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## Occupancy detection for enhanced energy disaggregation

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### Abstract

Non-Intrusive Load Monitoring (NILM) attempts to break down the aggregated electrical consumption signal into the power consumption of each individual appliance, which can provide helpful understanding on energy consumption patterns and helps reduce overall energy usage and costs. This paper proposes an occupancy-aided energy disaggregation approach to address the NILM problem. Our methodology encompasses three key steps: firstly, features extraction from environmental sensors through the training of a DAE model; secondly, inference of occupancy information using the K-means algorithm; and finally, the disaggregation process using a Recurrent Neural Network (RNN) model, incorporating the detected occupancy status alongside power data. Experiments conducted on our real-world dataset demonstrate that our method significantly outperforms the state-of-the-art models while having good generalization capacity, achieving roughly 40% Mean Absolute Error (MAE) gain and 30% Root Mean Squared Error (RMSE) gain on a specific appliances disaggregation compared to the conventional NILM approach where only the power data is used.

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**Keywords:** Energy disaggregation; NILM; Occupancy detection; RNN, K-means; Environmental-sensors

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### 1. Introduction

Enhancing energy efficiency is a significant challenge faced by modern households [1]. Smart grids, which can precisely measure and monitor energy consumption at the household level, provide detailed data for understanding user behavior patterns. By analyzing these patterns, effective strategies can be devised to enhance power efficiency [2]. Non-Intrusive Load Monitoring (NILM) is a critical aspect of this technology. It involves separating the aggregated energy consumption signals from a household (typically collected by smart meters) into individual appliance-level signals [3]. NILM serves not only to accurately decipher household power consumption patterns [4] but also supports tasks like load forecasting [5] and malfunction detection [6].

A key component of optimizing energy consumption is the ability to comprehend and reliably predict human presence

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within a space. This is because it makes it possible to create intelligent systems that can dynamically adjust energy usage based on occupancy data that is updated in real time.

By combining temperature, humidity, and CO<sub>2</sub> sensors, occupancy detection can be seen from a variety of angles and can accurately reflect the complex interactions between people and their surroundings. While temperature and humidity variations add context and enable a more nuanced understanding of space utilization patterns, CO<sub>2</sub> levels, which are directly influenced by human respiration, serve as a direct indicator of occupancy. This all-encompassing strategy adds to a thorough framework for energy disaggregation while also improving occupancy detection accuracy. This paper seeks to clarify the possibilities of using sensor-based occupancy detection as a boost for better energy disaggregation techniques by investigating these interrelated components. This work is opening the way to create intelligent energy management systems that can adjust in real-time, promoting a more sustainable and effective future for building operations, by deepening our understanding of how human presence interacts with the interior environment.

In this paper, we argue that existing neural-based models are not sufficient to tackle the problem of NILM. These models skip over an important step, which is to understand the environmental context and human behaviour, and instead concentrate on translating aggregated input signals directly into per-appliance signals. Understanding contextual information such as occupancy, activity patterns and environmental conditions can provide a deeper understanding of the dynamics influencing energy consumption. Occupancy detection, as a key component of context awareness, provides crucial insights into when and where occupants are present, enabling more accurate disaggregation of energy usage among different appliances and devices.

Our main contributions are three-fold (i) We introduce a novel approach which provide a wealth of *a-priori* knowledge about the environmental conditions in order to enhance the disaggregation performance; (ii) Accordingly, we propose to detect occupancy using CO<sub>2</sub>, temperature and humidity level data and then fed it to the energy disaggregation algorithm (RNN with attention mechanism); (iii) Experimental results on our own real-world dataset show that our method outperforms the state-of-the-art approaches.

The paper is organized as follows. In Section 2, we briefly present an overview of NILM DNN-based approaches and occupancy detection methods as reported in the literature. Section 3 presents our proposed method for energy disaggregation using occupancy information, while, Section 4 details the evaluation methodology. Finally, we analyse the experiment results in Section 5.

