Non-Intrusive Load Monitoring: A Computationally Efficient Hybrid Event Detection Algorithm

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***Abstract*—Non-intrusive load monitoring is widely appreciated technique for managing segregated-level energy-efficiency. Event detection algorithms play a crucial role in non-intrusive load monitoring applications. This paper proposes a new unsupervised hybrid event detection algorithm that tracks the difference and standard deviation of the aggregated load data. To evaluate the performance of the proposed algorithm, simulations are carried out on 24 hours of real-world load data from a single household having diverse load elements. This paper also assessed the sensitivity of the input parameter on the performance of the proposed event detector. The proposed hybrid event detection algorithm performed well and accomplished highly promising results.**

Keywords—Energy Monitoring, Non-Intrusive Load Monitoring Event Detection, Hybrid Algorithm.

I. INTRODUCTION

The modern power system is keenly interested in energy efficiency and conservation techniques. While significant research has already been done in this domain, it is still an open research question. Energy monitoring is a widely adopted approach to energy efficiency and conservation. Energy monitoring can be performed either at an aggregated or segregated level, which can further be classified into various granular-level categories. A hierarchical depiction of this categorisation is presented in [1]. The recent advancement in computational capabilities significantly enhanced the developmental prospect of more effective and robust energy monitoring techniques, particularly, software-driven segregated energy monitoring, commonly referred to as non-intrusive load monitoring (NILM). NILM is a process of extracting individual appliances' operation states by analysing the aggregated load data, monitored at a single metering point [2]. The concept of NILM was introduced by Hart [3], and numerous advancements are proposed in [2, 4-7]. A NILM system comprises four key components, namely data acquisition, event detection, feature extraction, and classification, as presented in Fig. 1 along with further categorisation.

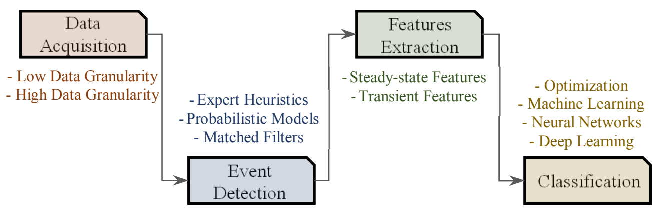

Fig. 1. NILM System Framework

A. Related Work

In NILM, an event refers to the transient portion among two steady-state portions of a time series load data [8]. These events correspond to the timestamps where the significant transition in energy consumption occurs, consequently, contribute to NILM process. Existing literature contains numerous event detection algorithms, and many of them have been applied in real-life NILM systems. For example, Anderson et al. [9] present a comprehensive discussion regarding event detection algorithms and proposed new performance evaluation metrics. They also identified three categories of NILM event detection approaches, namely (i) expert heuristics, (ii) probabilistic models, and (iii) matched filters. Expert heuristics approach introduces a set of rules based on prior information. Probabilistic models approach contemplates statistical parameters to estimate the transition probability in time-series load data. Matched filters approach compares a known signal (ground-truth; timestamps signalling the occurrence of actual events) with an unknown signal (input aggregated load data).

Real and reactive power is mostly used as an input to event detection algorithms for time-series load data [10]. However, other variables such as current signal [8, 10] and voltage distortion [11] are also used as inputs for event detection. Rehman et al. [12] proposed two event detection algorithms based on statistical features, namely variance and mean absolute deviation, where power is taken as an input variable. Similarly, the authors of [9, 13] also employed power as input for event detection, but the data was acquired using different sampling rates. Wild et al. [8] proposed an event detection algorithm based on kernel fisher discriminant analysis, where the current was employed as an input for event detection. In addition to time-series, event detection was also performed in the frequency domain. For example, De Baets et al. [14] proposed an event detector that had worked in the frequency domain and used Cepstrum analysis. Furthermore, a time-frequency based approach for event detection using a goodness-of-fit Chi-squared is proposed in [15]. It is worth noting that most of the event detections are based on high sampling data granularity.

B. Contribution

As depicted in Fig. 1, event detection is a pre-requisite for feature extraction and load classification. Thus, we propose an unsupervised hybrid event detector for NILM applications in this paper. The proposed event detection algorithm is easy to implement, i.e., low in complexity and computationally efficient, i.e., faster in computational performance. The algorithm also works on different data granularity, particularly low sampled data in the NILM context. The proposed algorithm precisely identifies the events within the input aggregated load data and also the starting and ending timestamps of the detected events.

The rest of the paper is organised as follows: Section II presents a detailed description of the proposed algorithm, particularly the working principle and implementation methodology. Section III presents the performance evaluation criterion of the proposed hybrid event detection algorithm. Simulation studies and results are presented in Section IV, followed by a conclusion in Section V.

