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Non-invasive load-shed authentication model for demand response applications assisted by event-based non-intrusive load monitoring

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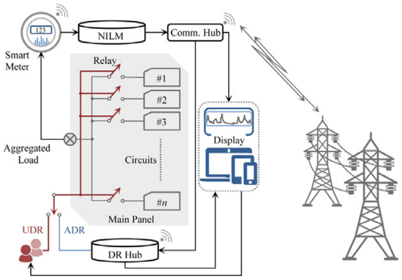
HIGHLIGHTS

- Proposes a non-invasive load-shed authentication model for demand response applications.
- Presents an enhanced event-based non-intrusive load monitoring approach assisted by an improved event detector and supervised machine learning based classification model.
- Validates the proposed model using a comprehensive real-world case-study based on high potential demand response load elements.
- Realizes the real-world scenario by employing low sampling load measurements for simulation and performance evaluation purposes.

GRAPHICAL ABSTRACT



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ABSTRACT

With today's growth of prosumers and renewable energy resources, it is inevitable to incorporate the demand-side approaches for reliable and sustainable grid operation. In this context, demand response is a promising technique facilitating the consumers to play a substantial role in the energy market by altering their energy consumption patterns in times of peak demand or other critical contingencies. However, effective demand response deployment faces numerous challenges including trust deficit among the concerned stakeholders. This paper addresses the mentioned issue by proposing a non-invasive load-shed authentication model for demand response applications, assisted by an improved event-based non-intrusive load monitoring approach. For the said purposes, an improved event detection algorithm and machine learning model: support vector machine with a combination of genetic algorithm and GridSearchCV, is presented. This paper also presents a comprehensive real-world case study to validate the effectiveness of the proposed model in a real-life scenario. In the given context, all the simulations are carried out on low sampling real-world load measurements: Pecan Street-Dataport, where electric vehicle and air conditioning are employed as potential load elements for evaluation purposes. Based on the presented case study and analysis of the results, it is established that the presented improved event-based non-intrusive load monitoring approach yields promising performance in the context of multi-class classification. Moreover, it is also concluded that the proposed low sampling event-based non-intrusive load monitoring assisted non-invasive load-shed authentication model is a viable and promising solution for the effective implementation of demand response applications.

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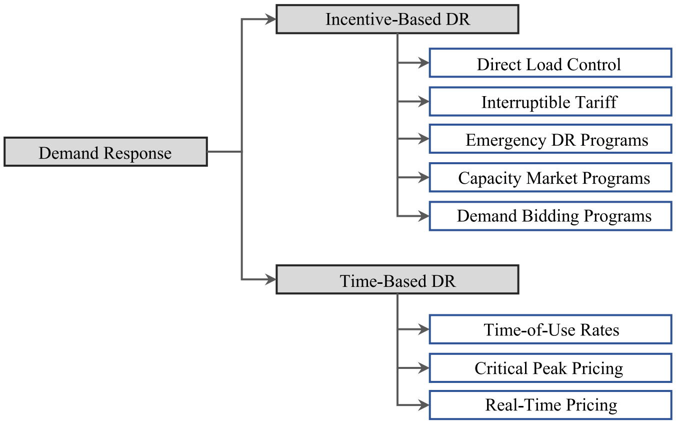

Fig. 1. Types of Demand Response Programs

1. Introduction

In today's power systems, the distributed renewable energy sources (DRES) play a key role and the amount of electricity generated by DRES is ever increasing. In a recent report, the International Energy Agency (IEA) forecasts that the share of renewable energy will accounts for over 40 percent of total generation by the year 2040 [1]. However, the intermittent and widely distributed nature of DRES poses a significant peril to the reliability of the power grid. To address these challenges of DRES, today's end-use facilities need to be more active and responsive to the power grid operations. In this context, the concept of smart grid (SG) is widely acknowledged, due to its incorporation of end-use facilities, i.e., going beyond the meter and exploring the end-user devices and demand-side energy management systems. In the smart grid environment, effective energy monitoring is inevitable and the recent worldwide deployment of smart meters plays a key role in the mentioned context. Today, the smart meter data analytics maximize the benefits of the SG [2] by contributing significantly towards load analysis, load forecasting, and load management [3].

1.1. Demand Response

Demand response (DR) is one of the many widely used applications adopted in the context of energy efficiency and conservation. DR refers to the approaches that alter the consumers' energy consumption either by reducing, shedding, or shifting loads to maintain equilibrium between power supply and demand. It is a key element of today's modern grid systems particularly in the presence of increasing numbers of DRES, as it plays a significant role in terms of improving grid reliability [4]. In the given context, a comprehensive survey covering numerous aspects of DR programs is presented in [5]. Further, Han and Piette [6] also present a comprehensive overview of DR programs and categorize DR into two main types: incentive-based and time-based DR. The former refers to the programs where the end-users get preferential tariff rates for altering their energy consumption patterns in times of system's contingencies. The latter is built on rising price signals and the corresponding reduction of end-users' energy consumption [6]. The two types of DR can be further categorized as presented in Fig. 1 and further details are given in [6].

Another aspect of DR is the corresponding controlling strategies of end-users' facilities, which play a key role in the effective deployment of DR programs. In this context, Piette et al. [4] classified the DR control into three categories: manual, semi-automated, and automated demand response programs. Manual DR, here referred to as user-assisted DR (UDR), is a technique where individual loads are controlled physically by the end-users based on the received DR instructions. Semi-automated DR refers to an approach where a pre-programmed DR strategy is initiated by a person via a centralized control system [4]. Finally, automated DR (ADR) refers to an approach that is completely non-invasive in terms of human involvement.

1.2. Non-Intrusive Load Monitoring

Effective energy monitoring is a way forward to energy efficiency and conservation. Energy monitoring can be carried out at different granularity levels broadly classified into two categories namely, aggregated and segregated energy monitoring, as shown in Fig. 2 [7]. Segregated energy monitoring, also referred to as load disaggregation, is an approach that converts aggregated load into appliance-level feedback. Load disaggregation can be performed using either intrusive load monitoring technique (ILM) or non-intrusive load monitoring (NILM) technique, as presented in Fig. 2. Intrusive load monitoring requires dedicated submetering (in addition to main metering device, i.e., smart meter), making it more intrusive in nature and non-scalable in the broader context of SG [2]. Contrary, the non-intrusive load monitoring technique requires a single main metering device and mainly relies on numerous software approaches to estimate the appliance-level information from the aggregated load data measured at a single metering point. NILM is a non-invasive and cost-efficient load disaggregation technique, consequently, it is one of the widely used load disaggregation techniques.

NILM methodologies are broadly classified into event-based and state-based approaches [8]. State-based NILM, also referred to as non-event or event-less NILM, represents the appliances' operation as a finite state machine and inference is performed using the state transition models, e.g., the hidden Markov model and its variants [2, 9]. On the other hand, event-based NILM methodology relies on the detection of an event (appliance state transition, i.e., turn- on or off). Later, the extracted features of the detected events are classified using diverse classification algorithms. Event-based NILM methodology is widely adopted due to its computational efficiency as compared to state-based NILM [2, 10]. An event-based NILM comprises four key components namely, data acquisition, event detection, feature extraction, and load classification. Fig. 3 graphically depicts an event-based NILM framework, further details regarding different aspects of NILM can be found in [8,11–15].

The NILM-based appliance-level feedback can significantly facilitate different stakeholders in the context of energy efficiency and conservation, as numerous studies established that providing real-time appliance-level consumption information could yield greater electricity-saving [16]. In the given context, the recent development of computational capabilities facilitates the NILM research and numerous work has been done by the research community. Among different components of the NILM system (Fig. 3), load classification is a key research focus where the researchers employed diverse techniques such as optimization [2,17], machine learning [18,19], artificial neural networks [20], and deep learning [21,22], towards accurate load classification.

