AI System for Monitoring States and Power Consumption of Household Appliances

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***Abstract*— Global warming is a major problem in the 21st century. One of the most effective ways to reduce greenhouse gas emissions is to save energy, in which electricity is the energy source with high demand and daily increasing. Residential electricity accounts for a large proportion of the total amount of electricity produced, thus if each individual can use electricity at home more effectively, it also means that we are slowing down the process of climate change. The feedback on the energy consumption of household appliances gives users a clearer view of daily electricity consumption, and this will help them to have more efficient ways to consume electricity. In this paper, the authors have built a system to monitor the on/off status and energy consumption of each electrical appliances in the house. The system only uses an electronic meter and software run machine learning algorithms on computers. The test result of the on/off state prediction feature has an accuracy of 93.60%.**

Keywords—Load monitoring; Real power; Reactive power; Machine learning algorithms.

I. INTRODUCTION

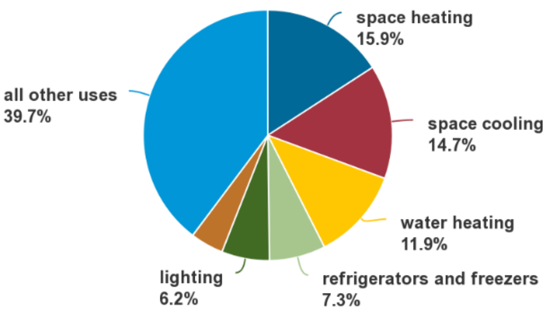

Fig. 1. US residential sector electricity consumption by major end uses 2018

Saving energy is one of the effective ways to reduce CO2 emissions, the leading cause of global warming. Electric power accounts for a large proportion of daily energy consumption, and the demand for electricity is constantly increasing. According to [1], electricity consumption in the US in 2018 was 16 times higher than the consumption in 1950. In 2018, in the US, electrical energy mainly came from three main sources: residential (38.5%), commercial (36.2%) and industry (25.1%). We can see that the residential sector accounts for a large proportion. More specifically, the amount of electricity consumed is mostly from air conditioning, water heating or lighting appliances (Figure 1). Therefore, if we control the operation of electrical appliances and adjust the way to use them, it is possible to reduce the daily electricity consumption significantly. According to research by Sarah Darby [2], feedback about the power consumption of electrical appliances positively impact the way we use electricity, so it is estimated that we can save about 5% - 15% of electrical energy. Similarly, Sébastien Houde and colleagues tested the effect of feedback on power consumption on large-scale [12]. The experiment was conducted in 1065 apartments in 8 months. Users will receive feedback on power consumption in real-time with an update cycle of 10 minutes. The results showed that power consumption decreased by an average of 5.7%, and the period of the highest reduction lasted continuously for about four weeks.

Regarding methods to monitor the states and energy of electrical appliances, many solutions have been proposed. Kun-lin tsai and his colleagues built a monitoring system and automatically adjusted home electricity consumption using machine learning algorithms [3]. Based on data from the International Energy Agency's survey, the electrical energy consumed by appliances in idle or standby mode accounts for 3% to 11% of the total electricity consumed in the home. [4], the author trained the system to recognize when a device is used or not. At intervals when the devices are not in use, and they are in standby mode, the system will automatically power off the devices to save power. To collect electrical data (voltage, current, power, etc.) from devices, the authors installed a range of smart sockets at each appliance. Then, these data will be transmitted wirelessly to a central device (Gateway) connected to the Internet to share data with users. However, the disadvantage of this monitoring method is that it is very costly and time-consuming to install smart sockets to each device, especially for large buildings.

Gierad Laput and his colleagues developed a compact board equipped with various sensors such as sound, vibration, light, motion, magnetic field, etc. [5]. This device not only detects the status of electrical appliances but also identifies other activities such as draining the faucet, taking a napkin, or closing the door. The system has two modes: manual training (users directly train the system their desired activities to identify) and automatic learning (the system will automatically learn and detect events). The device was tested for two weeks in various locations such as kitchens, offices, classrooms, etc. and achieved an accuracy of up to 96%. However, this method will have difficulty in collecting the energy consumption of electrical appliances because it does not directly measure electrical parameters.

