Real-Time Non-Intrusive Load Monitoring for Low-Power Appliances Using Odd Current Harmonics

Nimantha Madhushan*, Udari Perera, Uditha Wijewardhana, and Nishan Dharmaweera
Department of Electrical and Electronic Engineering, University of Sri Jayewardenepura, Ratmalana, Sri Lanka
Email: nimanthamk@gmail.com (N.M.), prasadini.udari@gmail.com (U.P.), uditha@sjp.ac.lk (U.W.), nishanmd@sjp.ac.lk (N.D.)

***Abstract*—Non-intrusive load monitoring (NILM) systems have gained immense popularity in the last two decades. Although many solutions were developed using the NILM approach, the majority of solutions failed to identify low-power-consuming appliances. However, a NILM system deployed in a domestic installation should be capable of identifying low-power-consuming appliances precisely. Therefore, we propose two real-time NILM solutions that can identify low-power residential appliances. These two solutions rely on active power and harmonic information extracted from the measured current waveform. We analyzed the performances of the two solutions using simulations and real-world experiments. Results indicate that both solutions can correctly identify appliances with an average accuracy above 90 percent.**

***Index Terms*—Non-intrusive load monitoring, event detection, supervised learning, support vector machine, appliance identification**

I. Introduction

Load identification and monitoring (LM) have been recognized as two important features of novel energy management systems [1]. Past evidence suggests that up to 15% of energy can be saved by adopting LM-based solutions [2, 3]. The LM systems can help consumers identify power-hungry devices and make alterations to appliance usage. Manufacturers could also use the information gathered via LM systems to produce more energy-efficient appliances [4]. Moreover, LM systems can provide a holistic overview to policymakers [4].

Non-intrusive load monitoring (NILM) concept was first introduced by G.W. Hart [5] in 1992. Unlike intrusive load monitoring systems (ILM) where each appliance is equipped with separate sensors, NILM systems require only a single measuring unit placed at the electrical service entry point of a building to take all the relevant readings [1, 4]. Thus, the cost of the NILM system is less and can be upgraded and maintained easily. Basic block diagrams of both ILM and NILM systems are shown in Fig. 1.

An NILM system involves four main steps: data acquisition, event detection, feature extraction, and appliance identification [6]. The appliance identification step often involves complex and computationally exhaustive algorithms. A non-event-based system may require the appliance identification algorithm to run continuously [7] leading to more computational resource usage. On the other hand, an event-based NILM system calls the appliance identification step only when a new event (e.g., device turned on or off) is detected.

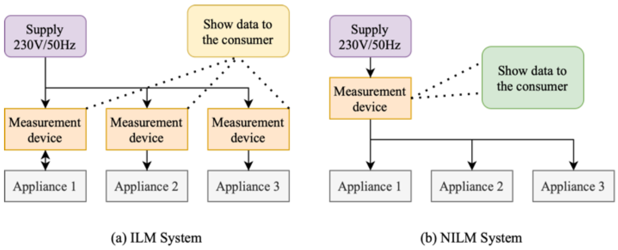

Fig. 1. Block diagrams of (a) ILM and (b) NILM systems.

Researchers have proposed many event-based and non-event-based NILM systems over the past two decades [7]. However, the majority of these available studies have only considered high-power-consuming appliances [8, 9] and gave little attention to energy-efficient low-power-consuming appliances [10]. Most high-power appliances are required to run a full operational cycle for short periods [8], and thus provide very little opportunity for energy conservation. On the other hand, low-power appliances such as routers and audio/video receivers run in the background 24/7 and all 365 days can be switched off during idle state to conserve energy. Also, low-power appliances such as bulbs, fans, and routers could also be identified and remotely switched off when consumers have left the premises. Hence, the identification of low-power-consuming appliances is rather helpful in reducing energy use and extending the life span of appliances [4, 6, 11, 12].

The Sense [13] and Emporia [14] are two commercially available products that utilize NILM to identify high-power residential appliances. While these two devices can detect and monitor high-power appliances accurately, they encounter difficulties in detecting low-power appliances. Nowadays, as most appliances fall under the category of low-power devices,

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*Corresponding author

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an NILM system should be capable of detecting such appliances correctly.

Further, a properly designed NILM system should have the ability to identify the different operating states of an appliance [7]. In most of the existing work, the accuracy of the proposed NILM systems was verified using simulations and laboratory experiments only, which could produce erroneous results in real-world tests [8, 9, 15].

In this work, we propose two real-time event-based NILM solutions to identify residential low-power appliances. Moreover, an effective event detection method is presented to capture the operating state transitions of selected devices. A support vector machine (SVM) algorithm is developed for appliance identification. The proposed solutions were tested in an actual residential environment with real appliances.

The remainder of the paper is organized as follows. A summary of the NILM systems is presented in Section II. The proposed methodologies are then explained in Section III. Next, the simulation and real-time results are discussed in Section IV. Finally, section V concludes the paper.

