Event-Detection Algorithms for Low Sampling Non-Intrusive Load Monitoring Systems based on Low Complexity Statistical Features

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***Abstract*-- One of the key techniques towards energy efficiency and conservation is Non-Intrusive Load Monitoring (NILM) which lies in the domain of energy monitoring. Event detection is a core component of event-based NILM systems. This paper proposes two new low-complexity and computationally fast algorithms that detect the variations of load data and return the time occurrences of the corresponding events. The proposed algorithms are based on the phenomenon of a sliding window that tracks the statistical features of the acquired aggregated load data. The performance of the proposed algorithms is evaluated using real-world data and a comparative analysis has been carried out with one of the recently proposed event detection algorithms. Based on the simulations and sensitivity analysis it is shown that the proposed algorithm can provide the results of up to 93% and 88% in terms of recall and precision respectively.**

***Index Terms*—Energy Monitoring, Event Detection, Non-Intrusive Load Monitoring, Smart Grids.**

I. Introduction

ENERGY efficiency and conservation are the key drivers towards the concept of the future smart grid (SG). The consumers who are expected to play a key role in this regard [1] not only can effectively participate towards the sustainable SG system but also can have direct feedback of meaningful real-time appliance level consumption information [2, 3]. Due to the worldwide deployment of smart meters, energy monitoring becomes more viable today. Numerous applications based on smart meter data have already been reviewed [4] for the application of SG in achieving load diversity and efficiency [5].

Energy disaggregation, also known as load or power disaggregation [6], contributes to the development of effective energy monitoring systems. This refers to a method aiming at an estimation of individual appliances' power consumption from the aggregated household electricity consumption. Numerous methods are available to perform load disaggregation. They can be broadly distinguished as hardware and software-based methods [3, 7] as shown in Fig. 1.

Intrusive Load Monitoring (ILM) and smart appliances are the techniques that lie within the domain of hardware methods whilst Non-Intrusive Load Monitoring (NILM) lies in the domain of software methods. ILM refers to a technique in which appliance level power consumption profiles are obtained using sub-metering sensors that are attached to individual appliances [8]. This technique is relatively simple but factors like multiple numbers of sensors, reliability, and cost can be some of the main deterrent concerns [7, 9]. Smart appliances are the appliances that have integrated capabilities to monitor and report their power consumption [10] but these appliances are not widely in use due to their high market prices and interoperability issues [11]. Alternatively, software methods provide attractive solutions to load disaggregation. A widely used technique is commonly referred as NILM or Non-intrusive Appliance Load Monitoring (NALM) or Non-Intrusive Appliance Load Monitoring (NIALM) [12-14]. The concept was first introduced by Hart [15] in 1984. Later, numerous techniques have been proposed that improve the early concept of NILM. A comprehensive review and outlook of the proposed NILM algorithms are presented in [3, 16-18].

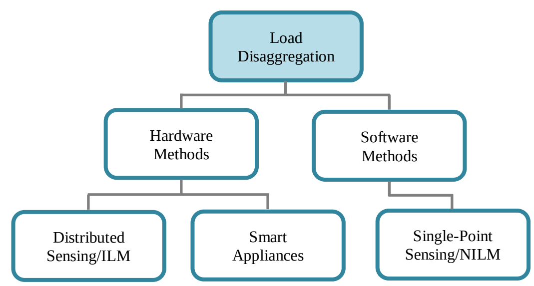

Fig. 1. Load Disaggregation Hierarchy

A. Non-Intrusive Load Monitoring

NILM is a widely used technique that disaggregates the load data acquired from a single entry point and identifies power consumption profiles of the individual appliances. Let consider a time-series power load curve monitored at a metering point. It can be represented as an algebraic sum of n number of appliances' load, as shown in Eq. (1).

$$P_{agg}(t) = \sum_{i=1}^{n} P_i(t) \quad (1)$$

The task of NILM is to identify the state of individual appliance loads $P_1(t)$, $P_2(t)$, ... from the given information of aggregated load $P_{agg}(t)$. A traditional NILM system consists of three main components, namely: *data acquisition*, *feature extraction*, and *classification* as shown in Fig. 2. Additional

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details can be found in [3].