## 2. Related works

In this section, we explore two distinct aspects of related research: (i) conventional energy disaggregation which use only power data information and (ii) environmental-aware energy disaggregation, which makes use of environmental factors air quality and occupant activity patterns.

### 2.1. Conventional energy disaggregation

Two decades ago, Hart proposed a non-intrusive method for disaggregating electrical measurements [3]. This method involved examining the overall load data to identify power consumption signatures for individual appliances. Unlike other approaches, Hart's methodology did not require installing equipment inside the customer's property. Instead, aggregated data for the building's energy usage could be obtained externally from the main electrical panel. The main objective of this process was to separate the whole-house energy data into its primary consumption components. Non-Intrusive Load Monitoring (NILM) algorithms proved effective in achieving device-specific energy disaggregation using only aggregated data from a single measurement point. As a result, NILM remains an attractive approach for energy disaggregation.

In literature, several techniques are commonly implemented for NILM approach. For instance, signal processing techniques such as Fourier analysis, wavelet transforms, and filtering are used to extract features from the aggregated data [7]. Machine learning algorithms such as Support Vector Machines (SVMs) [8] are employed to classify the extracted features and identify the corresponding appliances. Probabilistic models such as Hidden Markov Models (HMMs) [9] [10] and Bayesian Networks [11] are used to model the statistical dependencies between the appliances and improve the accuracy of the disaggregation results. Lastly, some studies have also explored the user behavior patterns

[12] to enhance the performance of NILM systems. Deep learning techniques, particularly deep neural networks, have emerged as powerful tools for NILM owing to their capacity to automatically learn hierarchical representations from raw data. Convolutional Neural Networks (CNN) [13], Recurrent Neural Networks (RNN) [14], and their variants [15] have demonstrated superior performance in load disaggregation tasks. Researchers have proposed various architectures, such as sequence-to-point models [16], attention mechanisms [17], and generative adversarial networks (GANs) [18], to enhance the accuracy and generalizability of deep learning-based NILM systems.

## 2.2. Environmental-aware energy disaggregation

Apart from the state data and appliance operational features, additional data can be used to enhance the precision of energy disaggregation, which is called environmental-aware energy disaggregation in this study. In a research by [19], the location of appliances was included in the analysis to determine appliance-level energy consumption; this resulted in improved energy disaggregation accuracy across multiple datasets via empirical validation. Additionally, another method involved analyzing WiFi/Bluetooth signals obtained from wearables and smartphones belonging to occupants in order to indirectly infer occupancy information. As further examples of incorporating information from additional sensors, ElectroMagnetic Field (EMF) sensing [20] was used to identify changes in the condition of appliances. Separately, in [21], scientists placed inexpensive sensors next to domestic appliances and used the ambient signals these sensors recorded to estimate how much power the appliances used. Furthermore, The authors in [22] used the aggregated power consumption as a source of occupancy information. Their method tackles the problem of indoor office occupancy detection based on statistical approaches. On the other hand, occupancy information [23] was used to improve energy disaggregation performance. The authors first infer the occupancy states of the house based on the analysis of collected aggregated power data. Then, by applying occupancy inference, they provide energy approximation for the appliances running in the unoccupied periods, and perform energy disaggregation using signal processing techniques for the appliances working in occupied periods. As far as we know this is only work that use occupancy-aided energy disaggregation. Compared with that, we propose to detect occupancy using additional information such as CO<sub>2</sub>, temperature and humidity data and we use deep learning models in particular RNNs to perform energy disaggregation.

## 3. Proposed Method

As shown in Fig 1 the proposed method consists of three-core components (i) features extraction, (ii) occupancy detection and (iii) energy disaggregation.