II. Background

In this section, we briefly discuss the four key steps of an NILM system namely data acquisition, event detection, feature extraction, and appliance identification. Then we summarized the advantages and disadvantages of the existing NILM systems.

In the data acquisition (DAQ) step, the relevant electrical measurements are recorded by tapping into the input line of the installation. In most previous work, data acquisition was performed either by using smart energy meters [16] or by using high-precision measurement equipment [17]. While these offer precise readings, they cannot be deployed in actual domestic environments due to complexity and associated high costs. Thus, a few works such as [15] have opted to design their own apparatus and capture relevant data.

In the event detection step, the operating state transitions of an appliance are identified. Switch ON, switch OFF, or a state change are recognized as common events of an appliance. Event detection is often performed by analyzing the active power variation [8, 18, 19], root mean square (RMS) current variation [20], or voltage distortion [21].

Different features are then extracted from the recorded data in the feature extraction step. Features can broadly be divided into the steady-state and transient-state [7]. The active power value is the most widely used steady-state feature in NILM systems [10, 19]. Additionally, the current harmonics [22, 23], voltage-current trajectory [24], and current waveform [15] have also been extracted as features. The voltage transients [21] and power transients [8] have been extracted as transient-state features.

The appliance identification step is the most crucial in an NILM system. Generally, supervised or unsupervised learning approaches can be used for this purpose with a single or combination of features as inputs. Among the supervised learning approaches, pattern recognition is the most commonly used method [6, 7]. Support vector machines (SVM) [23, 25] artificial neural networks (ANN) [19, 26], and k-nearest neighbor (k-NN) [15] are a few examples of such commonly used pattern recognition-based algorithms.

Although many NILM-based solutions were proposed in the past, their commercial viability is hindered by a number of limitations. Among them, some major drawbacks are low identification accuracy, difficulty in monitoring low-power-consuming appliances, proposed algorithms not being tested in real-time, and experiments being carried out in a controlled laboratory environment.

The majority of the solutions developed by the researchers can identify high-power appliances yet fail to correctly identify low-power devices [8, 9, 27, 28]. The solution proposed in [3], was verified with the publicly available REDD [29] dataset, and real-time tests were carried out with high-power-consuming appliances. Similarly, in [27] and [9], appliances consuming more than 140W power were used for the experiments. In [8], three high-power-consuming appliances (fridge, washing machine, and microwave oven) were used to evaluate the performance of the proposed solution.

On the other hand, in a few studies [2, 10, 17] tests have been performed on lower-power devices. However, such solutions often utilize high-precision measuring devices that are only feasible in a laboratory environment. Real-time experiments conducted in actual environments using low-cost measurement devices are a rarity [3, 15]. In our previous work [18, 25], we proposed a current harmonic-based solution to identify both low and high-power appliances in a controlled environment in real time.

Most solutions have been tested in an environment where an individual appliance is turned ON without any other devices running in the background [8], 10]. Furthermore, tests were carried out in a controlled laboratory environment [3, 15], or software-based simulations [14, 28, 29].

Moreover, the use of large-sized databases was a common attribute in most prior studies, as their solutions relied on data from individual appliances and all possible combinations [10, 13, 30, 31]. When the number of appliances increases, these databases grow exponentially, leading to more memory use. Table I provides an overview of how our proposed solution compares against existing work.

In several recent studies, authors have proposed solutions based on the analysis of current harmonics [31–34]. Although their results are comparable to the objective of this work, there are some key differences, which are highlighted in Table I. Researchers have also proposed and assessed transferable NILM (i.e., generalized) solutions using different public datasets [35–37], and have investigated their key differences thoroughly in [38].

Considering the above key issues, we believe that a solution that can provide real-time results in a realistic residential environment is yet to be developed. Therefore, this study aims to propose two real-time algorithms that can identify low-power residential appliances and evaluate their performance in terms of identification accuracy, memory use, and running time.

TABLE I: SUMMARY OF KEY ISSUES

Reference	Utilized/proposed a low-cost DAQ	Event detection (triggering)	Results based on public datasets instead of actual data	Tested with combinations and sequence operation	Real-time monitoring	Ability to detect low-power appliances
[2]	-	✗	✓	✗	✗	✓
[3]	✓	✓	✓	✓	✓	✗
[8]	-	✓	✗	✗	✓	✗
[10]	✗	✗	✗	✗	✓	✓
[15]	✓	✗	✗	✗	✓	✓
[16]	✗	✗	✗	✗	✗	✗
[17]	✗	✓	✗	✓	✓	✓
[19]	-	✓	✓	✗	✗	✗
[30]	✗	✗	✗	✗	✗	✗
[31]	✗	✗	✗	✓	✗	✓
[32]	✗	✗	✓	✗	✗	✓
[33]	✓	✗	✗	✓	✗	✓
[34]	✗	✗	✗	✓	✗	✓
[35]	✗	✗	✓	✓	✗	✗
[36]	✗	✗	✓	✓	✗	✗
[37]	✗	✗	✓	✓	✗	✗
[39]	✗	✗	✓	✗	✗	✗
[40]	✗	✗	✓	✗	✗	✗
Proposed	✓	✓	✗	✓	✓	✓

III. METHODOLOGY

Electric appliances in residential houses are generally categorized into four types based on their operational behaviors [4, 7].