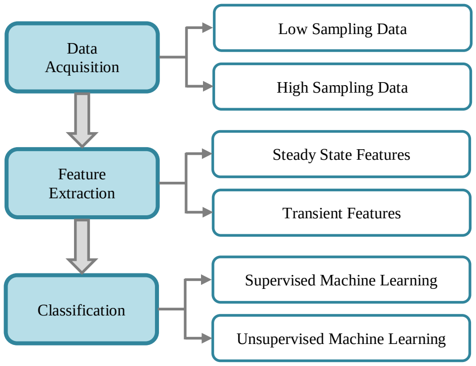

Fig. 2. Traditional NILM System Framework

Acquisition of the aggregated load data is a pre-requisite for any of the NILM systems. The aggregated load data can be composed of different variables (power, current, voltage, power factor etc.), and sampling rates. Feature extraction is a process to extract unique features (also referred to as signatures) from the acquired data. It can be broadly divided into two classes namely steady state and transient features. Both steady state and transient features are intended to identify the state changes in the operation of an appliance but differ in what data they are focusing on. The last component of the NILM system is classification and refers to the process of analyzing the features extracted from the acquired aggregated load data to identify specific appliances.

Early NILM research was focused on the disaggregation of high consumption loads [19-21]. Recently many of the algorithms are mainly focusing on high sampling rates [22] giving the opportunity to incorporate more appliance's electrical features [23]. This leads to accurately classify a greater number of appliances [2]. High and low sampling rates lead to the extraction of transient and steady-state features respectively. Armel et al. [2] presented a comprehensive analysis of the sampling rate (at which the aggregate data are acquired) and the corresponding number of appliances to be classified.

The working principle of the available NILM systems can be classified to be either event-based or non-event based [24] working principle of the method. The event-based NILM relies on event detection by using different edge detection algorithms on the acquired aggregated load data. Later-on features are captured from the extracted events and classified by a different set of rules using machine-learning algorithms. Figueiredo et al. [25] successfully detected steady state step changes, and features were classified by means of machine learning algorithms. On the other hand, the non-event based NILM does not rely on edge detection algorithms before the classification stage. Rather, all the samples of the acquired aggregated load data are considered for inference using statistical models such as Hidden Markov Model (HMM) [26-28]. A comparison between event-based and non-event based NILM is presented in Table I [7].

B. Event-Based NILM

An event is a fragment of a signal that deviates from the previous steady state and lasts until the next steady state has

TABLE I. COMPARISON OF EVENT-BASED AND NON-EVENT BASED NILM

Event-Based	**Non-Event Based**
It is computationally efficient due to event detection inference carried out only on the detected events.	Non-event based inference is carried out on all samples of the data. Hence, computational cost increases [29-31].
Events' false detection or misdetection may lead to errors.	Wrong estimation errors for a given sample can be corrected.

been reached [32]. Here it is worth mentioning that the turning ON and turning OFF of an appliance are considered as distinct events having their own starting and ending time respectively, as shown in Fig. 3.

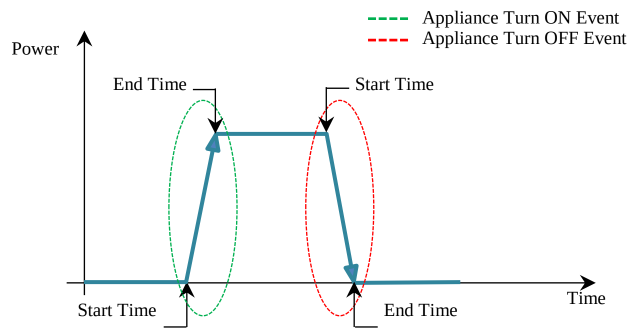

Fig. 3. Graphical Representation of an Event

The purpose of the event detection algorithm is to identify all turning ON and OFF edges of appliances within the acquired aggregated load data. A traditional event-based NILM system consists of data acquisition, data pre-processing, edge detection, feature extraction, and appliance classification [14]. After the aggregated load data are acquired, data pre-processing can be carried out to tackle power (load) measurement uncertainties. Data pre-processing can be performed either in the form of power normalization, thresholding, or filtering. The former aims at preventing uncertainties arising from data fluctuation that could cause misleading appliances' events. Thresholding aims at eliminating small power loads and the base-load from appliances that are running permanently and would both appear as noise. Lastly filtering is used for data smoothing and eliminating sudden peaks [13]. Later, edge detection is carried out to identify the events of appliances' turning ON and OFF. This is followed by the features extraction stage and finally, classification is done based on the extracted features.

To date, numerous event detection algorithms have been proposed and developed with diversity in terms of variables, data granularity, and techniques. Most of the existing work is based on appliance consumed power as an input variable with some exceptions, e.g., current harmonics used as an input feature to detect the events [32, 33]. De Baets et al. [29] performed event detection in the frequency domain by taking active power as input feature at a sampling rate of 60 Hz. Girmay et al. [34] proposed a time-frequency based event detection using a goodness-of-fit Chi-squared test.

