A Case Study on Obstacles to Feasible NILM Solutions for Energy Disaggregation in Quebec Residences

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ABSTRACT

The Non-Intrusive Load Monitoring (NILM) concept is suggested as a practical means for energy monitoring at the most disaggregated level. Notwithstanding, a viable solution to this idea for residential applications should overcome its common and specific issues raised by technical specifications of the case study. Knowing the fact that the former has been dealt with through basic research for many years, this study presents an applied research to examine actual implementations. It focuses on load disaggregation in Quebec residences by proposing a combinatory approach based on supervised and unsupervised machine learning techniques. The proposed method aims to identify major appliances by extracting overall heating demand from the aggregated one first while exploiting low sampling rate data of active power as the only source of information. The results of this work emphasize real circumstances under which existing NILM methods can be challenged. From a realistic viewpoint, this paper discusses essential remarks inevitable to achieve a fruitful NILM system, specifically, for the Quebec case.

CCS CONCEPTS

• **Computing methodologies** → **Machine learning**; • **Information systems** → **Data mining**; • **Hardware** → *Power and energy*.

KEYWORDS

Load disaggregation, non-intrusive load monitoring (NILM), datasets, baseboard heaters

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1 INTRODUCTION

From a practical standpoint, smart meters are the key element towards residential cost-effective energy-saving opportunities through the Non-Intrusive Load Monitoring (NILM) concept [5]. Currently, technical limitations of these emerging technologies on data provision fortify NILM approaches deployed in the context of a low-sampling rate system. In this context, only steady-state features of power demand, mostly active power, are usually utilized for NILM exercises [7]. Although the literature has a similar tendency regarding the information space, it takes advantage of measurements with fine granularity. The underlying motive for such an orientation is electrical properties of the public datasets. Regardless of the choice of mathematical method, relevant studies have been applied to common databases with sampling rates that can be considered high for real-world metering tools [1]. To be specific, the most popular datasets for NILM studies, particularly based on deep learning as state-of-the-art, supply data with a sampling frequency at ≥1Hz [2]. For instance, the lowest sampling size offered by REDD and UK-DALE is 0.5Hz and 1Hz, respectively, considering both aggregate and appliance levels [1].

The above situation can result in the inadequacy of existing NILM techniques for actual implementations. In addition, it can challenge generalization, validity, and reliability of case studies aimed at exploring NILM applications. This issue deteriorates when seeking solutions in specific geographical regions for which no pertinent database is publicly available [4]. This is the case of Quebec where residential power consumption behavior cannot be exemplified by existing datasets due to the type of in-use appliances. Regarding a feasible perspective, such behavior brings about NILM scenarios challenging to deal with through low-sampling methods. The aforementioned concerns necessitate conducting geographically-relevant NILM research that exploits data from smart meter readings in order to discover actual barriers. Indeed, overlooking real-world circumstances avoids achieving effective NILM systems.

Accordingly, this paper presents a thorough investigation into potentials of a low-sampling NILM practice in the context of Quebec. It tackles a realistic case study by exploiting only on-site measurements of active power of a set of houses with 15-minute sampling intervals. For this purpose, a combinatory load disaggregation is proposed in order to identify household major appliances through two steps. In the first stage, a supervised technique based on a deep learning model is employed to extract the overall heating demand from the aggregated load profile. In the second phase, an unsupervised scheme derived from clustering techniques is developed to search for remaining loads. Different evaluation metrics are used to reflect on the extent achievable and affordable through this analysis.

2 QUEBEC CONTEXT

The claim about the difficulty of NILM in Quebec has its roots in actual circumstances that can complicate load disaggregation task. In fact, NILM complexity mainly depends on number of loads, their power level differences, and the frequency of their operating state changes [9]. All these criteria are concerned with this case. Due to specific geographical location and common in-use appliances, Quebec households are mainly equipped with electric space and water heating systems. Except for common loads, each house is provided with several Electric Space Heaters (ESHs) (between 8 to 12 numbers) with high switching frequency. The power level of these loads are not only similar (almost identical) to each other but also close to other energy-demanding appliances such as Electric Water Heaters (EWHs), washing machines, and dryers. More importantly, due to high power demand and lengthy operation time, ESHs can avoid a clear representation of low-level trajectories related to a range of loads such as fridges, freezers, and lighting. With short operation duration and regular presence, EWHs are another device that worsen this condition [4]. These loads can cause difficult monitoring cases that are rarely encountered by existing disaggregation algorithms. As mentioned, current methods are applied for and tested on public datasets with properties that hardly cover cases like Quebec. The study in [3] demonstrates the impact of ESHs demand on the aggregated load profile by adding the related load of only four heaters to daily data from ECO, as another popular public dataset, at 1Hz sampling frequency.