1.3. Motivation and Contribution

Many research works have been done in the context of mentioned energy efficiency applications: DR programs and NILM systems. In the context of demand response, the research community not only developed numerous DR strategies but also successfully deployed them in different parts of the world. For example, Azuatalam et al. [23] investigated the feasibility of reinforcement learning to efficiently schedule and control the heating, ventilation, and air conditioning (HVAC) system in a commercial building for demand response purposes. The authors of [24,25] presented a comprehensive survey and overview regarding demand response programs. In terms of real-world deployment, the authors of [26] presented different case studies that are based on ADR programs for smart buildings and microgrids in different geographical regions. In New Zealand (NZ), a ripple control system for hot water cir-

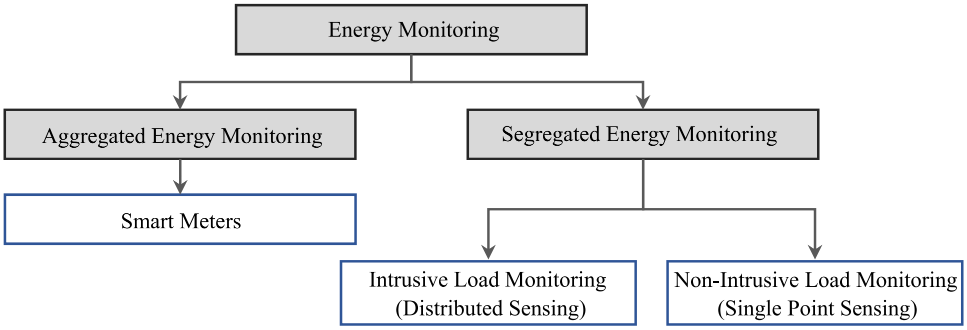

Fig. 2. Energy Monitoring Hierarchy

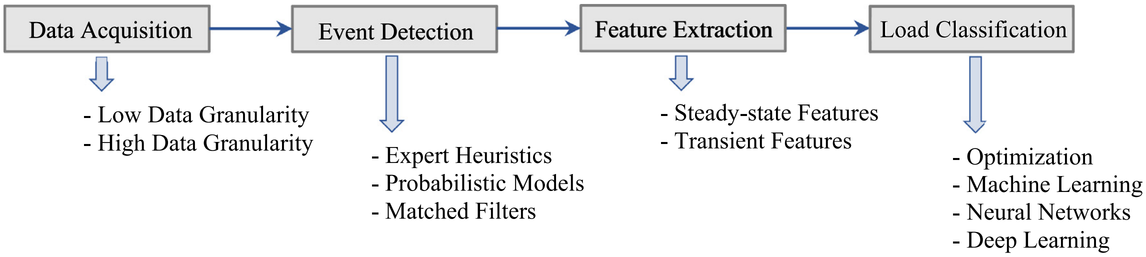

Fig. 3. Event-based NILM Methodology

cuits is introduced in the 1950s [27]. Further, Transpower[1] NZ, which owns and operates the national grid, started its early DR trials in 2007. Later in 2011, Transpower purchased a DR management system to further scale up its DR programs [28]. Despite being used for a long, the DR strategies are still an open research domain with constraints that limits their effective deployment in a real-world scenario. In this context, trust deficiency among DR program stakeholders is one of the constraints that limit the effective implementation of the DR program.

Likewise, in the context of NILM, tremendous research has been done in the last decade, however, most of the mentioned research focuses on algorithms' enhancement in terms of the number of appliances' inference and accuracy performance. Consequently, the research trend in the NILM domain revolves around high data granularity [2], as high sampling NILM systems yield a large number of appliances' inference with higher accuracy [16]. But high sampling NILM systems are cost prohibitive due to complex and high-end hardware requirements for data acquisition [12]. Further, high sampling NILM systems are not a viable option for the existing metering infrastructure, as the commercially available metering devices are not capable of data measurements at high sampling rates. Moreover, due to the more focus on NILM algorithms' improvement, very limited research has been done in terms of the actionable feedback of NILM systems to realize its real potential in terms of real-world energy efficiency applications.

To address these limitations, a system having interlinked modules of NILM and DR would be of great interest to the concerned stakeholders. Because appliance-level NILM feedback can significantly facilitate the DR program in numerous ways, as discussed in [29], where the NILM applications for DR are broadly categorized into offline and online NILM applications. The offline application relies on low data granularity for load disaggregation and can facilitate the concerned stakeholders in short-term as well as long-term perspective. In the short-term, the NILM provides individual loads' 24-hour operation status and corresponding consumption pattern. From a long-term perspective, the information provided by the NILM system can be highly valuable for day-ahead load-forecasting and consumers' usage patterns estimation [29]. On the other side, the online application relies on high data granularity for load disaggregation in real-time, which is beneficial for applications like buildings' energy equilibrium control [29].

Hence, the mentioned limitations of the existing DR and NILM literature and potential scope of an interlinked NILM and DR modules motivate us to carry out this research work, which addresses not only the research gaps in the context of DR and NILM domains but also provides a promising solution towards energy efficient systems. In the given context, this research work presents an offline application of the NILM system for the DR program, which not only addresses the shortcoming of research in the context of NILM applications but also addresses the trust-deficiency issue among the DR stakeholders in terms of effective load monitoring. Therefore, this research work presents a non-invasive load-shed authentication model assisted by a state-of-the-art NILM system for the effective deployment of demand response applications. The contributions of this research work are summarized as,

1 Presents a low complexity and improved event-based NILM approach for real-world low-sampling load measurements, having data granularity of 0.016 Hz.
2 Proposes a non-invasive load-shed authentication model for user-assisted DR program assisted by the presented NILM approach.
3 Presents a detailed performance evaluation along with a comprehensive real-world case study of the proposed model.

The rest of the paper is organized as follows: Section 2 presents the system design in terms of the research statement, proposed model, and evaluation criteria. Research methodologies, simulation studies, and analysis of the corresponding results are presented in Section 3. A real-world case study is presented in Section 4. Future research outlook and the conclusion of this study are presented in Sections 5 and 6, respectively.

2. System Design

This section presents comprehensive details of the system design in the context of the research statement, proposed non-invasive load-shed authentication model, and performance evaluation criteria.

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[1] https://www.transpower.co.nz/

2.1. Research Statement

Energy consumers require reliable energy and for the said, the utility providers strive to maintain an equilibrium between supply and demand. However, on occasions, the consumers start utilizing more energy and most importantly simultaneously, such as turning on the air conditioning units during hot summer days, and it is probable that this exhausts the available energy sources and puts stress on the power grid. The corresponding time and demand are referred to as peak time and peak demand, respectively. Moreover, if the peak demand exceeds the available energy supply, this may also cause energy disruptions. To address this short-term energy demand-supply issue, the utilities have two ways: either to build specialized powerplants namely, peaking power plants[2], or initiate demand response programs. The former is not only requiring huge capital investment but also costly to operate. The latter is an alternative and attractive solution to cater the peak demand, by offering different incentives to consumers to reduce their energy consumption at peak times. In this context, one of the widely adopted DR approaches is load curtailment, commonly referred to as the load-shed approach, where pre-selected consumers' loads are curtailed in time of need, i.e., during the peak demand or system contingencies, subsequently, yielding a significant amount of reduction in energy demand. However, the absence of a trust-worthy business model limits the effective implementation of the load-shed DR approach, as a trade-off exists among consumers and utility providers. For example, if the utilities opted to remotely control the consumers' loads (direct load control strategy), a fair possibility exists that the consumers may confront unpleasant circumstances due to the curtailment of their loads by the utilities at the time of their requirement. On the other hand, if the consumers control their loads by themselves based on the received DR instructions from the utility providers, referred to as the UDR program, there is a possibility that the consumers do not act accordingly while getting incentives from utility provider based on their existing DR agreements. This research work addresses the latter by proposing a non-invasive load-shed authentication model aiming to build a trust model that not only empower the consumers to control their loads but also facilitate the utility providers to effectively monitor the DR enrolled loads and authenticate its compliance with the DR instructions, consequently enabling the utility to eliminate the freeloaders[3].