Younghun Kim and his colleagues developed the ViridiScope monitoring system that deployed magnetic, light, and sound sensors together with an electric meter [6]. The authors attached a magnetic sensor to each power line of the device to monitor the power consumption of each load. The study shows that the power consumption of electrical devices has the same pattern as the magnetic field generated in the power line, so it is possible to establish a relationship between these two parameters. Light and sound sensors are used to identify the mode of operation of the device, combined with the magnetic sensor we can know the power consumption of each operating mode. This method solves the Gierad Laput energy collection problem, but installing the sensor to each device will be very time consuming and costly.

Motivated by the above studies, the aim of the authors in this paper is to use only one total electric meter, but it is still possible to monitor the on/off states and power consumption of each electrical appliance. This idea was first introduced by Hart in 1992 with the concept of "Nonintrusive Appliance Load Monitoring (NALM)" [7]. Also, the authors will apply a supervised machine learning algorithm combined with a 3-layer MLP (Multilayer Perceptron) neural network model to predict the on/off states of devices.

II. SIGNATURE OF APPLIANCES

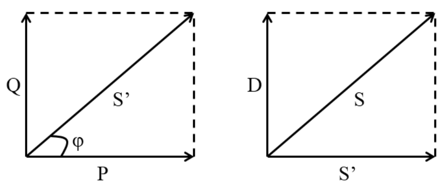

Fig. 2. Relationship between electric powers

The NALM method analyzes the graph of voltage, total current, and total power graph to obtain the operating states and power consumption of each electrical appliance. In our previous study, the authors predicted the states of household appliances by training the computer to learn all possible switching events [8]. More specifically, three electrical appliances need to be differentiated are a hair-dryer, a light bulb, and a kettle. Each device has on and off state, so the total number of possible outcomes is $2^3 = 8$. The advantage of this method is that the prediction results are highly accurate. However, a significant drawback is that as the number of devices that need to be recognized increases, the number of cases for training computer will increase exponentially. For example, when we need to recognize 10 devices, we have to train the system to learn 2^{10} cases. Therefore, this method of recognition will be very time consuming and difficult to apply in practice. In this paper, the authors use a new approach based on the identification characteristics of each electrical device, so there is no limit on the number of devices that need to be added to the identification system.

Table 1. Power consumption of various household appliances used for the experiment

No	Appliance	Real power (W)	Reactive power (VAr)	Power factor (cosφ)
1	Hair-dryer (mode 1)	455	13	0.99
2	Hair-dryer (mode 2)	893	31	0.99
3	Kettle 1	1374	5	0.99
4	Kettle 2	1958	50	0.99
5	LED lamp	22	11	0.89
6	Compact lamp	65	-8	0.99
7	Fan (with electronic circuit)	45	-12	0.96
8	Incandescent lamp	60	0	1.0
9	Chandelier	202	0	1.0
10	Heating lamp (mode 1)	260	0	1.0
11	Heating lamp (mode 2)	526	0	1.0
12	Fluorescent lamp	30	69	0.4
13	Heating bag	730	0	1.0

Based on the characteristics of the load, we can divide them into three categories: resistive loads, inductive loads, and capacitive loads. Resistive loads have the voltage and current in phase (e.g., an incandescent lamp or a kettle). Inductive loads usually have motors that cause the current to lag the voltage (e.g., a water pump or a vacuum cleaner). Capacitive loads often have electronic circuitry components that cause the current to lead the voltage (e.g., a control circuit for an electric fan or a laptop). The power of the load is characterized by real power (P), reactive power (Q), and harmonic power (D). Real power P represents the actual consumption power by the loads, so the powers of resistive loads dominate by P, Q, and D are insignificant. Power Q and D are both classified as reactive power, which is the power component returned to the grid and not consumed by the loads. Power Q is caused by the phase shift between the same frequency waves of voltage and current. Inductive loads have $Q > 0$, while capacitive loads have $Q < 0$. If loads contain non-linear components like diodes in rectifier circuits, the current waveform will appear harmonics. This results in the appearance of harmonic power D, which is the product of different frequency waves of voltage and current. From Figure 2, we obtain the apparent power S calculated as follows:

$$S^2 = P^2 + Q^2 + D^2 \qquad (1)$$

From the above analysis, it is possible to use three parameters P, Q, and D as signatures for each appliance. In this paper, the authors only use parameters P and Q. Table 1 shows the power consumption of some household devices that the authors will use for the experiment. It can be seen that most devices have a positive Q power; the fan contains a motor component but has a negative Q because it has an electronic control circuit containing the capacitors.

III. BUILDING MONITORING SYSTEM

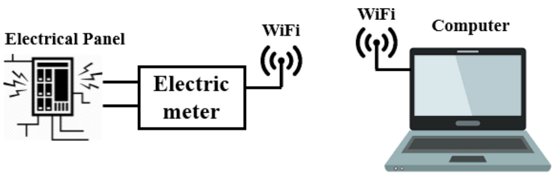

Fig. 3. The electric appliance monitoring system

The authors build a monitoring system with two main devices, electronic meter, and computer (Figure 3). The authors use the computer in this model for the purpose of testing the device recognition algorithm, the last model the authors aim is to use only electronic meters running machine learning algorithms (Figure 13). The electricity meter is installed in the electrical box, and it measures the following parameters: voltage (Urms), current (Irms), real power (P), reactive power (Q), and power factor (cosφ). These parameters will be transmitted via WiFi to the computer at the rate of 1Hz. The function of the computer is to store, display measurement data, and implement device state prediction algorithms.

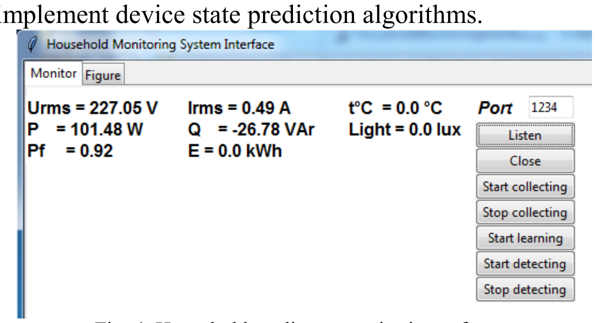

Fig. 4. Household appliance monitoring software

The authors designed the electronic meter with a processing circuitry based on the open hardware platform of Arduino Due [9]. The measurement circuit of meter based on the reference designs of Microchip [10, 11]. Power P and Q are the product of the same frequencies between voltage and current. The product of different frequencies between voltage and current is harmonic power D. To calculate power P, we need to take the average sum of $u(n)$ x $i(n)$ according to Equation 2. To calculate power Q, we do the same as for P, but the product between voltage and current shifted by 90 degrees (Equation 3). In which, $u(n)$, $i(n)$, and $i_{90\text{-}degree\text{-}shift}(n)$ are instantaneous voltage, instantaneous current, and instantaneous current shifted by 90 degrees. N is the number of samples; the authors set the sampling frequency is 2000Hz, the update rate for the computer is 1Hz, so $N = 2000$.

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

$$Q = \frac{\sum_{n=1}^{N}[u(n) \times i_{90-\deg ree-shift}(n)]}{N} \tag{3}$$

Computer software developed by the authors using the Python language (Figure 4). The function of the software is real-time displaying electrical parameters, training of neural networks to learn new devices and predictions the states of electrical appliances.

IV. BUILDING APPLIANCE STATES DETECTING ALGORITHM

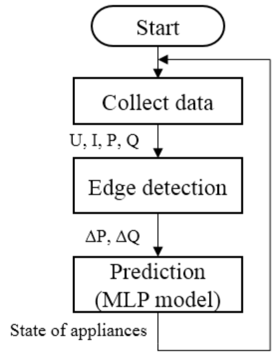

Fig. 5. Appliance states detecting algorithms flow chart

The process of identifying the on/off states of electrical appliances is shown in Figure 5. After receiving the electrical parameters from the meter, the computer runs the "edge detection" algorithm to check whether or not a device has just been turned on or off. The output of the "edge detection" algorithm is the value of ΔP and ΔQ, and then these two values are used as input of the 3-layer MLP model to predict which device has just been turned on or off.