- Type I: appliances having only two operating states (e.g., ON or OFF). Such devices will remain in either one of these states (i.e., single state or binary) at any given time. Examples are light bulbs and electric heaters. These appliances will exhibit two levels of power consumption.
- Type II: appliances that may operate in multiple unique states. Fans with different speed levels will exhibit such behavior and draw different levels of power depending on the speed selected. Such appliances are also called multi-state (i.e., stair-like) appliances.
- Type III: These types of appliances will draw varying amounts of power and do not exhibit a fixed number of power levels. Examples are power drills and light dimmers.
- Type IV: This includes appliances that remain switched ON for very long duration, such as routers and cable TV receivers. These are also called permanently connected loads.

As we aim to provide a solution for domestic consumers, six different commonly used low-power-consuming appliances were selected for this study (Table II). Generally, a single house uses many lighting appliances (i.e., bulbs) with different wattage values. Hence, four different wattage values were selected for LED bulbs and panel LEDs.

The LED TV has been categorized as a type-III appliance following the findings of prior research [19]. The screen is the leading power-consuming part in new LED or LCD TVs and the appliance's total power consumption may vary with the color status of the screen. However, the average power consumption of a TV shows little variation over time in real life.

TABLE II: DETAILS OF COMMONLY USED LOW-POWER APPLIANCES

Appliance	Wattage values (W)	Tag	Type
LED bulb	7, 9, 12 and 15	LED	I
Panel LED	9, 12, 18, and 24	PLED	I
Satellite TV decoder	12	DEC	IV
LED Television	59	TV	III
Mobile phone charger	5	MPC	I
Aquarium pump	20	AP	IV

Our proposed solutions involve the following four steps.

A. Data Acquisition

A microcontroller-based setup was developed for the data collection process. Using this setup, voltage and current readings were measured at a sample rate of 15 kHz. Using the gathered data, the first twenty-one current harmonics of appliances were then investigated. Please take note, that according to the basic principles of Nyquist theory, a minimum sampling frequency of 2.1 kHz is required to capture the data of 21 harmonics where the fundamental is at 50 Hz. The selected microcontroller setup thus provides a higher-accuracy waveform as it operates at a higher (15 kHz) sampling rate.

The collected data was transferred into the computer through a universal serial bus (USB) cable every two seconds. A Python-based program was developed to calculate different parameters from the received data. Active power, reactive power, apparent power, power factor, and the first twenty-one current harmonic values were calculated and stored in the computer.

According to the basic power triangle calculations, apparent is equal to the product of V_{RMS} and I_{RMS}. Now, by determining the phase difference (θ), between V_{RMS} and I_{RMS} waveform, real power (P) is calculated using (1), and reactive power (Q) is calculated using (2):

$$P = V_{\mathrm{RMS}} I_{\mathrm{RMS}} \cos(\theta) \tag{1}$$

$$Q = V_{\mathrm{RMS}} I_{\mathrm{RMS}} \sin(\theta) \tag{2}$$

The power triangle is produced based on these values, and the power factor is obtained by dividing the active power by the apparent power values.

Fast Fourier Transformation (FFT) was then applied to calculate the current harmonic values of waveform. The ready-made Fast Fourier Transform (FFT) function in the NumPy library was used to obtain the current harmonics of the given signal [41]. The total current signal is fed into the function, which then returns the calculated harmonic values. However, only the first twenty-one harmonic values were extracted from the output for the evaluation.

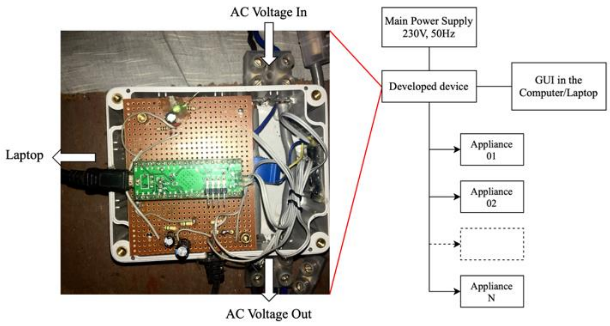


Fig. 2. Structure of the data acquisition setup.

