information that will help in improving NILM performance. The first naive idea we started with is to add raw sensors data to the aggregated power data as input and let the disaggregator algorithm deal with it.

TABLE I: SmartSense dataset features

Measurement device	Data type	Frequency	Appliances
EcoCompteur	global power consumption	7.5 Hz	coffee maker, kettle, fridge, oven,
ZigBee meter	individual power consumption	100 mHz	microwave, laptop, printer, light
Sensors node	sensors data	1 Hz	

The results show that disaggregation performance compared with the typical NILM improved slightly for the kettle while they stayed almost the same for the coffee maker.

We recognize that raw sensors data could have noise that could limit the disaggregator algorithm’s effectiveness. Consequently, it is essential to extract features, such as appliance states, from this data. The disaggregation process involves identifying when an appliance is being used and determining its state. We believe that by focusing on classifying appliances as either ON or OFF, we can further use this information to enhance the accuracy of the disaggregation process.

B. Proof of Concept

We thought that adding an a-priori information of appliances states could improve the disaggregation performance and gives a more accurate estimation of appliances individual power consumption. That is why before starting the implementation of our architecture, we made a Proof of Concept (POC). Indeed, the individual power consumption used as reference during the training phase of the disaggregation was transformed to 0 or 1 representing the states OFF and ON of an appliance, or No Activity and Activity. Then, these states information was added with the aggregated power data as an additional input of the standard NILM workflow. Finally, with this augmented input a typical disaggregation with NILMTK was performed. The duration of both the training and test dataset is 15 days. The results of disaggregation are depicted in Table II and Table III. The unmarked values indicate the outcomes obtained solely from the total power data, while the values marked with underlines show the results obtained from the suggested input, which includes both the total power data and the true states of a given appliance.

TABLE II: Evaluation of disaggregation performance of NILM and the SILM POC (underlined values)

Appliances	RMSE	MAE
Kettle	69.82	6.69
	<u>15.37</u>	<u>1.28</u>
Coffee maker	26.27	2.65
	<u>7.21</u>	<u>1.04</u>

TABLE III: Confusion Matrix of coffee disaggregation performance using the power data and the ON/OFF states as input

True Class	Predicted Class		Support	
	Negative	Positive		
Negative	132077 <u>132190</u>	116 3	132193	
Positive	126 <u>0</u>	1241 <u>1367</u>	1367	
		Precision	Recall	F1 Score
Negative	1.00	1.00	1.00	1.00
	<u>1.00</u>	<u>1.00</u>	<u>1.00</u>	<u>1.00</u>
Positive	0.91	0.91	0.91	0.91
	<u>1.00</u>	<u>1.00</u>	<u>1.00</u>	<u>1.00</u>

The results show that adding an a-priori information can improve significantly the disaggregation of a given appliance.

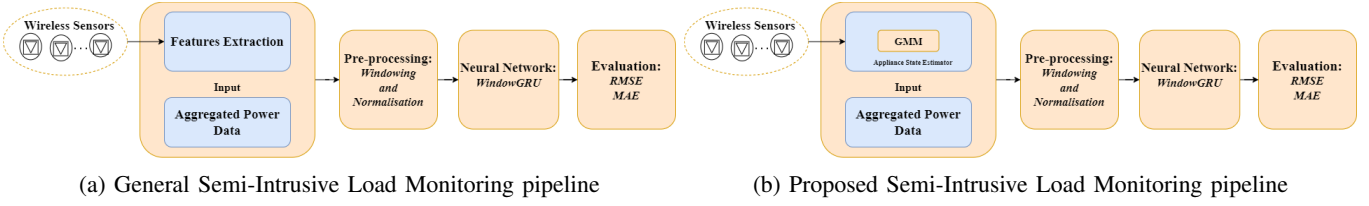


Fig. 4: Semi-Intrusive Load Monitoring syntopic

The results was validated for the coffee maker and the kettle. The challenge now is to implement the POC by finding a good estimator of the states of appliances from sensors data.

C. Gaussian Mixture Models as an estimator

Gaussian mixture models (GMM) are a probabilistic machine learning technique that can provide better approximation when the clusters are overlapping, as compared to k-means clustering [16]. Thus, the GMM model will be used in our case as the estimator/classifier of appliances states as shown in Figure 4b. In Gaussian mixture models, each cluster is modeled as a multivariate Gaussian distribution with the probability density function defined as:

$$f(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \Sigma^{-1}(\mathbf{x} - \boldsymbol{\mu})\right)$$

where $\mathbf{x} \in \mathbb{R}^n$ is the random vector, $\boldsymbol{\mu} \in \mathbb{R}^n$ is the mean vector, Σ is the $n \times n$ positive-definite covariance matrix, and $|\Sigma|$ is the determinant of Σ .

If a given appliance can be described by K different states, then for a mixture of Gaussians we have K Gaussian distributions.

$$p(X) = \sum_{k=1}^K \pi_k \mathcal{N}(X | \mu_k, \Sigma_k)$$

where $\mathcal{N}(X | \mu_k, \Sigma_k)$ represents the multivariate Gaussian distribution with mean vector μ_k and covariance matrix Σ_k , K represents the number of Gaussian mixtures, and π_k is the mixing proportion for the k th component, and $\sum_{k=1}^K \pi_k = 1$.

Since there is a mixture of Gaussians, the parameters μ_k , Σ_j , and π_k have to be determined. These parameters are estimated by using the Expectation-Maximization (EM) method [17]. EM consists of two steps (cf Algo 1). In the expectation step (E-Step), the initial estimates of the parameters are assigned using k-mean clustering and the probability of each latent variable is calculated. In the maximization step (M-Step), the parameters are modified to maximize the likelihood of the data with the initial assignments. These steps are repeated until a local optimum is achieved [18].