This paper proposes two low complexity and computationally fast event detection algorithms based on two different statistical features, namely variance and mean absolute deviation. The remaining of this paper is structured as follows: Section II presents the detailed phenomenon and working principle of the proposed algorithms; Section III presents the simulation studies and the corresponding results along with the performance evaluation. Sections IV and V present sensitivity and comparative analysis of the proposed algorithms respectively. Conclusions are drawn in Section VI.

II. Proposed Algorithms

This section presents the proposed algorithms with details of their basic working principles and implementation. The basic principle of both algorithms relies on a sliding window that runs over the acquired aggregated load data to extract distinct events. This is graphically presented in Fig. 4.

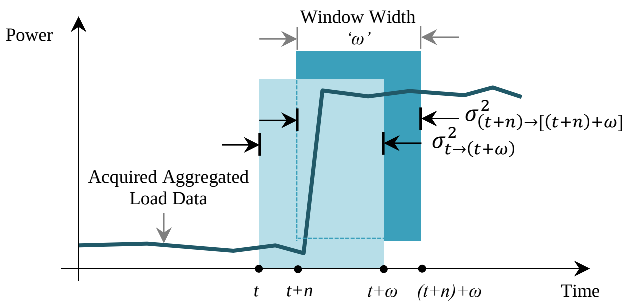

Fig. 4. Working Principle of the Proposed Algorithms

The sliding window of each algorithm tracks different statistical measures namely variance 'σ^2' and mean absolute deviation '*MAD*'. These measures are described in (2) and (3) respectively,

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}|\boldsymbol{x}_i - \mu_x|^2 \tag{2}$$

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|\boldsymbol{x}_i - \mu_x| \tag{3}$$

where μ_x is the mean of $\boldsymbol{x}$ as shown below in (4)

$$\mu = \frac{1}{n}\sum_{i=1}^{n}\boldsymbol{x}_i \tag{4}$$

The proposed algorithms are based on variance and mean absolute deviation and are then called hereafter *Variance Sliding Window* (VSW) and *Mean Absolute Deviation Sliding Window* (MAD-SW) algorithms respectively. The output of both proposed algorithms is in the form of starting and ending time indices of the detected events from the acquired aggregated load data. The descriptions of the proposed algorithms are as follows:

Algorithm

Input: Aggregated Load Data
Output: Start and End Time Indices of Detected Events

1. Acquire aggregated load data and process the data using median filtering technique
2. Select the sliding window width 'ω'
3. Initialize the filter with the corresponding statistical feature, i.e., $\boldsymbol{\sigma^2}$ or *MAD* (depending on the applied algorithm)
4. Using sliding window technique, compute iteratively the corresponding statistical features, i.e., $\boldsymbol{\sigma^2}$ or *MAD* (depending on the applied algorithm)
5. Select a threshold value 'δ' and compute the threshold signal representing the steady states and transient states
6. Use the derivation function to compute the corresponding edges and extract the starting and ending time instances of the detected events
7. Post-processing, i.e., event approval and delay correction due to window width

Detailed steps of the proposed algorithms are represented graphically in form of a flowchart as shown in Fig. 5.

