Design a System for Monitoring and Identifying Appliance and Home Activity using Machine Learning Algorithm

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***Abstract*—Recent years, one of the most major issues in the world is energy preservation, while electric energy accounts for a huge amount of total energy consumption over a year. Many solutions have implemented to reduce energy consumption, including encouraging to exploit renewable energy or utilizing energy more efficiently. Besides, a range of researches has conducted to improve the life quality of people, many of those are related to smart home applications. In this paper, we introduce two devices called Load Monitoring Device (LMD) and Activity Monitoring Device (AMD). The purpose of LMD is to provide feedback about operating states and energy consumption of electrical appliances in a house. This device will help people to consume electrical energy more efficiently. AMD with an acoustic sensor can detect a range of people's activities in a room. It also provides more appliances' data for LMD. Information in regards to people's activities is very helpful for smart home applications in the future.**

Keywords—Load monitoring; Activity recognition; Open source; LMD; AMD; Machine learning.

I. INTRODUCTION

Energy conservation is one of the greatest challenges facing society over the past few decades. In 2017, 85% of total world energy consumption came from fossil fuels [1]. Natural gas consumption for electric power is projected to increase significantly from 2019 to 2050 [2]. Therefore, we need to figure out feasible approaches to mitigate dependence on fossil fuels and utilize electric power more efficiently. In 2050, world-wide electricity generation from renewable resources will reach about 1700 billion kWh in comparison to over 2000 billion kWh from natural gas. In terms of using electric power efficiently, Sarah Darby suggested that feedback about consumption can be extremely valuable for energy savings. More specifically, this could positively influence our behavior to save about 5% to 15% energy usage [3]. Thus, it is essential to build a system that could help us monitor the energy consumption of every electric device in our house.

In addition to preserving energy, the system, along with Artificial Intelligence (AI) technology, could also be utilized in the smart home application. A decade ago, the idea of controlling thermostat, light and security systems remotely via smartphone would have seemed like futuristic science fiction, but 2017 proved to be the year of the smart home. According to Zion Market Research, the global smart home market is predicted to grow by 14.5% between 2017 and 2022 and reach $53.45 billion by 2022 [4]. Thanks to the rapid development of AI, the interaction between us and our own house will become more and more convenient.

Motivated by the two applications mentioned above, we introduce two devices called LMD and AMD. LMD is intended to install in the electrical panel in a room or a house; the function of this device is to monitor states and energy consumption of electric appliances. With a sound sensor, AMD is plugged to the wall socket in each room in a house to recognize people's activities; it can also provide additional information for LMD. In this paper, we initially only implemented research to monitor the operating state of some frequently used electrical appliances. Additionally, our devices were designed based on open hardware and open software platforms.

II. RELATED WORKS

A. Survey on Monitoring Electrical Appliances

Many traditional approaches related to load monitoring is to attach sensors to every individual appliance. Load data are wirelessly transmitted to a central unit. Users can access this and monitor the state and energy consumption of their devices. The disadvantage of this approach is that it is very time-consuming to install sensors to numerous appliances, especially in a large house or even a building. Therefore, the expense to deploy this system is also extremely high.

In 1982, the concept of Nonintrusive Appliance Load Monitoring (NALM) was released by Hart [5]. Hart's system use only a single device that is capable of analyzing the current and voltage waveforms of the total load. After that, NALM can detect the state of individual load, estimate their energy consumption and time-of-day variations. Depending on characteristics of electrical components, we can classify appliances in three types of loads that are resistive, inductive, and capacitive load. The phase between voltage and current depends on these characteristics of loads, and thus different loads have different active power (P) and reactive power (Q). However, Hart's method could only recognize devices that have two states on and off, and could not identify appliances that have multiple states and their power consumption varying continuously.

Laughman and colleagues proposed a solution using harmonic information besides active and reactive power [6]. Incandescent light bulb and computer have very similar P and Q when being turned on and off. However, Laughman pointed out that only the computer have 3rd current harmonic, and thus we can distinguish an incandescent light and a computer from this information.