2.1 Case study

The case study can be discussed considering the main steps of a NILM procedure comprising i) data supply by the acquisition system; ii) feature extraction for detecting appliances operational state; and iii) load identification through classifying specific signature(s) [5]. NILM requirements, especially the selection of disaggregation engine, strongly correlates with data sampling rate afforded by the first phase. Sampling rates of 3Hz and 1Hz are reported as the least prerequisites for a NILM task by means of regression and classification, respectively [1]. Nevertheless, this analysis utilizes data with 15-minute sampling intervals at both aggregate and circuit (panel) levels collected from 10 Quebec residences. Figure 1

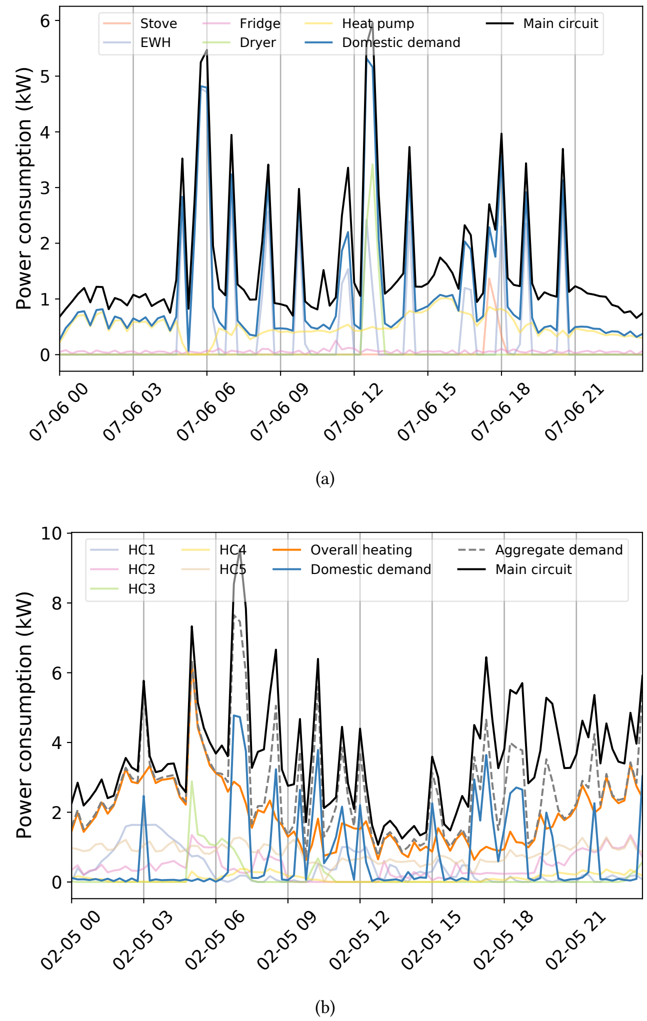

Figure 1: Power consumption patterns in a Quebec residence within one day in (a) warm and (b) cold seasons at a 15-minutes sampling rate.

illustrates the power consumption behavior of a Quebec dwelling for one day in warm and cold seasons. Generally, the Quebec case includes appliances with challenging operational trajectories, dissimilar across the seasons, that critically alter in lower sampling sizes. The domestic demand is subject to different multi-state and time-varying appliances. Nonetheless, the effect of EWH with frequent operations on the total load is the most significant matter. It can be observed that the patterns of these two demands are very similar in both shape and magnitude, which can notably influence other loads including major ones. Nonetheless, the case of Quebec demonstrates its specificity by presenting the load of several ESHs. The Figure 1(b) advertises this circumstance for the same house with ten heaters distributed among five Heating Circuits (HC). The remarkable impact of ESHs' load on the aggregate load profile can be clearly observed in this figure considering the domestic demand.

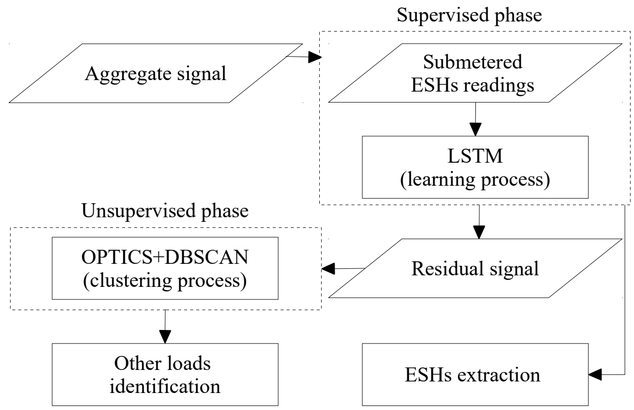

Figure 2: The proposed combinatory approach applied to the case study.