Fig. 2 shows the arrangement of the data acquisition setup. Each appliance's readings were recorded and stored in the computer for analysis. The data collection process was conducted in a controlled laboratory and an actual (i.e., uncontrolled) residential environment. The recorded average supply voltage of controlled and uncontrolled environments were 232.32 V and 240.80 V, respectively.

B. Event Detection

An event is identified by a sudden change in the active power. The overlapping sliding window, with a window size of twenty seconds (i.e., ten data points), was used to capture and analyze data. The readings taken of the "Switch ON" event, for three different appliances, are shown in Fig. 3.

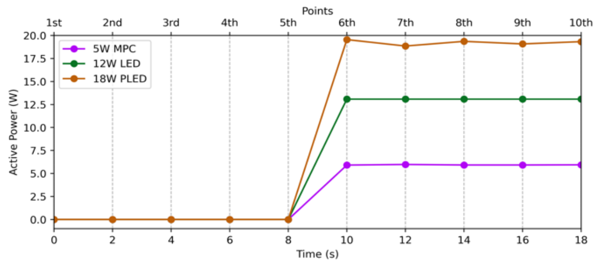


Fig. 3. Power variation at the switching-ON state of different appliances.

In Fig. 3, a significant change in active power is observed between the 8-10 seconds time period or 5th and 6th data points for all appliances. We observed similar results for other appliances when they transit from "Switch ON" to "Switch OFF" states.

Based on our analysis, it is evident that an event can be correctly identified when the power difference (P_{diff}) between the 5th and 6th data points of the sliding window exceeds 5W. The template matching method, which we first proposed in [18], is then used to distinguish between an accurate and inaccurate event by comparing it against pre-recorded events. The recorded events of different appliances were stored in a separate database after the normalization. If the P_{diff} is greater than 5W, all active power values in the certain window are normalized using the maximum value. During the template-matching process, the normalized values of the current window are compared with the recorded values.

Template matching helps the system avoid detecting wrong events caused by noise generated when TV channels are changed or when an LED transits between ON and OFF states momentarily [18].

C. Features of Appliances

In the beginning, the active power consumption of the selected appliances was scrutinized. The wattage and the average power consumption of these appliances are tabulated in Table III. The average power consumption of the TV was recorded for fixed brightness and sound levels.

TABLE III: AVERAGE POWER CONSUMPTION OF SELECTED APPLIANCES

Appliance	Wattage (W)	Average power consumption (W)
LED	7	7.43
	9	10.07
	12	13.47
	15	15.50
PLED	9	10.84
	12	12.12
	18	18.71
	24	23.52
DEC	12	6.55
TV	59	32.50
MPC	5	5.95
AP	20	22.48

Similarities were observed among different appliances, and therefore, identifying low-power appliances with only active power measurements was deemed too difficult [8]. Therefore, the odd current harmonics of appliances were also analyzed. The amplitudes of even current harmonics were insignificant, and thus, the effect of even harmonics was not considered in this study. Different appliances have unique harmonic patterns and amplitude values due to their non-linearity [20, 42]. As a result, the combination of active power and current harmonics has been used as features for the identification process, as in [20].

Finally, the same appliances with different wattage values were also investigated. Fig. 4 shows the harmonic variation pattern (fundamental to 17th) for two different wattage values of LEDs and PLEDs.

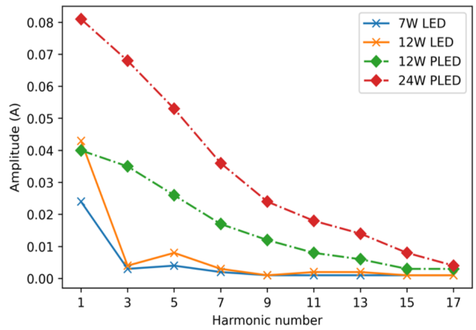


Fig. 4. Harmonic pattern variation of different wattage values.

In Fig. 4, it is observed that an appliance produces the same harmonic pattern even at different wattage levels. Therefore, instead of considering actual amplitude values, normalized values can be used for appliance identification.

Values were normalized by dividing each harmonic amplitude value by the fundamental value. The calculated first nine odd normalized harmonic values of different appliances are shown in Fig. 5.

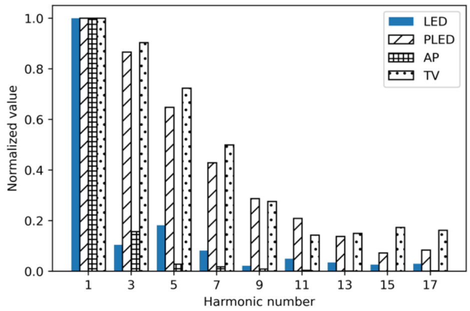


Fig. 5. Normalized harmonic variation of different appliances.

