

Home Energy Management System for Interconnecting and Sensing of Electric Appliances

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Abstract

Due to the variety of household electric devices and different power consumption habits of consumers at present, general home energy management (HEM) systems suffer from the lack of dynamic identification of various household appliances and a unidirectional information display. This study presented a set of intelligent interconnection network systems for electric appliances, which can measure the power consumption of household appliances through a current sensing device based on OSGi platform. The system establishes the characteristics and categories of related electric appliances, and searches the corresponding cluster data and eliminates noise for recognition functionality and error detection mechanism of electric appliances by applying the clustering algorithm. The system also integrates household appliance control network services so as to control them according to users' power consumption plans or through mobile devices, thus realizing a bidirectional monitoring service. When the system detects an abnormal operating state, it can automatically shut off electric appliances to avoid accidents. In practical tests, the system reached a recognition rate of 95%, and could successfully control general household appliances through the ZigBee network.

Keywords: HEM, Electric Appliances, power consumption habits, OSGi

1. Introduction

According to a research report of the Climate Change Society of the University of Oxford, if detailed power consumption data can be obtained, users can control the energy consumption situation of household appliances, and can save 5% to 15% of the power consumption in each month on average [1][2]. Therefore, HEMS have become an indispensable part of the smart grid. However, at present, most families still use traditional ammeters to record their monthly total power consumption. The recently promoted smart meters, such as Google PowerMeter [3] or Microsoft Hohm [4], can show the total household power consumption at present, but cannot show the power consumption of each household appliance, to say nothing of information about the household appliances that are consuming power. As a result, users cannot further improve their power consumption habits or avoid the use of so-called high-power electric appliances. A system that can accurately identify and detect electric appliances is a subject worthy of study. This study proposed a set of HEMS for interconnecting and sensing of electric appliances, which can measure the household power consumption through a current sensor, transmit the data back to the energy management platform, identify each electric appliance, and then determine whether it is working normally according to its staged power consumption and various effects caused by its power sine wave intervals, so as to avoid overloading problems arising from old or faulty electrical appliances. However, the use of older or large numbers of household appliances will cause power noise problems, which could result in the inaccurate identification of electric appliances and the occurrence of errors. Therefore, in this study, a set of power clustering algorithms was presented to determine the cluster value and cluster potential for measured power information. When an abnormal value arises from the system, it is identified as noise or an abnormal state according to the clustering characteristics. The main contributions of this study included:

1. Creating the ability to identify electric appliances by a single smart meter. The system achieves this function according to the power characteristics of each electric appliance. It does not require the use of identification devices such as RFID, or the matching of electric appliances with a power measurement module, and can therefore avoid additional power consumption or waste. It can also recommend appropriate electric appliances to the users through recording the power consumption of each electric appliance and comparing the operation of the same electric appliance system.

2. A high rate of accuracy. The power clustering characteristics of various electric appliances are discovered through power clustering algorithms, so as to improve the recognition rate of noise or abnormal states.

3. The establishment of an interconnection platform for electric appliances. In this study, the energy management platform was attained based on OSGi, so as to achieve the integration of mutual communication services between various electric appliances, the integration of different protocols, and the self-management and context control services of various electric appliances.

The rest of this paper is organized as follows. Section II presents related research and the technology of energy management systems. Section III introduces the framework of the proposed system, the identification of electric appliances and a detailed description of power clustering. Section IV shows the experimental results, and the conclusion is at the end.

2. Related Work and Background

This section introduces relevant recent research of HEMS and some basic knowledge about the OSGi service platform used in this study.