### 3.1. Features Extraction

Environmental sensors in particular temperature, CO<sub>2</sub> and humidity can indicate how spaces are being utilized, identify patterns of occupancy, and optimize building operations accordingly. However, raw sensor data often contains noise and redundancies, making it challenging to extract meaningful information directly. This is where techniques like Denoising Autoencoders (DAEs) come into play. A DAE is a type of artificial neural network trained to learn a compressed representation of input data by reconstructing it from a corrupted version. By training the DAE on these sensors data, it learns to extract essential features that capture the underlying patterns and characteristics of the environment. These features are then represented in a lower-dimensional latent space, which retains the most relevant information while filtering out noise and redundancies. This latent space representation serves as a compact and meaningful representation of the original sensor data. These extracted features are then be fed into occupancy detection algorithms.

### 3.2. Occupancy Detection

Given the absence of occupancy ground truth, the K-means algorithm was applied to the extracted features vectors. This algorithm requires specifying the number of clusters (k) beforehand. In occupancy detection case, this could correspond to the number of different occupancy states or patterns that we aim to identify. Once the K-means algorithm

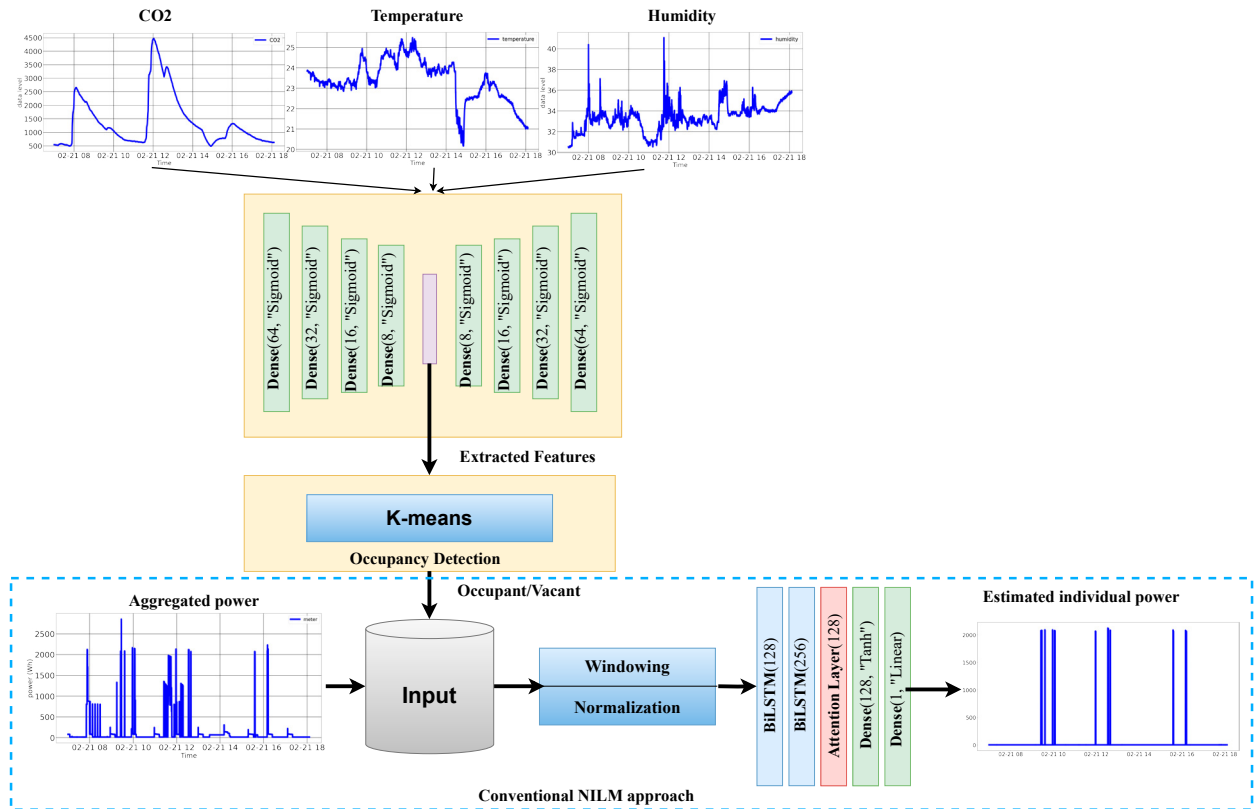


Fig. 1. The proposed architecture of occupancy-aided energy disaggregation.

is run, it iteratively assigns each data point to the nearest cluster centroid based on some distance metric (often Euclidean distance). Then, it recalculates the centroids of the clusters based on the mean of the data points assigned to each cluster. After a certain number of iterations or until convergence, K-means produces a set of cluster centroids representing distinct occupancy patterns within the building. These centroids can be interpreted as representative states of occupancy, such as "occupied," and "unoccupied."

