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Realization of Internet of Things Smart Appliances

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ABSTRACT
This study proposed a household energy state monitoring system (HESMS) and a household energy load monitoring system (HELMS) for monitoring smart appliances. The HESMS applies reinforcement learning to receive changes in the external environment and the state of an electrical appliance, determines if the electrical appliance should be turned on, and controls the signals sent to the HELMS according to these decisions. The HELMS implements an ON/OFF control mechanism for household appliances according to the control signals and the power consumption state. The proposed systems are based on the wireless communication network and can monitor household appliances' energy usage, control intelligent appliances, and decrease fire occurrence rates due to electrical appliance overloading. In addition to minimizing costs, the system does not change the original household appliance structures. When the control signals are transferred by the relay through wireless communication, the monitoring information is captured and recorded in a database. Thus, users can access the latest information regarding the performance of electrical appliances.

KEY WORDS: Reinforcement learning, Smart home, Energy consumption monitoring, Energy state monitoring system, Wireless communication network

1 INTRODUCTION

WITH the rapid development of technology and network communication techniques, electrical appliances are replacing human jobs. This change is driven by the easy access to electrical energy.

Electrical energy is indispensable to daily life. However, electrical appliances can cause fires through short-circuiting, degraded wires, or, most commonly, inappropriate use. The primary reason for such fires is that users do not monitor their usage of electrical appliances. To reduce the fires caused by human error, users should inspect whether appliances are completely turned off or exceeding the load limit.

Aging of the social structure is a major concern, especially in modern society. Fires because of elderly people not having adequate knowledge about using electrical appliances must be avoided, particularly because cold current and lower temperature increases the energy consumption.

Therefore, this study implemented an ON/OFF control scheme for controlling electrical appliances during different periods. The scheme operates in conjunction with a network with embedded equipment. The scheme was implemented on a socket with a wireless network and controlled an electric lamp through remote monitoring or relay. When approached, the lamp would light up. The scheme does not alter the structures of original household equipment. It monitors electricity changes to control electrical energy and judges the ON/OFF setting of the switch by analyzing statistics and data. Furthermore, information on the electrical appliance being monitored, such as the appliance name, switch state, power, voltage, current, switch time, and performance, is recorded in a database. This information can be used to achieve the ON/OFF control of electrical appliances, reduction of fires, and knowledge of the state of appliances from a web page, anytime and anywhere. These methods entail transforming equipment to control the use of electrical appliances and reduce fire disasters.

This study proposes a household energy state monitoring system (HESMS) and household energy load monitoring system (HELMS) for monitoring electrical appliances. The HESMS applies reinforcement learning to establish a decision system, judge the switching of electrical appliances, and send

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control signals to the HELMS. The HELMS monitors energy consumption to detect whether the load limit has been exceeded. Thus, this system protects the appliances from catching fire because of instantaneous high load currents. These two systems, together with a wireless communication network, can monitor the energy consumption of household appliances, control intelligent appliances, and decrease fire occurrence rates caused by the electrical appliance overloading.

Combined with the relay distribution, the hardware complexity described in the literature is alleviated in the proposed systems. In the proposed systems, a Raspberry Pi microcomputer serves as a relay to receive monitoring signals. Through the network interface within the Raspberry Pi and network access point, the monitoring information is transferred to the server and then the database. This obviated the necessity of designing circuits and purchasing additional equipment, thus reducing the cost of building the structure.

2 LITERATURE REVIEW

THE Internet of Things (IoTs) is a concept that mainly explores signal transduction between components and seamlessly integrates different communication interfaces. The transfer of signals from one component to another is the most crucial aspect of an IoT system. Chen et al. (2014) explored the development trends of methods extensively applying embedded processors, relays, and actuators on fixed and mobile platforms. They revealed that such methods were suitable for use in healthcare, energy management, and recreation for realizing high service quality, efficiency, and safety. Existing home networks were explored to determine their applicability to real life and their difficulties and development directions. Hong et al. (2010) proposed the application of SNAIL (sensor networks for an all-IP world) in an object space and an IP allocation method in the object space, which incorporates mobility, website functionality, synchronization, and information safety. They designed a mobile network protocol, MARIO, according to these four features. The communication protocol was designed on the basis of MIPv6, including the IPv6 address, 64 extended volume label symbols, routing communication protocol type, sensor and gateway network management services, intra-PAN and inter-PAN support, and a 6LoWPAN optimized route. To handle customer inquiries, the authors designed the network service on the basis of distributed resource (DRESS-WS).