2.1 HEMS

A good HEMS is necessary for a smart grid, and recently there have been numerous researches about this. HEMS research mainly involves three components. The first component is the power meter of the bottom device [5][6], which is mainly used to measure the voltage and current used by a single electric appliance or the overall system of electric appliances. Ye et al. [5] designed a module with a power sensor that can automatically cut off power supply once it detected that an electric appliance was in a standby state, so as to save energy. Cho HS, et al., [7] established a position tree of electric appliances using an SMPT (Smart Multi-Power Tap) above the meter and through the startup of the power tap, so as to provide the position information of electric appliances, and provide references for context-aware and energy management services. The second component is the transmission component. How to construct a complete network system for household appliances through effective wire transmission or wireless transmission of the meter information? Information network transmission systems have evolved from Bluetooth transmission [8] in 2003 to the most frequently used ZigBee [9][10][11] or power lines [12][13][14] at present. The last component is the system management platform [15][16][17][18][19]. Jahn M, et al. [15] measured the power consumption information of individual electric appliances using a smart socket, and established a hydra framework, enabling the power measurement system to have flexibility and expandability. Users identify household appliances with Ubilense through their mobile phones, which can also display power consumption information. Park S, et al. [20] reduced the amount of power consumption data and established a simulation display to be used in a system capable of transmitting large amounts of data used for long-term monitoring.

2.2 OSGi Platform

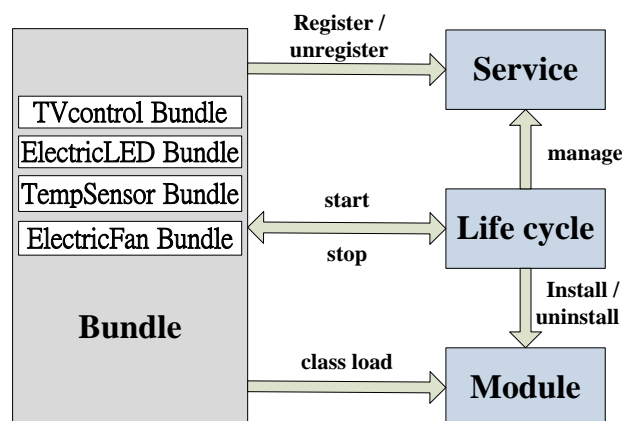


Fig. 1. Relationship of each layer

The OSGi [21][22][23][24][25] platform is developed by the OSGi Alliance; it supports the service providers and companies through the home gateway to provide service for devices. Through the OSGi service platform, services can be shared between bundles through the

service registry. The service provider bundle registers its service objects and service items in the service registry, and the service consumer bundle searches the service objects provided by other bundles in the service registry using the service items.

0 shows the relationship of each layer. Service layer register service in the service registry, life cycle layer manages the bundle's life cycle and defines the bundle how to start or stop as well. Module layer defines the bundle, which compost of Java class. And bundle can import or export with another bundle. OSGi platform are often employed in home security, healthcare [28], home gateway and so on.

3. Proposed System

This section introduces the overall system framework and expatiates on the various function modules.