II. Proposed Hybrid Algorithm

Consider a time-series aggregated power, $p_{total}(t)$, at a single metering point as an algebraic sum of i number of appliances' power, $p_i(t)$, as given in (1).

$$p_{total}(t) = \sum_{n=1}^{i} p_i(t) + m_{noise} \tag{1}$$

m_{noise} is the measurement noise comprises acquisition noise and base loads or loads not under consideration. As evident from (1) that along with individual appliance state transition, a state transition in aggregated power is recorded. These state transitions are referred to as events, and the proposed event detector intends to detect these variations in the aggregated power curve. For said purpose, the proposed hybrid event detector is a combinatorial form of two distinct features and corresponding methodology, i.e., power difference of two consecutive samples and standard deviation of a pre-defined number of samples, i.e., the width of moving window. Using a threshold value, the former detects all the state transitions among the two consecutive samples, and the later detects the state transition among a pre-defined set of samples. The final output is the mutual agreement of the two methodologies. The working principle of the proposed hybrid event detection algorithm is presented in Table I.

TABLE I. PROPOSED ALGORITHM

Algorithm

Required

-Aggregated load data, $\boldsymbol{x}$

-Select threshold value (ŧh) and moving window size (S)

Process

-Pre-process aggregated load data, $\breve{\boldsymbol{x}}$

-Compute the difference in consecutive $\breve{\boldsymbol{x}}$ as

$$\Delta_{\breve{x}} = \breve{x}(t+1) - \breve{x}(t)$$

-Compute iteratively standard deviation of $\breve{\boldsymbol{x}}$ with pre-selected moving window size as

$$\sigma_{\breve{x}} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left| \breve{\boldsymbol{x}}_i - \mu_{\breve{\boldsymbol{x}}} \right|^2}$$

-Compute the thresholding signal ŧh_{signal} by comparing ŧh value with $\Delta_{\breve{x}}$ and $\sigma_{\breve{x}}$ as

$$\text{ŧh}_{signal} = \begin{cases} 0, & \text{if } \sigma_{\breve{x}} \leq \text{ŧh and } \Delta_{\breve{x}} \leq \text{ŧh and } \Delta_{\breve{x}} \geq -\text{ŧh} \\ 1, & \text{else} \end{cases}$$

-Extract edges of thresholding signal to identify the starting and ending timestamps of the detected events

-Post-processing of the detected events in terms of approval and delay correction

Output

-Event detection along with corresponding starting and ending timestamps

The proposed hybrid event detection algorithm tracks the variation, i.e., state transitions, of aggregated load data and returns the output in the form of not only the transient portion, i.e., event, but also provide the corresponding starting and ending timestamps of the detected events.

III. Evaluation Criterion

The existing literature lacks a standardised framework for performance evaluation of an event detector in the NILM domain. Consequently, diverse performance metrics are employed by the research community to evaluate the event detection algorithms. In this research, we have employed some of the well-known and widely used performance metrics i.e., precision and recall to evaluate the performance of the proposed hybrid event detection algorithm. The details of each employed performance metric are as follows [16].

Precision refers to the percentage of detected events that are relevant and given as in (2).

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{2}$$

The recall is defined as the percentage of all relevant events that are correctly detected by the algorithm as provided in (3).

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{3}$$

The terminologies of true positive, false positive, and false negative used in (2) and (3) are defined as.

- *True Positive (TP):* An event presented in the ground-truth and detected by the algorithm, also referred to as true detection.
- *False Positive (FP):* An event detected by the algorithm but not present in the ground-truth, also referred to as false detection.
- *False Negative (FN):* An event presented in the ground-truth but not detected by the algorithm, also referred to as misdetection.

The individual appliance ground-truth data is essential to evaluate the event detection performance. Ground-truth refers to the timestamps when the individual appliance state transition, i.e., event, occurs. Moreover, for evaluation purposes, the starting timestamps of the events are considered in this research work, as it is the starting time index that initiates an event [17]. Furthermore, in this research work, a detected event by the proposed hybrid event detection algorithm is considered a true positive/true detection, if and only if the condition given in (4) is satisfied.

$$\text{abs}\,(t_{ground\text{-}truth} - t_{detected}) \leq \Delta t \quad (4)$$

where Δt, $t_{ground\text{-}truth}$, and $t_{detected}$ represent the tolerance value, ground-truth event starting timestamp, and detected event starting timestamp, respectively. The condition in (4) accommodates the slight mismatch between the detected events and ground-truth events.

IV. Simulations and Results

Comprehensive digital simulations are carried out on real-world data acquired from electricity consumption and occupancy (ECO) [18] dataset. The ECO dataset is mainly intended for NILM research, and load data are acquired from 6 Swiss households. The corresponding data contain 1 Hz of aggregated and appliance-level load data along with occupancy information[1].

