Low Complexity Event Detection Algorithm for Non-Intrusive Load Monitoring Systems

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Abstract— **In order to tackle today's energy and sustainability issues, there are two paths to be followed by the world community. Either they have to establish new generation plants with an expense of millions of dollars or to look deeper into the existing system to design and deploy techniques that can lead to a significant amount of energy saving. Today, researchers are extensively working towards energy efficiency and conservation via developing different techniques. In the said domain, energy monitoring is one of the key techniques which is an attractive and popular research topic in the field of sustainable energy. It is single-point sensing or commonly known as Non-Intrusive Load Monitoring (NILM) that is used to extract the appliance level energy consumption. For a NILM system, event detection plays a key role and is a pre-requisite for the later stages of the system. In this paper a simple and low complexity event detection algorithm is proposed. Digital simulation and sensitivity studies have been carried out using real world data to check the performance and sensitivity of the proposed algorithm. Furthermore, the results of the proposed algorithm are compared with the existing event detection algorithm for evaluation purposes.**

Keywords—Non-Intrusive Load Monitoring, Event Detection, Smart Grids, Smart Meters

I. INTRODUCTION

In the last few decades, power system encounters a tremendous change in terms of distribution networks due to the presence of renewable energy resources like wind turbines, photovoltaic, and geothermal systems. Today energy does not only flow from a large power plant to the end-users but it is also produced from a large number of distributed generators having intermittent nature and located at the consumer end. Hence in this era, it is critical to manage effectively the flow of energy along with the sustainability of the grid in terms of maintaining a proper balance between supply and demand. Thus, a concept of a *'Smart Grid System'* comes into existence. A smart grid technology is an updated electrical grid system based on analogue or digital information and communication systems. Unlike the conventional grid system, a smart grid is a bi-directional system which collects and acts on the information concerning the behavior of the providers and the end users in an automated way to increase the efficiency, reliability, and sustainability of the production and distribution of electricity.

Due to the integration of digital tools and systems, smart grids offer many promising solutions (e.g. energy monitoring, demand response…) to the end users so that the end-users can play a major role for improving the overall efficiency of the system [1]. In order to facilitate the end-users to play a significant role, it is mandatory for the utility's provider to give a direct feedback[1] to the end-users on their consumption at appliance level, which will lead to significant amount of energy saving [2, 3]. In this context, energy monitoring (also known as load disaggregation) plays a key role with the objective to increase the energy consumption awareness by providing detailed energy consumption pattern to the end users.

In the last decade, the worldwide deployment of smart meters provides a solid ground for energy monitoring at appliance level within a building. Load disaggregation is a phenomenon, where the aggregated load of a household is converted to segregated loads. It can be performed via different methods, which can be broadly categorized as hardware based solutions and software based solutions [3] as depicted in Fig. 1.

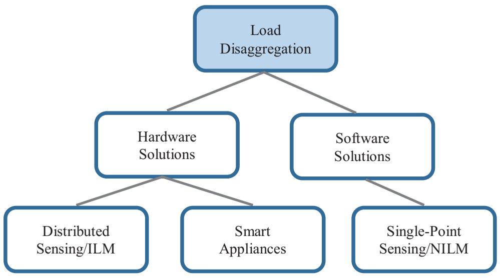

Fig. 1. Load Disaggregation Hierarchy

Hardware based solutions comprise distributed sensing or Intrusive Load Monitoring (ILM) and Smart Appliances. The former is a method where each appliance is exclusively monitored via a smart plug/socket, where the latter i.e. smart appliances are those appliances that have the built-in ability to monitor and report their own consumption [4]. Both techniques i.e. ILM and employing smart appliances require considerable hardware and investment costs, hence not suitable for large scale deployment. On the other hand, software based solution

[1]Direct Feedback; refers to real time appliance level consumption information.

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comprises an attractive approach namely single-point sensing commonly known as Non-Intrusive Load Monitoring (NILM) or Non-Intrusive Appliance Load Monitoring (NALM) or Non-Intrusive Appliance Load Monitoring (NIALM) [5, 6]. NILM technique was first introduce by Hart, where the aggregated load of a household is acquired at the metering point (avoiding intrusion to the inside premises of the household) and can be decomposed into diverse consumption profiles of appliances operating within the household under consideration [6].