Moreover, the inequality between loads from the main switch and total demand (domestic and aggregate consumption in Figure 1(a) & (b), respectively) demonstrates the presences of unknown load, which is remarkably large. This incident is a fundamental issue of load disaggregation studies that can notably challenge its performance. Regarding the feature extraction, algorithms that are generally applied to steady-state (macroscopic) electrical features of appliances' operating states in the context of a power-based load disaggregation are promoted. However, Quebec case studies evidence that even a sampling rate of 1 minute is not satisfying to rely on capturing electric baseboards behavior through active power demand due to their high switching frequency. Besides, the disaggregation process takes advantage of unsupervised and supervised methods. The former can assist with low-cost generalization capabilities of NILM while the latter can offer promising solutions at the cost of a proficient database [4]. Although an unsupervised technique is favored for the Quebec case due to the shortage of data, the potential concerns with its relevant NILM practice makes a blind load disaggregation infeasible. However, since ESHs operate only within cold seasons, a longer acquisition period is required to provide sufficient data regarding NILM supervised procedures.

2.2 Methodology

The above explanations define the methodology for tackling the NILM of the case study presented in Figure 2. The method takes advantage of a combination of supervised and unsupervised algorithms to disaggregate ESHs and other loads, successively. A combinatory approach is supported by the fact that removing ESHs from overall signal can assist with treating its residual with common NILM methods. Additionally, it is encouraged since the remaining demand is yet complicated owing to the domestic loads behavior, especially EWHs.

2.2.1 Supervised procedure. Deep learning offers effective supervised schemes for load disaggregation. As a complex model of deep learning, Long Short-Term Memory (LSTM) networks have been utilized for estimating sequential patterns in time-series. Due to their capability to learn long-term temporal dependencies, these types of networks are promising for sequence modeling. They can be utilized to capture the dynamic of ESHs and estimate their share in the overall demand. The LSTM network is developed in Python by means of Keras as a deep learning API. Accordingly, a sequential model with five hidden layers and one output layer is chosen. The hidden structure consists of three fully connected LSTMs and two Dense layers with different number of neurons. The network is compiled by Adam as the optimization method and mean square error as the loss function. Additionally, the tanh and relu are used in terms of non-linear and rectified linear activation functions in the first and last layers, respectively. The network is trained through a sliding window that maps 7 samples of aggregate power consumption to the next (8th) instance of total heating demand. The training phase is carried out within 100 epochs.

2.2.2 Unsupervised procedure. The unsupervised mechanism utilizes density-based clustering techniques to capture operation sequences of possible appliances in the residual signal. Particularly, DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is employed that allows for time-series clustering. DBSCAN requires the definition of two parameters that account for Epsilon, as distance measure from neighboring points, and MinPts, as minimum number of points for a valid dense region. Different methods have been offered to estimate the Epsilon, but not satisfying for this case. Therefore, the utilization of OPTICS (Ordering Points To Identify the Clustering Structure) as another density-based clustering method is suggested. OPTICS is able to provide information about clusters structure in time-series data, and, thus, not only facilitates the choice of Epsilon but also explains the prospective clusters. Subsequently, an ON/OFF sequence constructor is applied to every cluster in order to capture the operation profile of a potential load. To be specific, the constructor exploits operation time and level (power) to create a sequence in an unsupervised manner [6].

3 RESULTS AND DISCUSSION

The NILM task is evaluated in details for one Quebec house and reported by Proportion of Total Energy Correctly Assigned (TECA), Mean Absolute Error (MAE), Mean Square Error (MSE), and F1-score [8]. It is noted that the results for other residences are similar. The practice commences with learning the ESHs behavior by means of the developed LSTM network. The main issue with this network, like other deep learning models, is the sufficient data requirement, which matters the current practice. In fact, the data from Quebec houses spans one year, and, thus, only one cold season is available to learn and examine the behavior of ESHs. Table 1 presents the test results for the selected dwelling across one week in cold season. In terms of a regression problem, it can be noticed that load profiling results are satisfying for ESHs regarding TECA values. In fact, an acceptable disaggregation practice should have a minimum accuracy of 80% [6]. Other metrics should be analyzed comparatively. In this regard, their results demonstrate that the method performs efficiently since the overall ESHs load in this house reaches 10kW. However, inadequacy in capturing the peaks and causing unwanted variations in lower demands after extraction are the significant concerns passed along to the next step. Generally, addressing these issues requires to handle the limited amount of data for learning, the impact of heating demand on overall usage, and the trend of heating pattern mainly its sudden, large fluctuations.