Towards effective monitoring of DR enrolled loads, NILM can play a significant role. In this context, let us consider that at a single metering point, the time-series load consumption is an algebraic sum of the m number of loads' consumption, given as in (1).

$$\mathrm{L}_{\mathrm{total}}(\mathrm{t}) = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{L}_{\mathrm{i}}(\mathrm{t}) + \mathrm{n}(\mathrm{t}) \tag{1}$$

where $\mathrm{L}_{\mathrm{total}}(\mathrm{t})$, $\mathrm{L}_i(\mathrm{t})$, and $n(t)$ represents the total aggregated load, the load of i^{th} appliance, and measurement noise, respectively, where $i = 1, 2, 3, \ldots, m$. The $n(t)$ comprised of acquisition noise along with other household appliances' consumptions not under consideration. The task of NILM is to estimate the operation state of the individual load, $L_i(t)$, with the only information of aggregated load, $\mathrm{L}_{\mathrm{total}}(\mathrm{t})$. In this context, let us consider a household having A household appliances and a single day has T timeslots, where $\boldsymbol{A}=\{1, 2, \ldots, a, \ldots, A\}$ and $\boldsymbol{T}=\{1, 2, \ldots, t, \ldots, T\}$. During the NILM process, a DR enrolled appliance a, given that $a \in A$, is monitored and estimated for D days, where $\boldsymbol{D}=\{1, 2, \ldots, d, \ldots, D\}$. Under the given conditions, the proposed NILM will monitor and estimate the operation status, s, of the given household appliance, yielding $\mathrm{s}_{\mathrm{a}}^{\mathrm{t,d}}$ as given in (2).

$$\mathrm{s}_{\mathrm{a}}^{\mathrm{t,d}} = \begin{cases} 0, & \text{Appliance turn} - \text{off} \\ 1, & \text{Appliance turn} - \text{on} \end{cases} \tag{2}$$

where, $\mathrm{s}_{\mathrm{a}}^{\mathrm{t,d}}$ represents the operation status: turning-on and turning-off, of the given household appliance a at timeslot t in day d. This outcome of NILM, i.e., $\mathrm{s}_{\mathrm{a}}^{\mathrm{t,d}}$, can be utilized by the utility provider to effectively monitor the operation status of the DR enrolled appliances for DR program compliance purposes, i.e., load-shed authentication of DR enrolled appliances. Consequently, establishing a trust-worthy[4] non-invasive load-shed authentication model that not only facilitates the consumers by empowering them to control their loads and but also enables the utility providers to eliminate the freeloaders by non-invasively monitoring the consumers' DR enrolled load elements without affecting consumers' privacy.

2.2. Proposed Model

Based on the presented research statement, an event-based NILM assisted non-invasive load-shed authentication model for demand response applications is proposed, as presented in Fig. 4. The proposed model comprises different interlinked modules namely, the NILM system, smart DR hub, communication hub, in-house display, smart meter, and relays. Each module has a specific task to perform, such as NILM takes inputs from the smart meter as an aggregated load data and extract appliance-level information using the event-based methodology, presented later in detail. The smart DR hub handles all the DR related instructions/controls information among the concerned stakeholders: consumers and utility providers. Relays are employed to connect/disconnect specific loads according to the DR instructions, where the communication hub is responsible for all the information flow among different modules of the proposed model as well as among the concerned stakeholders: consumers and utility providers.

Effective implementation of non-invasive load-shed authentication involves different stages and flow of information. In this context, Fig. 5 graphically depicts different stages and the corresponding sequential flow of information among the concerned stakeholders in terms of establishing a DR program and pursuing the non-invasive load-shed authentication of enrolled DR loads in case of UDR.

2.3. Performance Evaluation Criteria

As the proposed model primarily relies on the NILM system, hence the reliability of the proposed non-invasive load-shed authentication model is directly linked to the NILM performance. Therefore, the presented event-based NILM is extensively evaluated using well-known performance metrics of accuracy, precision, recall, and f-score [30, 31]. Another performance metric that is rarely used in the NILM context, i.e., the Kappa index, is also employed to evaluate our NILM approach. Kappa index is calculated using both accuracy and expected accuracy [32], and due to its inter-rater reliability[5], it is a more robust measure to evaluate machine learning models. For benchmarking, distinct labels in terms of agreement strength are assigned to a range of Kappa index values [33], presented in Table 1. The higher the Kappa index value the better the agreement; mostly Kappa index > 0.40 is desirable [32]. Further to evaluate the multi-class inference performance of the presented approach, the receiver operating characteristics (ROC) curves and area under the curve (AUC) [34,35] are also employed in this study.

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[2] Generally, peaking power plants, also known as peaker plants, are run only at the times of peak demand.

[3] Freeloaders are those consumers who acknowledge DR instructions but do not act accordingly, while at the same time getting incentives from the utilities based on the pre-existing terms of DR program.

[4] Trust-worthy refers to a state-of-the-art effective monitoring of DR enrolled appliances towards DR compliance authentication.

[5] The degree of agreement between two or more raters.

