Semi-supervised Event Pairing Method for Non-intrusive Load Monitoring*

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1. Introduction

Over the past years, concern about energy efficiency has been such grown to lead to Paris Agreement, just to name one. The agreement sets tight time-table global warming limits, aiming at adapting towards a slow-down climate change that can only be achieved with the participation of all energy sectors.

Energy efficiency is an essential key to slowing down global warming. The smart grid initiative brings significant actors in the prosumers side (consumers and producers) to not only increase renewable energy share but also motivate consumers into efficient use of resources. It is required a feedback technique that provides knowledge about energy single-device consumption to manage successful end-user participation. Yet, it is worth noting industry that makes up the share more than one-third of global energy needs.

This thesis presents an all-inclusive Non-intrusive Load Monitoring (NILM) algorithm design that intends in covering the challenges of a residential and industrial environment. Even though there have been plenty of NILM approaches contributions, most of them are in the household domain. The ongoing development with Industry 4.0 and Smart Factories emphasizes the importance of employing technology like NILM, enabling a well-informed decision-making process. Therefore, this work seeks to contribute by giving a comprehensive overview of the considerations to apply a NILM solution to the field of industrial application.

1.1. Problem Statement and Objectives

The event-based NILM classification is characterized by first recognizing events from the aggregated power signal. Then, appropriate labels are assigned to the detected events. The labeling process is done for each of the active cycles in the aggregated power signal. Finally, the switching events within the active cycle are paired and then designated to a specific appliance along with its estimated power consumption. Therefore, this work concentrates on the following research objectives/challenges.

Challenge 1: Accurately detect state-change (ON/OFF) events while recording their important features in an environment that may include many simultaneous events and overlapping state-changes.

Challenge 2: Pairing and classifying events within an active cycle that may include several appliances and operation modes. The electric devices may be of the same kind, which brings another level of complexity to the problem since they may have a resemblance in their electric signature.

Challenge 3: Defining the physical variables from which the features are derived to obtain the fingerprint of the electric devices.

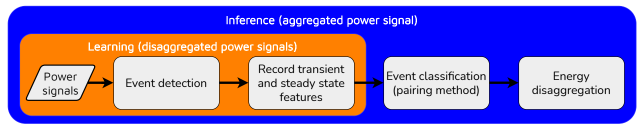

Figure 1. Disaggregation pipeline.

2. NILM Approach Design

The building blocks that describe the disaggregation pipeline (Figure 1) start with the data extraction, followed by the cluster-based event detection module, then the feature extraction is performed based on the detected events. These first three components are common for the learning and inference procedures. The modules that concern only the inference side are event pairing (where appliance classification occurs) and energy disaggregation.

2.1. Event Detection

The event detection part is the core of this solution. The training and test phase depends on the event detection. In training, it is used for appliance-specific feature extraction, while in testing, the detected events are divided into the available electricity-powered devices given their features.

*This document represents a summary of the master thesis project. The source code of this work is publicly available at `https://github.com/links-nilm-thesis-21/load-disaggregation`

The detector consists of a clustering algorithm, the Density-based spatial clustering of applications with noise (DBSCAN). The cluster-based solution aims at grouping two consecutive steady states, i.e., two different operation modes in a given time interval. If two operation modes are recognized within the time interval, it means that an event occurred. DBSCAN is constructed to distinguish outliers or noise. Therefore, given the time interval where two consecutive steady states were detected, the outliers (if any) represent the transient state samples.