This research acquired load data of one day from a single household for simulation purposes. It used median filtering for data pre-processing to eliminate the noise from the acquired aggregated load data. Median filtering is a digital filtering technique widely used in the NILM context, as it preserves the edges while eliminating the undesired signal attributes. A detailed discussion of the median filtering technique and its working principle is presented in [13].

Table II shows the details of household and corresponding load data acquired for simulation purposes.

TABLE II. Acquired Household Details

Description	Details
Household ID	02
Acquired data timeframe	01 July 2012
No. of days	01
No of acquired load data samples	86400
No. of individual appliances	12

Fig. 2 graphically depicts a portion of the acquired aggregated load data along with the ground-truth profiles of a few individual appliances [18].

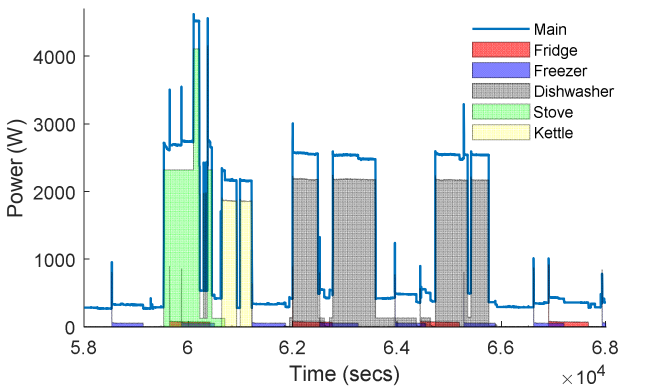

Fig. 2. ECO Load Data (continuous blue line represents the aggregated load data, i.e., Main)

Details of various input parameters employed in digital simulations are presented in Table III.

TABLE III. Simulation Parameters

Description	Details
Threshold	10 W
Δt	3 sec
Moving window width	6 samples

Comprehensive simulations are carried out on aggregated load data, presented in Table II, using the parameters in Table III. The proposed hybrid event detector detected a total of 229 events. Table IV presents a portion of the detected events within the input pre-processed aggregated load data and their comparison with the ground-truth events of different appliances. Table IV also highlights the status of the detected events in terms of true, false, and mis- detection, along with the corresponding appliances' states based on ground-truth.

TABLE IV. Detected vs Ground-truth Events

Detected Events		Ground-Truth	
Starting Timestamp	**Status**	**Starting Timestamp**	**Appliance State**
814	True Detection	815	Fridge Turn-on
1599	True Detection	1598	Fridge Turn-off
4754	True Detection	4754	Freezer Turn-on
6065	True Detection	6065	Freezer Turn-off
27519	False Detection	-	-
-	Misdetection	31393	Entertainment Turn-on
42208	True Detection	42209	Entertainment Turn-off
48113	True Detection	48114	Kettle Turn-on
48283	True Detection	48285	Kettle Turn-off

Furthermore, Fig. 3 graphically depicts a portion (for visual clarity) of event detection results and corresponding benchmarking with ground-truth profiles of different individual appliances. It is worth noting that all the power profiles presented in Fig. 3 are pre-processed with a median filtering technique. From the presented results in Fig. 3, it is evident that the ground-truth events are precisely detected by the proposed hybrid event detector, even the minor state transitions within aggregated load data initiated by appliances like the fridge and freezer are detected, as highlighted[2] in Fig. 3a.

Table V presents a complete performance analysis, as per the simulation parameters in Table III, in terms of true detection, false detection, misdetection, precision, and recall performance metrics.

TABLE V. Performance Results

Description	Details
True detection (TP)	186
False detection (FP)	43
Misdetection (FN)	37
Precision	81.22 %
Recall	83.41 %

[1] https://www.vs.inf.ethz.ch/res/show.html?what=eco-data

[2] In Fig. 3, the highlighted detected events (in orange color) along with corresponding appliance state are based on the available ground-truth profiles of the appliances. It is worth noting that non-invasive load (state) inference is not within the scope of this research work.