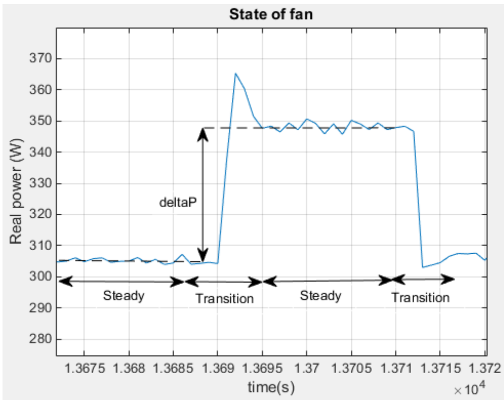

Fig. 6. Rising and falling edge when turn on and off the fan

A. Edge detection algorithm

Every time an electrical device is turned on or off, a power graph will appear a rising of a falling edge (Figure 6 shows the power graph when the fan is turned on and off), the period to switch from this stable power level to another level is called the transition period. The steady period is defined as the period when the power change does not exceed a preset value; the authors set the oscillation range of 15W for P and 8VAr for Q. Therefore, the current system cannot identify devices with real powers of less than 15W. The algorithm takes a group of 4 consecutive samples and compares the difference between the measurement results to determine whether it is in the transition or steady phase. For example, if the difference is less than 15W, the algorithm is in the steady phase. If the difference is greater than 15W, the algorithm is in the transition phase. When an edge occurs, the difference in the mean between the two steady periods is the value of ΔP or ΔQ that needs to be found.

B. Appliance states detecting algorithm

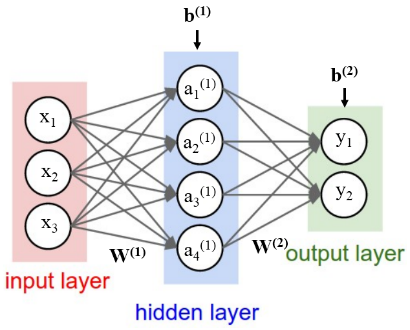

Fig. 7. 3-layer MLP neural network model

Figure 8 depicts a graph between the real power P and the reactive power Q of some electrical appliances [7], showing that the power data P and Q of each device are in the circled areas. Thus, to identify each device, we have to find the boundaries separating the circled areas, such problems are called classification problems. Neural network model is commonly used to solve classification problems, some of which are mentioned as Softmax Regression, Multilayer Perceptron (MLP), Convolutional neural network (CNN), etc. Softmax Regression can find linearity boundaries between circled areas, but as the number of devices increases, the model becomes more complicated. MLP with a hidden layer model can create nonlinear boundaries, thus resulting in a much more accurate classification than Softmax Regression. Compared to MLP, CNN reduces the number of connections between layers, suitable for applications that need a very large number of connections such as image classification applications. With a small number of connections due to limited input and output information, the authors will use a 3-layer MLP network model (Figure 7) with a supervised learning method for electrical appliance identification application.

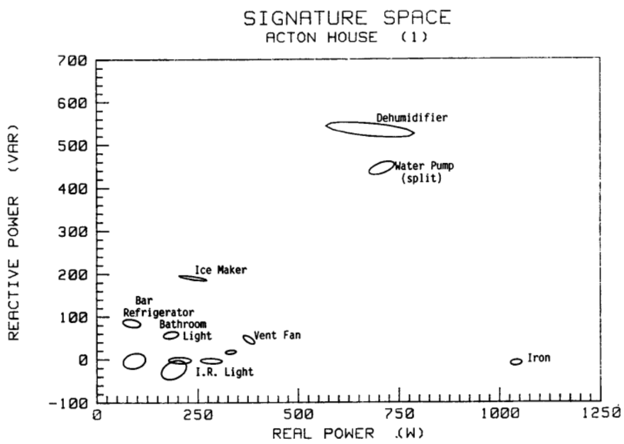

Fig. 8. Power consumption of some household appliances [7]