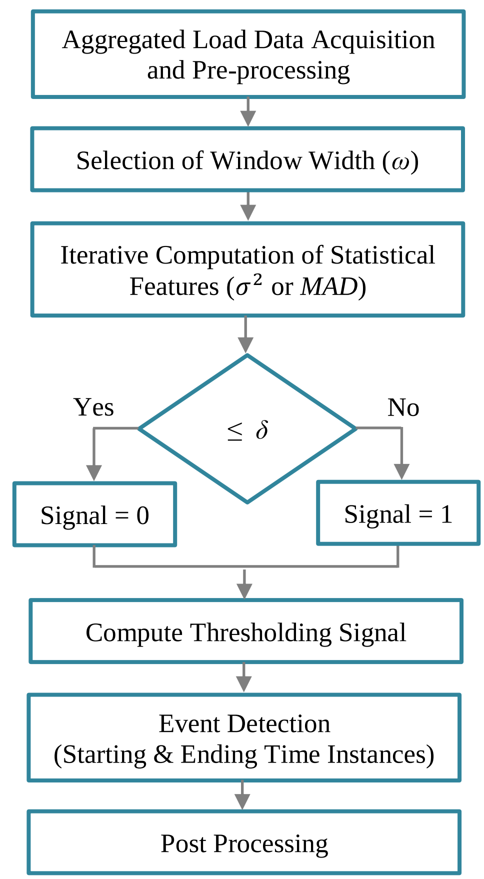

Fig. 5. Flow Chart of the Proposed Algorithms

III. Simulation and Results

For a realistic testing of the proposed algorithms, simulation studies have been carried out based on a comprehensive real-world dataset: Dataport [35]. Dataport is the largest load disaggregation data source, operated and owned by Pecan Street Inc., a non-profit research institute founded in 2009. Dataport is comprised of electricity consumption profiles for 722 houses [36] in the United States of America at a low sampling rate of 1 minute. Every house consists of aggregated average power consumption data as well as power consumption profiles of more than ten different appliances including but not limited to, air condition, microwave, dishwasher, oven, furnace, refrigerator etc. Furthermore, the ground-truth[1] power signals of the said appliances are also available in Dataport.

A. Simulation Parameters

Simulations have been carried out on a total of 360 hours (15 days) of aggregated load data acquired from Dataport. MATLAB has been used as the primary computational tool. As the simulations are run on real-world data, (aggregated) power measurement uncertainties need to be taken care of before applying the event detection algorithm. In this paper, power measurement uncertainties in form of noise/data spikes are considered. In order to remove these spikes, for avoiding any interference with event detection, median filtering is used as a data pre-processing technique [37]. The threshold value 'δ' has been selected to 250W. This value leads to the reduction of errors due to minor fluctuations in the acquired aggregated load data. It is also more viable for the events detection of high consumption appliances such as *Electric Vehicle* (EV) charging and *Air Conditioning* (AC).

To define the needed accuracy of the proposed algorithm to perform well, a parameter named as a delay tolerance 'Δt' is introduced. A detected event will be considered as a true positive if and only if $|t_g - t_d| \leq \Delta t$, where t_g is the starting time of ground-truth event and t_d is the starting time of the detected event by the proposed algorithm. Sensitivity analysis on delay tolerance has not been carried out in the present simulations and Δt has been set equal to zero. Similarly, for the presented simulations and corresponding results, the window width has been kept constant to 5 samples. A comprehensive sensitivity analysis in terms of window width will be discussed in Section IV. Table II presents various parameters regarding Dataport and the proposed algorithms used for the simulation studies and results.

TABLE II. SIMULATION PARAMETERS REGARDING DATAPORT AND ALGORITHMS

Dataport Data ID	26
Data Timeframe	June 18 - July 2, 2014
Sampling Rate	1/60 Hz (1 minute)
No. of Data Samples	21600
Window Width 'ω'	5 samples
Pre-processing Technique	Filtering (Median Filter)
Threshold Value 'δ'	250 W
Delay Tolerance 'Δt'	Zero

B. Results and Evaluation

For results and evaluation purposes, the starting time indices[2] of the detected events are considered because they initiate the events regardless whether that event is related to appliance turning ON or turning OFF. Furthermore, this paper is considering two specific appliances for evaluation purposes: EV and AC. These appliances are selected due to their high-energy consumption and their corresponding future impacts on the energy market. Hence, these high consumption loads can be a potential flexibility control and consumption/bills reduction lever from the grid and consumer point of view, respectively. Moreover, high consumption appliances are more viable to accurately disaggregate while acquiring the aggregated load data at low sampling rate. The EV energy consumption profile is also of interest as it has been less studied in the available literature in terms of NILM. For example, Clements-Nyns et al. [38] analyzed the impact of EV charging and found it as a significant load element specifically for smart grid system analysis.

Table III presents the results of the VSW algorithm in form of starting time indices of the detected events along with the corresponding sequence number.

TABLE III. VSW ALGORITHM RESULTS

Detected Events' Sequence	Starting Time Indices of the Events		
	VSW Algorithm's Detection	Ground Truth Data	
		AC	EV
1	16	16	-
2	54	54	-
3	96	95	-
14	1101	1101	-
15	1135	1135	-
16	1185	-	1185
17	1238	1238	-
18	1272	1272	-
19	1281	-	1281
20	1298	-	1298
21	1318	1317	-
Not Detected		3715	-
Not Detected		4153	-
97	6210	6210	-
98	6234	-	6234
99	6247	-	6246
100	6502	-	6502
101	6615	-	6614
102	6643	6643	-
103	6686	6686	-
Not Detected		9780	-
147	9837	-	9836
148	9879	9878	-
149	9923	9922	-
150	9949	-	9949
Not Detected		-	10020
207	13968	13968	-
208	14030	14030	-
209	14083	14083	-
261	16945	No Actual Event Occurred	
262	16970	No Actual Event Occurred	
321	21058	-	21058
322	21083	-	21083
323	21103	21103	-
324	21160	-	21159