A NILM system is mainly comprised of three phases namely, *data acquisition*, *feature extraction* and *appliance classification* [7]. The NILM process starts with the acquisition of aggregated data at the metering point, then the signatures/features of interest are extracted and finally classification of the appliances are carried out as shown in Fig. 2 with some refined details [2].

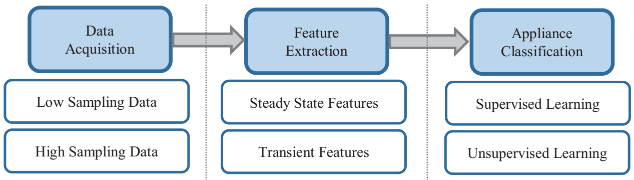

Fig. 2. Non-Intrusive Load Monitoring Framework

In event-based NILM systems, a stage known as *event detection* is introduced after *data acquisition*. Event detection is a pre-requisite for the later stages and overall play a significant role in the NILM system. Event detection is performed on all acquired samples but the later stages are only fed with the detected edges. Hence it provides an ease in term of complexity and computational power to the later stages of *feature extraction* and *appliance classification* [7]. The purpose of event detection is to detect all the ON/OFF events of the appliances within the acquired aggregated load data where an event is defined as part of signal that deviates from the previous steady state and lasts until the next steady state has been reached [8]. It is worth mentioning that the turning ON and turning OFF of an appliance are considered as individual events having their own starting and ending time respectively.

Several event detection algorithms have been proposed and developed so far with lot of diversity in terms of acquired data granularity and techniques used. Ref. [9] performs event detection in frequency domain by considering aggregated active power of 60 Hz as input where Ref. [10] presents a simple event detection algorithm based on active and reactive power at 1 Hz of sampling rate. Ref. [11] adopted time-frequency based approach for detecting the events by using a goodness-of-fit Chi-squared test. Most of the available work related to event detection is based on active and reactive power as an input with few variations. For instance Ref. [8] proposed event detection based on Kernel Fisher Discriminant Analysis (KFDA) where current harmonics are used as features to detect the events.

This paper proposes a low complexity and fast computational event detection algorithm to detect the ON/OFF events of loads for NILM system. The rest of the paper is structured as follows; Section II presents the details of the proposed algorithm where Section III discusses the simulation and the corresponding results of the proposed algorithm. Finally the paper is concluded in Section IV.

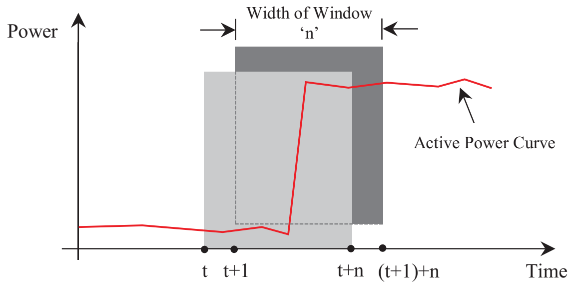

Fig. 3. Mean Sliding Window Algorithm Illustration

II. Proposed Event Detection Algorithm

This section briefly discusses the proposed algorithm, called hereafter Mean Sliding Window (MSW) algorithm. The algorithm is based on a scanning window that runs over an active power consumption curve. The basic working phenomenon is depicted in Fig. 3. The proposed algorithm detects the mean value of the active power consumption curve using a sliding window. Events are extracted from the resulting signal using a pre-defined threshold value 'δ'. The final output of the algorithm is in the form of starting and ending time instances of the detected events.

The proposed algorithm is defined in details by the following steps:

1. Acquire aggregated load data,
2. Preprocess the acquired aggregated data using filtering techniques,
3. Select the sliding window width *'n'*,
4. Compute iteratively the mean 'μ' of the power consumption curve and the corresponding difference
5. Select the threshold value 'δ' for event detection
6. Using δ, compute threshold of the signal representing steady state and transient states
7. Compute edges from the previous step using derivation function and extract the starting and ending indices of the events.