Ruzzelli and colleagues implemented an Artificial Neural Network (ANN) to disaggregate appliance activities [7]. The input of ANN is constructed by signatures of appliances from various parameters such as P, Q, peak voltage and current, RMS voltage and current, etc. Their experiment showed that ANN could achieve accuracy greater than 84%.

Another approach is to observe electrical noise on residential power lines generated by the abrupt switching of an appliance or device while in operation [8]. Patel and colleagues classified loads into three types that are resistive loads, inductive loads, and loads with solid-state switching. Purely resistive loads do not create noise when operating. However, transient noise could appear when turning the mechanical switch on and off. Inductive loads like brush motor generate noise while in operation. Solid-state switching components like MOSFETs found in computer emit noise that is synchronous to an internal oscillator. Patel employed Support Vector Machine (SVM) to recognize appliances. An experiment was conducted in 6 houses in 6 weeks, and the overall classification accuracy in the first house is about 85%.

B. *Survey on Home Activities Detection Systems*

Gierad Laput and colleagues deployed a system that uses only a single board to sense many appliances and activities in a room [9]. For example, when a faucet is running, the sensor board could detect the vibration induced by service pipes behind the wall and the sound from running water. The reason for this is that the sensing board includes a wide variety of sensors such as thermal camera sensor, magnetometer, accelerometer, microphone, humidity, temperature, etc. and could be plugged into any wall sockets in a room to operate. Two machine learning modalities were implemented: manual training (users train system by supplying supervised labeled data) and automatic learning (the system attempts to extract activities via unsupervised learning techniques). The system was conducted over two weeks in various places: a kitchen, an office, a workshop, a common area, and a classroom. Overall, the system could achieve an average sensing accuracy of 96%.

Fogarty and Hudson proposed a feasible approach that attaches microphones to a home's plumbing system [10]. Based on water usage patterns, we could detect numerous activities in a house. Four sensors were deployed for activity recognition: one was attached to the entrance of cold water, one was placed beside the water heater and the last two sensors were couple with two pipes where wastewater leaves the house. After six weeks, if the system is placed away from systematic noise sources, it could identify 100% of clothes washer usage, 95% of dishwasher usage, 94% of showers, 88% of toilet flushes, 73% of bathroom sink activity lasting ten seconds or longer, and 81% of kitchen sink activity lasting ten seconds or longer.

Jianfeng Chen *et al.* described an acoustics-based system that is capable of identifying and recording activities in a bathroom [11]. The ultimate purpose of this system is to aid in the care of incontinence and dementia. The system was trained to recognize five activities in the bathroom: showering, flushing, washing hands, urination (male) and human sighing. Overall, the system could achieve an encouraging accuracy rate of above 84%.

Overall, motivated by the above studies, we combined both load monitoring and home activity identifying function in our system. We will discuss more detail about our system in the next section below.

III. PROPOSED SYSTEM DESIGN

A. *Open-source Hardware and Software Design Concepts*

In 1997, Bruce Perens launched the Open Hardware Certification Program, which had the goal of allowing hardware manufacturers to self-certify their products as open. Open-source hardware also enables many people to redesign, rebuild, and share experiences and knowledge. Likewise, it is said that open source software is more reliable because there are many independent programmers contribute to testing and fixing bugs. Therefore, open-source would help people to conduct their projects faster and more economical.

Recent years, Arduino is a well-known open-source hardware and software Italian company. They released a variety of development boards such as Arduino Uno, Arduino Yun, Arduino Due, etc. and the designs of these boards are all public. In this paper, we use the design of Arduino Due board for our electrical load monitoring device.

Besides, Orange Pi is an open-source single-board computer module produced by Shenzhen Xunlong Software. It contains various functions and peripherals in one board such as WiFi, HDMI, an input port for the microphone, USB, etc. This board has strong hardware based on ARM® Cortex™-A7 chip, thus it can run many operating systems like Android4.4, Ubuntu, etc. In this paper, we use Orange Pi Zero board for analyzing sounds of some appliances in a house.