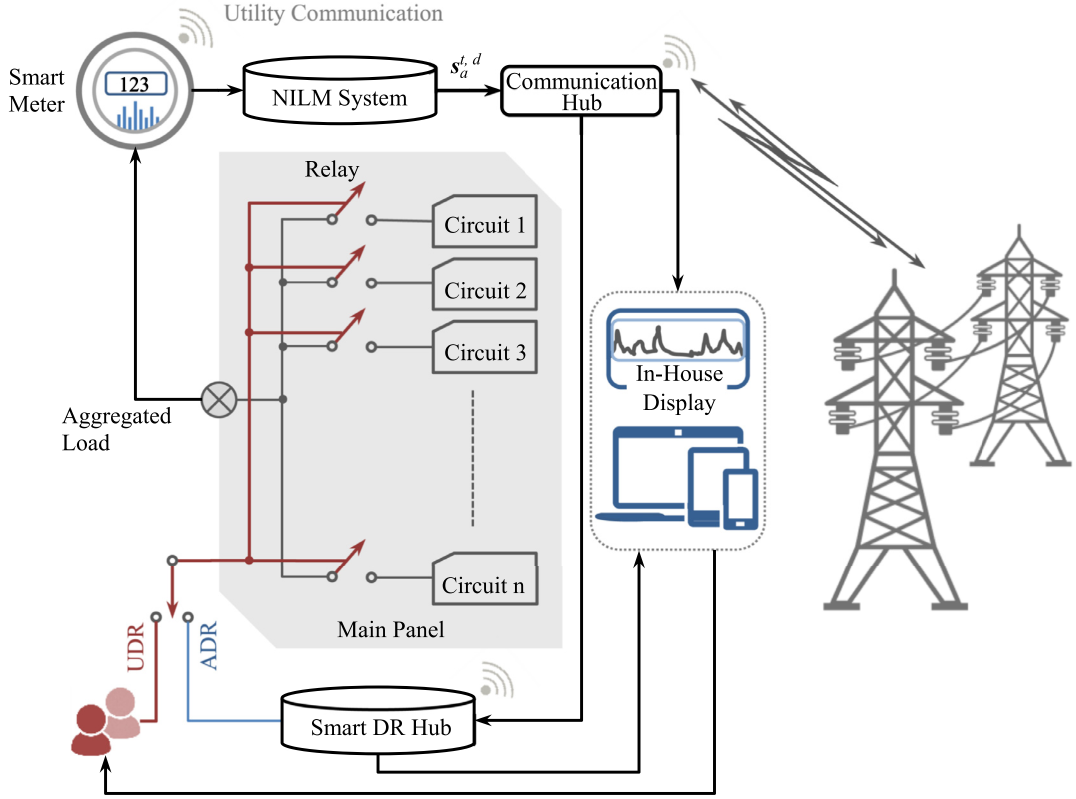

Fig. 4. Proposed NILM Assisted Non-Invasive Load-Shed Model for DR Applications

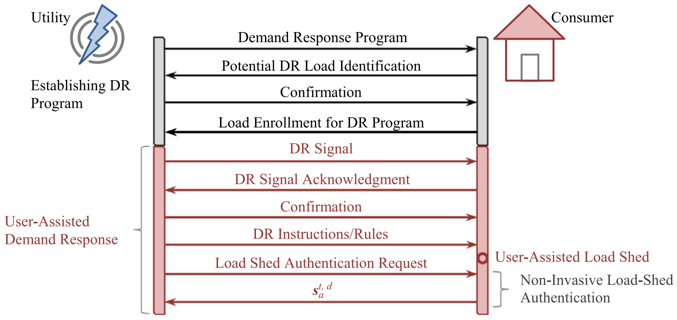

Fig. 5. Information Flow in UDR Program

Table 1
Kappa Index Range

Kappa Index Value	Agreement Strength
Less than 0	Poor
0–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.0	Almost Perfect

3. Simulation Methodology and Results

In this research work, an event-based NILM approach has been employed with enhancements made in the context of improved event detection and classification model. Comprehensive digital simulations are carried out using MATLAB version R2018b and Python 3.6.7 with Scikit-Learn[6] [36] version 0.21.3. The research methodology of the improved NILM approach is presented graphically in Fig. 6, where the details of each block are presented in the following sub-sections.

3.1. Data Acquisition and Pre-processing

To realize the real-world potential of the proposed model, simulations are carried out using low granularity load data acquired from a real-world load disaggregation database: Pecan Street's Dataport [37]. The mentioned database is the world's largest load disaggregation research database [38], owned and operated by Pecan Street[7] Inc.; a research institution located in the United States of America. It contains both aggregated and individual appliance-level power profile at a granularity of 0.016 Hz, i.e., one (measurement) reading every 60 s. Moreover, within the employed database, two load elements: electric vehicle (EV) charging and air conditioning (AC) unit, have been selected for evaluation purposes within the scope of this study. The selected load elements are not only high consumption loads but also shiftable-interruptible [39,40] in nature, as they can be interrupted and resumed. These attributes make the EV and AC as high potential load elements from the perspective of flexibility control and energy saving in the context of DR applications. Furthermore, the selected high consumption load elements are a more viable option for non-intrusive inference in the context of the low sampling NILM systems [16,41]. In the given context, within the scope of this research, an aggregated load data of up to 360 h, i.e., 15 days, have been acquired from three completely diverse households, given that the selected households have both load elements, i.e., EV and AC. Details of the acquired load data are presented in Table 2, where

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[6] Scikit-Learn is a machine learning library for Python programming language. https://scikit-learn.org/stable/index.html

[7] https://www.pecanstreet.org/

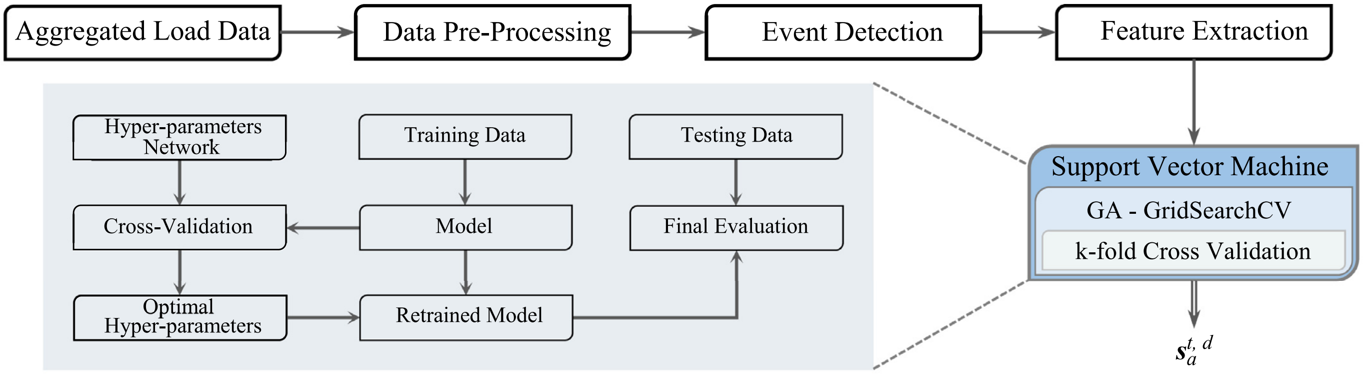

Fig. 6. Proposed Event-Based NILM Methodology

Table 2
Acquired Load Data at Data Granularity of 0.016 Hz

Household ID	Training Data 26	Testing Data 26	661	3036
Acquisition Timeframe	June 18–July 2, 2014	August 1–4, 2014	August 1–4, 2017	June 18–21, 2014
Number of Days	15	4	4	4
Number of Hours	360	96	96	96
Number of Samples	21600	5760	5760	5760
Ground-truth Events	334	98	169	236