### 3.3. Energy disaggregation

In this paper, our focus lies in exploring the contribution of occupancy information on energy disaggregation. As such, rather than developing novel disaggregation techniques, we opt to use existing approaches in particular RNN with attention mechanism [24].

Energy disaggregation is the process of estimating energy usage for individual appliances. We achieve this by combining readings from the mains power meter (which measures total energy consumption) with detected states from a binary classifier. Our trained RNN model with attention consists of two BiLSTM layers that extract relevant features, followed by an attention layer. Finally, two dense layers create high-level representations followed by a linear activation function, estimating the power consumption value of the each appliance.

The inputs are sequences of aggregate energy readings and detected states  $x$  while the target values are sequences of appliance energy readings  $y$ . Assuming an output and the corresponding target value are denoted as  $\hat{y}$  and  $y$  respec-

Table 1. SmartSense dataset features.

Measurement device	Data type	Sampling Rate	Duration	Appliances
EcoCompteur	global power data	7.5 Hz	3 years	coffee maker, kettle, fridge
ZigBee meter	individual power data	100 mHz		oven, light
Sensors node	sensors data	1 Hz		PC, printer

tively, the loss can then be calculated using Mean Squared Error (MSE):

$$\text{MSE}(y, \hat{y}) = \frac{1}{T} \sum_{t=1}^T (y(t) - \hat{y}(t))^2 \quad (1)$$

where  $T$  represents the total number of samples within one recording, with  $t$  serving as the index of a specific sample ranging from 1 to  $T$ . The MSE loss quantifies the average squared difference between the true and predicted values across all samples, providing a measure of how well the model is performing in a regression task.

## 4. Evaluation methodology

### 4.1. Dataset and Performance Metrics

The dataset used in this article is called SmartSense developed in our lab for the purpose of this work. It comprises a comprehensive collection of data including energy consumption and environmental sensor readings from the IRISA lab in France. These readings were recorded at a low frequency, approximately every 10 seconds, over a period exceeding three years. Notably, the dataset involves a wide range of data, including both lab-level energy usage (aggregate readings) and appliance-level energy usage (appliance readings) for more than 10 different types of appliances, in addition to environmental sensors data such as humidity, CO2 level, temperature from each office. For the purposes of this article, our focus is primarily on the energy disaggregation of three specific appliance types: kettle, coffee maker and computer as these are the appliances most used across our lab and which need the human presence to be activated. For more information on the hardware, software, and details of the data collection process, please visit the project's official website<sup>1</sup>. The dataset files are easily accessible via this storage space<sup>2</sup>. A summary of SmartSense features is shown in Table 1.

We quantitatively evaluate the performance of our proposed method with both regression and classification metrics. To assess the performance of the regression task, we adopt three standard metrics used in NILM, namely the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Normalized Disaggregation Error (NDE) [25]. The MAE and RMSE quantify the error in predicted power at every time point, given by

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

where  $T$  represents the total number of time points,  $\hat{y}(t)$  denotes the predicted power at time  $t$ , and  $y(t)$  is the true power at time  $t$ . The NDE metric measures the normalized error of the squared difference between the prediction and

<sup>1</sup> <https://smartsense.inria.fr/>

<sup>2</sup> <https://files.inria.fr/smartsense/>

the ground truth, defined as

$$\text{NDE} = \frac{\sum_{t=1}^T (y(t) - \hat{y}(t))^2}{\sum_{t=1}^T y^2(t)} \quad (3)$$