B. *System Architecture*

As illustrated in Fig. 1, LMD works as a total energy meter that can monitor the power consumption of electrical appliances in a room or a house. Moreover, by applying Machine Learning method in LMD to analyze total load waveforms, LMD is capable of recognizing which appliances are running or not. Besides, by using an acoustic sensor on Orange Pi Zero board, AMD can identify various activities in a room.

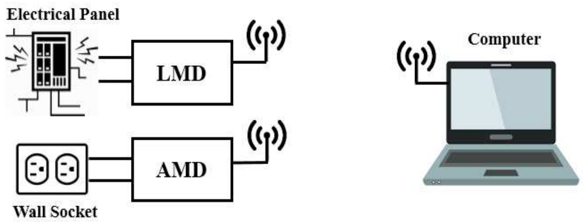

Fig. 1. System Architecture

In our system, both LMD and AMD can not only collect sensor's data but also run analyzing algorithm and wirelessly transmit results to the computer for display.

C. Load Monitoring Device (LMD)

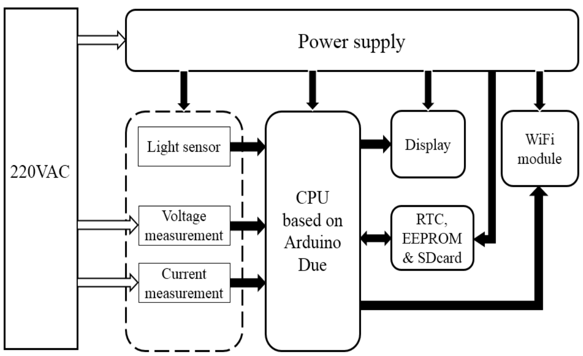

Fig. 2. The hardware of Load Monitoring Device

Fig. 2 illustrates the hardware design of LMD. Because LMD is installed to the electrical panel, the power supply is converted from 220VAC power line. LMD contains three measurement channels which are a light sensor, voltage, and current measurement. The voltage and current measurement schematic were built based on references design from Atmel Corporation [12, 13]. Likewise, as mentioned above, the CPU block was designed based on open-source hardware board Arduino Due. This block will collect, calculate and analyze data from sensors before displaying results on an LCD screen, storing energy consumption with corresponding real-time on EEPROM and sending results to the computer via WiFi.

After sampling and calculating from voltage and current data, LMD returns six electrical parameters which are Urms, I_{rms}, active power P, apparent power S, power factor cosφ and energy consumption E. With a sampling rate of 2000Hz, U_{rms} and I_{rms} parameters can be calculated by Equation (1).

$$U_{rms} = \sqrt{\frac{\sum_{n=0}^{N-1} u^2(n)}{N}} \qquad I_{rms} = \sqrt{\frac{\sum_{n=0}^{N-1} i^2(n)}{N}} \tag{1}$$

Active power is calculated from *u(n)* and *i(n)* as shown in Equation (2).

$$P = \frac{\sum_{n=1}^{N} [u(n) \times i(n)]}{N} \tag{2}$$

Where *u(n)* and *i(n)* are the instantaneous values of voltage and current respectively at sample *n*. *N* is the number of samples collected (*N* = 2000, *N* is equal to the sampling rate)

Besides the power consumption monitoring function, the ability to detect the state of electrical appliances is an outstanding feature of LMD. There is a wide range of achievements in AI technology, and AI has become a phenomenon in the world. Some highlights of AI in recent years are successfully understanding human speech, autonomously driving a car, or even competing human at the highest level in strategic game systems like Chess and Go.