Perumal et al. (2011) proposed a simple object access protocol (SOAP)-based operating framework and joint coordination method for intelligent interoperable smart homes. The framework provided a platform-independent stretch heterogeneous system integration and end-to-end communications with open standards. The operating mechanism of the framework involved applying extensible markup language (XML) to exchange signals. The framework offered various services, namely the implementation of custom data from heterogeneous resources, management of all data sources, and initiation of communication between heterogeneous systems. The main components were service software, which can locate the application programming interface of the corresponding data interface of heterogeneous equipment, and a built-in structured query language application for the corresponding frame structure required to produce structured query language. Moreover, the framework can enable the implementation of rules in a database, achieve dynamic maintenance service stubs, process and inspect SOAP information, and realize the database module of electrical appliances. Network communication was deployed in Ethernet networks, because they have the efficiency of a clearly defined structure, available bandwidth, and timely response. Zanella et al. (2014) advocated combining different terminal systems with IoT technology and providing public access to digital services. However, to establish universal IoT architecture, numerous types of equipment and connections between layers and services are necessary. They designed IoT systems that employed new communication technologies to serve city management and residents, and explored the technology and communication protocol of IoT and its structure based on network services. Sehgal et al. (2012) explained the management of embedded equipment resources. The purpose of embedded equipment is to minimize fabrication costs, storage and memory capacity, and improve processing abilities and network communication efficiency. However, it does not provide large adjusting spaces. The interoperability and flexibility of IoT should be strengthened to enable the application of different IP network management and safety communication protocols to equipment with limited resources. This can thus enable the recognition of a resource minimum, which is typically hidden in IoT equipment.

When the temperature of an environment changes, people naturally consider turning on air conditioners or heaters. Lowering or raising indoor temperatures might cause electrical appliances to catch fire because of electric overload. Therefore, to ensure the safety of elderly people when using electrical appliances, a method for effectively managing the energy of household appliances is necessary. Such a method can enable users to obtain energy consumption details of such appliances in real time. A system platform could be created through the integration of network communication techniques and various appliances. Subsequently, various appliances and even the human body position can be monitored. People’s electrical appliance usage behavior can be used to determine the health status of the electrical appliance users. The currently used household energy monitoring systems can be divided into three stages:

(1) Equipment deployment: Installing sensors with network communication functions on each type of electrical appliance.
(2) Network communication: Integrating different types of network communication technology and receiving and sending the control signals of various electrical appliances through Bluetooth or Wi-Fi.
(3) System platform: Integrating different types of electrical appliances and providing the energy consumption conditions of these appliances through common network communication technology.

Network management of household energy through sensors can be used to detect usage habits of electrical appliances, obtain instant health information, and even dynamically control the appliances. The management could also reduce energy consumption through an algorithmically constructed mechanism. Building a self-adaptive smart home environment and architecture through the present technology has been discussed. Qela et al. (2012) claimed that energy could be managed and operational safety ensured by using an adaptive learning algorithm and monitoring environmental temperature changes with a communication thermostat. Therefore, the author established an intelligent temperature control system, namely OLA (observe, learn, and adapt), that can compare new input information with the information stored in the knowledge base. The decision-making system subsequently deploys the most appropriate output results automatically and adds the results to the corresponding groups.

Methods of controlling electrical appliances in smart homes are typically applied in the connection between appliances and sockets. Such methods monitor the appliance usage state without changing the original structures of appliances. Byun et al. (2012) proposed ZigBee-based intelligent self-adaptive sensors for solving efficiency limitations and cost concerns as well as the problem of achieving a wide were network at home. They divided the sensing method into self-adaptive projects that were based on situations and events to sense network, hardware, and media practices. Finally, the method was applied to smart homes. Yoshikawa et al. (2013) proposed using a single coil to supply electrical energy to all electrical appliances through wireless transmission. And, the IEEE 802.15.4 is also used in recent IoT commercial products for smart home applications (Dinh et al. 2016). Every sensor node senses environment temperature, humidity, light cover intensity, and moment. The information provided by sensor nodes is collected by the central node. Resolved electrical appliances and control commands are downloaded to every sensor node to determine energy consumption. Finally, the control command is transmitted to electrical appliances through the sensor nodes. Kong et al. (2015) proposed a cepstrum-filtering-based load dissociation technique, which can control the ON/OFF events of many electrical appliances simultaneously. Furthermore, for each piece of wireless equipment, the operating format and mode of network operation can be customized on initiation. Hsieh et al. (2014) proposed a collaborative software and hardware design that enables users to change the mode of network operation easily by clicking on or dragging an image without any underlying hardware knowledge.