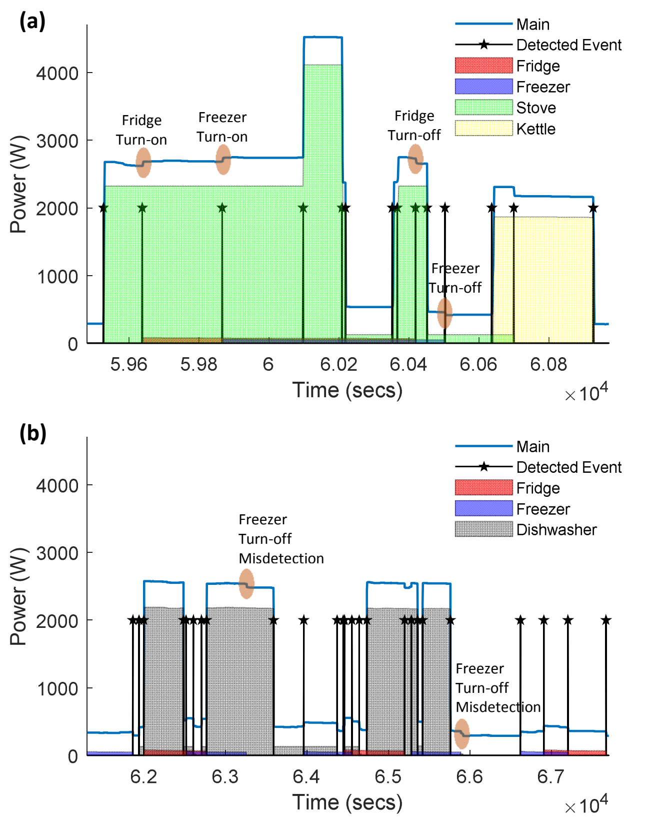

Fig. 3. Event Detection Results (continuous blue line and vertical black line represent pre-processed aggregated load data and starting timestamps of detected events, respectively)

Although there are some false and misdetection, as highlighted in Fig. 3b, the overall performance results, Table V, shows that the proposed hybrid event detector precisely detected most of the ground-truth events and achieved greater than 80% performance in terms of both precision and recall.

A. Sensitivity Analysis

The proposed hybrid approach tracks two different phenomenon, i.e., the power difference between consecutive samples and the standard deviation of a pre-defined number of samples using a moving window. The latter relies on the width of the moving window, i.e., the sample size for standard deviation. Consequently, it is necessary to carry out a sensitivity analysis in terms of moving window width to identify an optimal sample size for the given problem. Thus, we considered different sample size and carried out comprehensive simulations to determine an optimal width of the moving window; results presented in Table VI.

TABLE VI. SENSITIVITY ANALYSIS RESULTS

Metrics	Sample Size of Moving Window							
	2	3	4	5	6	7	8	9
Total detection	250	241	240	234	229	216	210	196
True detection	196	192	192	191	186	175	171	161
False detection	54	49	48	43	43	41	39	35
Misdetection	27	30	30	32	37	48	52	62
Precision (%)	78.40	79.67	80	81.62	81.22	81.02	81.43	82.14
Recall (%)	87.89	86.49	86.49	85.65	83.41	78.48	76.68	72.20

Fig. 4 exhibited the overall performance trend of the proposed hybrid event detection algorithm in terms of precision and recall over the different sample size of the moving window.

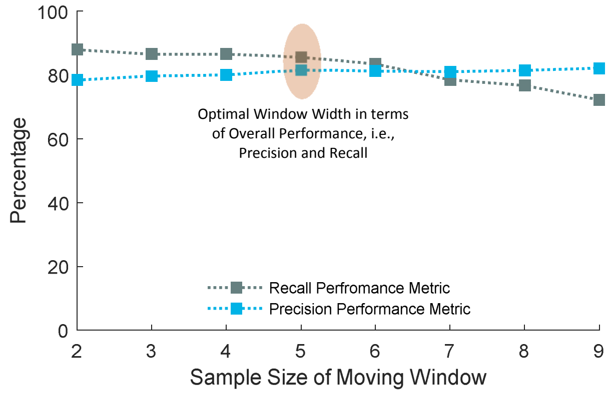

Fig. 4. Sensitivity Performance Results

As evident from the results presented in Table VI and Fig. 4, the sample size of the moving window significantly influences the performance of the proposed event detector. It is observed that a trade-off exists in terms of sample size and performance metrics, i.e., precision and recall, respectively. In terms of optimal sample size (of moving window) in the context of overall detection performance, the sample size of 5 emerged as an optimal value (highlighted in Fig. 4) due to the smaller number of misdetection and false detection. At the given sample size of 5, the proposed hybrid event detector attained very good results, i.e., 85.65%and 81.62% for recall and precision performance metrics, respectively.

V. CONCLUSION

This paper proposed an unsupervised hybrid event detection algorithm for the non-intrusive load monitoring applications. The algorithm is able to successfully detect events of different appliances within the input aggregated load data. The proposed hybrid event detection algorithm is computationally faster and easy to implement within a NILM application.

Comprehensive simulations are carried out on load data acquired from the ECO dataset having the low data granularity of 1 Hz. It is evident from the extracted results that the proposed hybrid event detection algorithm works well and attained promising results. Moreover, a comprehensive sensitivity analysis in terms of the sample size of the moving window is also carried out. It is concluded that for the given problem, the proposed event detection algorithm performs best at moving window width, i.e., sample size, of 5 and attained 81.62% and 85.65% in terms of precision and recall, respectively.

Towards non-invasive load inference, integration of the proposed hybrid event detection algorithm within a complete non-intrusive load monitoring system is a topic of future research.

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