The results obtained through the analysis evidently show that the current harmonics of appliances can be used in two different ways (either normalized values or actual values of harmonics) to identify low-power appliances and they can be described as follows:

When in sequence operation (i.e., sequentially switching on devices), the differences measured in both the active power and current harmonic, before and after switching ON/OFF the appliance, were used to gather the relevant features of the new appliance. The flowchart of the developed solutions is depicted in Fig. 6 by indicating common steps for both.

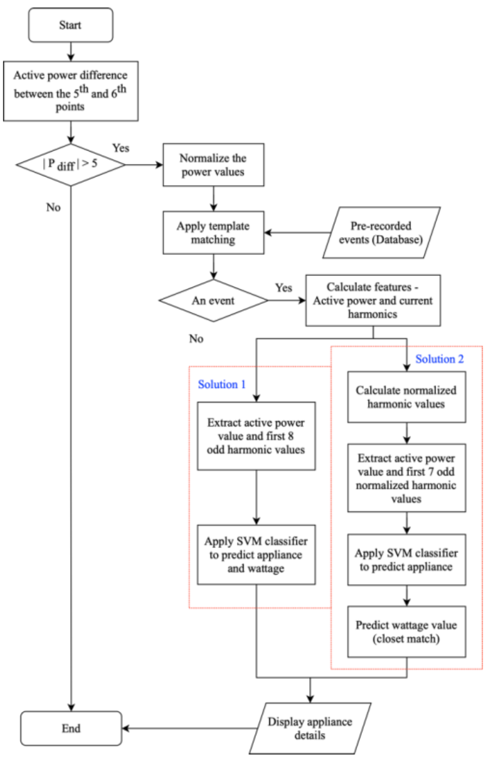


Fig. 6. Flowchart of the solution.

D. Appliance Identification Algorithm

For the purpose of training, a database was created by analyzing the operational behavior of twelve low-power-consuming appliances. Each appliance was turned on and the voltage and current values were recorded during a full operation cycle. To eliminate any measurement errors and biases, 500 records were gathered for each appliance by repeating this process. In total, 6000 samples were recorded in the database for all twelve appliances. As the sample size was deemed insufficient to develop a deep neural network from scratch, a shallow learning technique was used to construct the solution.

The proposed algorithm relies on the Support Vector Machine (SVM) supervised learning approach, an effective approach used in classification and regression models. Further, tests performed using inbuilt machine-learning models in the scikit-learn Python library, revealed that support vector machine (SVM) and random forest (RF) show higher accuracy levels compared to decision tree (DT) and multilayer perceptron (MLP) models. Thus, SVM is well suited for machine-learning solutions with a relatively limited amount of data. Among the many possible kernels in SVM [30, 43], in this study, we applied multi-label classification with the linear kernel. Two variations of the algorithm, named Solution 1 and Solution 2, were developed to explore the tradeoff between performance, accuracy, and complexity.

1) Solution 1

The active power value and the amplitudes of the first eight odd current harmonics were utilized as features in Solution 1. In Table IV, Column 3 shows the labels assigned for each appliance at the specific wattage. Since only one label is used to represent an appliance of a certain wattage, a single classifier is sufficient for the entire identification process. Each appliance was connected to the acquisition setup and the respective power and harmonic amplitude values were recorded. The same procedure was repeated 500 times and the obtained data were recorded in a database.

2) Solution 2

The active power value and the first seven normalized odd current harmonic values were used in this solution. A total number of eight inputs were initially used in the algorithm as features. However, since the normalized value of the fundamental harmonic is 1.0, for all appliances, it was not considered. In Table IV, Column 4 shows the assigned labels in this solution. Unlike solution 1, here, a single label is assigned for an appliance regardless of the wattage level.

The appliance's wattage was stored in a separate column in the database. For example, under the "0" label, there are four wattage levels as shown in Table IV. This method has a lower number of labels compared to the first solution. In this method, one classifier is used to predict the appliance, and the closest match is used to predict the wattage value of the appliance.

The performance of both developed algorithms was discussed in Section IV.

TABLE IV: ASSIGNED LABELS FOR EACH SOLUTION

Appliance	Wattage (W)	Assigned label	
		Solution 1	Solution 2
LED	7	0	0
	9	1	
	12	2	
	15	3	
PLED	9	4	1
	12	5	
	18	6	
	24	7	
DEC	12	8	2
TV	59	9	3
MPC	5	10	4
AP	20	11	5

IV. RESULTS AND DISCUSSION

The two proposed solutions can be used to identify residential low-power appliances, either using the actual current harmonic values (Solution 1) or using the normalized values (Solution 2). However, these techniques require different memory and processing usage. For example, when feeding the actual current harmonic values, a unique profile (i.e., label) must be created and stored for each appliance that may come in different wattage values. On the other hand, if the normalized values are used, one profile can be used to identify an appliance that may come in different wattage values. Table IV provides a simple summary of how labeling is performed with these two techniques. By the look of it, the normalized values in Solution 2 reduce the burden on memory and processing yet require an additional step to identify the wattage of the appliance.