Table 3
Improved Event Detection Algorithm

```
Improved MSW Algorithm
1. Acquire pre-processed aggregated load data, $x$
2. Select threshold value, $\delta$, and sliding window width
3. Compute iteratively the mean value, $\mu_x$, with pre-selected sliding window
   width and extract the difference of the consecutive values, $\Delta\mu_x$
   where, $\mu_x=\frac{1}{n}\sum_{i=1}^{n} x_i$ and $\Delta\mu_x = \mu_x(t+1)-\mu_x(t)$
4. Compute the thresholding signal as
for $i$ = length of $x$ do
    if $-\delta \leq \Delta\mu_x \leq \delta$ then
        signal($i$) = 0
    else
        signal($i$) = 1
    end if
end for
5. Compute edges from the previous step and extract starting and ending
   time indices of the detected events
6. Post-processing
-event approval and delay correction due to window width
-the detected event is true if and only if, $|t_d-t_g| \leq \Delta t$, where $t_d$, $t_g$, and $\Delta t$
 represent the detected event starting time index, ground-truth event starting
 time index, and delay tolerance, respectively.
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the training and testing data are used as an input to the training and testing phases of the classification model, respectively.

As the acquired data is based on real-world load measurements, measurement errors such as data spikes, are inevitable. These measurement errors affect further processing, hence data pre-processing is essential to eradicate the measurement errors. Median filtering [42] is employed to eliminate the data spikes within the acquired load data. The employed median filtering technique successfully eliminates the undesired impulses and ripples from the signal while preserving the edges for later processing, i.e., event detection. Further, it is also worth noting that in terms of data acquisition, the poorly monitored time-period is not considered within the scope of this study.

3.2. Event Detection and Feature Extraction

As depicted in Fig. 6, the data pre-processing is followed by event detection, where the mean sliding window (MSW) algorithm [43] is employed for event detection purposes. However, in this study, the performance of the MSW algorithm is further improved by incorporating additional post-processing measures in terms of delay tolerance conditions that influence the true positive detection, consequently, enhancing the overall event detection performance. A detailed methodology of the improved MSW event detection algorithm employed in this study is presented in Table 3.

To validate the effectiveness of the post-processing, i.e., incorporation of delay tolerance, towards event detection performance improvement, comprehensive sensitivity analysis is carried out on real-world training data. Fig. 7 presents the corresponding results in terms of f-score performance metric.

As evident from Fig. 7 that incorporating delay tolerance facilitates the event detector performance, as with delay tolerance a minimum of 8.67% performance improvement has been recorded compared to without incorporating delay tolerance. It is expected as delay tolerance increase the margin of true detection, subsequently enhances the overall event detection performance. Hence, based on the presented improved event detection methodology and performed sensitivity analysis, further simulations are carried out on diverse set of load data: Table 2. For the given input, the algorithm accurately detects the events along with the corresponding starting and ending time indices. In the given context, simulation parameters and the subsequent results are presented in Table 4.

As evident from Table 4 that for diverse input aggregated load data, the improved event detector attained promising performance with a result of > 93% in terms of precision, recall, and f-score performance metrics. In the context of NILM, these detected events are a mere indication of state transitions within the aggregated load data, and further meaningful information from these detected events needs to be extracted for the explicit appliance state inference, commonly referred to as features[8]. Within the scope of this research, five distinct features based on statistical, geometrical, and power features, i.e., event- width, mean, standard deviation, variance, and peak-to-peak power magnitude, are extracted for each detected event, these features are mathematically expressed in

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[8] Feature refers to a unique consumption pattern of an appliance.

Table 4
Event Detection Simulations and Results

Parameters	Window Width	6-minutes			
	Threshold Value	250 W			
	Delay Tolerance	1-minute			
		Training Data	Testing Data		
	Household ID	26	26	661	3036
Results	Total Detected Events	323	99	163	231
	Precision %	96.90	96.97	98.77	94.80
	Recall %	94.84	97.95	96.40	93.19
	F-Score %	95.86	97.46	97.57	93.99

1-minute of delay tolerance is selected for simulation purposes, as it is evident from Fig. 7 that performance improvement is marginal for $\Delta t > 1$.

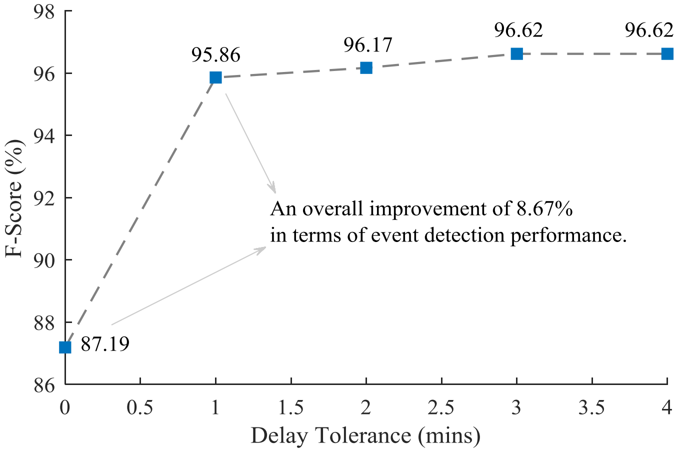

Fig. 7. Performance Sensitivity Analysis in terms of Delay Tolerance

(3)–(7), respectively.

$$\text{width} = t_d^e - t_d^s \tag{3}$$

$$\text{mean} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

$$\text{standard deviation} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left| x_i - \text{mean} \right|^2} \tag{5}$$

$$\text{variance} = \frac{1}{n}\sum_{i=1}^{n} \left| x_i - \text{mean} \right|^2 \tag{6}$$

$$\text{peak} - \text{to} - \text{peak power} = P_d^e - P_d^s \tag{7}$$

where, t_d^s and t_d^e represent the time indices where the detected event starts and ends, respectively. P_d^s and P_d^e represent the power magnitude of the detected event at starting and ending time indices, respectively. Moreover, x_i represents the active power values of the detected event and n is the number of samples within the detected event. The extracted five load features for each detected event are later used as an input to the classification model to classify the explicit appliance operation state within the aggregated load data.

3.3. Load Classification

Feature extraction is followed by the load classification stage, where the support vector machine (SVM) is employed as a classification model. SVM is a supervised learning model that relies on the concept of a 'margin', i.e., either side of the hyperplane that separates two data classes, as depicted in Fig. 8 [44].

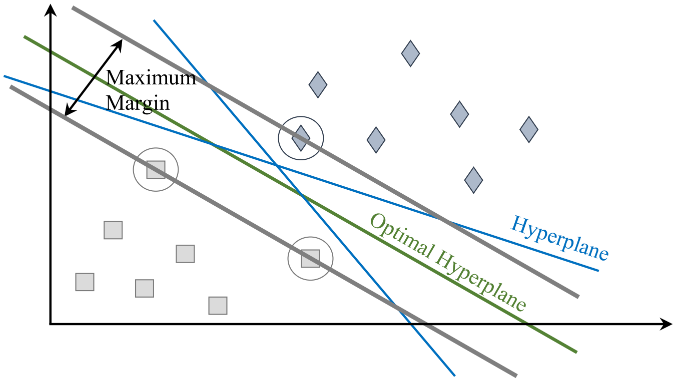

Fig. 8. SVM Maximum Margin Concept

In the given context, SVM requires to find the solution of an optimization problem expressed mathematically in (8) [41], where further details[9] can be found in [36].