The input vector **x** of the network is ΔP and ΔQ derived from the "edge detection" algorithm. The output is the on/off status of each electrical device. In this paper, the authors predict the states of 12 devices, while two devices have various operating modes (Table 1). Each device has two states of on and off, so the total number of outcomes is 32. This is also the number of neurons of output vector **y** (Table 2 and 3).

$$\boldsymbol{x} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{4}$$

Table 2. Output vector **y**

Output	1	2	3	…	32
$\boldsymbol{y}$ (Output vector)	$\begin{bmatrix}1\\0\\0\\...\\0\end{bmatrix}$	$\begin{bmatrix}0\\1\\0\\...\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\\1\\...\\0\end{bmatrix}$	…	$\begin{bmatrix}0\\0\\0\\...\\1\end{bmatrix}$

Table 3. Device states correspond to each output

Output	State
1	Hair dryer (mode 1) is on
2	Hair dryer (mode 1) is off
3	Hair dryer (mode 2) is on
…	…
32	Heating bag is off

Each input vector **x** will correspond to an output state. The training process is to use collected input and output data (also called a Training set) to find the optimal set of **W** and **b** coefficients (Figure 7). **W** and **b** are the relationships between input and output. Then, when a new input (does not belong to the training set) appears, the model uses this new set of coefficients **W** and **b** to return the prediction result.

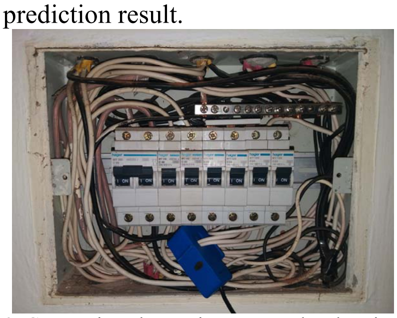
Fig. 9. Connecting electronic meter to the electrical box

For example, in case of training the model to learn a new device (a fan), the system training process is as follows (look at the software interface in Figure 4):

• Connect the computer to an electronic meter via WiFi, after receiving the electrical parameters, press the "Start collecting" button. The software will automatically run the algorithm "edge detection" when found an edge, the software will store it.

• Turn on the fan, wait until the software notifies you when an edge is detected. Then turn off the fan and continue waiting for the notification. Repeat the on/off process several times (at least 3 times). Make sure that no other device is turned on/off during the training process.

