# Real-Time Appliances Recognition for Non-Intrusive Load Monitoring Using CNN

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***Abstract*—Up to now, the details of the load-level power consumption are generally not available to the customers who wish to get more information about their power usage. This paper shows the result of using Convolutional Neural Networks (CNN) to recognize the type of any electrical appliance while operating as well as its power consumption. This approach allows the monitoring on a loads power consumption on every electrical appliance individually. By applying an envelope function to the signal, the appliance can be recognized successfully even it only consumes a small amount of energy during its operation. The performance was evaluated on three electrical appliances at different power consumption level.**

***Index Terms*—Convolutional Neural Networks (CNN); Current Sensor (CT); Envelope Signal; Non-intrusive Load Monitoring (NILM); Power Factor (PF); Root Mean Square (RMS); Spectrogram.**

## I. INTRODUCTION

Lowering the daily power consumption is a critical problem nowadays to reduce the carbon footprint. Residential and industry consume about 60% of the worldwide electricity usage [1]. In the United States, buildings consume approximately 75% of the total produced electricity [2]. The report claims that 80% more buildings will be in place by 2050 yields higher energy demand [1].

However, saving electricity could be a challenge as customers do not usually provide a resource that contains the whole details about their power usages. Studies in [3] have proved that when providing users with real-time power consumption feedback, at the aggregate level, it helps them to change their behaviour and save up to 15% of electricity.

Traditionally, to monitor the power consumption for every appliance in a building, we need to install a current sensor into each appliance individually. Installing such a sensing infrastructure is intrusive and costly [4]. Therefore, researchers are started to develop an effective non-intrusive load monitoring (NILM) techniques.

NILM could be defined as the process of disaggregating a household's total electricity consumption into its contributing appliances through a single point of measurement at the main power feed. In the 1990s, Hart [5] proposed the first NILM approach to disaggregate energy. Figure 1 shows an example of disaggregating a mixed energy signal into its original sources using a NILM algorithm. In this example, NILM able to differentiate the electrical signal at the main power meter as the combination of three electrical appliances: refrigerator, dishwasher and microwave power signal.

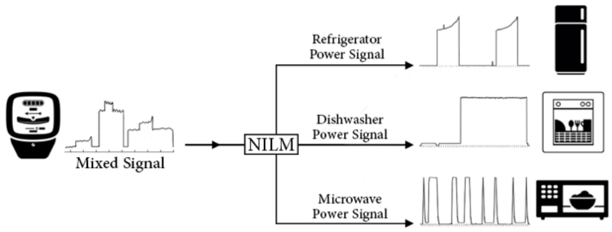


Figure 1: Energy Disaggregation Example

The NILM algorithms have been improved significantly since their introduction, researchers have published several paths on energy disaggregation to improve the initial design. However, there are still many challenges that need to be addressed.

In this paper, we developed a method to determine the type of the appliance which is currently operating by combining both event detection algorithms and supervised NILM techniques. An appliance recognition approach using Convolutional Neural Networks (CNN) that depends on load signature to differentiate the various type of electrical appliances. With this approach, we able to develop a real-time power monitoring system to provide the detailed usage to the end-users.

## II. APPLIANCE SIGNAL ACQUISITION

The first step of any NILM application is to capture the load signal and store it in digital form. Figure 2 illustrates the steps of this process. The current sensor (YHDC SCT-013-030) is used to maps the current value into a voltage between 0V and 1V. The maximum input current of this sensor is 30A [6].

The second step is to connect the current sensor into Analogue to Digital Converter (ADC). To preserve the detail signature features for our appliances, we need to digitalise the analogue signal with a high sampling rate. A dedicated ADC from Microchip (MCP3202) was used in this project. This

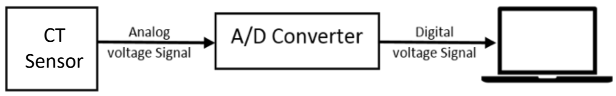


Figure 2: Signal Acquisition Steps

chip has 12-bit resolution and sampling rate up to 100,000 samples per second [7].