The behavior patterns of opening and closing household equipment differ according to people's daily routines. Predetermining information about what type of electric machine should be opened at what period is difficult. Even if an appliance database with opening types and times already exists, it may not adapt to every person's daily routines. Therefore, researchers in the field of machine learning have established methods for determining the actions to be performed according to the current state through interaction with the environment and real-time records of ambient changes. These methods obviate the necessity of adding information in the database in advance.

The aforementioned methods implemented by researchers in machine learning can be divided into two categories: the characteristics learning method and characteristics learning problem. The characteristics learning method uses Markov decision-making to search for optimal control by simplifying the problem. It achieves the present state through the agent’s interaction with the environment. The agent is responsible for sensing the state of the environment and extracting actions. The entire learning process is divided into sensing, actions, and goals.

Whereas supervised learning uses existing samples, reinforcement learning transforms environmental changes into learning experience through interactions with the environment and a statistical model or neural network. However, a living environment has numerous unknown variables, and this is advantageous for the agent of reinforcement learning. Reinforcement learning has a major problem: achieving a balance between exploration and exploitation. To obtain substantial gains, agents must identify effective gains from past actions. If the present action is not the current state of the target action, the agent must mine known gains to search for a more favorable action. Another major problem is that clear end guidance must be received in an unrecognized environment. Sutton et al. (1998) explained that machine learning constantly interacts with surroundings and achieves or approaches optimal control through one or more agents. Guo et al. (2004) reported that balancing between exploration and exploitation has a considerable impact on the effectiveness of reinforcement learning. In a state of pure exploration, agents quickly obtain the local optimum strategy. However, an overemphasis on strengthening the mining process reduces the efficiency of Q-learning in reinforcement learning, and even accelerating learning processes cannot improve efficiency. On the basis of the Q-learning (Suryadevara et al. 2015) architecture in this paper, the simulation annealing algorithm was developed to balance exploration and exploitation.

The resources of a single-chip microcomputer, including memory and hard disk size and processor speed, are extremely limited. Thus, such a computer has a considerably lower efficiency than that of a desktop computer, but its expansion properties and flexibility are considerably higher. Therefore, a microcomputer, such as the Raspberry Pi, can be used for achieving a simple control system for the opening and closing processes of household equipment. The default operating system of the Raspberry Pi is the ARM version of LINUX based on Debian, known as Raspbian. In this study, programs were completed on a personal computer and the code was transferred to the Raspberry Pi for compiling and execution.

3 SYSTEM PLATFORM ARCHITECTURE AND DESIGN

FIGURE 1 presents the HESMS and HELMS proposed in this study. The HESMS is based on a reinforcement algorithm and simulates the switching state of household equipment and establishes switching periods. The HELMS receives control signals generated by the HESMS. The electricity demands of the HELMS vary depending on stimulation appliance, and its control signal is produced according to the actual control of the opening and closing processes of household equipment. Moreover, whether the quantity of household equipment exceeds the maximum quantity of equipment should be monitored. In addition, a graphical interface should be developed to provide real-time monitoring data and obtain the updated state of household equipment. The historical data should also be recorded in the database.

3.1 Home energy state monitor system

Figure 1(a) illustrates the flowchart of the HESMS. This system simulates a home environment, with household equipment such as lights, TVs, electric fans, and electric heaters being regarded as objects of the electrical appliance simulation. The system applies a modified reinforcement learning algorithm to learn people's household equipment usage habits and establish an R array to record the household's states and Q array to collect real-time states of household equipment. These arrays are used to analyze the household equipment requiring operation in the morning, noon, afternoon, and evening, and a control message is subsequently produced to open or close such equipment.