For comparison purposes, the ground-truth starting time indices of the events related to the appliances, i.e., AC and EV, are also presented in Table III. It can be observed that most of the events are precisely detected by the VSW algorithm albeit with some misdetection. For example, AC and EV trigger events at time indices 3,715 and 10,020 respectively but the

[1] Ground-truth refers to the time indices representing when the events actually occur.
[2] Starting time indices of detected events presented in Tables III and IV, and that on the abscissas of Figs. 6-9 are same.

VSW algorithm does not detect these events at all, leading to false negative detections. Whilst the VSW algorithm detected events at time indices 16,945 and 16,970 but no actual ground-truth events are present at these instances; this leads to false positive detections. Similarly, due to zero delay tolerance, events detected at sequence number 3, 21, 99… are not considered as true positive detections.

The results for the MAD-SW algorithm are presented in the same way. Table IV presents the starting time indices and the corresponding sequence number of the detected events by MAD-SW algorithm along with the ground-truth starting time indices of the events of the two said appliances. It is noteworthy that the ground-truth data of appliances shown in Tables III and IV are acquired for the same data identification (ID) and timeframe as presented in Table II. It can be observed from the results presented in Table IV, that most of the events are precisely detected by the MAD-SW algorithm albeit with some misdetection.

TABLE IV. MAD-SW ALGORITHM RESULTS

Detected Events' Sequence	Starting Time Indices of the Events		
	MAD-SW Algorithm's Detection	Ground Truth Data	
		AC	EV
1	16	16	-
2	54	54	-
3	95	95	-
20	1298	-	1298
21	1317	1317	-
22	1326	1326	-
23	1392	1392	-
24	1432	1432	-
76	4874	-	4874
77	4916	-	4916
78	5117	-	5117
79	5218	5218	-
Not Detected		5361	-
Not Detected		6800	-
149	9774	-	9774
150	9780	9780	-
151	9836	-	9836
152	9878	9878	-
216	13968	13968	-
217	14011	-	14011
218	14030	14030	-
219	14083	14083	-
220	14119	-	14119
317	19960	-	19960
318	19989	-	19989
319	20015	-	20014
320	20115	No Actual Event Occurred	
321	20170	20171	-
322	20251	20251	-
338	21058	-	21058
339	21083	-	21083
340	21103	21103	-
341	21125	No Actual Event Occurred	
342	21159	-	21159
343	21174	No Actual Event Occurred	

For parameters presented in Table II, the total number of detected events by VSW and MAD-SW algorithms are 324 and 343 respectively. It is worth mentioning here that, due to space limitation Tables III and IV present a portion only of the detected events by VSW and MAD-SW respectively. Fig. 6 graphically presents a portion of the detection results by the VSW algorithm in terms of pre-processed acquired aggregated load data and the final output of the algorithm in form of starting time indices of the detected events.

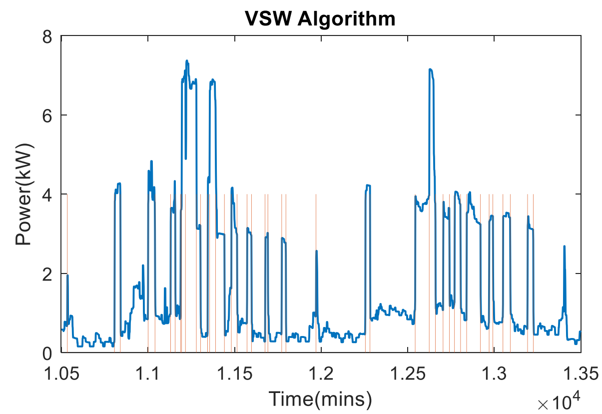

Fig. 6. Pre-processed aggregated load data (in dark cyan) and events detected by the VSW algorithm (in orange)

To further elaborate the results, Fig. 7 graphically presents the detected events and their comparison with the ground-truth signal of the appliances under consideration: AC and EV.

