International Journal of Electrical and Computer Engineering (IJECE)
Vol. 16, No. 2, April 2026, pp. 675∼686
ISSN: 2088-8708, DOI: 10.11591/ijece.v16i2.pp675-686

A real-time appliance monitoring approach with anomaly detection for residential houses

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Article Info

Article history:

Received Jun 13, 2025
Revised Dec 18, 2025
Accepted Jan 16, 2026

Keywords:

Anomaly detection
Appliance identification
Demand side managment
Event detection
Intrusive load monitoring
Non-intrusive load monitoring

ABSTRACT

Monitoring electrical appliances in residential buildings is essential for minimizing energy waste and enhancing safety through the early detection of abnormal conditions. While researchers have investigated both intrusive and non-intrusive load monitoring approaches, the non-intrusive approach has emerged as preferred due to its cost-effectiveness and noninvasive implementation. Despite considerable progress in appliance monitoring and fault detection systems over the past two decades, critical challenges and limitations persist. This paper proposes a low-complexity appliance identification and monitoring solution to overcome those issues. Furthermore, the proposed solution is integrated with an abnormal condition detection mechanism for critical appliances, aiming to save energy and ensure the safety of the power system. Furthermore, the solution incorporates user feedback via a dedicated mobile application, enhancing adaptability and performance. The proposed solution has been validated in real-time environments using both custom and publicly available datasets, demonstrating improved accuracy in energy monitoring and increased consumer safety.

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1. INTRODUCTION

Residential electric energy monitoring systems have become a trending research area in recent decades due to the global energy crisis, rising energy costs, and various environmental concerns [1]–[5]. Traditional energy meters provide only the total energy consumption of the house and, fail to offer insights into the usage of individual appliances [6]. As a result, consumers are unable to effectively manage specific appliances, leading to energy waste, reduced appliance longevity, and causing hazardous operational conditions. However, an accurate load monitoring (LM) mechanism has the potential to address these mentioned issues, allowing for better energy management and improved protection of the power system in the residential premises [6], [7]. Furthermore, they also play a role in mitigating global climate change by reducing unnecessary electricity consumption [3]–[5], [8], [9].

An accurate LM systems have been shown to significantly cut electricity usage, leading to savings of up to 20% for consumers [2], [6], [7]. By identifying energy-hungry appliances and suggesting optimizations, these systems empower users to control their energy consumption and reduce their overall energy bills. Additionally, manufacturers also benefit from introducing new energy-efficient appliances based on the analytical data collected from LM systems [2]. Beyond energy savings, LM systems can contribute to a wide range of applications, such as anomaly detection of appliances for enhanced protection of power systems and ambient assisted living applications for elderly people [10]–[13].

Abnormal condition detection, or anomaly detection, is gaining importance due to its ability to prevent system failures and damage to appliances [11]–[13]. Identifying malfunctioning appliances early helps consumers avoid costly repairs and potential safety hazards [11]. Anomalies in power consumption patterns can indicate devices that are not operating as intended, allowing users to take corrective actions swiftly. Moreover, integrating anomaly detection into load monitoring systems can contribute to the overall safety and efficiency of the power grid [14]–[16]. Such systems also benefit elderly individuals, who can use this technology to ensure their appliances are functioning optimally, enhancing their quality of life in assisted living environments [10]–[13].

Non-intrusive load monitoring (NILM) and intrusive load monitoring (ILM) are the two concepts used to address both energy management and anomaly detection. The NILM techniques allow for the monitoring of individual appliances by analyzing the aggregated power signal from a single measurement point, usually at the main energy entry point of the house [6], [17], [18]. The first concept was introduced by G.W. Hart in 1992 using active and reactive power values of appliances [19]. This method is cost-effective compared to ILM, which requires installing measuring apparatus on each device [2], [17], [18], [20]. The Sense [21] and Emporia [22] are two commercially available products that rely on LM approach, where Sense energy meter utilizes NILM approach and Emporia follows ILM approach. NILM has proven effective in identifying operating appliances and detecting abnormal operations in real-time, making it ideal for anomaly detection applications [11]. Furthermore, event-based NILM approaches, which track the switching on and off of appliances, are particularly suited for real-time anomaly detection.