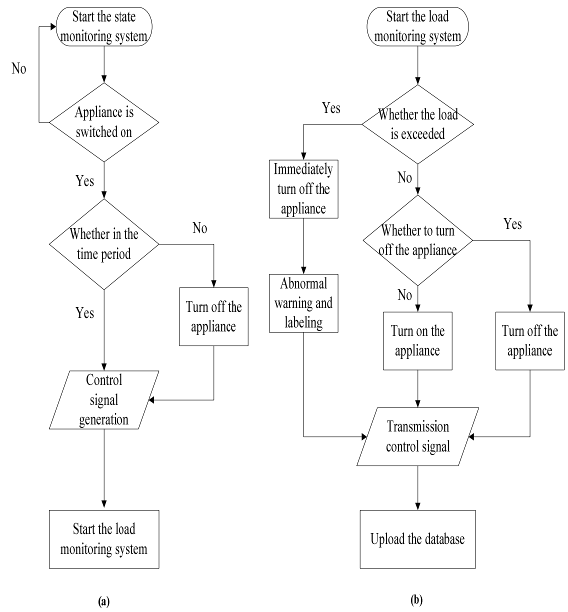

Figure 1. Home energy management procedure (a) Home energy state monitoring system; (b) home energy load monitoring system

The HESMS algorithm can be divided into four parts. First, an R array is used to record real-time household equipment appliance states, and instant messages are transmitted to a Q array at 30 min. Second, four periods are defined, namely morning, noon, afternoon, and evening, with each period lasting 6 hour (h). One week is then used to learn people’s household equipment usage routines in a day. Third, Q array messages are analyzed and a judgment is made about the type of household equipment to operate during each period. Finally, each piece of household equipment is controlled and managed. The detailed steps are outlined as follows:

(1) Behavior model pattern: The period is divided into four parts with each lasting 6 h. Real-time records of appliance usage state are transmitted to the R array. The R array contains four elements: lights, televisions, fans, and kettles. The numbers 0 and 1 represent closing and opening processes, respectively. Messages from the R array are transmitted to the Q array every 30 min (Figure 2).

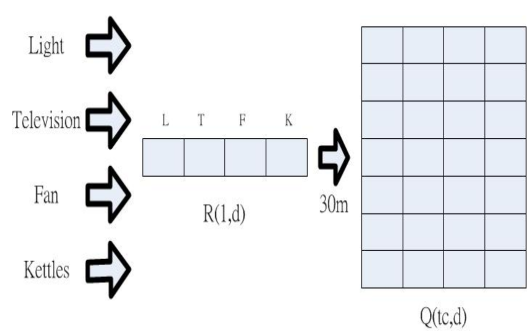

Figure 2. Recording of household equipment instant messages

(2) Experience learning: The Q array summarizes R array instant messages concerning household equipment. A period of 1 week is required to learn people's household equipment usage routines. The numbers 1 and 0 represent opening and closing processes, respectively. Time is written in the 24-h notation. These equipment usage routines include appliances such as lights, televisions, fans, and kettles. The period is divided into sections from 0 to 24 with an interval of 1 which adds 1 every hour from 0 to 24 o'clock.

(3) Decision analysis: The R array data are summarized, and household equipment usage corresponding to each period is analyzed and used to judge which piece of household equipment is subsequently opened. In Eq. (1), R represents the array of real-time recordings of household equipment usage and tc (time counter) represents a counter, with 30 min being added every time a message is received. When time t is equal to 30 min, the messages are transmitted to the Q array. Messages recorded in the R array are summarized, and the household equipment that should be subsequently opened is determined by analyzing the data corresponding to each time. However, the quantity of household equipment in use may increase or decrease. Therefore, when the R array sets D as the quantity of household equipment in use, and when the transmission of the R array is completed, t is initialized to 0. In Eq. (2), if the time is shorter than 30 min, the Q array messages remain unchanged and the R array does not transmit real-time information regarding the state of household equipment. Because the daily routines of household equipment are determined in a period of 1 week, and because the Q array records messages every 30 min, 1 day contains 48 arrays and 1 week contains 336 arrays.

$$\mathrm{Q}(\mathrm{tc},\mathrm{d}) \leftarrow \mathrm{Q}(\mathrm{tc},\mathrm{d}) + \alpha\big(\mathrm{R}(1,\mathrm{d})\big), \quad \mathrm{t} = 30\mathrm{m} \tag{1}$$

$$\mathrm{Q}(\mathrm{tc},\mathrm{d}), \quad \mathrm{t} < 30\mathrm{m} \tag{2}$$

(4) Time control: The Q array data analysis results are used to judge which household equipment should be opened during the current period. Household appliances marked as 1 in the Q array are opened, whereas those marked as 0 are not. For example, in the Q array, light is marked as 1 in the morning, whereas TV, fan, and kettle are marked as 0. Therefore, in the morning, lights are opened, whereas TV, fan, and electric kettle are not. Table 1 presents the modified Q-learning algorithm.