## III. Appliance Consumption Calculator

As mentioned in pervious section, the current sensor maps current into voltage value between 0-1V. This information is used to obtain the amount of power consumed by the load. This is done by extracting the Root Mean Square voltage ($V_{RMS}$) and current ($I_{RMS}$) values. There are two methods to obtain $V_{RMS}$ *value*, analytical method and graphical method [8].

In every sinusoidal voltage waveform, there are many instantaneous voltages, and the number of instantaneous voltages dependents on the sampling rate. For example, if the waveform is divided into *n* mid-ordinates, then at instance of time equals N=2 (as shown in Figure 3), the instantaneous voltage of the alternative current waveform is $V_2$. Similarly, at the instance, when time equals to *n*, the instantaneous voltage is $V_n$. To compute the $V_{RMS}$:

1) The instantaneous voltage values of every instance of the periodic signal is obtained, such as $V_1$, $V_2$, $V_3$ until $V_n$. The *squared* part of RMS refers to find the *squared* values of every voltage value of the alternative current signal. Then add all these values together.
2) To obtain the *mean* part, the sum of squares calculated in the previous step needs to be divided by a number of the sampling rate.
3) Taking the square root of the results yields the *squared* part.

These three steps can be summarized as:

$$V_{RMS} = \sqrt{\frac{\sum_{i=1}^{N}(V_i)^2}{N}} \tag{1}$$

where: $V_i$ = Input voltage.
$N$ = Number of samples.

Then, we can use $V_{RMS}$ value from Equation (1) to calculate $I_{RMS}$ using the following equation:

$$I_{RMS} = 2\sqrt{2}\,\frac{i_{Max}}{AREF} \times V_{RMS} \tag{2}$$

where: $i_{Max}$ = Maximum current the CT can measure.
$AREF$ = ADC reference voltage.

With this $V_{RMS}$ *and* $I_{RMS}$, the power consumption can be calculated.

In Alternative Current (AC) circuits, there are two types of power, *apparent power* and *real power*. Here, we are interested in real power because it represents the actual amount of energy consumed by the load [9]. While the power consumption of any appliance equals the result of current multiplied by voltage; however, in AC circuits, we need to consider the term called *power factor* (PF). It is the ratio of the actual electrical power dissipated by an AC circuit [10]. So, the equation to calculate the real power would be:

$$P = V_{RMS} \times I_{RMS} \times PF \tag{3}$$

where: P = Real power in watt.
PF = Power factor.

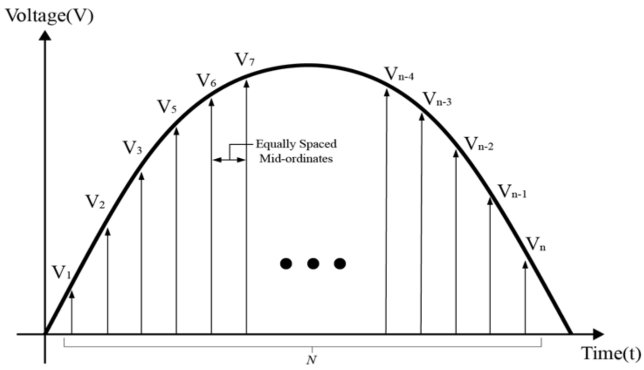


Figure 3: Calculate Root Mean Square Current Graphically

## IV. Machine Learning Implementation

In this stage, appliances signature is analysed to classify the type of electrical appliance. Three different appliances were used in this study: *lamp*, *hairdryer* and *heater*, as shown in Table 1.

Table 1
Appliances' Maximum Power Consumption

| Appliance | Maximum Power (W) |
|---|---|
| Lamp | 20 |
| Hairdryer | 1000 |
| Heater | 2000 |

### A. Envelope Signal Generation

Since the electrical appliances in the market operate at a sinusoidal alternative current of 50 to 60 hertz (Hz) [11], relying only on the frequency domain itself will not be beneficial to distinguish between each appliance. However, each appliance has unique signature and amplitude. To generate this unique pattern, the *envelope* function is used to extract the amplitude information of the electrical signal [12]. A formal definition of the envelope term is that boundary within which the signal is contained in the time domain. This boundary has an upper and lower part, and each part is a mirror image of the other. In practice, when speaking of the envelope, it is customary to consider only one of them as *the envelope* (typically the upper boundary). Figure 4 shows the upper side of the envelope (the orange signals) for each heater, hairdryer and lamp respectively.