Despite the promise of appliance identification solutions and anomaly detection solutions proposed during the past two decades [2], [15], [23], several challenges remain unresolved [2], [5], [15], [23], [24]. Most of the proposed solutions used expensive and complex hardware arrangements to acquire data from the power system [5], [6], [25]–[28], targeted only identification and monitoring of selected high-power-consuming appliances [3], [29]–[34], required labeled datasets for both appliance identification and abnormal operation detection [2], [20], [35]–[40], and used high computing power to run the appliance identification solutions.

In response to these challenges, a low-complexity appliance identification and monitoring system that combines both LM approaches to enhance the monitoring and management of residential electric appliances. Our approach focuses on improving real-time detection capabilities to ensure timely identification of abnormal conditions. The system is tested using both a custom dataset and publicly available datasets, yielding results that demonstrate its effectiveness in providing accurate, real-time appliance monitoring and anomaly detection. A comparison between the proposed solution and state-of-the-art methods is presented in Table 1. Key contributions are as follows.

a. Real time appliance identification and monitoring system was proposed for residential houses covering all the electric appliances in the premises. Low complexity machine learning solution was proposed for appliance identification to reduce the computational power requirement when it is deployed in real world settings.
b. Low-complexity data acquisition (DAQ) system was developed to acquire data from power system and it is easy to install in the house. Since, the cost of the solution is primary concern of consumers, expensive hardware component is not suitable for real world settings.
c. An accurate event detection methodology was proposed to identify events of both low and high-power consuming appliances. By identifying low power consuming appliances such as light bulbs, fans, consumer can switch OFF unwanted appliances and actively contribute to the energy savings strategies.
d. A consumer feedback mechanism was introduced to enhances system accuracy and user experience by developing a mobile application. The developed application can be used for view consumption data in real time and give correct appliance names to the system.
e. Real time anomaly detection methodology also proposed in parallel to the appliance identification to detect abnormal operations of critical appliances in the house.

The outline of the paper as follows. Section 2 explain the prototype development and proposed appliance identification and monitoring solution. Tested results are discussed in sections 3 and 4 describes the conclusion of the research work.

Table 1. Comparison with existing appliance identification solutions

Ref.	Real time monitoring	Can identify low power consuming appliances	Low cost DAQ system	Can detect new appliances	Ability to detect anomalies	Can be Generalized
[5]	X	X	X	X	X	X
[12]	X	✓	✓	X	X	X
[17]	✓	✓	✓	X	X	X
[26]	X	X	X	X	X	X
[27]	X	X	X	X	X	X
[28]	X	✓	X	X	X	X
[30]	X	✓	X	X	X	X
[34]	X	✓	X	X	X	X
Proposed	✓	✓	✓	✓	✓	✓

2. METHOD

The proposed appliance identification and monitoring solution follows both intrusive and non-intrusive monitoring approaches to reduce the complexity of the total system. Appliances can be categorized into two groups based on their average power consumption patterns: linear and non-linear. Non-linear power-consuming appliances include washing machines, high-performance laptops, and computers. Therefore, two types of DAQ units are included, such as the main unit (MU) to acquire total energy consumption and auxiliary units (AUs) to acquire individual energy consumption of non-linear power-consuming appliances. Figure 1 illustrates the overall block diagram of the proposed approach.