3.2 Home energy load monitoring system

For each household, the electric energy consumed is allocated according to the electric power distribution equipment. The fixed power source voltage for alternating current (AC) types is 110 V, but the rated current is based on the different requirements of household appliances.

Table 1. Home energy state monitoring algorithm

```
Public class HESMS {
    Initiate all Q(tc ← d) values and setup all home appliances
      parameters as Integer.
    Public HESMS() {
      Repeat:
        if any home appliance is turned on {
            R table records this immediately, and marks this
              appliance as 1.
            if (t = 30) {
                Q table records values from the R table.
                tc adds a 30-min period.
            } else {
                Q table stop recording.
            }
            t initializes to 0.
        } else {
            R table record immediate, and mark this appliance
              as 0.
        }
    }
}
```

$\mathrm{Q}(\mathrm{tc} \leftarrow \mathrm{d})$:control signal
Tc: time counter
T = time
α: learning rate

Figure 1(b) presents the flowchart of the HELMS. When the HELMS receives control messages from the HESMS, it immediately starts to monitor the energy load. In this study, we set the upper limit of the voltage at 110 to 120 V, the limited range at less than 5%, and the maximum current at 10 A. If household equipment exceeds the limits, the power is disconnected immediately and the state is recorded to ensure that the household equipment load does not increase indefinitely. The potential situations can be divided into three types:

(1) Situation 1: If the received energy state of household equipment is set to off, the system records this state and uploads it to the database.

(2) Situation 2: If the received energy state of household equipment is set to on, it enters the condition judgment mode. If the voltage and current are within the limited range, the system determines that the energy load of household equipment is safe and then opens the specific equipment. The state message is then recorded and uploaded to the database, and the next message is received.

(3) Situation 3: If the voltage or current is not within the specified range, the system determines that the energy load of household equipment is not safe. Thus, the system disconnects the concerned household equipment immediately. Subsequently, the state message is recorded and uploaded to the

database, and the specific household equipment is labeled as dangerous equipment. Finally, the monitoring results are transmitted back to the HESMS and then to the HELMS.

Table 2. **Home energy load monitoring algorithm**

```
public class HELMS{
  public HELMS () {
      set LR initial to true;
      receive M;
      if M set to ON {
           switch(D) {
                case light: //Check if it passed the current limit (LR)
                                // first. If so, it must be closed.
                        if LR, set to true { if light off { turn on light } }
                        else { stop monitor and turn off light
                                  immediately }
                         break;
                case Television:
                        if LR, set to true { if television is off { turn on
                                   television } }
                        else { stop monitor and turn off the television
                                   immediately }
                        break;
                case fan:
                        if LR, set to true { if fan is off { turn on light } }
                        else { stop monitor and turn off fan
                                  immediately }
                        break;
                case kettles:
                        if LR, set to true { if light is off { turn on
                                  kettles } }
                        else { stop monitoring and turn off kettles
                                  immediately }
                        break;
           }
      } else {
           Terminal normally;
      }
  }
}
```

Message(M): From result of HESMS
Limited Range(LR): Voltage limited 110~120V and A limited to less than 23A
Data(D):Lights, televisions, fans, and kettles

In these three situations, if the initial message and the received message indicate that the household equipment is turned on, the monitoring process continues until the household equipment is turned off. During the process, if the energy load of the monitored household equipment is not within the specified range, the power is immediately disconnected, and the equipment is labeled as dangerous. Table 2 presents the algorithm of the HELMS. When the HESMS message is received, the system determines whether the household equipment is on or off, and then monitors whether the voltage and current exceed the specified range. If these conditions are true, the household equipment is opened. Otherwise, the household equipment is disconnected and the monitoring process is finished. Table 3 shows the range of energy loads of each piece of household equipment.

Table 3. **Current and voltage limits**

Item	Electric current	Voltage	Power
Light	<3A	110V to 120V	<360W
Television	<4A	110V to 120V	<480W
Fan	<5A	110V to 120V	<600W
Kettles	<24A	110V to 120V	<2880W

3.3 *Layout conditions*

In this study, equipment under control (EUC) refers to the four appliances: lights, televisions, fans, and kettles. These appliances were chosen because of their necessity in daily life. In this study, the relationship between the EUC and time, combined with the Raspberry Pi, was emphasized to realize household appliance monitoring.