In this code, K is the number of Gaussian components in the GMM, N is the number of data points, π_j is the mixing coefficient for the j -th Gaussian component, μ_j and Σ_j are the mean and covariance of the j -th Gaussian component, γ_{ij} is the responsibility assigned to the j -th Gaussian component for the i -th data point, $\mathcal{N}(x_i | \mu_j, \Sigma_j)$ is the Gaussian density function evaluated at x_i with mean μ_j and covariance Σ_j . The EM algorithm iterates between the E-step (Expectation step),

Algorithm 1 Expectation-Maximization Algorithm for Gaussian Mixture Model

Require: Data points x_1, x_2, \dots, x_N ; number of mixture components K

- 1: Initialize parameters: π_j, μ_j, Σ_j for $j = 1, 2, \dots, K$
- 2: **while** not converged **do**
- 3: E-Step:
- 4: **for** $i = 1$ to N **do**
- 5: **for** $j = 1$ to K **do**
- 6: $\gamma_{ij} \leftarrow \frac{\pi_j \mathcal{N}(x_i | \mu_j, \Sigma_j)}{\sum_{k=1}^K \pi_k \mathcal{N}(x_i | \mu_k, \Sigma_k)}$
- 7: **end for**
- 8: **end for**
- 9: M-Step:
- 10: **for** $j = 1$ to K **do**
- 11: $\pi_j \leftarrow \frac{\sum_{i=1}^N \gamma_{ij}}{\sum_{i=1}^N \sum_{j=1}^K \gamma_{ij}}$
- 12: $\mu_j \leftarrow \frac{\sum_{i=1}^N \gamma_{ij} x_i}{\sum_{i=1}^N \gamma_{ij}}$
- 13: $\Sigma_j \leftarrow \frac{\sum_{i=1}^N \gamma_{ij} (x_i - \mu_j)(x_i - \mu_j)^T}{\sum_{i=1}^N \gamma_{ij}}$
- 14: **end for**
- 15: **end while**

where responsibilities are updated, and the M-step (Maximization step), where parameters of the Gaussian components are updated until convergence (classical threshold).

D. Results

a) *Dataset:* The dataset used for the simulations below was exported from SmartSense platform. In this paper we are interested in disaggregating the appliances of the lab's kitchen (Coffee maker, kettle, microwaves, oven and lights). The duration of the training and test dataset is 15 days.

b) *States estimation phase:* During this stage, a GMM model was used through the Python library Scikit-Learn. For each appliance the training data was used to fit two models for each class, ON and OFF. The log-likelihoods of each class were then determined, and the test data samples were assigned to the class with the highest likelihood. For conciseness, the solution is first applied in 1 dimension with CO2 sensor but can be extended to higher dimensions. The duration of training data and test data is 15 days. They contains data from 25 different sensors such as CO2, humidity, temperature, etc. The initial findings focused on determining the states of the coffee maker and kettle and they are presented in Table IV and Table V.

c) *Disaggregation phase:* During this stage, the previously estimated states were incorporated into the overall power consumption, and the standard NILM pipeline was executed

TABLE IV: Confusion Matrix of coffee maker states estimation from sensors data with K = 9 and CO2 sensor

True Class	Predicted Class		Support	
	Negative	Positive		
Negative	99726	32464	132190	
Positive	141	1229	1370	
		Precision	Recall	F1 Score
Negative	1.00	0.75	0.86	
Positive	0.04	0.90	0.07	

TABLE V: Confusion Matrix of kettle states estimation from sensors data with K = 7 and CO2 sensor

True Class	Predicted Class		Support	
	Negative	Positive		
Negative	91189	41380	132569	
Positive	315	676	991	
		Precision	Recall	F1 Score
Negative	1.00	0.69	0.81	
Positive	0.02	0.68	0.03	

using NILMTK. Table VI presents the outcomes for the coffee maker and kettle and compares it with the disaggregation performance using only the power consumption as input. The unmarked values indicate the outcomes obtained solely from the total power data, while the values marked with underlines show the results obtained from the suggested input, which includes both the total power data and states information.

TABLE VI: Evaluation of disaggregation performance

Appliances	RMSE	MAE
Kettle	69.82	6.69
	<u>48.66</u>	<u>3.11</u>
Coffee maker	26.27	2.65
	<u>21.95</u>	<u>1.64</u>

According to the table above, our approach surpassed the conventional NILM disaggregation with only CO2 sensor and demonstrated that incorporating sensors data about the environment can enhance NILM disaggregation.

IV. CONCLUSION

Our study aimed to evaluate the effectiveness of a new NILM approach for disaggregating energy consumption data from smart meters and wireless sensors into individual appliance-level data. This new approach is based on integrating additional features to the input that were obtained from specific sensors data that provide additional information from each appliance environment. Our results show that the approach achieved high accuracy in identifying individual appliances compared to the conventional NILM approach.

However, our study also had some limitations that should be considered when interpreting the results. First, the algorithm was trained and tested on a relatively small dataset (15 days), which may limit its generalizability to other settings. Second, the accuracy of the algorithm varied not only across different appliance categories but also the sensors data (in this work

we used only CO2 data). The difficulty here is to find the optimal combination off various sensors data that enhance the disaggregation performance for a given appliance but our solution is able to increase the GMM dimension.

Future research could explore ways to further improve the accuracy and robustness of NILM algorithms, particularly for challenging appliance categories such as printer and laptop whose consumption may depend on their activity.

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