III. Simulation & Results

A. Algorithm Simulation Parameters

In order to test the proposed algorithm, a real world dataset is used and for the said purpose the data have been acquired from Pecan Street Inc. Dataport [12] which consist of aggregated as well as segregated power consumption profiles of different appliances. Different parameters used for the simulation and testing of the proposed algorithm are presented in Table I.

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TABLE I. PARAMETERS FOR SIMULATION

Data Acquisition Granularity	1 min sampling rate (1/60 Hz)
No of Data Samples	1440 (24 Hours)
Data ID	26
Data Timeframe	July, 01, 2014
Sliding Window Width *'n'*	5 Samples
Pre-Processing Method	Median Filtering
Threshold Value *'δ'*	250 W

B. *Simulation Results*

Based on the aforementioned parameters, the simulation is carried out on one day data acquired from Pecan Street Inc. Dataport. The corresponding results in form of the starting time indices of the detected events that are extracted from the pre-processed aggregated load data are presented in Table II.

TABLE II. COMPARISON OF DETECTED EVENTS AND GROUND TRUTH EVENT DATA OF INDIVIDUAL APPLIANCES

Events	**Detected**	**Ground Truth**	
	Starting Time 'Aggregated Data'	Starting Time 'Air Condition'	Starting Time 'Car'
1	5	5	1178
2	58	58	1241
3	94	94	1270
4	153	153	1295
5	186	186	
6	255	255	
7	284	284	
8	368	368	
9	375	375	
10	720	720	
11	768	768	
12	803	803	
13	840	840	
14	890	890	
15	951	951	
16	1140	1140	
17	1178		
18	1241		
19	1270		
20	1295		
21	1396		
22	1401		

Table II also presents the ground truth starting time indices of appliances' turning ON and turning OFF events for the same data ID and timeframe as of acquired aggregated load data. In this paper, the presented ground truth data are limited to two appliances that are *electric car* and *air-condition*. This selection is made due to their high-energy consumption and their future impacts. The charging of a car is becoming a significant load element particularly for smart grid system analysis [13] where the available literature regarding NILM in general and event detection in particular has not focused on energy consumption of electric car.

Furthermore, it is worth mentioning here that it is the starting time indices of an event that are linked with the triggering of a particular event i.e. turning ON or turning OFF an appliance. Hence, for the evaluation of the proposed algorithm, the starting time of the detected events will be compared with the ground truth starting time of the events acquired from Pecan Street Inc. Dataport as already presented in Table II.

It is evident from the data presented in Table II, that all the starting time instances of the detected events within the aggregated load data are exactly matched with the ground truth starting time instances of the events of the appliances that are under investigation.

Fig. 4 graphically depicts the acquired aggregated load data, pre-processed aggregated load data and the final outcome of the proposed algorithm in terms of the starting time instances of the detected events. It is clear from Fig. 4 that most of high consumption appliances' events are detected successfully comparatively to the lower variation in the power consumption curve. The same was expected due to the pre-defined parameters particularly data acquisition sampling rate and the threshold value of 1/60 Hz and 250 W respectively.

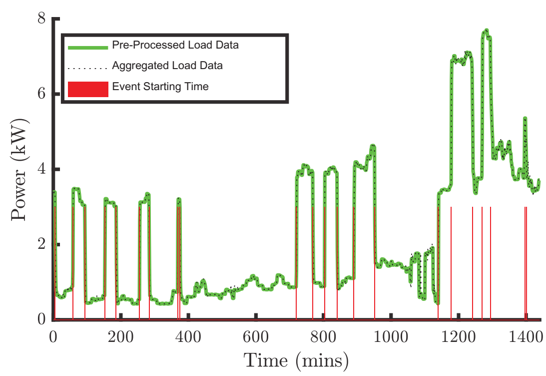

Fig. 4. Detected Events Within Aggregated Load Data

Fig. 5 presents both the starting and ending time instances of the detected events within the acquired aggregated load data by the proposed MSW algorithm.