Because the Raspberry Pi is powered by direct current (DC) voltage, it must be connected to the EUC through a relay. Nevertheless, the EUC is an ordinary household appliance powered by AC voltage. Therefore, if the EUC is directly connected to the Raspberry Pi, it burns out because of excess current. This consequently necessitates the use of a relay to bridge the EUC and Raspberry Pi. Thus, a device with a heavy current could be controlled by one with a low current, and the EUC could be connected to the general-purpose input/output of the Raspberry Pi to control the switch (Figure 3).

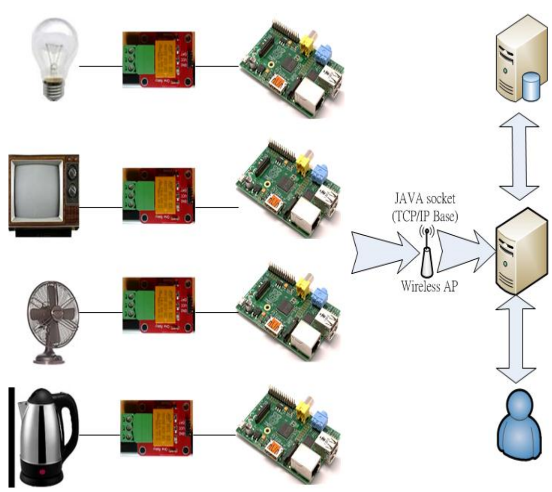

Figure 3. **Structure of the network connection**

3.4 *Appliance energy monitoring system interface*

This interface provides users with the monitoring data of the appliance system. It helps the users to determine whether appliances are powered off. In addition to conveying appliance data, the interface conducts an abnormity judgment on the appliance monitoring data received from the Raspberry Pi through a user-defined algorithm and workflow. The current data are not recorded in the database until an abnormity or the powered-off signal occurs. By contrast, if no abnormity or powered-off signal occurs, monitoring continues. The working process, including the monitoring, receiving, sending, and abnormity judgment on the data, is completed by the Raspberry Pi, whereas the database only records and sends data to the interface of the users. Figure 4 shows the user interface, displaying the date and historical data in the database.

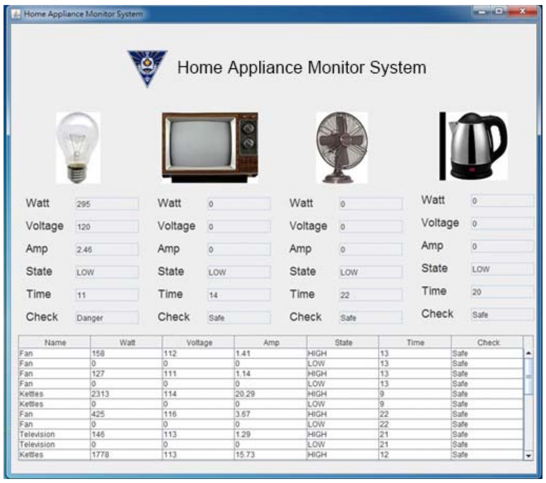

Figure 4. **Appliance energy monitoring system interface.**

4 INTEGRATION AND VALIDATION OF THE SYSTEM

THE experiment conducted in this study was oriented toward intelligent appliances. The first step of this experiment was to define the input message, data-processing module, and output message. The input message was then used to judge whether the appliance was on or off by focusing on materials, determine the last time the appliance was operated, and identify the variation of the electronic load. The data-processing module comprises an online, intelligent, reflection, and graphic interface. Finally, according to the result from the data-processing module, the appliances could be turned on or off on the basis of the output message.

If the Raspberry Pi was plugged in to a 5-V DC current, its Status Light ACT was under high potential condition. Additionally, if the Raspberry Pi was connected to a wired network, its Light Fox, Light Link, and Light 100 were under high potential condition. However, if it was connected to a wireless network, the light was under a low potential condition. Therefore, attention should be paid to ensure that the transformer could provide a current that was equal to or higher than 1 A.