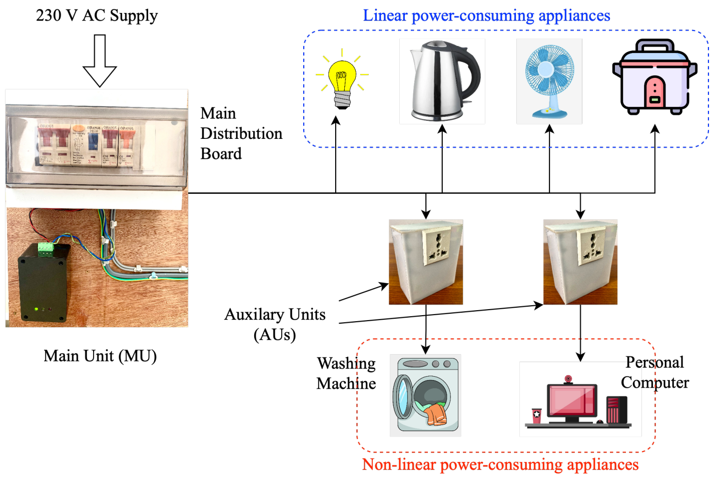


Figure 1. Basic block diagram of the proposed hybrid appliance identification and monitoring solution

2.1. Data acquisition system

The ESP-8266 (i.e., Node MCU) microcontroller board was used as the main processing part of developed measurement units and it is used in most of Internet of Things (IoT)-based projects. It has built-in wireless fidelity (Wi-Fi) facility enables the transfer of recorded data to a cloud service. Google Firebase online database was used in this work as the cloud service. The data transfer rate is configured for 10-second intervals based on the experimental data [6]. The PZEM-004T energy meter module was used to read the active power, root-mean square (RMS) current, RMS voltage, power factor (PF), and frequency of the power system. Figure 2 illustrates the overall process of the developed solution.

2.2. Appliance identification and monitoring process

The NILM approach was used to identify linear power-consuming appliances. The consumption of those appliances can be calculated by subtracting AU data from MU data. Consumption of non-linear power-consuming appliances can be directly viewed from AU data and it follows ILM approach. NILM concept consist with four steps: data acquisition, event detection, feature extraction, and appliance identification. The steps are discussed as follows.