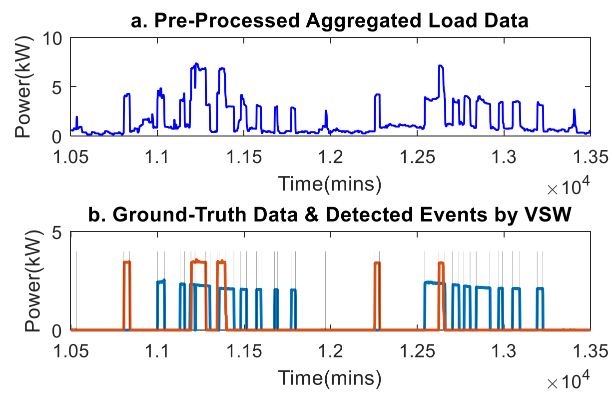

Fig. 7. (a) Pre-processed acquired aggregated load data, (b) Ground-truth signal of AC and EV appears in dark cyan and orange color respectively along with the events detected by VSW algorithm appearing in black

Likewise, Figs. 8 and 9 depict the event detection results of the MAD-SW algorithm and comparison of detected events with the ground-truth signal of the appliances respectively.

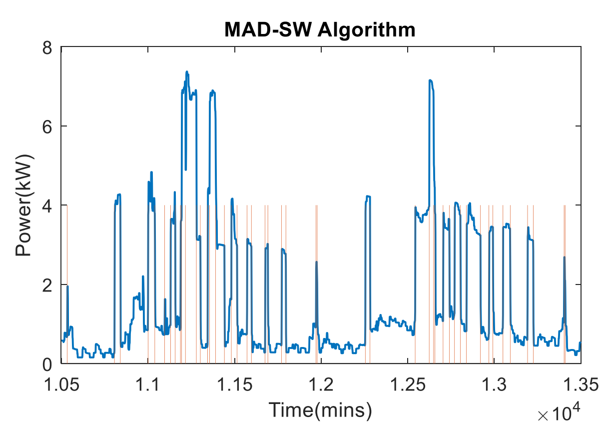

Fig. 8. Pre-processed aggregated load data (in dark cyan) and events detected by the MAD-SW algorithm (in orange)

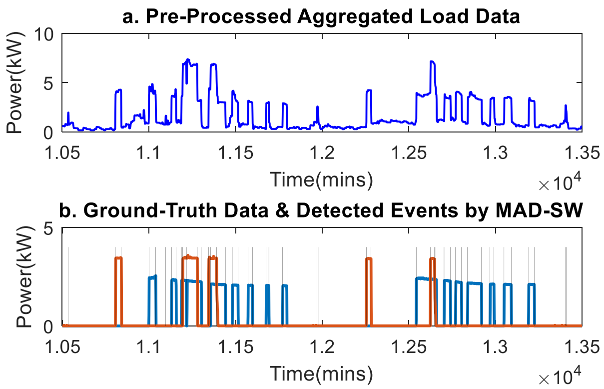

Fig. 9. (a) Pre-processed acquired aggregated data using median filtering, (b) Ground-truth signal of AC and EV appears in dark cyan and orange respectively along with the events detected by MAD-SW algorithm appearing in black color

It is evident from Figs. 6 and 8 that most of the high consumption peaks in the acquired aggregated load data are effectively detected comparatively to the lower variation in the aggregated data. This is expected and required because of the pre-defined parameters presented in Table II particularly the acquired aggregated data granularity and the threshold value [39] of 1/60 Hz and 250W respectively.

For evaluating the performance of the proposed algorithms, this paper opted for widely used performance metrics, namely precision, and recall [17]. Precision is defined as the ratio between truly detected and overall detected events and is given in (5),

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive+False Positive}} \tag{5}$$

Recall is a measure of the detection of events occurred in reality and is given in (6),

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \tag{6}$$

The definitions of true positive, false positive, and false negative are given [40] in Table V.

TABLE V. TERMINOLOGIES DESCRIPTION

Algorithm Prediction	**Actual Event Occurred**	**Actual Event Didn't Occur**
Detected	*True Positive*	*False Positive*
Not Detected	*False Negative*	*True Negative*

Based on these metrics, the performance of the proposed algorithms (as per the simulation parameters presented in Table II) are presented in Table VI.

TABLE VI. PROPOSED ALGORITHM PERFORMANCE

Performance Metric	**VSW Algorithm**	**MAD-SW Algorithm**
True Positive	261	300
False Negative	67	29
False Positive	63	43
Precision	80.556 %	87.464 %
Recall	79.573 %	91.185 %

It is evident from Table VI that due to a low number of false negative and false positive (particularly for input parameters presented in Table II), the proposed MAD-SW outperforms VSW both in terms of recall and precision.