2.2. Feature Extraction

The approach considers the three feature categories, i.e., steady and transient state and non-traditional attributes. Specifically, the selected steady-state property is the power interval $\Delta\Pi$ corresponding to an operation mode. Apart from gathering the states of operation, other significant attributes are collected from the transient section. Selected features are the transient state duration ΔT_{Ψ}, transient spike $\delta\Psi$, transient power change $\Delta\Psi$. The features are computed in the active P and reactive Q (if available) power signals as in Equations 1 through 4. Finally, the chosen non-traditional feature is the time of the day. It was chosen because it can prove significant to *well-behaved* appliances, such as machines in an industrial environment where tasks are repetitive each week.

$$\Delta\Pi^{X} = \text{mean}\left(\Pi_2^{\text{X}}\right) - \text{mean}\left(\Pi_1^{\text{X}}\right) \tag{1}$$

$$\Delta\Psi^{X} = \max\Psi^{X} - \text{mean}\left(\Pi_1^{\text{X}}\right) \tag{2}$$

$$\delta\Psi^{X} = \max\Psi^{X} - \text{mean}\left(\Pi_2^{\text{X}}\right) \tag{3}$$

$$\Delta T_{\Psi} = T_{\Pi_2}(0) - T_{\Pi_1}(N_{\Pi_1}) \tag{4}$$

In Equations 1 through 4, $X \in \{P, Q\}$, Π_2 and Π_1 are the first and second steady-state segments, respectively. Ψ is the transient section, T_{Π} is the steady-state timestamp, so $T_{\Pi_2}(0)$ is the second steady state timestamp evaluated in the first sample. Finally, N_{Π_1} is the total number of samples in the first steady-state, meaning that $T_{\Pi_1}(N_{\Pi_1})$ is the first steady state timestamp evaluated in the last sample.

2.3. Classification

A fivefold classification procedure is implemented after the feature extraction. The technique starts with the active cycle identification. Then, each event within the active cycle is assigned a label (i.e., an appliance) based on its respective power interval. A tiebreaker method is applied to the events that are designated multiple tags. As a complement of the tiebreak method, an event pairing approach is proposed to match the rising (ON) with falling (OFF) events within the active cycle with the most probable appliance. To conclude, a final attempt is made to match the events that did not find a match with the already established pairs. The unmatched events require to be chronologically in between the already defined pair, and the power interval label should match.

2.4. Energy Disaggregation

To close the NILM cycle, the event pairs formed in the previous step provide the amount of time a device was used and the measured power withdrawal in that interval, from which the appliance-specific energy consumption calculation is made. The energy is computed by multiplying the duration interval with the transition power.

3. Dataset Selection

Residential Use Case The residential use case exploits house 1 of the REDD dataset for the algorithm validation. The time series considers 23 days of data. The dataset provides the separated power signal sampled every 3 seconds of an oven (OV), a microwave (MW), kitchen outlets (KO), bathroom GFI (BGFI), a washer/dryer (W/D), a refrigerator (RFG), and a dishwasher (DW).

Industrial Use Case The industrial use case adopts heavy-machinery data from a poultry feed factory located in Brazil. The dataset includes 1 Hz data points of two pelletizers (PI and PII), two double-pole contactors (DPCI and DPCII), two exhaust fans (EFI and EFII), and two milling machines (MI and MII).

4. Experimental Results

Table 1 lists the event detection without appliance discrimination results for the industrial and residential use case. The results demonstrate accurate detection, which suggests that an initial signal filtering is not required, unlike many other event-based approaches.

Domain	TP	FP	FN	Precision	Recall	F-score
Residential	561	153	122	0.79	0.82	0.80
Industrial	2506	416	322	0.86	0.89	0.87

Table 1. Event detection without discrimination.

Multiple-labeled events after the interval association phase are the subject of the event pairing method. The results of the residential event association are summarized in Table 2.

The classification performance for the dishwasher was poor, there are a massive amount of FP related either to another electric device or not associated with any ground truth event. The predicted labels associated with the dishwasher are misclassified with five out of six other appliances, which means that the widespread mode transitions implicate more possible false connections. In general, the precision metric is better than the recall, regarding the total amount of predicted events. The correctly detected ones appreciably tend to be more, on average. On the other hand, among the

Appliance	TP	FP	FN	Precision	Recall	F-score
DW	82	157	29	0.34	0.74	0.47
MW	100	40	40	0.71	0.71	0.71
RFG	189	42	81	0.82	0.70	0.75
BGFI	4	0	18	1.00	0.18	0.31
KO	2	4	14	0.33	0.13	0.18
OV	34	10	3	0.77	0.92	0.84
W/D	40	0	23	1.00	0.63	0.78
Average				0.71	0.57	0.58

Table 2. Appliance-level event detection performance.

actual events, on average, around half of them will not be recognized.