3.1 System Architecture

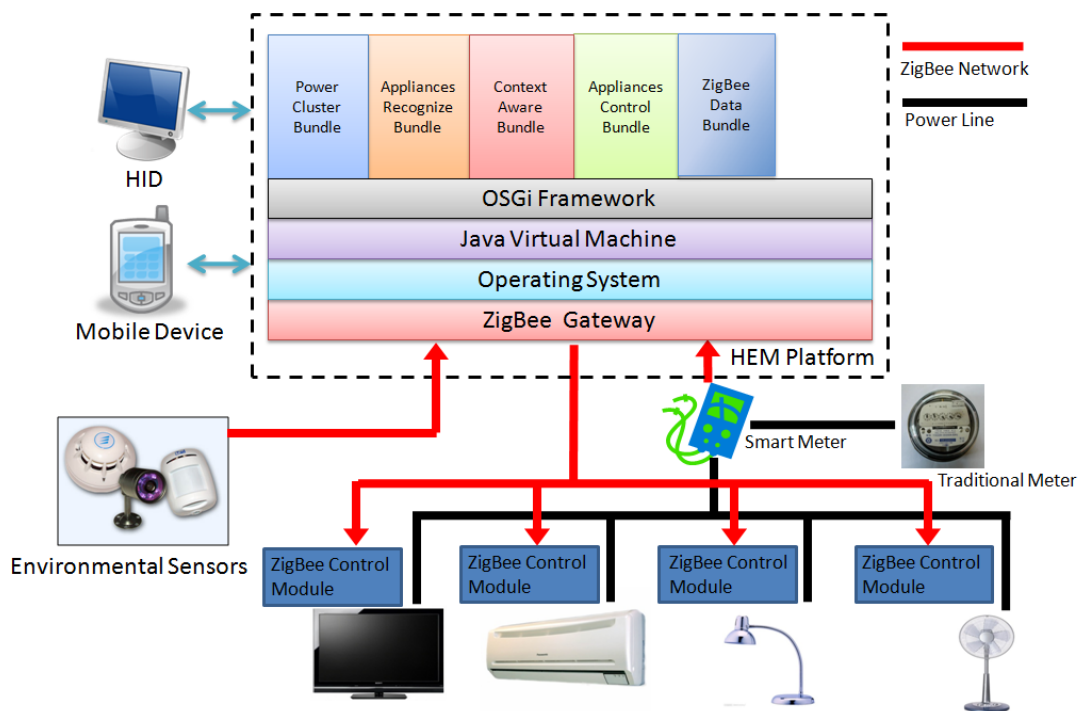


Fig. 2. The overall system framework of HEMS

0 shows the overall system framework of HEMS proposed in the present study. The system measures the power consumption of various household appliances (including voltage and current) through a smart meter, transmits the data results to the energy management platform through a ZigBee wireless network, records the power consumption through the management platform, identifies electric devices according to the database system, and then displays relevant information through an HID or a mobile device. Users can directly transmit control commands through a remote controller a mobile device, and the system can also achieve adaptive context-aware control through a context-aware module as well as users' power consumption plans. Its energy management platform can transmit control signals through a

ZigBee network, convert signals to IR signals through the ZigBee control module, or directly control the relay switches of electric appliances to achieve a complete control service platform. Its main functions include:

1. Achieving the integration of various electric appliance systems.
2. Achieving energy-saving mechanisms through an intelligent home network.
3. Providing remote operation and automation functions of various household appliances.
4. Achieving the use of a sensing controller.

3.2 Smart meter

In this study, household power consumption was measured using a smart meter, which is mainly composed of an energy metering integrated circuit (IC), voltage and current sampling circuits, and a microprocessor, to obtain the voltage and current signals.

The energy metering IC used in this paper was the ADE7763 chip produced by Analog Devices, which can be connected with a variety of power measurement circuits, including the current converter circuit and the low resistance voltage divider circuit. During current measurement, the current analog signal is sampled from the current converter circuit, amplified through a programmable gain amplifier (PGA), and then subsequently converted to a digital signal through an analog/digital converter (ADC). Current information obtained in such a manner has large amplitude, and it must be differentiated through a high pass filter so as to obtain a correct waveform level for further integration processing through an integrator. The current signal is obtained through the root mean square (RMS) operation, and its expression is shown in Eq. 1.

$$I(\text{RMS}) = \sqrt{\frac{\int_0^T I^2(t)dt}{T}} \quad (1)$$

Due to the time signal sampling, Eq. 1 must be converted to Eq. 2.

$$I(\text{RMS}) = \sqrt{\frac{\sum_{j=1}^N I^2(j)}{N}} \quad (2)$$

The process of Eq. 2 in the hardware is as follows: after the integration of the digital signal, the square of the current signal is obtained through a multiplier, and is accumulated through a low pass filter. The RMS current value can then be obtained from the square root operation.