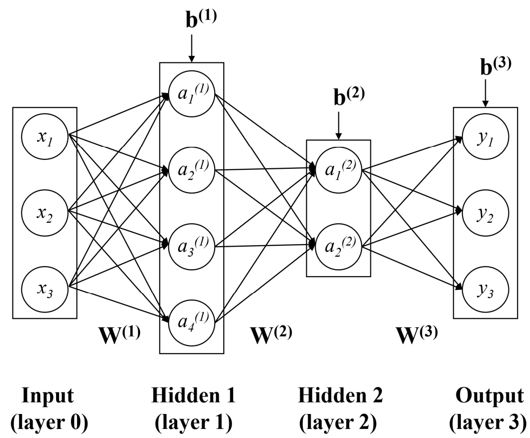

Fig. 3. Four layers Multilayer Perceptron (MLP)

Machine learning (ML) is a subset of AI, and it is the scientific study of algorithms and statistical models that computer systems use to perform a specific task effectively without using explicit instructions, relying on patterns and inference instead. ML algorithms build a mathematical model that use sample data as model input for training. After the training phase, our model can implement specific tasks we trained like making decisions or predictions. There are four major types of ML which are supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. In this paper, we deploy the supervised learning technique along with Multilayer Perceptron (MLP) for training MLD to recognize the state of electrical appliances.

$$\boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \\ \dots \end{bmatrix}; \boldsymbol{a}^{(l)} = \begin{bmatrix} a_1^{(l)} \\ a_2^{(l)} \\ \dots \end{bmatrix}; \boldsymbol{y} = \begin{bmatrix} y_1 \\ y_2 \\ \dots \end{bmatrix} \tag{3}$$

$$\boldsymbol{W} = \begin{bmatrix} w_{11}^{(l)} & w_{12}^{(l)} & \dots \\ w_{21}^{(l)} & w_{22}^{(l)} & \dots \\ \dots & \dots & w_{ij}^{(l)} \end{bmatrix}; \boldsymbol{b} = \begin{bmatrix} b_1^{(l)} \\ b_2^{(l)} \\ \dots \end{bmatrix} \tag{4}$$

MLP consists of at least three layers of nodes: an input layer, a hidden layer, and an output layer. As described in Fig. 3 Equation (3) and (4), the input, hidden layer and output layer are represented by vector $\boldsymbol{x}$, $\boldsymbol{a}$ and $\boldsymbol{y}$ respectively. Connections between the two layers are represented by matrix weight ($\boldsymbol{W}$) and bias ($\boldsymbol{b}$).

Equation (5) and (6) describes the relationship between the input and output layer.

$$\boldsymbol{z}^{(l)} = \boldsymbol{W}^{(l)}\boldsymbol{a}^{(l-1)} + \boldsymbol{b}^{(l)} \tag{5}$$

$$\boldsymbol{a}^{(l)} = g\left(\boldsymbol{z}^{(l)}\right) \qquad g\left(z\right) = \frac{1}{1+e^{-z}} \tag{6}$$

Where l is layer number, l = 1, 2, … L (L is the last layer, input vector is $\boldsymbol{a}^{(0)}$, output vector is $\boldsymbol{a}^{(\mathrm{L})}$), $g(z)$ is Activation Function.

In our application of identifying the state of three common appliances which are a light bulb, a kettle, and a hairdryer, we deploy a three layers MLP. Input vector $\boldsymbol{x}$ contains five parameters: Urms, Irms, active power P, power factor cosφ, and illuminance E_v.

$$\boldsymbol{x} = \begin{bmatrix} U_{rms} \\ I_{rms} \\ P \\ \cos\varphi \\ E_v \end{bmatrix} \tag{8}$$

In the supervised learning technique, the system will predict the highest possible outcome of a new input based on many pairs of training inputs and outputs. We call the training data as a Training Set. The number of neurons in the output vector depends on the number of appliances we need to recognize.

TABLE 1. POSSIBLE OUTCOMES OF OUTPUT LAYER

Outcomes	1	2	3	4	5	6	7	8
$\boldsymbol{y}$ (Output vector)	$\begin{bmatrix}1\\0\\0\\0\\0\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0\\1\\0\\0\\0\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\\1\\0\\0\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\\0\\1\\0\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\\0\\0\\1\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\\0\\0\\0\\1\\0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\\0\\0\\0\\0\\1\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\\0\\0\\0\\0\\0\\1\end{bmatrix}$

$$\boldsymbol{x}^{(1)} = \begin{bmatrix} 220.0 \\ 5.0 \\ 1000.0 \\ 0.8 \\ 700 \end{bmatrix}; \boldsymbol{y}^{(1)} = \begin{bmatrix} 0\\1\\0\\0\\0\\0\\0\\0 \end{bmatrix}; \boldsymbol{X} = \begin{bmatrix} | & | & \\ x^{(1)} & x^{(2)} & \dots \\ | & | & \end{bmatrix}; \boldsymbol{Y} = \begin{bmatrix} | & | & \\ y^{(1)} & y^{(2)} & \dots \\ | & | & \end{bmatrix} \tag{9}$$