Appliance	TP	FP	FN	Precision	Recall	F-score
MI	170	64	2772	0.73	0.06	0.11
MII	91	30	3025	0.75	0.03	0.06
PI	31	972	249	0.03	0.11	0.05
PII	36	525	284	0.06	0.11	0.08
EFI	2	20	92	0.09	0.02	0.03
EFII	0	0	54	0.00	0.00	0.00
DPCI	9	527	383	0.02	0.02	0.02
DPCII	11	756	350	0.01	0.03	0.02
Average				0.21	0.05	0.04

Table 3. Machine-level event detection performance.

Table 3 lists the results of the event-appliance matching for the industrial case. Even designing an algorithm aware of multi-mode appliance intersection, event feature separation, and event pair matching considering the most probable appliance. The solution fails in distinguishing appliances in industrial settings, where there is a continuous operation, and temporal dependency between them is highly correlated. However, the most frequent-event appliances (MI and MII) show that the FP count is reduced compared to the total number of detections.

Appliance	TP	FP	FN	Precision	Recall	F-score
MI	2463	188	479	0.93	0.84	0.88
PI	38	183	242	0.17	0.14	0.15
EFI	1	3	93	0.25	0.01	0.02
DPCI	21	1	371	0.95	0.05	0.10
Average				0.58	0.26	0.29

Table 4. Event detection performance only considering one machine of each.

After assessing the possible reasons for the low performance of the algorithm in the industrial domain, one appliance of each kind was selected to evaluate the capabilities of the proposed solution by removing the simultaneous events caused by the correlated temporal dependency of devices of the same class. The aggregated power signals are now just the contributions of MI, PI, EFI, and DPCI. The event detection performance is summarized in Table 4. The quality of the inferred events increased for all appliances, especially for MI. The considerable improvement is attributed to the fact that the extracted power transition intervals are not the sum of two machines (for simultaneous events), so the first association step is correctly assigned to the actual machine.

5. Conclusions

In general, the solution proves to detect events accurately even with a noisy signal. However, the algorithm could improve in the classification step, where the kernel density estimation showed that is not the most appropriate approach to search for feature separation. The features are still very similar in their specific categories causing a false connection of events to appliances that do not belong.

Furthermore, active cycle detection allows in the residential case a near-real-time solution, as the ON interval does not last long and power consumption is calculated after that. This is not the case for the industrial setting, as the active cycle can last at least one full day because the candidate ground state is found in the last falling edge of a working day. So, the energy consumption estimation will be given daily instead of near-real-time.

5.1. Future Work

The semi-supervised event pairing method presented here is not adequate for an industrial setting that has simultaneous events. The algorithm does not distinguish which appliances are operating as the rising/falling edge does not correspond to the learned power intervals. Moreover, the complexity of the disaggregation task increases if more machines of the same kind are operating, and it is hard to tell the difference as they exhibit similar characteristics. The overlap of the same equipment affects the algorithm's performance.

The sampling frequency may have an impact to treat high event parallelism like the one studied in this investigation with the factory in Brazil. Research affirms that a high-frequency sampling rate is a requirement to discriminate the possible simultaneous events. The events could be distinguished with a faster sample rate, and the simultaneity likelihood will decrease. Provided that over time, computational capabilities to process elevated amounts of inputs and compressing methods to store massive amounts of data are being improved continuously, data collection campaigns should aim at higher frequency data.

In summary, the challenge of recognizing machines of the same kind is still an open issue. Discriminating devices that perform the same assignment adds another complication to the disaggregation task because their power signature is indistinguishable. Unlike the various devices in a residential environment, which possess a unique fingerprint. Promising approaches that can consider this matter can be deep neural networks, as they can extract features not so obvious, thanks to their multi-neuron-layer structure.