In order to measure how accurately each space occupancy is detected, we use classification metrics such as precision, recall and F1-score [26]. Due to the extreme imbalance in the dataset, we will consider only the recall metric. The F1 score is interpreted as the harmonic average of precision ( $P$ ) and recall ( $R$ ):

$$F1 = \frac{2 \times P \times R}{P + R}, \quad P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN} \quad (4)$$

where  $TP$ ,  $FP$ , and  $FN$  stand for true positive, false positive, and false negative, respectively. A space is considered "Occupied" when the active power consumption of any appliance within it exceeds a certain threshold. It is labeled "Unoccupied" when no active appliances are drawing power. In our experiments, we employ a threshold of 20 Watts for labeling the disaggregated loads. Precision, recall, and F1-score return a value between 0 and 1, where a higher number corresponds to better classification performance.

#### 4.2. Data preprocessing

The SmartSense dataset has different sampling rates based on the collected data, as shown in table 1. As a result, resampling becomes necessary in the preparation of training data. To reduce the introduction of missing values, a resampling rate of 10 seconds was implemented. Furthermore, we addressed data gaps using forward-filling, assuming that the gaps were caused by data transmission issues. Finally, each appliance type, the aggregate, and the environmental sensors data were normalized by subtracting mean values and dividing by the corresponding standard deviations. The training phase is performed with a sliding window technique over the input data, using overlapped windows of length  $L$  with hop size equal to 1 sample. As stated in reference [27], it is critical to ensure that the window size for input and output pairs is large enough to cover the entire activation of an appliance. However, it should not be too large to accommodate contributions from other appliances.

### 5. Results

The dataset used in the following experiments covered a full 30-day period. It was then divided into separate subsets for training and testing, each lasting 15 days. This dataset includes the overall power consumption as well as the particular power usage trends for each appliance. The global power includes at the same time the power consumption of 18 appliances: 9 computers, 1 video projector, 1 printer, 2 coffee maker, 1 kettle, 1 fridge, 1 TV, 1 microwave and 1 oven. We are primarily concerned with breaking down the power usage of the most used appliances in the lab' break room such as the kettle and the coffee maker as well as the computer.

Table 3 summarizes the outcomes of our experiments for both our approach and the basic NILM pipeline. The table includes results for three metrics that were calculated for each appliance separately. The values reported consist of the predicted value of the target appliance consumption and the estimated consumption. Due to the lack of occupancy ground truth labels, we provide in Table 2 the confusion matrix report for occupancy detection in both the lab's break room and an office room. This report evaluates the F1-score, recall, and precision, comparing the predicted occupancy states with the appliance states in each room. Specifically, the office room's evaluation considers the computer as the indicator of occupancy, while for the lab's break room, the kettle and coffee maker serve as occupancy indicators. The results indicate highly accurate occupancy detection in the office room, achieving a recall rate of approximately 95%. Conversely, the detection performance is slightly lower for the lab's break room, with an 85% recall rate.

For instance, Fig 2 shows a visualization of the detected occupancy of the office room.

Table 2. Confusion Matrix report of occupancy states detection from CO2, Temperature and Humidity data

Appliance	State	Precision	Recall	F1 Score	Support
Kettle	OFF	1.00	0.60	0.75	140986
	ON	0.02	0.83	0.03	1214
Coffee maker	OFF	1.00	0.60	0.75	140859
	ON	0.02	0.89	0.04	1341
Computer	OFF	0.98	0.99	0.99	107672
	ON	0.96	0.94	0.95	34528