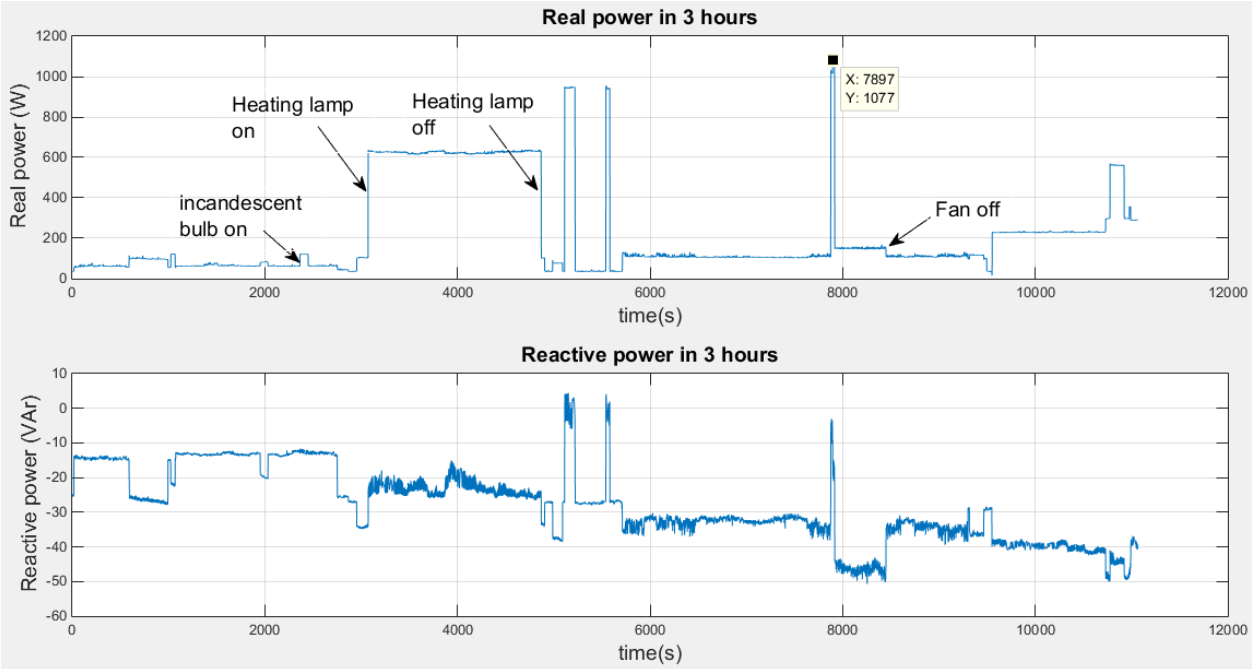

Fig. 10. Power consumption graph in 4th test day

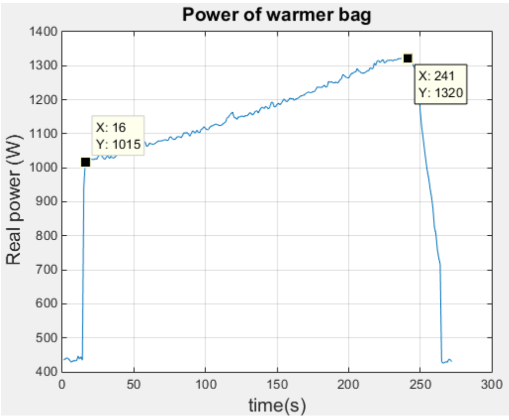

Fig. 11. Power of heating bag

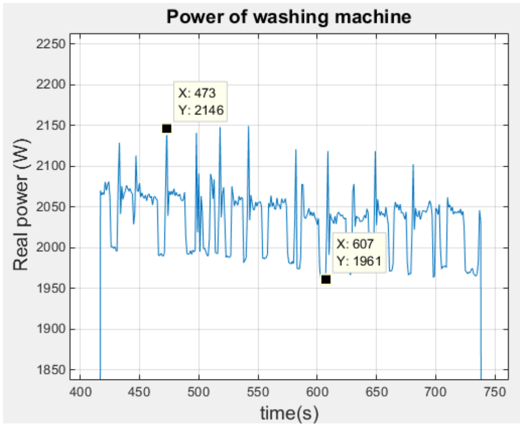

Fig. 12. Power of washing machine

• Click "Stop collecting" and label each data just collected (assignment labels are defined in Tables 2 and 3).

• Click "Start learning" to have the software update the **W** and **b** coefficients with new fan data.

• Click the "Start detecting" button, the software will run the device status detection program with the new set of **W** and **b** coefficients.

Repeat the above steps while continuing to add a new device to the model. The time for training the system to add a new appliance depends on the number of times the device is turned on/off. The more on/off times, the more accurate the prediction results, but it will take longer to train the system.

V. EXPERIMENT

The authors implemented the experiment on the 3rd and 4th floors at a private home, including the bedroom, bathroom, and laundry room. The electronic meter was connected to the electrical box using the current transformer as shown in Figure 9; the current transformer was connected to measure power simultaneously on both the 3rd and 4th floors. The test predicts the status of 12 devices (Table 1), in which the hair-dryer and the heating lamp have various modes, so a total of 32 on/off cases need to be identified. Because the system was installed in the private home, the experiment was conducted in the evenings from Monday to Friday. On Saturday and Sunday, we performed the test for all day, and the testing period lasts for three weeks.