$$\begin{aligned} &\text{minimize}\left(\frac{w^T w}{2} + C\sum_{i=1}^{n}\xi_i\right) \\ &\text{subject to}\begin{cases} y_i\left(w^T\, \emptyset(x_i) + b\right) \geq 1 - \xi_i \\ \xi_i \geq 0 \end{cases}, \; i = 1, 2, 3, \ldots, n \end{aligned} \tag{8}$$

where 'w' and 'b' represent the hyperplane's normal vector and offset, respectively. 'C' is the penalty parameter of the error term 'ξ' and '∅' represents the kernel function. The input vectors 'x_i' and 'x_j' are mapped to a higher dimensional feature space plane using the kernel function. Different kernel functions are defined as in (9) [41].

$$\emptyset(x_i)^T\emptyset(x_j) \equiv K(x_i, x_j) = \begin{cases} \langle x_i, x_j \rangle, \text{Linear} \\ \exp\left(-\gamma \left\| x_i - x_j \right\|^2\right), \text{Radial Basis Function} \\ \tanh\left(\gamma \langle x_i, x_j \rangle + r\right), \text{Sigmoid} \end{cases} \tag{9}$$

where 'x_j' represents the unlabelled input and 'γ' and 'r' are kernel specific parameters.

In this study, SVM is opted not only for being a well-established and frequently used classifier in the context of NILM [18] but it also possesses promising attributes, such as good generalization capabilities, high accuracy performance, and insensitive to data dimensionality [44]. Moreover, SVM is faster in training/testing, effective in high-dimensional spaces, and also work in multi-class classifications [45]. All these attributes of SVM make it a prominent candidate for the given multi-class classification problem. However, it is worth noting, also evident from (8) and (9), that the SVM performance relies on the optimal selection of hyper-parameters[10], such as the 'C' value, kernel function

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[9] https://scikit-learn.org/stable/modules/svm.html

[10] Parameters not learnt directly within the estimators are referred to as hyper-parameters

Table 5
Load Classification Simulation Parameters

	Parameter	Details	
Genetic Algorithm	Population size	50	
	Mutation probability	0.1	
	Crossover probability	0.5	
	SVM Kernel	['linear', 'sigmoid', 'RBF']	
Cross-Validation	k-fold	10	
GridSearchCV	SVM	C	[1e^{-7}, 1e^{+7}, 15]
		Gamma	[1e^{-7}, 1e^{+7}, 15]

'∅', and the corresponding gamma 'γ' value [46]. In this context, this research work proposes a unique combination of genetic algorithm (GA) and GridSearchCV[11] for the optimal tuning of the mentioned hyper-parameters of the SVM model towards improved classification performance.

The genetic algorithm is a well-known computational algorithm used for searching the global optimum in a complex, infinite, and non-differentiable space [47]. The GA initially starts with a randomly selected solution from a set of available solution space and evaluate the fitness function for each solution and rank them accordingly. To optimize the fitness function and attain the optimal solution, the population evolves using several processes namely, reproduction, crossover, and mutation [48]. GridSearchCV is a Scikit-Learn class, which provides computational capabilities to perform an exhaustive search over specific parameters for a classifier. In this context, a set of parameters is stored in a dictionary and later each parameter is evaluated by fitting the necessary learning model. Towards optimal classification performance, Table 5 presents the details of the simulation parameters and hyper-parameters' search space employed in this research study.

Comprehensive simulations are carried out using the GA and GridSearchCV to extract the optimal hyper-parameters of SVM for improved classification performance. Based on the GA simulations, the radial basis function (RBF) emerged as an optimal SVM kernel function for the given problem. For the given kernel function, further simulations are carried out using GridSearchCV to further investigate the optimal values of other corresponding hyper-parameters: C and Gamma. In the given context, the simulation results in terms of validation accuracy (normalized) against different values of C and Gamma for the SVM (with the RBF kernel) model are presented in Fig. 9 in the form of a heat-map.

It is evident from the results presented in Fig. 9 that for the given problem, the optimal value of C and Gamma are 10 and 0.1, respectively (highlighted by the white box in Fig 9), as for the given values, the validation accuracy of 92% is achieved.

Further, the generalization capability of our trained SVM model, based on the extracted optimal hyper-parameters, is extensively evaluated on a diverse set of unseen real-world testing data. The testing data comprise of three different households having IDs: ID 26, ID 661, and ID 3036, details given in Table 2. It is worth noting that ID 661 and ID 3036 are completely different households compared to the one used for training purposes, i.e., ID 26. Moreover, in the context of ID 26, the testing data are acquired from completely different timeframe compared to training data timeframe, subsequently, the testing data are completely unseen during the training phase, as evident from the data acquisition timeframe given in Table 2. In the given context, comprehensive simulations are carried out to evaluate and validate the generalization capability of our trained classification model. The corresponding household-level classification results in the form of accuracy and Kappa index are presented in Table 6.

It is evident from the results presented in Table 6 that the optimally trained SVM model attained promising household-level classification performance, i.e., > 87% in terms of accuracy and Kappa index performance metrics. It is also observed that testing household ID 26 attained slightly higher performance compared to other testing households: ID 661 and ID 3036, but it is expected as the other testing household: ID 661 and ID 3036, are completely different households, having diverse attributes, compared to the household ID 26, which is used for SVM training purposes. However, irrespective of the mentioned diversity factor, our trained classification model achieved promising performance results, i.e., > 93% and > 87% in terms of accuracy and Kappa index performance metrics, respectively. Further, it is also worth noting that for all diverse testing households, the attained Kappa index performance lies in the "almost perfect" region, as discussed in Table 1 [33].

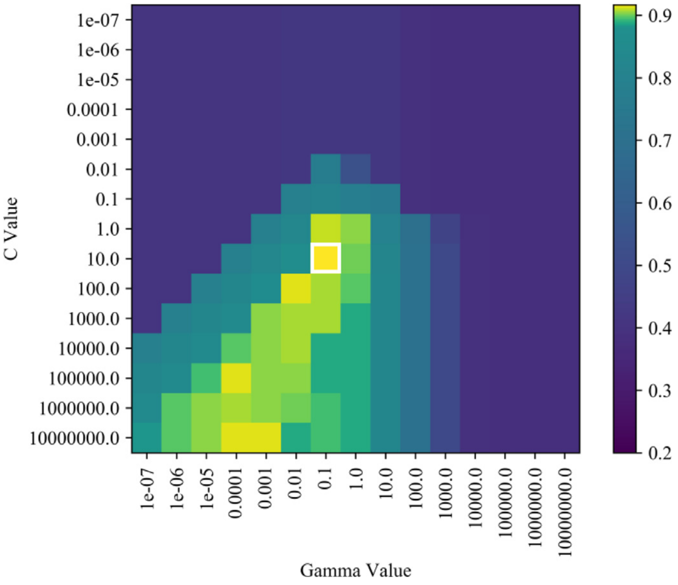

Fig. 9. SVM Validation Accuracy in terms of C and Gamma Values (Color-coding represents different performance values, depicted by the vertical bar)

Table 6
Testing Data Household-Level Classification Results

	Diverse Testing Real-world Household Data		
	ID 26	ID 661	ID 3036
Accuracy (%)	96.87	93.16	93.60
Kappa Index (%)	94.77	87.58	88.33