The Raspberry Pi was mainly connected to an appliance monitoring system through Wi-Fi. The Raspberry Pi collected control signals into a packet and transmitted them to the home monitoring system. The appliance monitoring system then read the packet. Thus, after the packet was confirmed, the monitoring system demonstrated the conditions of the appliances. Figure 5 illustrates the appliance conditions that were determined after the appliance monitoring system received the signal packet from the Raspberry Pi. If the conditions of appliances change (thick line area) the system links to the database to load the latest data (fine line area).

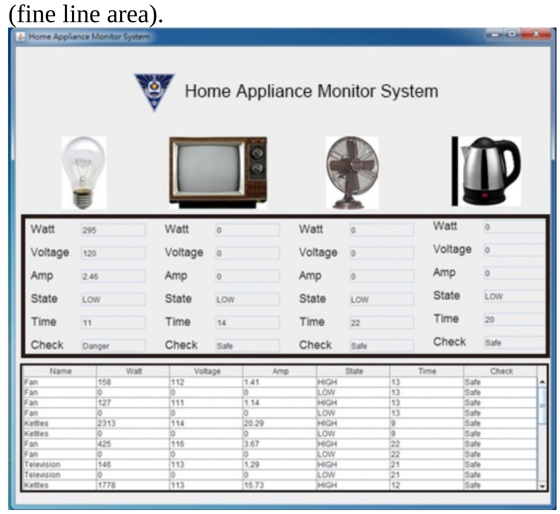

Figure 5. **Appliance status in real-time monitored by the appliance monitoring system.**

The efficacy of the Raspberry Pi and the wireless communication environment can both influence the linkage efficiency. This study tested the time required for receiving and uploading data to the database. The test revealed that this system took 0.183 s to send a message the first time, and after the second time, the average time shortened to less than 0.1 s. Moreover, the time required for successful data reception was 18.258 s for the first time. This is because in this process, additional time was required to connect the system and Raspberry Pi, wait for system's reaction, and adapt to the procedural structure. After the second time, the average time for successful data reception was 3 s. Furthermore, the first successful time required to upload the date to the database was 0.4 s, and this is because the variation of the appliances' condition to update new data required additional time. However, the average time of successful data uploading was less than 1 s after the second time, with stable data transmission, reception, and uploading.

The opening and closing periods differed for each electrical appliance. Herein, time is represented in the 24-h time notation. According to the system operating mechanism, electrical appliances were judged to determine whether they were in an open period. If the electrical appliances were not in the open period, they were closed. If the electrical appliances were in the open period, those that were in use could not be closed automatically. A control signal was generated for appliances that could not be directly opened or closed. Table 4 presents the test data for the period control.

When the signals generated from the appliance condition monitoring process were received, the electric current and voltage of the appliances were tested to determine whether they exceeded the specified limits and evaluate whether they have been protected against electric currents. Each appliance was allocated its own electric current and voltage limits, and if these were exceeded, the appliance was forcibly closed. Voltage was determined according to standard household electricity usage. Thus, the voltage was maintained at 110 to 120 V. Table 5 presents the results of the load control function test. The results reveal the usefulness of the system. An alert is provided in real time when any problem occurs due to any electrical component.

The system also records the load monitoring results in the database. By keeping records of past electrical operations, users can obtain the latest electrical usage condition at any place or time through the Internet. It also informs the users whether the electrical appliances are being used. If the condition of an appliance in the monitoring page is denoted as dangerous, this indicates that the appliance cannot be used and has been forcibly closed. Table 6 shows the message representation format for the database.

Monitoring data recorded in the database could be used in a smart grid for reducing electricity bills, saving power, and transferring power by acquiring learning experience through learning reinforcement. In the four periods defined in this study, the electric current of closed appliances was almost zero. On the basis of the method described in (Misra et al. 2013), the appliance could be closed by the smart grid and the extra power could be transferred to a storage system. If another appliance was detected to be on, the storage system transferred the additional electric power to the open appliances. Thus, the period of peak use of electricity consumption could be shortened, thereby reducing household electricity consumption and costs.

In a smart family, the main purpose of the system is to detect and monitor the station of electrical switches. Through intensive study, the system can determine which appliance to open and automatically transmit the results to the users. Therefore, users can obtain electricity usage information at any time, particularly when family members are away from home. They should not be concerned about whether home appliances are open because the system is combined with the fire control administration. If a continuous electrical danger signal appears three times, the system immediately informs the fire brigade and users, reducing the probability of fires caused by electrical appliances.