Each appliance has two states which are On and Off state, and thus there are 2^3 = 8 possible outcomes. Therefore, we build the output vector with 8 neurons and 8 possible outcomes as shown in Table 1.

For example, Equation (9) describes a pair of input and output vector with the sensor's data. Vector $\boldsymbol{x}^{(1)}$ is corresponding to vector $\boldsymbol{y}^{(1)}$. When we merge all m vectors, we have matrix $\boldsymbol{X}$ and $\boldsymbol{Y}$. Total collected data is matrix $\boldsymbol{X}$ and $\boldsymbol{Y}$. We divide this data into two sets called Traning Set and Development Set with a ratio of 70 – 30 respectively. Traning Set is used to train the system and Development Set is used to test how well the system can predict outcomes based on new inputs. The aim of the MLP learning process is to try to ensure that predicted outputs are as close as possible to observed outputs by figuring out optimum $\boldsymbol{W}$ and $\boldsymbol{b}$. To evaluate how close of these two types of outputs, we use the Error Function as shown in Equation (10).

$$J = \frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{K} -y_k^{(i)} \log_e a_k^{L(i)} - (1-y_k^{(i)})\log_e(1-a_k^{L(i)}) \tag{10}$$

Where a_k^L is predicted output k of the output layer, y_k is observed output corresponded to a_k^L, K is the number of neurons of output layer (K=8), m is total collected data in Training Set. We need to find $\boldsymbol{W}$ and $\boldsymbol{b}$ to ensure that function J is minimum. Solving Equation (10) to find minimum value is a complicated task, and thus we need to deploy Gradient Descent and Backward Propagation algorithm [15].

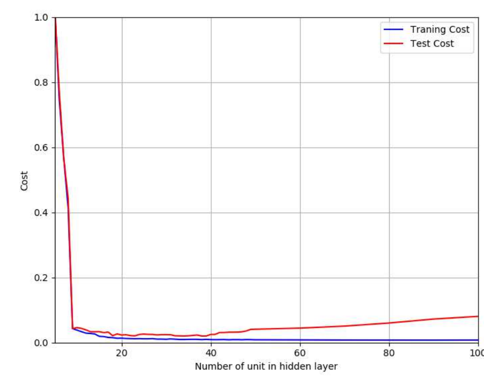

Fig. 4. Choosing the number of neurons in the hidden layer

To find the optimum number of neurons in the hidden layer, we tried a range of values to obtain the minimum value of J. As illustrated in Fig. 4, the best number of neurons in the hidden layer is 20.

D. Activity Monitoring Device (AMD)

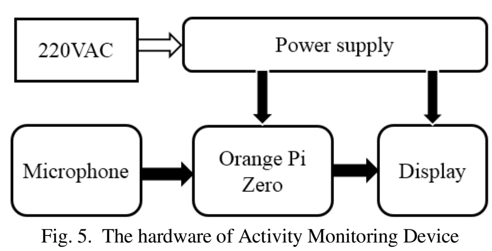

Fig. 5. The hardware of Activity Monitoring Device

Unlike LMD, AMD is plugged into the wall socket to detect activities in a room. The main purpose of AMD is to recognize the daily life activities of people by recording noises from the environment.