The performance of the two proposed solutions was measured in terms of identification accuracy, elapsed time, and memory usage. Two methods were involved in evaluating the performance and accuracy of the two solutions; simulation and real-time experiments. First, data were divided into 80% for training and 20% for testing. The algorithm was trained using the training dataset and performed the evaluation using the testing dataset. Fig. 7 and Fig. 8 show the obtained results as a confusion matrix [44] for Solutions 2 and 1, respectively. The performance of the identification process can be evaluated using a benchmarked FScore (i.e., F1 score or F measure) matrix shown in Eq. (3) [28]. The terms, Precision and Recall, are described Eqs. in (4) and (5), respectively.

$$\text{FScore} = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}) \quad (3)$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \quad (4)$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}) \quad (5)$$

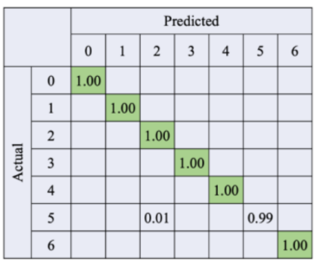


Fig. 7. Confusion matrix for Solution 2.

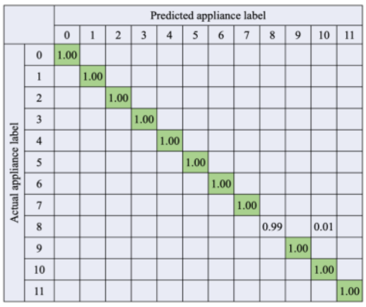


Fig. 8. Confusion matrix for Solution 1.

TABLE V: PERFORMANCE EVALUATION OF SIMULATION-BASED TEST

Appliance	Wattage (W)	Solution 1			Solution 2		
		FScore	Precision	Recall	FScore	Precision	Recall
LED	7	1.00	1.00		1.00	1.00	1.00
	9	1.00	1.00	1.00			
	12	1.00	1.00	1.00			
	15	1.00	1.00	1.00			
PLED	9	1.00	1.00	1.00	1.00	1.00	1.00
	12	1.00	1.00	1.00			
	18	1.00	1.00	1.00			
	24	1.00	1.00	1.00			
DEC	12	0.99	1.00	0.99	0.99	0.99	1.00
TV	59	1.00	1.00	1.00	1.00	1.00	1.00
MPC	5	0.99	0.99	1.00	0.98	1.00	0.99
AP	20	1.00	1.00	1.00	1.00	1.00	1.00

TP is defined as the true positive of the predictions and FP is the false positive. FN is defined as a false negative. Table V provides the performance evaluation of the two simulation-based tests.

On average, Solution 1 achieved an accuracy of 99.89%, and Solution 2 reached 99.91% accuracy. Both solutions achieved a similar level of accuracy for simulation-based experiments. The identification accuracy of MPC and DEC was slightly lower due to the similarity of features; both of these are switched-mode power supply-based appliances and have the same rated power value.

Next, real-time tests were performed using both solutions. First, appliances were switched ON and OFF individually when no other appliances were operating in the system. Next, multiple numbers of appliances were switched on one by one (i.e., sequentially). Please take note that the device identification algorithm was run in real-time on a connected laptop with Intel Core i3 2.1GHz CPU speed and 8GB DDR3 RAM with a dedicated NVIDIA GeForce 920M 2GB graphic memory.

Over 200 individually and sequentially switched ON and OFF events were tested in real time. The selected appliances were sequentially switched ON and OFF for one hour. The exact sequence was applied for both algorithms. The recorded aggregated and individual active power variations of the system are shown in Fig. 9. Tables VI and VII show the identification results and elapsed time of both solutions. The average elapsed time for prediction of the first and second solutions were

0.020906 s and 0.0356 s, respectively.