Figure 4 also illustrates the purpose of using envelope as identity for appliances. It contains both amplitude value and frequency, makes it possible to generate a fingerprint for any specific load.

### B. Spectrogram Generation

A spectrogram is a representation of how the frequency of a signal changes with time. It is a visual way of representing the signal strength, or *loudness*, of a signal over time at various frequencies present in a particular waveform. The spectrogram is built from a sequence of spectra by stacking them together in time and by compressing the amplitude axis into a *contour map* drawn in a range of colours. Spectrogram graph comes with two geometric dimensions: the horizontal axis represents time while the vertical axis represents frequency, a third dimension pointing out the amplitude at the

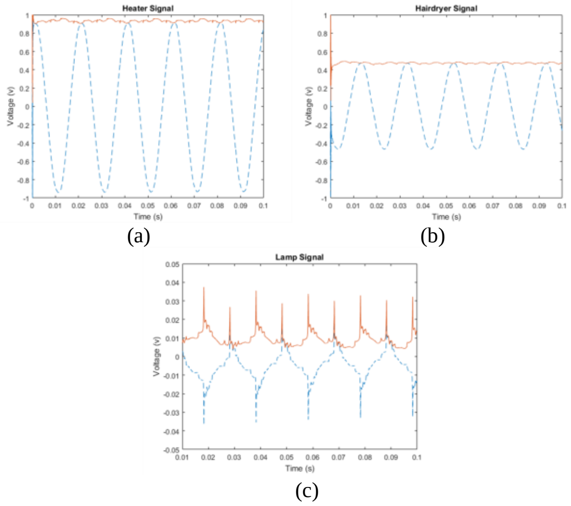


Figure 4: (a) Heater Signature (dashed) and Envelope Signal of It
(b) Hairdryer Signature (dashed) and Envelope Signal of It
(c) Lamp Signature (dashed) and Envelope Signal of It

particular time of a particular frequency.

In this study, the spectrogram is generated by taking the short-time Fourier transform of the envelope signal [13]. Figure 5 shows the spectrogram version of the envelope signals in Figure 4 with a window size of 512 and sampling frequency at 56 kHz. The green colour feature images in Figure 5 represents the low-energy ranges where the red colour represents the high-energy ranges. With the spectrogram, a fingerprint is obtained for each appliance: the heater, hairdryer and the lamp. The next step is to use machine learning to recognise the appliance type when it operates.

### C. *Convolutional Neural Network Data*

Convolutional Neural Network (CNN) has shown excellent performance in many computer vision and machine learning problems. Many solid papers have been published on this topic, and quite some high-quality open source CNN software packages have been made available [14].

In machine learning, an unknown universal dataset is assumed to exist, which contains all the possible data pairs as well as their probability distribution of appearances in the real world [15]. This acquired dataset is called the *training set* (training data) and used to learn the properties and knowledge of the universal data set. In general, vectors in the training set are assumed independently and identically sampled from the universal data set. What we desire is that these learned properties can not only explain the training set but also be used to predict unseen samples or future events.

To evaluate the performance, 100 data samples for each load were recorded. These features are split into training and validation data, where 30% of them were used as training data and the remainder, 70%, as validation data. The CNN detection algorithm processes the data and then predicts the type of electrical appliance.

Figure 6 summarises overall processes to identify the appliance type. Firstly, the record appliance signal is obtained using the current sensor. Secondly, the envelope signal is computed to generate the spectrogram, which represents the frequency spectrum. Finally, the trained CNN will recognise the electrical appliances accordingly based on the spectrogram.