During the voltage measurement, the sampling method is the same as that of the current signal, but the difference is that after passing through the ADC, the analog voltage signal needs to be integrated through a low pass filter, followed by the root mean square operation. Here the instantaneous power consumption can be calculated as per Eq. 3.

$$p(t) = v(t) \times i(t) \quad (3)$$

The instantaneous voltage $v(t)$ and instantaneous current $i(t)$ in Eq. 3 can be expressed as Eq. 4.

$$v(t) = \sqrt{2} \times V \sin(\omega t) \quad (4)$$

$$i(t) = \sqrt{2} \times I \sin(\omega t) \quad (5)$$

V and I in Eqs. 4 and 5 are respectively the RMS values of the voltage and current, so Eq. 3 can be expressed as Eq. 6.

$$p(t) = VI - VI\cos(2\omega t) \quad (6)$$

The actual power can be obtained through the instantaneous power, as shown in Eq. 7.

$$P = \frac{1}{nT} \times \int_0^{nT} p(t)dt = VI \quad (7)$$

Therefore, in the actual hardware implementation process, current and voltage signals are obtained through sampling and calculation, integrated through a low pass filter, and subsequently averaged after gain adjustment through a multiplier to obtain the actual power. The two parameter, $I(\text{RMS})$ and power (P), are applied to appliance recognition described in Section 3.3.3.

After the power system characteristics are measured using an energy metering IC, in order to link smart meters with the household power consumption management system, the energy metering IC performs relevant measurements after receiving commands from the microprocessor. The results are then transmitted to the microprocessor, which must have a communication interface for external transmission, allowing administrators to remotely understand the measurement results, monitor household power consumption systems, or issue additional commands to the microprocessor. The structure of the communication interface is shown in 0. After powering-on, the relays are controlled by the micro-controller unit (MCU), and sockets control whether to power on. If necessary, current values obtained from a current sensor will be converted to digital signals through a digital-to-analog converter (DAC). The digital signals are transmitted to the MCU and then to the load side. The MCU can also transmit data or commands to the central control center through ZigBee sensors, or record data in the electrically-erasable programmable read-only memory (EEPROM).

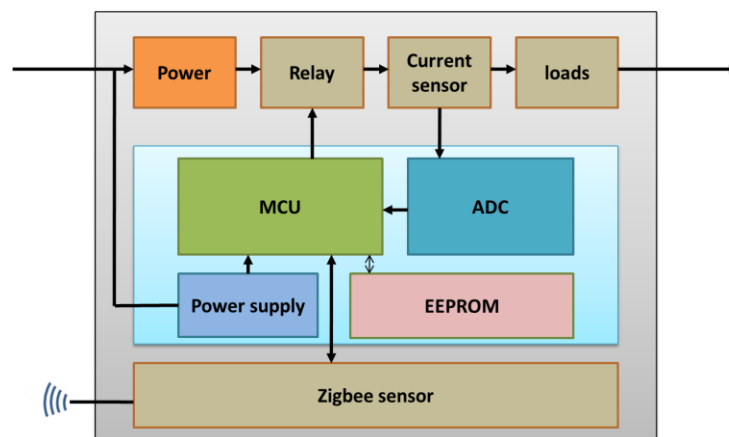


Fig. 3. The design of smart socket

3.3 Energy management service platform

The energy management service platform is responsible for receiving smart meter data through the ZigBee network, normalizing the data and creating power clusters. After noise filtering according to clustering characteristics, the platform identifies electric appliances by

comparing the power characteristics with the database, and receives surrounding context information with the aid of the context sensing module. The platform performs the corresponding context control, and transmits commands to the ZigBee control module through the ZigBee network. The energy management service platform is built on the OSGi framework. Its major function bundles include a ZigBee data bundle, a power cluster bundle, an appliance recognition bundle, a context-aware bundle and an electric appliance control bundle.

3.3.1. ZigBee Data Bundle

The ZigBee data bundle is mainly responsible for receiving information transmitted by smart meters and surrounding context sensing modules. The OSGi platform reads data from the ZigBee data bundle, and the packet format is shown in 0.