Further, as the given problem is a multi-class classification task, appliance-level evaluation is also carried out. In the given context, the confusion matrix and the ROC curves along with AUC are employed for the performance evaluation of the trained model in terms of each class. In this research work, total four classes are inferred for each testing household, labeled as, Class 0, Class 1, Class 2, and Class 3 and these classes represent AC Turn-off, AC Turn-on, EV Turn-on, and EV Turn-off, respectively. Fig. 10 depicts the appliance-level classification performance (normalized) of our trained model for two of the employed testing households in the form of a confusion matrix, i.e., evaluating the

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[11] https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

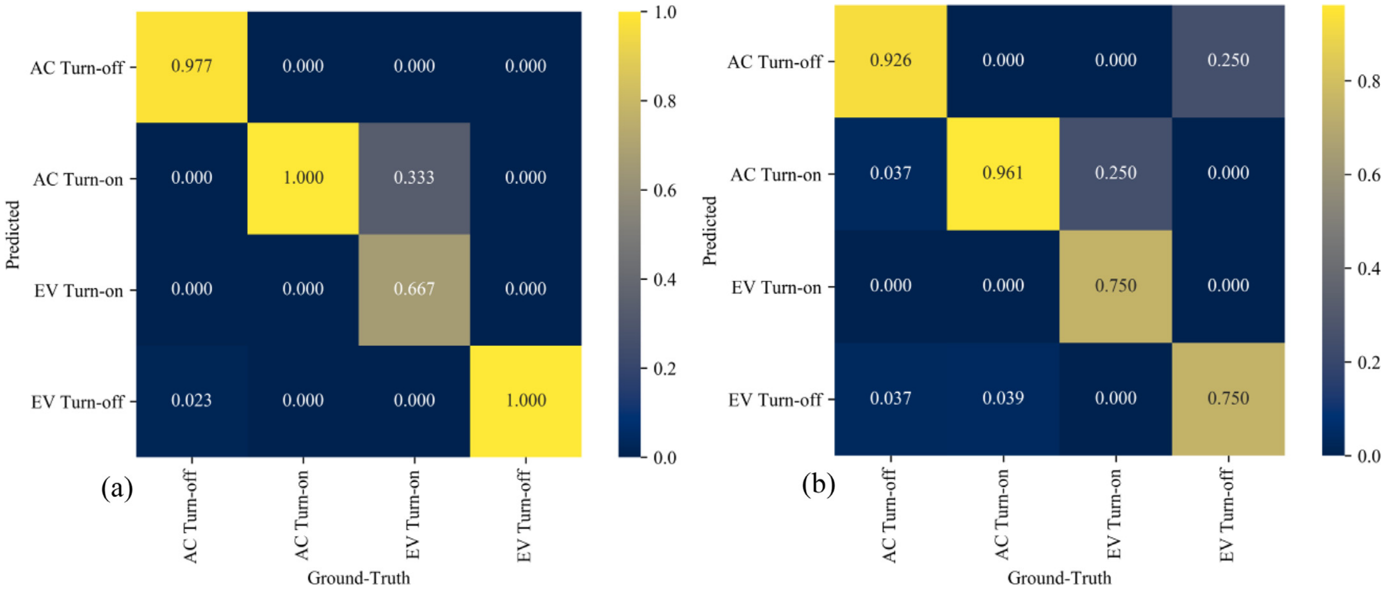

Fig. 10. Testing Data Appliance-Level Classification Results (a) Household ID 26, and (b) Household ID 3036

trained model's prediction against actual ground-truth. Further, Fig. 11 depicts the ROC curves results for each class of the diverse testing households along with the corresponding AUC results.

It is evident from the results presented in Figs. 10 and 11 that our trained SVM model achieved promising appliance-level classification performance for different testing household data. From the results in Fig. 11, it is also observed that for each class the corresponding ROC curves get to the top-left corner that implies the best performance [35], which is also evident from the AUC results of each class for diverse testing households, where the minimum recorded AUC result is 95%.

4. Case Study

As established from the presented simulations and corresponding results that the presented NILM approach with an improved event detector and classification model yields promising inference performance. The outcome of NILM in the form of $s_a^{t,d}$, containing the inference results of different appliances, here AC and EV, play a significant role in the non-invasive load-shed authentication model, discussed in Section 1 and Section 2. In this context, to validate our proposed NILM assisted non-invasive load-shed authentication model: Fig. 4, a comprehensive real-world case study is carried out for the UDR program. For the said purposes, household ID 26 presented in Table 2 is employed for digital simulations.

Let us consider, a utility provider initiates a UDR program and approached the potential consumers. The consumer, here household ID 26, signs up and enrol two of its high consumption and potential DR load elements: here air conditioning unit and electric vehicle. As per the DR agreement, both stakeholders agreed that based on the DR instructions the enrolled loads will be controlled manually by the consumer, where the utility provider will access the consumer's NILM feedback, installed at consumer's premises as shown in Fig. 4, to monitor the DR enrolled loads for load-shed instructions compliance authentication. Regarding the process, a detailed flow of information among the concerned stakeholders within the initiated UDR program is shown in Fig. 5.

Assuming, on the first day of a month the utility provider has to carry out scheduled maintenance that requires 5 h of timeslot. On the given day, the mentioned work is scheduled for 09:00–12:00 and 18:00–20:00 h. To maintain the reliability of the services a DR signal is sent to the participating consumers. The given consumer, i.e., household ID. 26, acknowledges the DR signal and in response, the utility provider sends the confirmation, as shown in Fig. 5. Later, the DR instructions are sent to the confirmed consumer to curtail their enrolled loads for the mentioned timings. Now, according to the DR agreement, the consumer is obliged to curtail the enrolled loads at the given time and day. On the other side, the utility provider can access the NILM inference information, $s_a^{t,d}$, of the DR enrolled load elements of the given household for load-shed compliance authentication purposes. In the given context, the utility provider retrieves the NILM information of the given consumer to validate the consumer's compliance with DR load-shed instructions. The retrieved NILM based feedback along with other load information concerning the day and time of scheduled maintenance is presented in Fig. 12. It is worth noting that the inference results presented in Fig. 12 are extracted using the presented improved event-based NILM approach, where comprehensive simulations are carried out on a real-world household load data: household ID 26. In this context, Fig. 12 also validates the retrieved NILM inference results by benchmarking them against the actual ground-truth[12] appliance profiles.

From the retrieved NILM information, results presented in Fig. 12, it is observed that the participating consumer curtailed their enrolled loads: EV and AC, for 09:00–1200 h (highlighted in light grey color), however, for 18:00–20:00 h the consumer does not comply with the received/acknowledged DR instruction and operates the enrolled DR load elements (highlighted in light grey color). This implies that the given consumers partially comply with the received load-shed (DR) instructions.

The NILM feedback: $s_a^{t,d}$, of the given consumer/household, retrieved by the utility provider for the non-invasive load-shed authentication purposes is further elaborated in Table 7, where the retrieved NILM feedback is presented in the form of appliance explicit states' time indices inferred by the NILM and the corresponding 24 h time format. Table 7 also highlights the operation duration of the enrolled DR loads elements for the given day of scheduled maintenance. It is also observed from the results presented in Table 7, that the given household[13] does not entirely comply with the received DR load-shed instructions and the

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[12] Individual appliance ground-truth profiles are available in the database employed in this research work.

[13] The presented case study and corresponding results are explicitly intended for the proof of concept and validation of the proposed NILM assisted non-invasive load-shed authentication model. Hence, the corresponding analysis does not imply by any means that the given household/consumer is a freeloader.

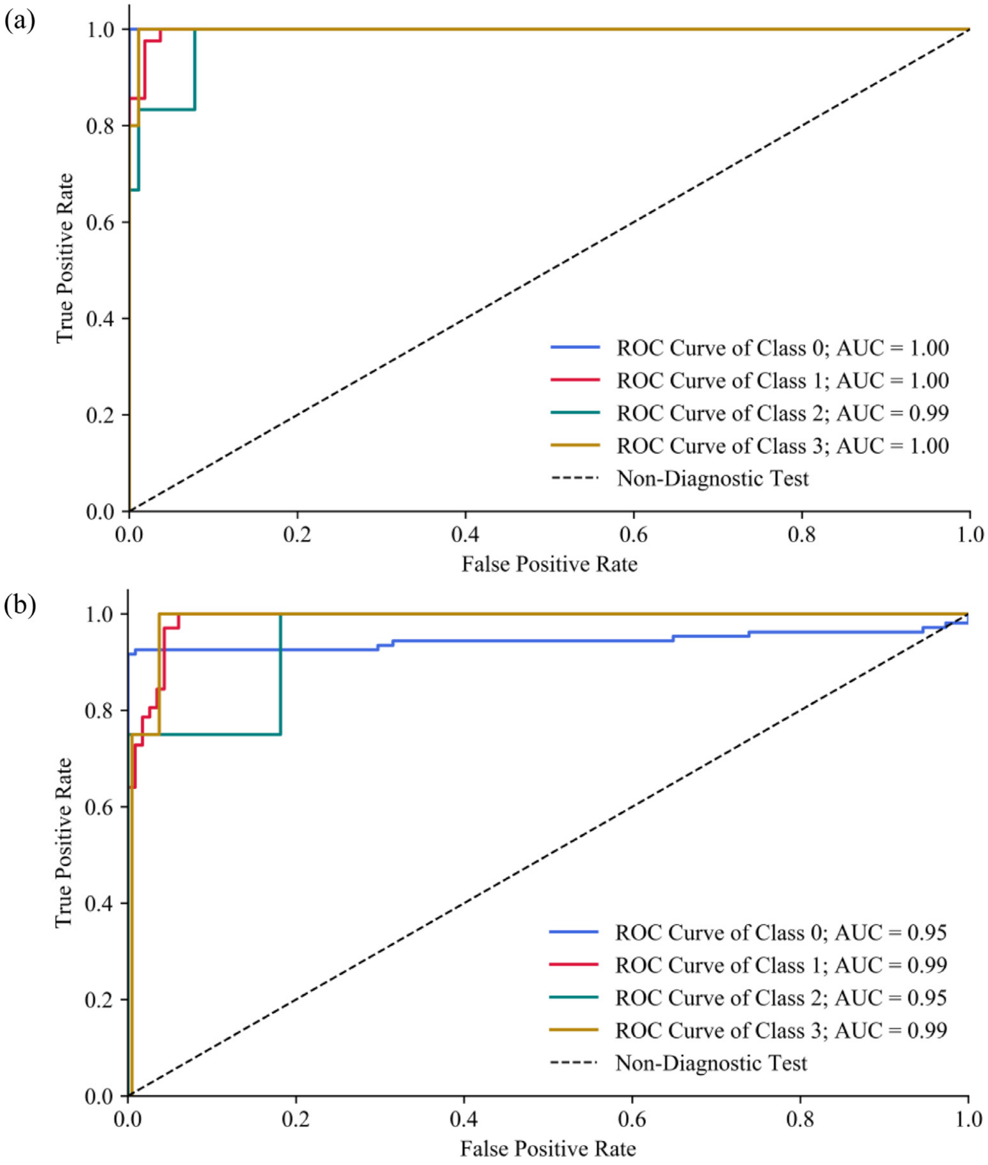

Fig. 11. Multi-Class Classification Results in terms of ROC Curves and AUC (a) Household ID 26, and (b) Household ID 3036

Table 7
Enrolled DR-Appliances Non-Invasive Inference Results for Load-Shed Authentication

	Turn-on Time Index	24 h Format	Turn-off Time Index	24 h Format	Duration (mins)
Electric Vehicle	**1090**	**1810**	**1134**	**1854**	**44**