IV. SENSITIVITY STUDIES

The proposed algorithms are comprised of different input parameters that can affect their performance, e.g., sliding window width 'ω', delay tolerance 'Δt', and threshold value 'δ'. Within the scope of this paper, a sensitivity analysis has been carried out to investigate the effects of the sliding window width 'ω' on the performance of the algorithms where the rest of the parameters are kept constant as presented in Table II. Fig. 10 presents the corresponding results of the sensitivity analysis in terms of precision and recall performance metrics for the VSW algorithm.

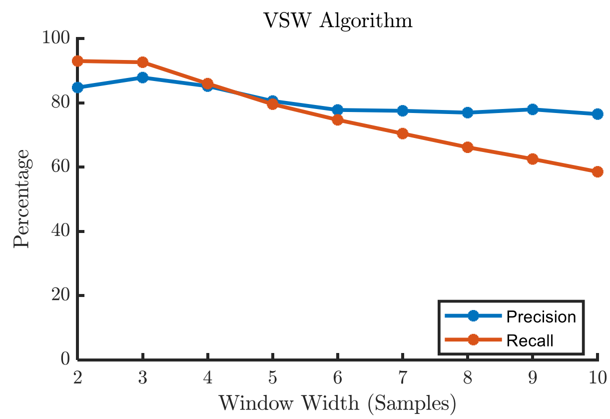

Fig. 10. Effect of 'ω' on Performance of VSW Algorithm

The sensitivity analysis in terms of window width leads to the conclusion that overall performance (in terms of precision and recall) of the VSW algorithm is optimal at ω equals to 3. Furthermore, the recall metric shows a continuous drop with increasing window width. This is due to the increase in the false negative detection as a function of window width.
Similarly, Fig. 11 depicts the sensitivity analysis results in terms of precision and recall for the MAD-SW algorithm.

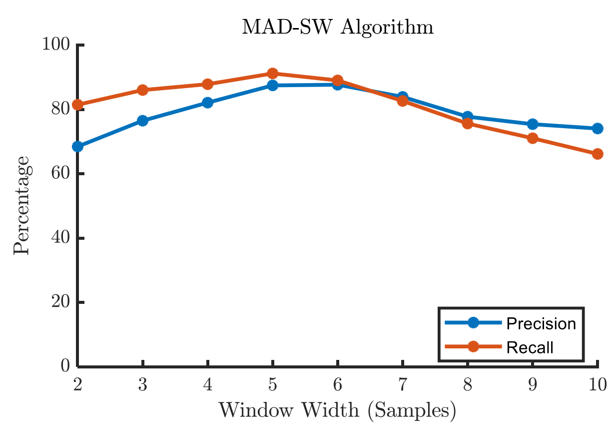

Fig. 11. Effect of 'ω' on Performance of MAD-SW Algorithm

It is observed that the proposed MAD-SW algorithm optimally performs at a window width of 5. For ω>5 the overall performance in terms of precision and recall shows a continuous drop. The drop is due to the rise of false positive and false negative respectively.

As a result, it is concluded that increasing the window width leads to an increase in false positive and false negative detections. Consequently, the performance of both algorithms degrades. Overall this sensitivity analysis leads to the conclusion that the optimal performances of the proposed algorithms rely on the selection of an optimal value for the input parameter ω which varies according to the algorithm.

V. Comparative Analysis

In order to validate the proposed algorithms, a comparative analysis has been carried out where the VSW and MAD-SW algorithms are compared with the existing event detection algorithm known as High Accuracy NILM Detector (HAND) [41]. The HAND algorithm tracks the standard deviation of the aggregated load data using a moving window. The HAND algorithm has been implemented, and simulations have been carried out using the same parameters as presented in Table II. Fig. 12 graphically compares of the proposed algorithms against the HAND in terms of precision performance metrics at different window width.

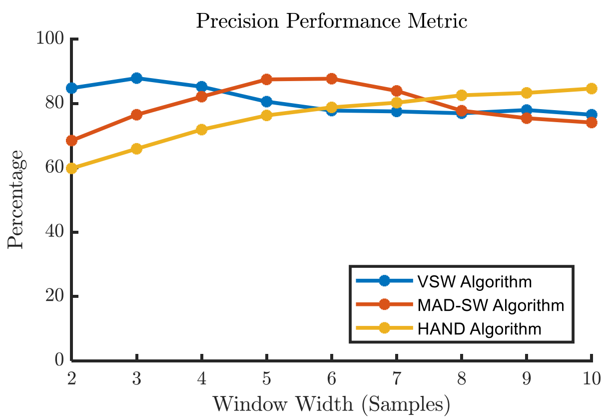

Fig. 12. Precision Performance Metric Comparison

Similarly, Fig. 13 depicts comparative results of VSW, MAD-SW, and HAND algorithms in terms of recall performance metric for different values of ω.