Subsequently, the clustering is applied to the same days for discovering the possible loads. Table 2 shows the outcomes of this step. It can be observed that the constructed profiles can only represent the major appliances. In fact, the ESHs estimation error, resultant fluctuations, and unknown usage lead to creating impractical clusters with wide variance that rarely stand for actual devices of lower power levels. Moreover, the sequence creation is not able to find a possible load in the third day. Regarding a 15-minute sampling interval, clustering results point out key facts about the residual signal. First, the notable loads advertise very similar behavior such a way that their separation is almost impossible within an unsupervised system. This creates a sequence that describes more than one device. Second, the behavior of an appliance changes within consecutive intervals, and thus, the constructor offers different sequences to explain its corresponding operation or fails to capture it completely. Third, the rate of overlapping increases. These situations cause a complicated interpretation of valid loads. It can be seen that in the 1st day, one actual device is captured through four possible loads while in the 4th day, one possible load stands for three actual appliances. Nevertheless, similar loads created within the days like 2.9kW can assist with constructing actual models by use of priori knowledge. In addition, all loads in Table 2 are related to EWH since it holds the highest portion of domestic usage, as discussed. EWH either owns a sequence or shares it with other devices. Moreover, the last column describes total amount of energy consumption that is estimated by all possible loads within a day. It is noted that all created sequences characterize a combination of specific appliances and a portion of unknown demand with no label to report.

According to the clustering results, EWH is the only appliance that can be represented by specific daily clusters like 3.8kW in the 1st day. Therefore, it can be considered for further evaluation by NILM accuracy metrics. This is beneficial since EWHs are the second major load in Quebec residences with a promising potential for energy saving. The result of such an examination is provided in Table 3. In this Table, F1-scores of total outcomes are also presented to estimate the overall ON/OFF sequence. Considering the fact that the last step is impacted by all issues, accumulated within the entire process, the total results are fair for the half of the days.

This analysis demonstrates the technical barriers to NILM in Quebec in accordance with demand specifications, data availability, and smart meter properties. Accordingly, a mechanism that takes advantage of pertinent data with higher sampling rates, additional information, supervised techniques, more sophisticated algorithms, and other technologies like smart plugs is suggested. Indeed, such practice can initiate a pilot scheme towards a feasible solution.

Table 1: Results of ESHs load estimation in overall demand

Day	TECA (%)	MAE (kW)	MSE (kW)
1st	86	0.48	0.57
2nd	86	0.41	0.52
3rd	86	0.47	0.37
4th	84	0.53	0.58
5th	84	0.47	0.73
6th	85	0.37	0.36
7th	85	0.38	0.33

Table 2: Results of other loads identification in residual signal

Day	Detected load (kW) and related device				
	1st	2nd	3rd	4th	Energy (%)
1st	3.8 EWH	2.3 EWH Stove	1.9 EWH Stove	4.6 EWH	30
2nd	2.9 EWH	2.5 EWH	1.8 EWH	-	37
3rd	-	-	-	-	-
4th	2.9 EWH Stove Dryer	4.4 EWH Stove	3.7 EWH Stove	-	38
5th	3.8 EWH Stove	3.2 EWH Stove Dryer	-	-	23
6th	3.1 EWH	-	-	-	34
7th	2.9 EWH Stove	4.9 EWH	-	-	35

Table 3: Results of EWH identification in residual signal

Day	Load (kW)	F1-score (%)	TECA (%)
1st	3.8	25	54
	4.6	25	55
	Total	44	-
2nd	2.9	30	54
	2.5	21	55
	1.8	39	59
	Total	62	-
6th	3.1	69	66
7th	4.9	39	59

4 CONCLUSION

This paper presents a practical analysis to reveal NILM obstacles faced in Quebec residences. It proposes a combinatory approach by using supervised and unsupervised schemes accounting for deep learning and clustering methods, respectively. The proposed technique is aimed at disaggregating loads through two steps where overall heating demand is extracted from the aggregate one at first. The developed framework exploits real data of a set of houses at a low-sampling rate regarding real-world deployments of metering systems. This study discusses significant remarks for actual implementations that their negligence can bring common NILM methods to a halt in specific geographical regions like Quebec.

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