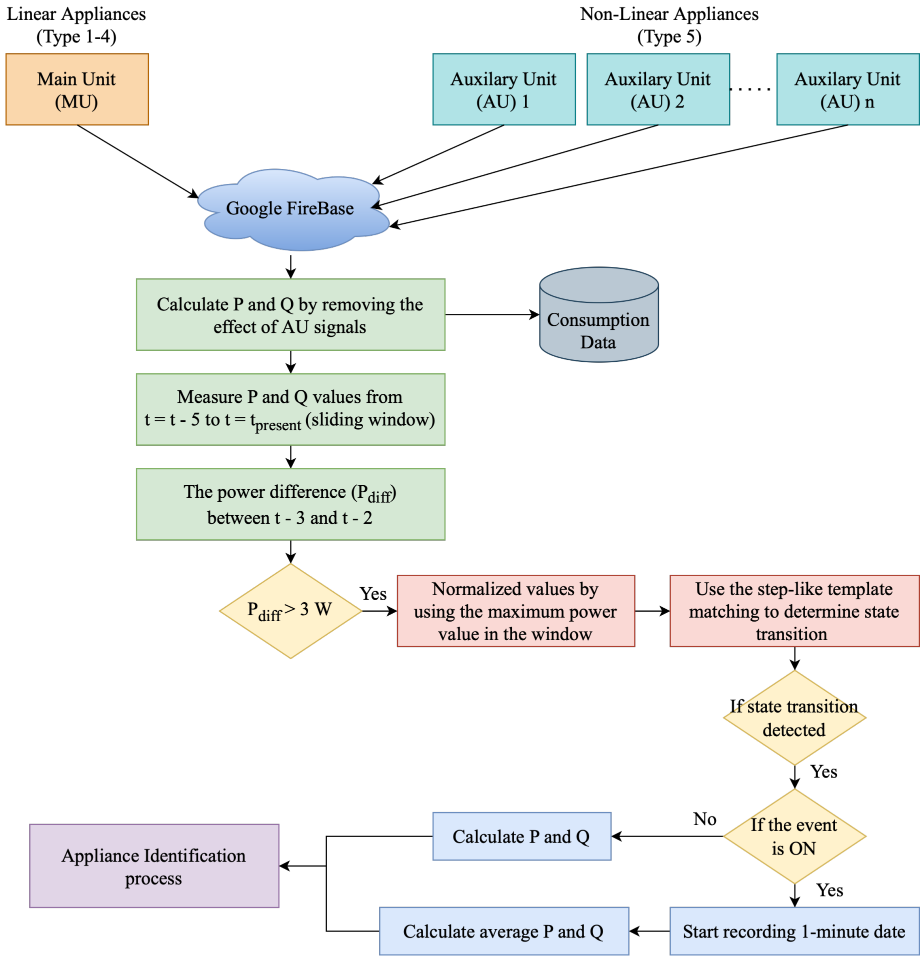


Figure 2. Basic block diagram of the overall process

2.2.1. Event detection

The event detection methodology proposed here is only used to identify state transitions (i.e., events) of linear power-consuming appliances. Active power variation was selected as the best feature to detect events in the power system. The event detection methodology proposed in our previous work was used with a 50-second overlapping sliding window [6]. Since the data recording interval is fixed at 10 seconds, sliding windows consist of 5 data points.

2.2.2. Feature extraction

Since the research work targets a low-complexity appliance identification solution, power values were selected for appliance identification. Based on the experimental data, a threshold value of $(P_{threshold})$ 350 W was defined to divide high and low-power-consuming appliances. Figure 3 shows the scatter plot of active power (P) and reactive power (Q) of commonly used different low-power-consuming appliances. According to that, P and Q values can be used for appliance identification. In Figure 3, the black-colored curve represents a newly observed appliance, which closely resembles the profile of a pedestal fan. Consequently, the new appliance is identified as a pedestal fan.

For high-power-consuming appliances such as electric kettles and rice cookers, their distinct operating durations provide an additional discriminatory feature not typically present in low-power appliances [6]. Therefore, both the power values and operational time are used to correctly identify those appliances. Equation (1) is used to calculate the active power value (P_{new}) of an appliance that experiences a state transition.

$$P_{new} = |P_{after} - P_{before}| \quad (1)$$

The power values of the appliance for 1 minute are recorded after detecting an "ON" event as per the procedure shown in Figure 2. The system then calculates the average power consumption value (P_{after}) from the recorded values. The power values before the event (P_{before}) are used to obtain the average values of the 1^{st} and 2^{nd} points of the event window [6]. In the case of an OFF event, the P_{after} values are calculated by getting the average of the 4^{th} and 5^{th} points. The P_{before} values are calculated from the average of the 1^{st} and 2^{nd} points. The same process is then repeated with reactive power values.

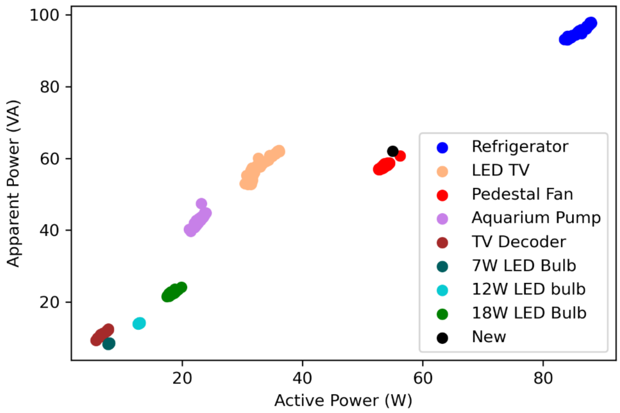


Figure 3. Scatter plot of P and Q values of different set of residential appliances