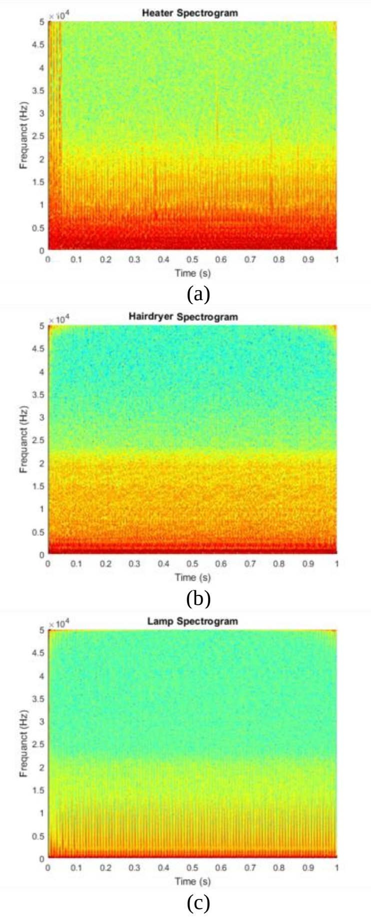


Figure 5: (a) Spectrogram Version of Envelope Signal for Water Heater,
(b) Spectrogram Version of Envelope Signal for Hairdryer
(c) Spectrogram Version of Envelope Signal for Lamp

## V. Real-time Energy Monitoring

Alongside appliances recognition, a monitoring algorithm has been developed to detects when a specific load has been set to ON/OFF. Figure 7 illustrates this concept. The horizontal axis shows the time in seconds while the vertical axis represents the power consumption in kilowatts (kW). This graph provides important feedback to users by showing the state and energy consumption for the individual load.

From the graph, one can note that the heater is switched ON after 82 seconds, then switched OFF at 144 seconds. During this time, the energy consumption will be calculated which is about 2kW.

## VI. Conclusion

In this work, we demonstrated a way of recognising appliance type using CNN that is beneficial to the NILM. We presented the recognition stages, starting from the signal acquisition, obtaining the energy consumption, creating load signature and using CNN to identify the actual appliance. Lastly, we used all this information to create a real-time monitoring system for users.

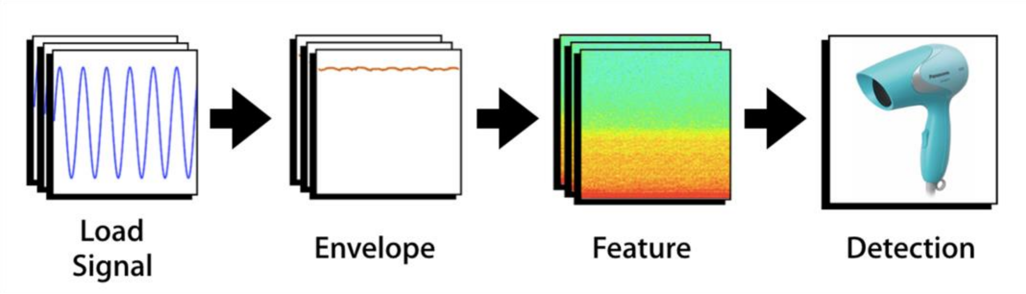


Figure 6: Appliance Detection Stages.

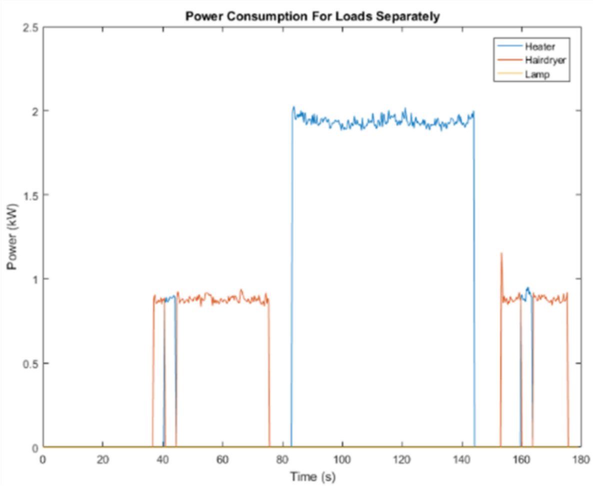


Figure 7: Heater, Hairdryer and Lamp Energy Usage

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