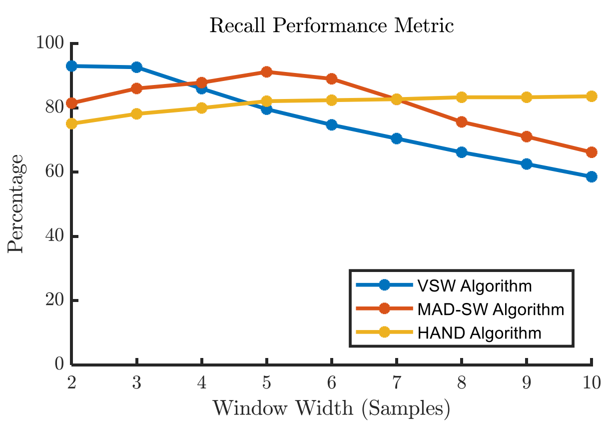

Fig. 13. Recall Performance Metric Comparison

It is evident from the comparative analysis presented in Figs. 12 and 13 that, at ω equal to 2 and 3, the VSW algorithm outperforms the other algorithms in terms of overall performance, i.e., precision and recall. For ω equals to 5 and 6, the MAD-SW algorithm outperforms the other algorithms. The HAND algorithm has optimal results for $\omega \geq 8$ for which the proposed algorithms are not performing optimally. Furthermore, it is observed that with the increase in window width, the false positive and false negative detections by the HAND algorithm decrease thereby increasing its overall performance. It is concluded that each algorithm performs optimally at different window widths ω.

VI. Conclusion

This paper proposed two new event detection algorithms namely, VSW and MAD-SW algorithms, for event-based NILM systems based on statistical features and a sliding window. Beside low complexity, the proposed algorithms are computationally fast due to their iterative computational method.

Computational simulation studies were carried out on a real-world load data set and the proposed algorithms were compared against an existing event detection algorithm. It is shown that the outcome of the proposed algorithms is promising in terms of performance metrics. The window width sensitivity analysis for the proposed algorithms has shown that there is a tradeoff between the selection of an optimal window width and optimal performance. It is also observed that both proposed algorithms follow a trend of performance degradation with an increase in window width beyond the optimal window width value.

Future work will focus on the validation of the robustness of the proposed algorithms by testing them on different data sampling rate, particularly low sampling rate. To further investigate the effect of window width on the performance of the proposed algorithms, an extended sensitivity analysis will be carried out by considering different input parameters, namely, delay tolerance and threshold value. Finally, power measurement uncertainties, which could affect the event detection, would need to be investigated.

VII. Acknowledgment

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IX. Biographies

Attique Ur Rehman received the B.E. degree in electrical engineering from Air University, Islamabad, Pakistan in 2009, and the M.Sc. degree in electrical engineering, information technology and computer engineering from RWTH Aachen University, Germany in 2013. Currently, he is pursuing his Ph.D. degree from Auckland University of Technology, New Zealand.

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Prof. Lie has regularly attracted external funding for projects with industry and supervises several postgraduate students on a wide range of research topics.

Brice Vallès received his Ph.D. degree in fluid mechanics from Norwegian University of Science and Technology, Norway in 2001.

He has more than 15 years of experience in data science and energy sector that includes Schlumberger and IRIS in Norway. Since 2010 within New Zealand, he worked in different roles at UniServices, Inland Revenue and Genesis. Currently, he is working as a Wholesale Analytics Manager at Genesis Energy Ltd. New Zealand. His keen interest is in sequential data assimilation to update simulation models in real time.

Dr. Vallès is also actively involved in business development, strategy, planning, and marketing.

Dr. Shafiqur Rahman Tito obtained his Ph.D. degree in electrical engineering from Auckland University of Technology in 2016.

His employment experience included 12 years of teaching at different national and international level. He also worked as a Program Leader of Electrical Engineering at International College of Auckland, New Zealand. Currently, he is working as a Lecturer at Manukau Institute of Technology, New Zealand. His fields of research included Energy Optimization and Hybrid Renewable Energy Systems.

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