2.2.3. Appliance identification

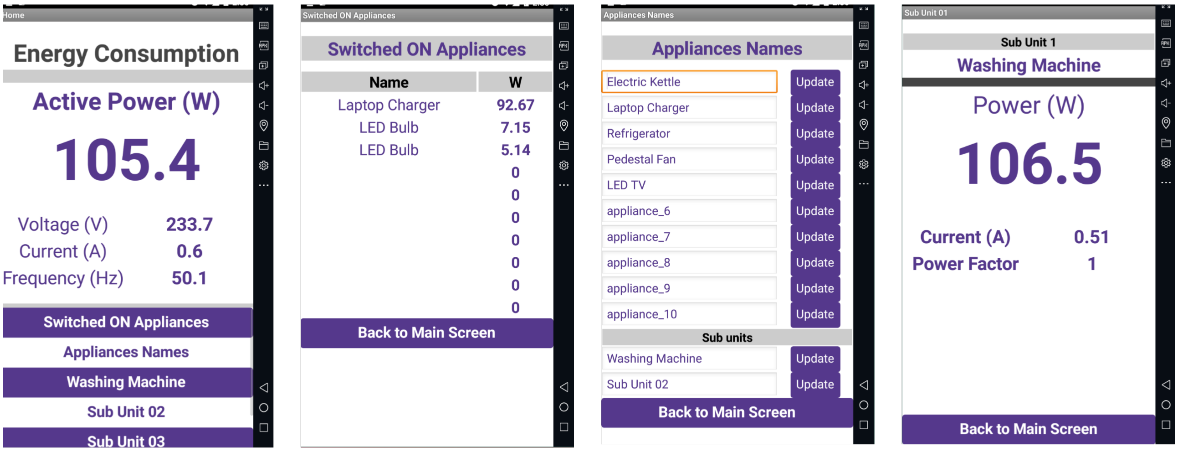
Since every house has lighting loads, at the beginning, the database is only fed with data about light-emitting diode (LED) bulbs. Other appliance data will be stored in the database automatically after installing the system. The proposed appliance identification process follows a self-supervised learning approach, and a training period of one month (i.e., 30 days) from the system installation date was defined based on the experimental results. During that period, it is assumed that each appliance will be operating. The k-Nearest Neighbors (k-NN) model was utilized for the prediction process.

If a "switching-on" event is detected by the system, the average power values (i.e., active and reactive values) of the newly switched-on appliance are calculated. It then determines whether it is a low or high-power-consuming appliance. The k-NN model uses the updated database to predict a low-power-consuming appliance. The system then calculates the power differences (P_{diff}) between the predicted and actual appliances. Based on the experimental results, a 10 % margin of P_{diff} is allowed for all appliances [6]. If the calculated P_{diff} surpasses the threshold, it can be an indication of the presence of a "new appliance" and a temporary database was used to store appliance details during the training period. The system checks the temporary database for any matched appliances before creating a new entry. A match indicates that the appliance has been in operation before, and therefore, the details of the appliance are permanently stored in the main database.

If any high-power-consuming appliance is found, the identification process will be run in the switching-off state. Until then, it is shown as an appliance, indicating consumption without assigning any name. Both the power values and operational time are considered for the prediction of these appliances. At the switching-off state, the same 10 % of power level (P_{diff}) and 5-minute time margin were used for the verification process. The database stores the data from those appliances along with their operational times. The same process discussed above will be followed to store new appliance data.

2.3. Mobile application

A mobile application was developed to show consumption data to consumers and gather feedback. Figure 4(a) illustrates the main screen of the app, and the total active power consumption, system voltage, total current, and frequency of the system are visible to the consumer. By clicking the "Switched ON Appliance" button in the main screen, consumers can see operating appliances in the system shown in Figure 4(b). Consumers can enter correct names using the screen shown in Figure 4(c). Before entering the correct name, the appliance name is shown as "appliance_n". The variable n can take any integer value from 1 to 10. The solution allows for the storage of 10 new appliances. Additionally, the same screen allows for the entry of AU names. The consumption details of non-linear power-consuming appliances can be seen from the screen shown in Figure 4(d).