	1234	2034	1283	2123	49
Air Conditioning	-	-	24	0024	-
	51	0051	99	0139	48
	154	0234	187	0307	33
	242	0402	271	0431	29
	334	0534	368	0608	34
	890	1450	915	1515	25
	935	1535	976	1616	41
	1018	1658	1066	1746	48
	1113	**1833**	**1202**	**2002**	**89**
	1221	2021	1251	2051	30
	1306	2146	1440	2400	134

enrolled loads are operated for 44 (EV) and 89 (AC) minutes during the second half of scheduled maintenance, i.e., 18:00–20:00 (highlighted using bold in Table 7).

From the presented real-world case study and the corresponding analysis of the results, it is established that the proposed non-invasive load-shed authentication model assisted by the low sampling event-based NILM approach is a viable and promising solution for the UDR program. The proposed model significantly facilitates the UDR program in terms of effective deployment and monitoring of DR enrolled load elements, consequently, not only minimizes the peak demand and reduces stress on energy systems but enables the utilities to eliminate the freeloaders. It is also worth noting that the proposed NILM assisted

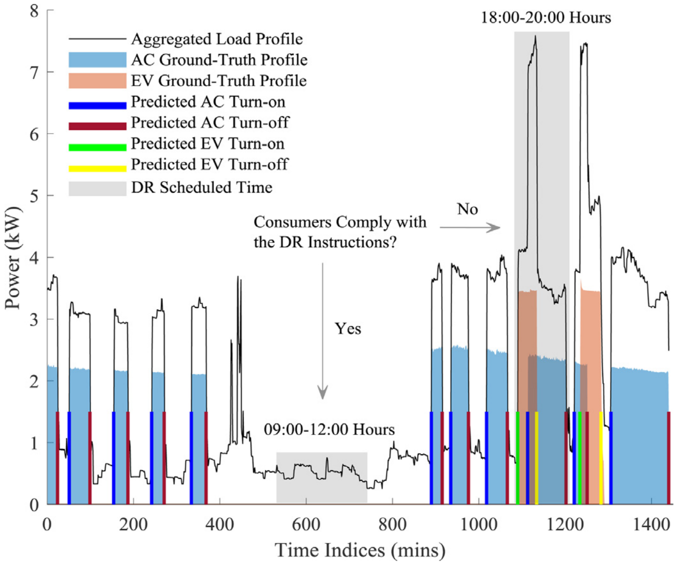

Fig. 12. NILM Assisted Load-Shed Authentication (validating the consumer's load operation in compliance with the received DR instructions)

model is computationally more efficient in terms of storage needs and communication bandwidth because only the NILM feedback, $s_a^{t,d}$, is processed/transferred among the concerned stakeholders for non-invasive load-shed authentication purposes. Moreover, based on the low sampling NILM approach, the proposed model is a more viable option in the context of real-world applications.

5. Research Outlook

The proposed non-invasive load-shed authentication model is a step towards realizing the potential of NILM systems in the context of real-world energy applications. In addition to the presented NILM application for the UDR program, numerous other DR programs can also be significantly facilitated by the NILM feedback: $s_a^{t,d}$, such as, in the case of the ADR program (also depicted in Fig. 4), the extracted appliances' pattern, i.e., time of use and duration as shown in Table 7, can be further utilized by the utility providers to formulate more efficient and effective ADR control strategies, while maintaining the consumers' comfort. NILM system can also play a significant role in the context of numerous promising energy efficiency applications. For example, the NILM feedback can substantially contribute to the load forecasting system and the corresponding outcome would be highly valuable not only to the utility companies but also to the policymakers to formulate more effective policies for energy efficiency and conservation. Furthermore, the NILM feedback can facilitate the load shifting techniques in the context of demand side management, as inference information of high consumption load elements, such as AC and EV could lead to more effective load shifting strategies, eventually not only flatten the peak load demand but also enable more savings at the consumers' end [49].

Concisely, the NILM has solid potential towards energy efficiency and its real-world actionable feedback will facilitate all the concerned stakeholders including utility providers, consumers, policymakers, and manufacturers. In this context, a detailed overview of NILM applications towards smart and sustainable grid systems is presented in [7]. Hence, the way forward is to focus on the real-world applications of the NILM system rather than only focussing on algorithm performance and the numbers of load elements to be inferred. Moreover, to realize the real-world NILM applications, the research community need to build low data granularity based load databases having detailed load measurements for a wide range of load elements. These low data granularity load databases will not only ease the computational requirements: storage and processing, but also facilitate the researchers to develop more robust low sampling NILM algortihms. Further, developing the low sampling NILM algorithms will significantly expedite the real-world deployment of NILM systems, particulalrly in the presence of the existing metering infrastructure, which is not capable to measure at higher sampling rates.

6. Conclusion

This paper presents a non-intrusive load monitoring assisted non-invasive load-shed authentication model for the demand response program. For the said purposes, an improved low sampling event-based non-intrusive load monitoring methodology is presented and comprehensively evaluated on diverse real-world load measurements of up to 360 h, i.e., 15 days. A real-world case study is also presented to validate the proposed non-invasive load-shed authentication model.

The employed non-intrusive load monitoring system is facilitated by an improved version of the event detector: mean sliding window algorithm, and classification model: support vector machine. The former is improved using a post-processing step where the latter is enhanced with a pre-processing module comprising of genetic algorithm and GridSearchCV. It is noted that for all the input data, the improved event detector yields promising performance with a result of > 93% in terms of all performance metrics: precision, recall, and f-score. Similarly, for the entirely diverse and unseen testing data, the presented improved classification model yields promising classification performance, i.e., greater than 87% and 93% in terms of Kappa index and accuracy performance metrics, respectively. It is also worth noting that for all testing data the classification results in terms of the Kappa index lie in the 'almost perfect' region. The improved non-intrusive load monitoring system is further employed to assist the non-invasive load-shed authentication model and to validate the complete framework, a real-world case study is carried out. Based on the presented case study and analysis of the corresponding results, it is concluded that the non-intrusive load monitoring assisted non-invasive load-shed authentication model is a viable solution towards the effective deployment of demand response applications.

The presented study established that non-intrusive load monitoring has a solid potential for real-world energy efficiency applications. In this context, it is emphasized that future research needs to be more focussed on low-sampling non-intrusive load monitoring systems and most importantly the research community needs to further explore the actionable feedback of non-intrusive load monitoring systems in the context of energy efficiency.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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