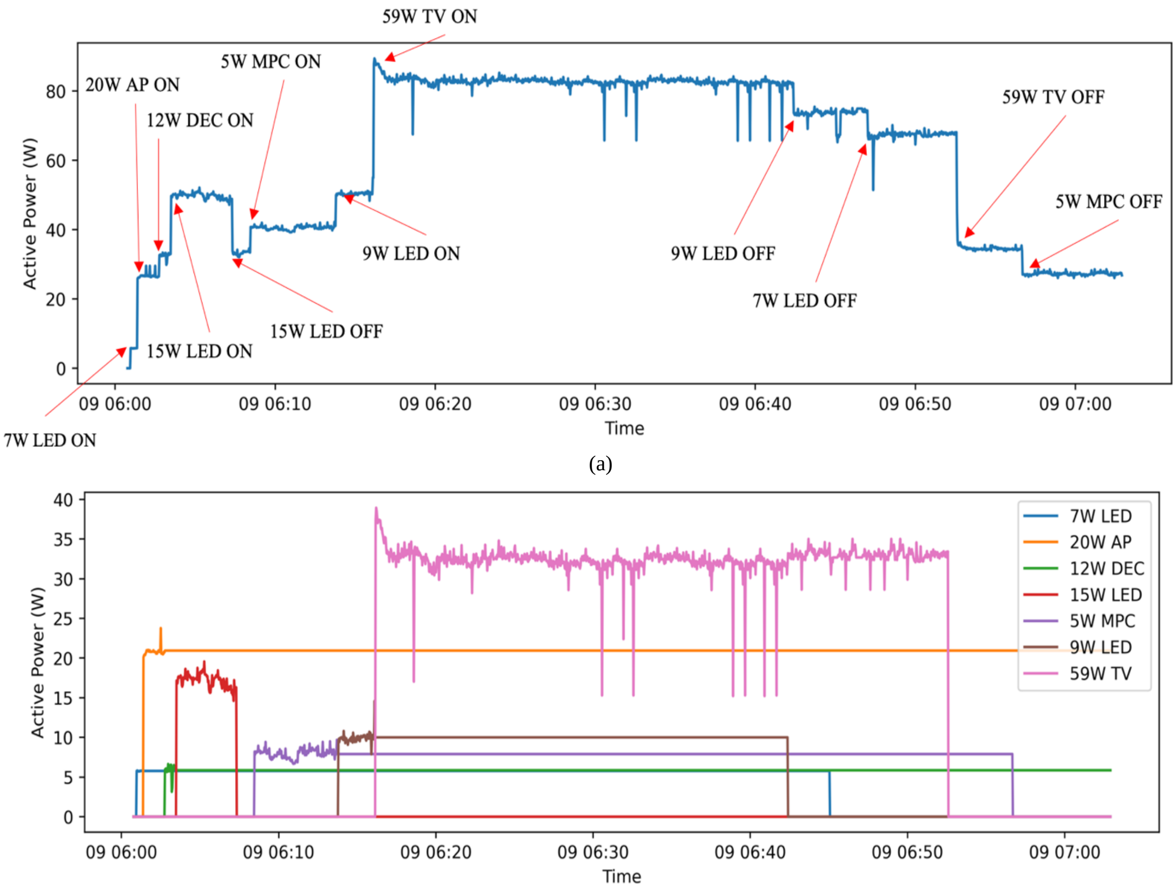
The DEC was identified wrongly due to its feature similarity with MPC, and it can be solved by analyzing the operating time of the appliances. Further, the TV was identified as 24W PLED when transitioning from ON to OFF states.

TABLE VI: SUMMARY OF SOLUTIONS

Characteristics	Solution 1	Solution 2
Simulation-based accuracy (%)	99.89	99.91
Real-time individual operation accuracy (%)	98.00	99.00
Real-time sequence operation accuracy (%)	91.00	93.00
Elapsed time (s)	0.020906	0.0356
Numbers of labels in SVM	High	Low

TABLE VII: RESULTS OF THE SEQUENCE

Appliances in the background	New appliance	Event	Solution 1	Elapsed time (ms)	Solution 2	Elapsed time (ms)
-	7W LED	ON	7W LED	82.503	7W LED	82.282
7W LED	20W AP	ON	20W AP	11.626	20W AP	27.603
7W LED + 20W AP	12W DEC	ON	12W DEC	18.193	12W DEC	28.302
7W LED + 20W AP + 12W DEC	15W LED	ON	15W LED	14.192	15W LED	30.051
7W LED + 20W AP + 12W DEC + 15W LED	15W LED	OFF	15W LED	12.039	15W LED	36.736
7W LED + 20W AP + 12W DEC	5W MPC	ON	12W DEC	22.266	5W MPC	26.295
7W LED + 20W AP + 12W DEC + 5W MPC	9W LED	ON	9W LED	19.703	9W LED	35.158
7W LED + 20W AP + 12W DEC + 5W MPC + 9W LED	59W TV	ON	59W TV	6.762	59W TV	13.069
7W LED + 20W AP + 12W DEC + 9W LED + 5W MPC + 59W TV	9W LED	OFF	9W LED	19.504	7W LED	53.282
7W LED + 20W AP + 12W DEC + 5W MPC + 59W TV	7W LED	OFF	7W LED	17.795	7W LED	80.273
20W AP + 12W DEC + 5W MPC + 59W TV	59W TV	OFF	24W PLED	8.845	59W TV	27.168
20W AP + 12W DEC + 5W MPC	5W MPC	OFF	5W MPC	17.452	5W MPC	31.799



(a)

(b)

Fig. 9. Tested sequence (a) aggregated active power (b) average active power variation of each appliance.