(a) (b) (c) (d)

Figure 4. Screens of the mobile application, (a) main screen, (b) screen of switching ON appliances screen, (c) names of appliances, and (d) consumption of non-linear appliances

2.4. Abnormal conditions detection process

The proposed non-intrusive appliance identification method does not have any supervised parameters (i.e., labeled data). Therefore, the abnormal condition detection system cannot operate during the training period. After the training period of the system ends, the detection process will start automatically.

A statistical approach was used to detect abnormal conditions of a selected set of appliances [11]. In statistics, a value in a normal distribution greater than $(\mu + 2\sigma)$ or less than $(\mu - 2\sigma)$ is defined as an anomaly value [41]. The mean value of the distribution is defined as μ, and σ is the standard deviation of it. Most of the previously published works [15], [23], [39], [42] used labeled data. Therefore, they followed the 3σ rule to define whether it was an anomaly or not. That rule consisted of 99.7 % data from the distribution [11], [43]. However, that rule is not suitable because the proposed system does not have labeled data. Therefore, the 2σ rule was used for the proposed method.

Four commonly used appliances were selected for the abnormal condition detection process: rice cookers, electric kettles, refrigerators, and light bulbs [11]. Light bulbs normally operate during the night and early morning hours. Some houses, such as bathrooms and storerooms, may also operate during the daytime [11]. Those operations are mainly based on consumer behaviors. During the training period of the system, the operating times are recorded automatically by the system. If any lighting load operates differently from the recorded times, it can be defined as an abnormal operation. Based on the experimental data, a threshold value of 2 hours was used.

Electric heaters and rice cookers are the main heating appliances in most residential houses in South Asian region. For them, both the operational time and power values are considered for anomaly detection. A continuous monitoring mechanism was proposed for these appliances. The maximum allowable time is calculated from previous data using the $(\mu \pm 2\sigma)$ condition, and the system continuously checks whether the appliance is operated for more than that time. If any variation is detected, the system automatically sends an alert to the consumer. Further, at the switching-off state, the average power consumption is also checked with previous data, and if any variation is detected, an alert is sent to the consumer.

The refrigerator is the main cooling appliances in Sri Lankan residential houses and it shows a gradually decreasing power consumption. Therefore, power consumption in the ON and OFF states is different [15], [11]. Furthermore, the refrigerator will operate several times per day. Both the operational period and time between the two operations mainly depend on consumer behaviors and the load of the refrigerator. The proposed method checks four parameters [11]: i) The average power at the switching ON state, ii) The average power at the switching OFF state, iii) Operational time, and iv) Duration between two consecutive operations. All the parameters are checked at the switching-off state of the appliances. Allowable values are calculated from the previous data using the $(\mu \pm 2\sigma)$ condition.

3. RESULTS AND DISCUSSION

The proposed solution was tested in both real time and simulation based experiments. First, the non-intrusive appliance identification process was tested across three data sets. Second, the proposed abnormal condition detection process was tested by adding artificial anomalies into the original operations (i.e., without anomalies) of selected appliances. The standard accuracy matrix was used to analyze the performance of the proposed solution [44]. The *Accuracy* values of each test can be observed using (2).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

Where *TP*, *FP*, *TN*, and *FN* are the true positive, false positive, true negative, and false negative cases, respectively. True positive is an outcome where the implemented model correctly predicts the positive class; false positive is an outcome where it predicts the positive class incorrectly; true negative is where the model predicts the negative class correctly; and false negative is where the model predicts the negative class incorrectly.