5 CONCLUSION

THIS study used a Raspberry Pi (a highly used material in the market) as a controller for various types of home appliance. Through a reinforcement learning algorithm, this study developed a system for detecting the opening time and load limits of electrical appliances. The system is tested every day and night during one week to verify the performance. This system generates an on or off control message. In addition, a load limit is defined for various electrical appliances. Thus, when an on or off message is received for an appliance, the system judges whether to immediately shut down the appliance or receive a new control message according to the load limit. Subsequently, the system continues to monitor the load limit of other electrical appliances. The system can achieve the energy monitor through both of the

Table 4. Period control test

Name	State	Period	Name	State	Period	Name	State	Period
Television	HIGH	22	Kettles	HIGH	20	Light	HIGH	12
Television	LOW	22	Kettles	LOW	20	Light	LOW	12
Light	HIGH	19	Kettles	HIGH	20	Fan	LOW	20
Television	HIGH	14	Kettles	LOW	20	Kettles	HIGH	19
Television	LOW	14	Television	HIGH	20	Kettles	LOW	19
Light	HIGH	18	Television	LOW	20	Light	HIGH	9
Light	LOW	18	Kettles	HIGH	22	Light	LOW	9
Television	LOW	11	Kettles	LOW	22	Television	LOW	14
Light	LOW	21	Light	LOW	12	Kettles	LOW	20
Television	HIGH	20	Fan	HIGH	20	Kettles	HIGH	22
Television	LOW	20	Fan	LOW	20	Kettles	LOW	22
Kettles	HIGH	14	Light	HIGH	21	Kettles	HIGH	11
Kettles	LOW	14	Light	LOW	21	Kettles	LOW	11
Kettles	HIGH	19	Television	HIGH	20	Television	HIGH	14
Kettles	LOW	19	Television	LOW	20	Television	LOW	14
Kettles	HIGH	22	Light	HIGH	11	Light	HIGH	14
Kettles	LOW	22	Light	LOW	11	Light	LOW	14
Television	LOW	12	Television	HIGH	10	Fan	HIGH	17
Kettles	HIGH	17	Television	LOW	10	Fan	LOW	17
Kettles	LOW	17	Kettles	HIGH	19	Light	LOW	9
Light	HIGH	18	Kettles	LOW	19	Fan	HIGH	13

Table 5. **Load control test**

Name	State	Power	Voltage	Electric current	Safe / Danger
Television	HIGH	115	116	0.99	Safe
Television	LOW	0	0	0	Safe
Light	HIGH	205	111	1.85	Safe
Television	HIGH	208	112	1.86	Safe
Television	LOW	0	0	0	Safe
Light	HIGH	122	119	1.02	Safe
Light	LOW	0	0	0	Safe
Television	LOW	126	110	1.15	Danger
Kettles	HIGH	152	115	1.32	Safe
Kettles	LOW	0	0	0	Safe
Kettles	HIGH	1761	114	15.45	Safe
Kettles	LOW	0	0	0	Safe
Television	HIGH	333	118	2.82	Safe
Television	LOW	0	0	0	Safe
Kettles	HIGH	618	118	5.24	Safe
Kettles	LOW	0	0	0	Safe
Light	HIGH	108	116	0.93	Safe
Light	LOW	0	0	0	Safe
Fan	LOW	427	120	3.55	Danger
Kettles	HIGH	1414	112	12.63	Safe
Kettles	LOW	0	0	0	Safe
Light	HIGH	285	114	2.5	Safe

Table 6. **Database message format**

Name	Watt	Voltage	Electric current	State	Time (24-hour time system)	Safe / Dange
Length	11Bytes	6Bytes	11Bytes	11Bytes	6Bytes	11Bytes
Data type	String	String	String	String	String	String

wireless or internet network. In the future, a mobile app can be developed to monitor the home appliances in real time.

The proposed system operates under the principle of cost minimization as well as the premise that the original architecture of home appliances is not altered. A relay powered by 3-A DC and 250-V AC transmits control signals to the corresponding appliances. Moreover, appliance data can be captured by combining the controller and Wi-Fi wireless communication technology. The data are displayed on a Java-based user interface, showing the real-time status and historical information of various types of home appliances. Users can obtain the latest information about home appliances at any time through a network terminal device that can access the Internet.

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NO potential conflict of interest was reported by the authors.

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