TABLE VIII: COMPARISON OF RESULTS WITH PREVIOUS WORKS

Study	No. of appliances	No. of low-power appliances	Simulation accuracy (%)	Real-time accuracy (%)	Required to feed combinational data in advance	Running on the edge/ cloud
[2]	20	9	98.91	-	No	-
[10]	4	4	100.00	-	Yes	-
[15]	7	5	-	94.71	Yes	Edge (Raspberry Pi)
[17]	15	8	98.03	-	No	-
[31]	6	3	81.80	-	Yes	-
[33]	8	6	98.00	-	Yes	-
[34]	5	2	66.60	-	Yes	-
[45]	20	4	-	94.02	No	Edge (Laptop)
Solution 1	12	12	99.89	94.50	No	Edge (Laptop)
Solution 2	12	12	99.99	96.00	No	Edge (Laptop)

Table VIII shows how our work compares against previous work. Compared to existing work, our proposed solutions were tested and verified for more low-power-consuming appliances in a real, uncontrolled household environment. Further, several studies required data on appliance combinations to be fed into the database [10, 15, 31–34] beforehand. However, the proposed solution only required data on individual appliances, yet accurately identifies appliances even when in sequential operations.

Future directions: Our database included data from many appliances, out of which only 6 different appliances were used for actual tests. As the size of the database increases the likelihood of having multiple appliances with similar features also increases. As a result, an event will be connected to the wrong device that is not present in the actual test environment. For example, the 24W PLED was not used in the tested sequence of the actual operation. However, the switching OFF event of the TV was wrongly identified as 24W PLED in Solution 1, due to the similarity of features. To mitigate such errors, the database can be custom-developed to include only the data of available appliances at a particular premises with the help of consumer inputs [46].

Moreover, appliances with similar features can be further differentiated by using time parameters, such as the switch on time and operational time. Furthermore, future works include modifying the identification algorithm for both low and high-power-consuming appliances to produce a complete solution. Such a solution will involve two stages; in the first stage, an appliance will be categorized based on the active power as high-power or low-power [20]; if the appliance is identified as a low-power, then the solution proposed in this paper could be used to pinpoint the exact appliance and the wattage. In our future work, the processing that was carried out by the laptop will be offloaded to a custom-designed edge unit.

V. CONCLUSION

An accurate real-time NILM methodology is vital for an improved load monitoring system. This research proposes two Solutions that utilize supervised learning techniques and rely on different input features. The proposed solutions can detect low-power-consuming appliances correctly. Six commonly used household electric appliances were selected, and tests were conducted using simulations and real-world experiments. Proposed solutions achieved over 90% accuracy and correctly predicted the appliance within one second in real-time testing. Between the two solutions, the second solution consumes marginally more time yet consumes less processing power. Thus, in our opinion, Solution 2 is highly effective in real-time NILM systems.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Nimantha Madhushan is an M.Phil. student, and he developed the proposed solutions and tested them. Further, he drafted the first edition of the paper. Udari Perera engaged with the testing works of algorithms and provided support to write the paper. Nishan Dharmaweera and Uditha Wijewardhana funded and supervised the research work, provided guidance with the experiments, and helped in writing the paper and addressing comments. Finally, all authors approved the final version of the paper.

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Nimantha Madhushan received a B.Sc. degree in electrical and information engineering from the University of Ruhuna, Matara, Sri Lanka, in 2019. He is currently reading his M.Phil. degree in electrical and electronic engineering at the University of Sri Jayewardenepura, Ratmalana, Sri Lanka. He is currently a research assistant at the Department of Electrical and Electronic Engineering, Faculty of Engineering, University of Sri Jayewardenepura (USJ). His research interests include non-intrusive load monitoring and power system measurements.

Udari Perera received a bachelor of engineering degree (Hons.) in chemical and process engineering from the University of Moratuwa, Sri Lanka, in 2016 and MSc in research in chemical engineering from Monash University, Malaysia, in 2020. She is currently working as a research scientist at the Department of Electrical and Electronic Engineering, Faculty of Engineering, University of Sri Jayewardenepura (USJ). Her research interests include smart sensing materials and process modeling and optimization.

Nishan Dharmaweera (Member, IEEE) received the bachelor of engineering degree (hons.) in electrical and computer systems engineering, in 2009, and the Ph.D. degree in optical networks from Monash University, Malaysia, in 2014. From 2015 to 2016, he worked as a postdoctoral researcher with the FORCE Research Center, Chalmers University of Technology, Sweden. He joined the Department of Electrical and Electronic Engineering, University of Sri Jayewardenepura, as a Senior Lecturer. His research interests include optical communications, network optimization, applications of electromagnetics, and the Internet of Things.

Uditha Wijewardhana (Member, IEEE) received the Ph.D. degree in telecommunications engineering from the Centre for Wireless Communications, University of Oulu, Finland, in 2020. He is currently a Senior Lecturer with the Department of Electrical and Electronic Engineering, University of Sri Jayewardenepura. His research interests include the application of optimization techniques for signal processing and wireless communications, compressed sensing, and machine learning.