3.1. Real-time appliance identification

A custom appliance list was used as the first data set to verify the validity of the proposed solution. The work involved twelve different types of linear-power-consuming appliances. Since light bulbs are available at every house, LED light bulbs with three different wattage values were used. Before applying the appliance identification process, the event detection process was tested on over 300 pre-recorded events. The proposed process achieves a 98 % accuracy level in simulation-based testing. After that, the total solution was tested in a real-world house with a set of selected appliances. The time taken for the detect event was analyzed, and on average, 0.000223 seconds (0.2 milliseconds) were observed in real-time operations. The summary of the identification result of the custom data set is shown in Table 2. The identification of the satellite television decoder and 7W LED bulb showed the lowest accuracy compared with other appliances due to the similarity in average power consumption values.

Table 2. Identification results of appliances in the custom dataset

Appliance	Rated wattage (W)	Identification accuracy (%)
LED bulb	7	94.50
LED bulb	9	100.00
LED bulb	12	100.00
Electric heater	1000	100.00
Electric kettle	1800	100.00
Toaster	800	100.00
Rice cooker	900	100.00
Pedestal fan	55	96.00
Hair dryer	750	100.00
LED Television	59	100.00
Refrigerator	70	100.00
Satellite television decoder	12	90.00
Aquarium pump	20	100.00
Air conditioner	1800	100.00

3.2. Simulation-based test results

Secondly, two publicly available data sets was used to verify the generalization of our proposed methodology. The Tracebase data set was made in Germany using 40 different appliances in more than 10 households and office environments [45]. In that data set, there are appliance-based active power recordings with two different sampling rates: 1 Hz and 1/8 Hz. The proposed methodology necessitates that appliances have reactive power values. Therefore, these values are calculated using average PF values [46]. The selected appliances from the Tracebase dataset, as well as the identification accuracy are shown in Table 3.

The vacuum cleaner and the hair dryer are two comparable energy-intensive devices. Nevertheless, their operational durations vary. The hair dryer functioned for around 5 minutes, while the vacuum cleaner operated for a duration of 12 minutes. Consequently, the operational period of the appliance can enhance the system's accuracy in identifying things. In certain states, the LCD television's power consumption was comparable to that of a refrigerator, resulting in the lowest accuracy. A total of 10 different appliances were tested in the Tracebase dataset, and an average of 89.47 % accuracy level was obtained.

The second data set is the iAWE [47] and three appliances were tested with the proposed non-intrusive identification solution. The achieved accuracy values are shown in Table 4. Since the number of appliances used for the test is less, a higher accuracy level was observed.

Most of the proposed appliance monitoring solutions achieved over 90% accuracy level for only a selected set of appliances [3], [30]–[34]. However, those require labeled data, rely on a selected set of appliances, and are tested only for simulations. The solution proposed in this research does not rely on labeled data, and it is a generalized solution. Further, the solution can work in real work settings in real-time. Therefore, the solution is more reliable for monitoring all the appliances in a residential house.

Table 3. Identification results of appliances in the Tracebase dataset

Appliance	Average power consumption (W)	Identification accuracy (%)
Electric kettle	2164.87	100.00
Lamp	41.63	100.00
Vacuum cleaner	1131.88	100.00
Toaster	717.17	100.00
Hair dryer	1190.09	100.00
Cooking stove	828.05	91.67
Laundry dryer	2523.08	83.00
Liquid crystal display (LCD) television	45.44	30.00
Refrigerator	190.71	90.00
Freezer	73.89	100.00

Table 4. Identification results of appliances in the iAWE dataset

Appliance	Average power consumption (W)	Identification accuracy (%)
Air conditioner	1694.31	100.00
Water motor	593.46	100.00
Refrigerator	128.80 – 108.50	100.00

3.3. Abnormal condition detection test results

The next step of the solution involved testing the proposed anomaly detection approach on identified appliances across the three datasets. Four appliances from the custom dataset, three appliances from the Tracebase dataset, and one appliance from the iAWE dataset were used in this testing phase. The selected datasets were augmented by introducing anomalies manually as previously done in [11].