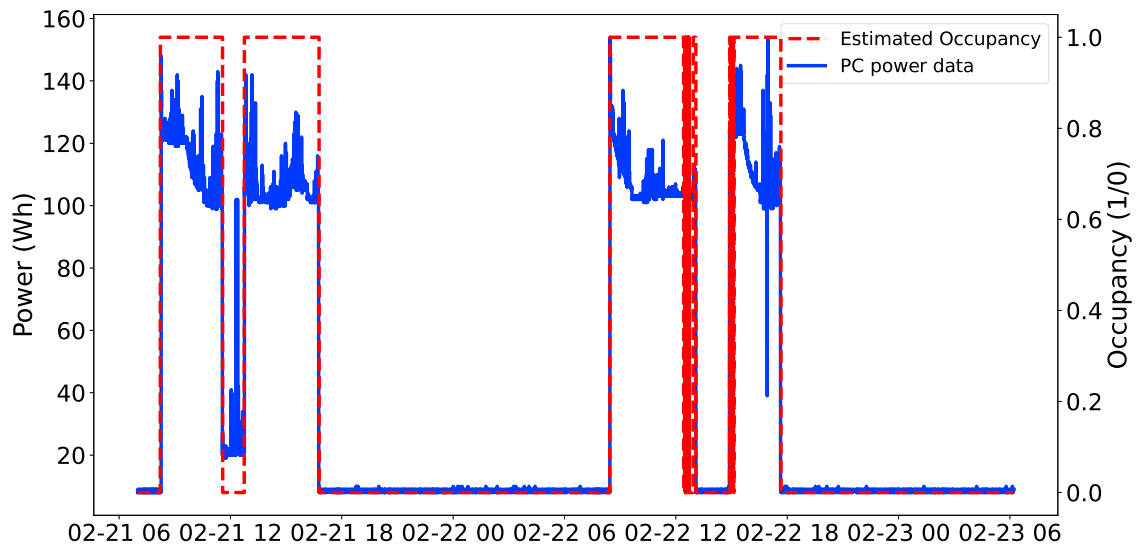


Fig. 2. Visualization of the detected occupancy of the office room.

Table 3. Evaluation of disaggregation performance of basic NILM and our proposed method (in bold)

Appliances	RMSE	MAE	NDE
Kettle	110.11	14.72	0.96
	<b>108.3</b>	<b>11.68</b>	<b>0.77</b>
Coffee maker	88.9	15.07	1.11
	<b>79.73</b>	<b>12.54</b>	<b>1.03</b>
Computer	30.54	16.69	0.96
	<b>21.67</b>	<b>8.85</b>	<b>0.65</b>

According to the performance metrics outlined in Table 3, our approach exhibits significant improvements over conventional NILM disaggregation, particularly evident in the case of computer appliance usage, where we observe a noteworthy 30% reduction in RMSE, NDE, and over 40% decrease in MAE. On the other hand, the improvements for



the kettle and coffee maker appliances are more modest. This disparity can be attributed to the fact that while these appliances require the user's presence for operation, they don't necessarily need continuous presence throughout their activation duration. Therefore, the influence of incorporating space occupancy information may have been less pronounced for these appliances.

Nonetheless, the overall findings indicate the efficacy of integrating space occupancy information into NILM disaggregation methodologies, affirming its potential to substantially enhance performance across various appliance categories.

## 6. Conclusion

This paper presents a novel approach or addressing the energy disaggregation challenge, which aims to breakdown smart meter data into individual appliance-level usage. Our approach is based on a two-step procedure: firstly, we use environmental sensor data, such as CO<sub>2</sub>, temperature, and humidity readings, to detect occupancy space states (occupied/unoccupied). Given the absence of occupancy ground truth, we employ for this task an unsupervised learning techniques, specifically the K-means algorithm. Secondly, these predicted occupancy states as well as the aggregated data are then fed to an RNN attention which acts as a disaggregator to estimate the individual power data.

Experimental evaluation on the SmartSense dataset shows good disaggregation performance. Overall, the proposed method can accurately capture the dependencies between the appliance's usage, efficiently detect occupancy states related to the use of some appliances and estimate their corresponding power consumption. Compared to existing DNNs approaches for NILM, the advantage of the proposed approach comes from its ability to provide an *a-priori* knowledge on users presence which enhance the probability of using the appliances in the space room.

Future work should investigate others sensors type such as the audio and light sensors which can increase the occupancy detection.

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