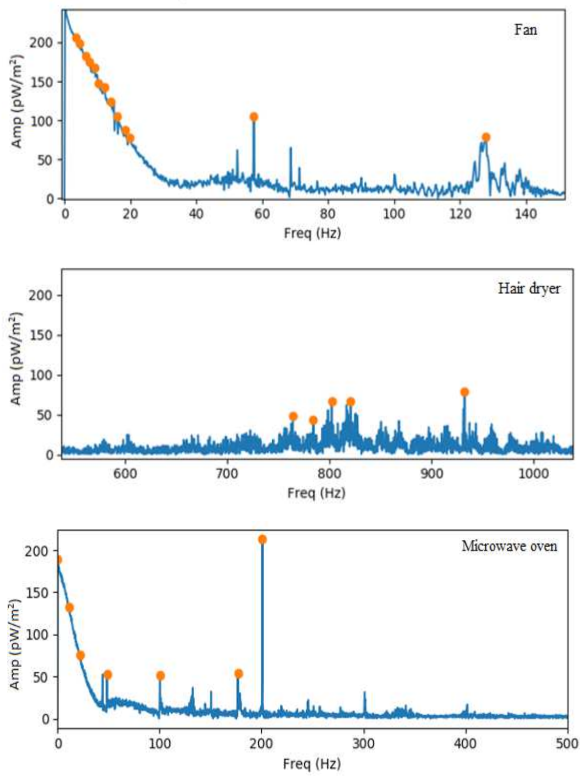

Fig. 6. Spectrums of three appliances

In this paper, we conduct experiments on analyzing sounds from three frequently used appliances which are a fan, hairdryer, and microwave oven.

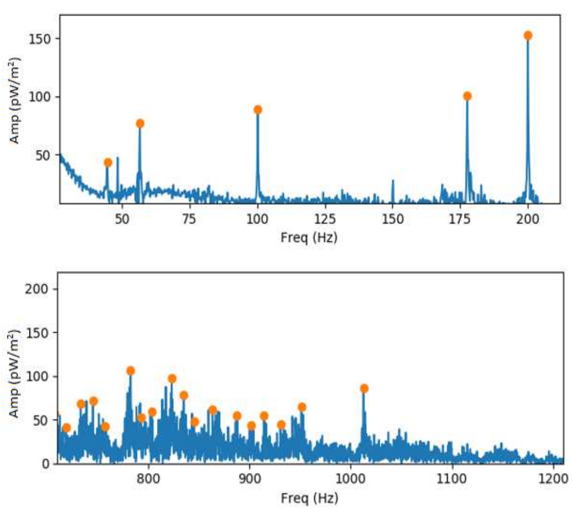

Fig. 7. Spectrums of three appliances when operating at the same time

The noise source of fan almost comes from bearings and blades when rotating. The noise source from the hairdryer is very loudly and it is generated by the heating element, front and rear grilles, and air filters. The sound of the microwave oven is from the cooling fan that prevents magnetron from heating up. After analyzing sounds of the three appliances at a distance of 1 meter, we figured out the key feature is a peak occurring in the spectrum of each appliance as shown in Fig. 6.

The peak in fan's graph occurs at a frequency range of 57 – 58Hz, the numbers of hair dryer and microwave oven are 900 – 940Hz and 195 – 210Hz respectively. Therefore, we can employ this feature as Signature of each appliance. When all of the three appliances operate at the same time, the Signatures still appear clearly as described in Fig. 7, and thus we can base on this feature to differentiate appliances.

IV. EXPERIMENTAL RESULTS

Based on open designs from Arduino, we successfully created the first version of LMD as illustrated in Fig. 8. Our device is capable of measuring Urms, Irms, real power P, power factor cosφ, energy consumption E, and illuminance E_v. All of these parameters are transmitted to the computer for monitoring.

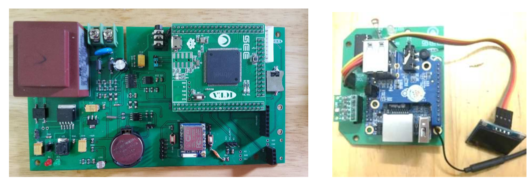

Fig. 8. The first version of LMD and AMD

To enhance the accuracy of the device, in this paper, we only calibrated current measurement channel. After being calibrated, the accuracy of the current channel was improved from 4.1% to only 1%. In terms of recognizing electrical appliances, we conducted an experiment on three appliances which are a light bulb, a kettle, and a hairdryer. The total collected data point is 2275, where 1691 data point is Training Set, and the number of Development Set is 584. After the learning process to find optimum values for $\boldsymbol{W}$ and $\boldsymbol{b}$, we had the minimum value of error function J is 0.013.