The obtained results are shown in Table 5. For refrigerators and freezers, anomalies are checked at the switching OFF state. Both the operational time and consumption values are checked. For heating appliances (i.e., kettles and rice cookers) and light bulbs, real-time monitoring was considered. On average the proposed anomaly detection methodology achieves, a 99% accuracy level for real-time testing [11].

Table 5. Abnormal condition detection accuracy levels

Dataset	Appliance	Operational time - Real-time monitoring	Detection ratio operational time - at the switching OFF state	Power-based anomalies - at the switching OFF state
Custom	Refrigerator	-	12/12	10/10
Custom	Rice cooker	10/10	10/10	10/10
Custom	Electric kettle	11/12	11/12	9/9
Custom	Light bulbs	12/12	-	-
iAWE	Refrigerator	-	10/10	10/10
Tracebase	Refrigerator	-	10/10	12/12
Tracebase	Freezer	-	11/12	10/10
Tracebase	Water kettle	7/8	8/8	9/9

Based on the observed results, the proposed non-intrusive appliance identification method can accurately identify linear-power-consuming appliances in real time. Unlike other approaches, it does not depend on labeled data and demonstrates strong generalization capability. Additionally, since the solution employs conventional machine learning algorithms, its complexity is significantly lower than neural-network-based appliance identification methods.

The proposed system also requires fewer AUs than systems using an ILM approach, such as the Emporia energy monitoring system [22]. As a result, it is more cost-effective than ILM solutions. Furthermore, the anomaly detection mechanism does not rely on labeled data and can adapt to appliances with varying consumption patterns.

3.4. Future works

The proposed solution works on the cloud service, and there may be privacy concern issues by consumers. Therefore, implementation of the total system in an edge computing device will increase the security. Future work includes the development of an edge computing device to identify and monitor all the appliances. It can be used to integrate renewable sources and can be used as a single dashboard to manage all the power sources. Further, propose an appliance name verification process to enhance the accuracy, which also includes future works.

4. CONCLUSION

This study presents a hybrid appliance identification and monitoring system that synergizes the strengths of NILM and ILM approaches to address critical challenges in residential energy management. The proposed solution achieves real-time identification of linear-power-consuming appliances using a low-complexity, self-supervised k-NN model, eliminating dependency on labeled datasets and reducing computational overhead compared to neural-network-based methods. By integrating AUs only for non-linear appliances, the system significantly lowers hardware costs relative to full ILM systems like Emporia, while maintaining high accuracy of 89% on average across datasets.

Validation across custom and public datasets confirmed the system's generalizability and effectiveness in diverse residential settings. Future work will focus on edge computing integration to address privacy concerns and renewable energy integration, further advancing the system's utility in smart grids and demand-side management. By bridging gaps in affordability, real-time capability, and unsupervised learning, this research contributes to sustainable energy consumption, enhanced safety, and consumer empowerment in residential energy ecosystems.

ACKNOWLEDGMENTS

This research was supported by the Science and Technology Human Resource Development Project, Ministry of Higher Education, Sri Lanka, funded by the Asian Development Bank (Grant No: R1/SJ/02).

FUNDING INFORMATION

This research was supported by the Science and Technology Human Resource Development Project, Ministry of Higher Education, Sri Lanka, funded by the Asian Development Bank (Grant No: R1/SJ/02).

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject Administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding Acquisition
Fo	: **Fo**rmal Analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

- The supporting data of this study are openly available in ”iAWE” at https://iawe.github.io, [47].
- The supporting data of this study are openly available in ”Tracebase” at https://github.com/areinhardt/ tracebase, [45].
- The data that support the findings of this study will be available in Github repository named ”appliance_data” at https://github.com/NimanthaMadhushan/appliance_data.

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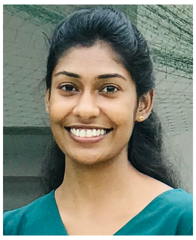

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