Before conducting the monitoring algorithm for a long time, the authors trained the MLP model all 32 on/off cases. A total of 215 data points were collected; 70% of data points were used for Training set and 30% for Test set. The accuracy of predicted results with Test set is 93.65%. After three weeks of testing at home, the system detected a total of 766 on/off events, incorrectly predicted 49 events, and thus achieved an accuracy of 93.60%. Figure 10 depicts the load graph during the 4th test, which also shows some on/off events.

During the testing of the identification algorithm, the authors discovered several disadvantages of the system. Firstly, the current identification method based on ΔP and ΔQ is only useful when the power of the device does not change too much during operation. A typical example is the heating bag, observing Figure 11, we can see the power consumption of the heating bag increases over time, and even at different temperatures, the power is also different. Figure 12 depicts the power of the washing machine while in clothes soaking mode, and we can see that the machine power oscillates continuously between 1961W and 2146W. Furthermore, in different washing modes, the change in power is also different. Therefore, the algorithm cannot obtain the exact ΔP value. However, after conducting a survey of appliances in the testing room, which is the bedroom, bathroom, and laundry room, the number of devices with a continuously variable power accounts for only about 20%. Therefore, with recognition algorithms based on ΔP and ΔQ, we can predict the state of many devices in the home. Second, the "edge detection" algorithm is currently difficult to distinguish between compact and incandescent lamps (Table 1) because they have the same real power P. The compact lamp has an average value of reactive power Q of -8VAr, in many cases, this power is only about -5VAr so the algorithm cannot detect this edge (as mentioned earlier in section IV-A, when reactive power Q oscillation is less than 8VAr, the algorithm is still in the steady phase). Therefore, the experiment shows that the system has repeatedly predicted the event of turning on/off the compact lamp to the incandescent lamp.

VI. CONCLUSION AND FUTURE WORK

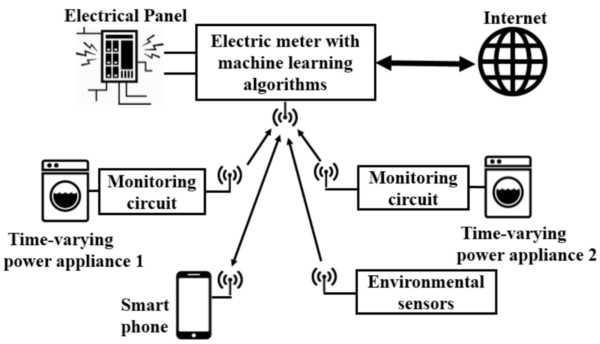

Fig. 13. Future monitoring system

In this paper, the authors have initially built a system for monitoring the status of electrical appliances in the house, applying supervised machine learning algorithms along with the MLP neural network model. The signature of each device is its real power P and reactive power Q. The system uses an "edge detection" algorithm to detect a change from the total power whenever a device is turned on or off. The system then uses this ΔP and ΔQ information with the trained MLP model to return predicted results. The experiment was conducted for three weeks on the 3rd and 4th floors at home. The authors trained the system of learning 12 devices, in which the hair-dryer and the heating lamp have various modes. The system detected 766 on/off events, incorrectly predicted 49 events, thus achieving an accuracy of 93.60%.

However, during the test, the authors found that the system had difficulty in identifying devices with constantly changing power such as the heating bag or the washing machine. In addition, the system is also difficult to distinguish devices with nearly the same power. To solve these two problems while ensuring the minimum number of equipment to be installed, the authors propose a new model described in Figure 13. In addition to measuring electrical parameters function, the improved electronic meter will run machine learning algorithms, and thus it can predict the state of devices. Since the number of appliances with variable power over time relatively small (only about 20% of the number of devices in the three test rooms), it is possible to install separate monitoring circuits for those devices. In addition, to be able to distinguish the same devices in different locations, we installed an additional circuit board containing the environmental sensors in each room. According to the research survey [5], with only two acceleration and sound sensors, the sensor board can distinguish most devices in the room. Moreover, the system also allows the use of smartphones to train and monitor the system.

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