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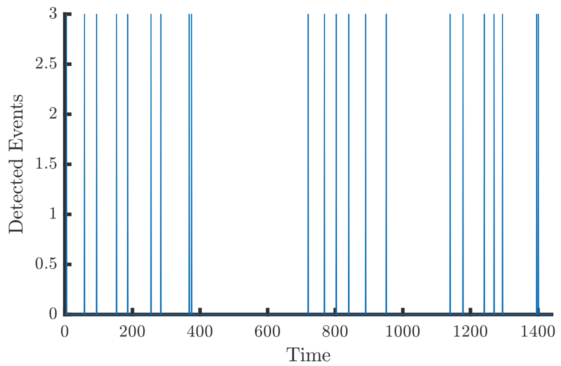

Fig. 5. Starting and Ending Time Instances of Detected Events

For verification and reliable results, the signature and accurate ground truth time instances of the individual events of the appliance that are under consideration of this paper are also presented graphically in Fig.6.

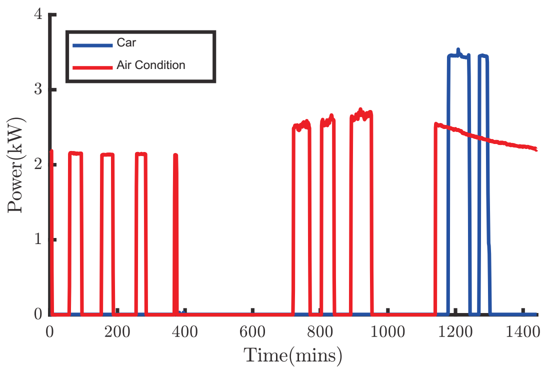

Fig. 6. Ground Truth Events of the Appliances

Table III shows the details of energy consumption data of car charging based on the ground-truth as well as on the ON and OFF time indices of the detected events corresponding to the car. (Note: appliance classification is not within the scope of this paper.)

TABLE III. ENERGY CONSUMPTION OF CAR

ON Event	OFF Event	Duration	Energy (kWh)	Total Energy
19:37:00	20:40:00	01:03:00	3.57	4.99 kWh
21:09:00	21:34:00	00:25:00	1.42	

C. Algorithm Evaluation

Researchers used various performance metrics in order to evaluate the load disaggregation and event detection algorithms. In literature, there is no single standardized performance metric available for evaluation purposes. Some of the available and widely used performance metrics in the literature are, *accuracy*, *precision*, and *recall* [14].

Accuracy is the total energy assigned correctly to an individual appliance and is given as

$$\text{Accuracy} = \frac{\text{Correct Matches}}{\text{Total Possible Matches}}$$

Precision is the ratio between truly detected and total detected events and is given as,

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

Recall is defined as the measure of detection of events occurred in reality and is given as,

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

where the terminology of true positive, true negative, false positive and false negative are explain in Table IV [15].

TABLE IV. METRICS DEFINITION

Algorithm Prediction	Actual Event Occurred	Actual Event Didn't Occurred
Detected	*True Positive (TP)*	*False Positive (FP)*
Not Detected	False Negative (FN)	True Negative (TN)

Furthermore in [16] a performance metric known as *hit rate* is presented, that is denoted by *'D'* and is given as,

$$D = \left(\frac{a \times a}{d \times g}\right) \times 100$$

where *'a'* is the detection success, *'g'* is the number of actual events in the measurements and *'d'* is the total number of detected events.

In order to get a comprehensive evaluation of the proposed MSW algorithm, all of the aforementioned performance metrics are taken into account except *accuracy* because it is sometimes ambiguous, particularly for appliances that are mostly in OFF state [14]. For example, an algorithm predicting that an appliance is always OFF, will be having 95% of accuracy if the said appliance is actually ON for 5% of the time. Hence, this paper, the evaluation metrics of *recall*, *precision* and *hit rate* are selected in order to authenticate the overall performance of the proposed algorithm and the corresponding results are presented in Table V for the parameters presented in Table I.

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TABLE V. ALGORITHM EVALUATION RESULTS

Performance Metrics	Results
True Positive	20
False Positive	2
False Negative	0
Recall	100%
Precision	91%
Hit Rate	91%

D. Sensitivity Study

In order to investigate the effects of different parameters on the performance of the proposed algorithm, a sensitivity test has been carried out. For the presented work, the threshold value *'δ'* and the data acquisition sampling rate have been kept constant at 250 W and 1/60 Hz respectively. The window width *'n'* has been varied to check its effect on the performance of the proposed MSW algorithm. Fig. 7 presents the sensitivity test results for the proposed MSW algorithm. It is observed that at *n=3* the overall MSW performance in terms of all evaluating performance metrics is at its lowest comparatively to the rest of its values. At *n=5* the proposed MSW algorithm leads to the optimal solution towards significant performance. But a clear trade-off exists between opting performance metrics and the corresponding optimal parameter values.