TABLE 2. CONFUSION MATRIX

Total: 584	a	b	c	d	e	f	g	h	
a	**73**	0	0	0	0	0	0	0	73
b	0	**75**	0	0	0	0	0	0	75
c	0	0	**74**	0	0	0	0	0	74
d	0	0	0	**75**	0	0	0	0	75
e	0	0	0	0	**71**	0	3	0	74
f	0	0	0	0	0	**70**	0	2	72
g	0	0	0	0	0	0	**70**	0	70
h	0	0	0	0	0	0	0	**71**	71

Applying $\boldsymbol{W}$ and $\boldsymbol{b}$ in our system and using Development Set for testing, LMD can achieve the accuracy of 99.78%. Table 2 provides more specific information, the bold numbers are the number of times that LMD predicted correctly, and the numbers on the right are total testing times.

TABLE 3. POSSIBLE OUTCOMES

	Kettle	Hairdryer	Light bulb
a	Off	Off	Off
b	Off	Off	On
c	Off	On	Off
d	Off	On	On
e	On	Off	Off
f	On	Off	On
g	On	On	Off
h	On	On	On

Fig. 9 describes the first version of AMD based on Orange Pi Zero board. We did another experiment to identify three electrical appliances which are a fan, a hairdryer and a microwave oven based on their noises. The experiment was implemented in four different distances that are 0.5m, 1m, 1.5m and 2m. AMD tried to record and recognize operations of three appliances several times for each distance. The results are shown in Table 4. We can see that the best-predicting accuracy of AMD is at a distance of under 1.5m.

TABLE 4. AMD TEST RESULTS

	0.5m	1m	1.5m	2m
Fan	40/40 (100%)	40/40 (100%)	35/40 (88%)	19/40 (48%)
Hair dryer	40/40 (100%)	39/40 (98%)	37/40 (93%)	25/40 (62.5%)
Microwave oven	20/20 (100%)	20/20 (100%)	19/20 (95%)	13/20 (65%)

V. CONCLUSIONS AND DISCUSSIONS

This paper presents two devices call LMD and AMD. LMD is intended to install at the electrical panel of a room or a house. LMD provides information about energy consumption and detects which appliances are operating. This device creates real-time energy awareness for homeowners, and thus they will base on this feedback to adjust the habit of using electrical appliances. Meanwhile, AMD is intended to install in any wall sockets in the room. The role of this device in our system is to recognize activities in a room.

We successfully created LMD and AMD based on open-source hardware and software platforms. LMD can work as an energy meter by providing several basic electrical parameters. It can also identify three appliances with an accuracy of 99.78%. The results of recognizing appliances of AMD are encouraging at a distance of under 1.5m. However, there are numerous disadvantages that we need to improve our system in future work. Firstly, with the current method of differentiating electrical appliances, adding new appliances into the system can be problematic. As discussed above, if we have n devices, we need to train the system to identify 2^n outcomes that can occur in real life. Therefore, when there is a large number of appliances in a room, this approach is very time-consuming. Secondly, it is essential to monitor the power consumption of every single device in the system. This feedback can give us an overview of the status of each appliance, and thus we will tend to build a plan to use energy more efficiently. Thirdly, we need to equip more sensors for AMD such as light sensor, vibration sensor, and temperature sensor to be able to recognize more activities in a room. Fourthly, in this paper, we only perform experiments on several frequently used appliances, and thus our future work is needed to conduct in actual conditions. More specifically, we should install many AMDs in various rooms, LMD in the electrical panel and test their performances for a long time. Finally, it is necessary to improve hardware to achieve better measurement accuracy.

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