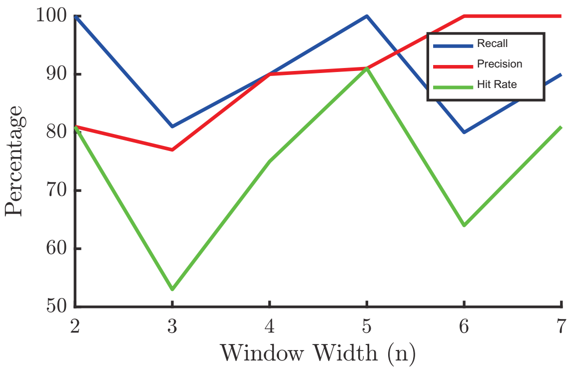

Fig. 7. Effects of Window Width 'n' on Different Performance Metrics of MSW Algorithm

E. Comparison Study

To further evaluate the proposed MSW algorithm we compared with a recently proposed algorithm: High Accuracy NILM Detector (HAND) [17]. It tracks the variation of standard deviation of the acquired data using a moving window. For comparison purposes the HAND algorithm is implemented and simulation studies are carried out using the same parameters as presented in Table I. The overall performance of the HAND algorithm in terms of *recall*, *precision* and *hit rate* is depicted in Fig. 8. It is worth mentioning here that the delay tolerance 'Δt' defined in [17] for HAND algorithm is not taken into account for obaining the results shown in Fig. 8. Here we used a 'Δt' equal to 0 i.e. a detected event with starting time 't_s' will be considered as a true positive if and only if Δt=0.

It is evident from Figs. 7 and 8 that there is a trade-off between the selection of algorithm and the performance metrics. Where, HAND is superior in terms of *recall* whilst MSW comparitively performs well in *precision* particularly for *n>3*. If all the three performance metrics are taken into account then comparitively MSW outperforms HAND particularly at window width of 5.

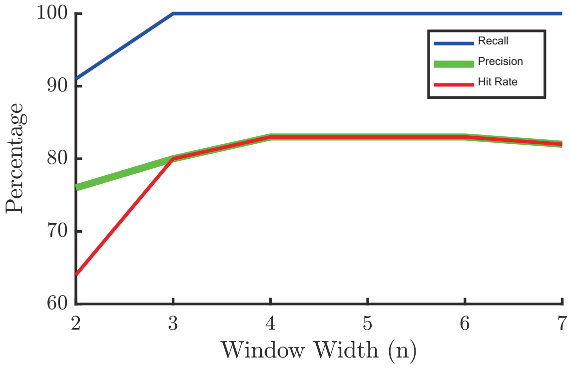

Fig. 8. Effects of Window Width 'n' on Different Performance Metrics of HAND Algorithm

IV. CONCLUSION

This paper presents a simple and low complexity event detection algorithm for load disaggregation. The simplicity of the proposed algorithm lies within the concept of utilizing sliding window based on mean value of power consumption curve. Furthermore, due to its iterative computation it is computationally faster.

Based on the simulations on a real world dataset, it is concluded that the proposed algorithm performs well for detecting high consumption appliance events at low sampling rate. At window width *n*=5, the algorithm attains 91%, 100% and 91% of *precision*, *recall* and *hit rate* respectively. Further it is also observed that varying the algorithm's parameters affects the performance metrics of the proposed algorithm in terms of events detection and a trade-off exists between the selection of performance metrics and optimal parameter values.

For future work, focus will be on the development of more generic algorithms with optimal parameters selection. The proposed algorithms will also be tested on different datasets having different granularity in terms of data acquisition.

During the literature review, it was also observed and worth mentioning here that in order to move forward more focus is required towards the standardization of load disaggregation algorithms' performance metrics [3, 14], benchmarking framework [14] and the availability of state-of-the-art load datasets [18].

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