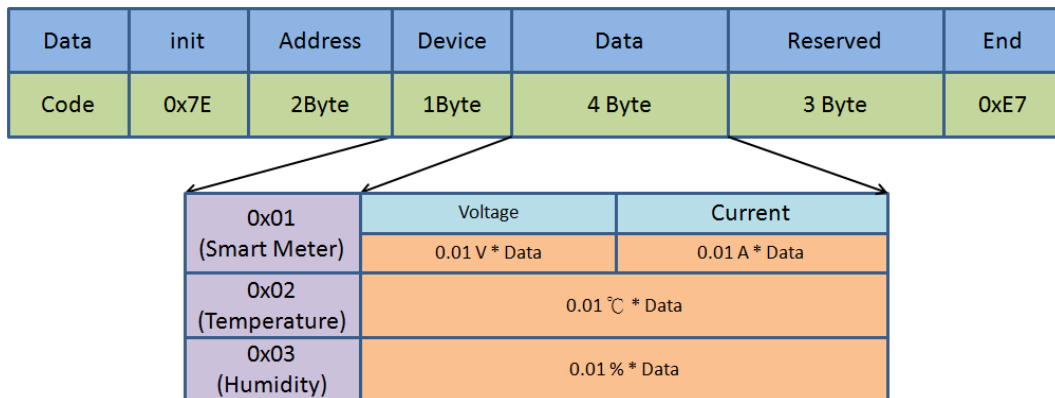


Fig. 4. Packet format of ZigBee Data Bundle

In the present study, the device type was divided into the smart meter, temperature sensors and humidity sensors. As for the smart meter, the first two bytes of its data are defined as the voltage value, while the last two bytes are the measured current values, calculated through multiplying the measured data by 0.01 V (A). As for the temperature and humidity, these are simple numerical data, which are respectively the measured data multiplied by 0.01 °C (%).

3.3.2. Power Cluster Bundle

Upon receipt of the voltage and current information, the voltage information must first be normalized to 110V. Different rooms or the number of connected electric appliances are likely to affect the voltage level, which falls within a range of $110 \pm 10V$. During wireless transmission, the transmission interference and noise effect will often give rise to incorrect values, as shown in 0 (A), which will affect the accurate identification of electric appliances. As for an electric appliance under a variety of operating states, the conversion between its current and phase angle presents a clustering distribution, as shown in 0 (B), and the final clustering distribution will present in a fixed number of regions. According to the above characteristics, whether the current is in the same state can be judged by whether the subsequent trace value falls within the clustering range through clustering operations. If a value beyond the clustering range arises, it must be observed whether abnormal clustering values or instantaneous noise distributions arise. Through the power clustering algorithm, the recognition rate of electric appliances can be effectively improved, and abnormal error detection rates caused by noise can be reduced.

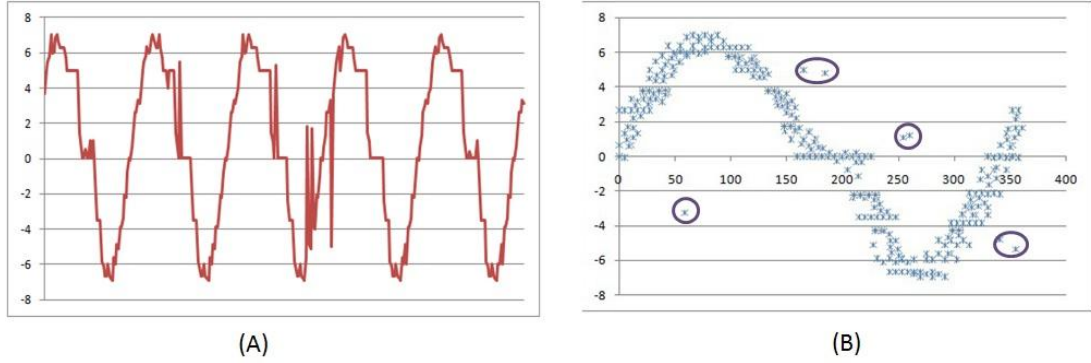


Fig. 5. The clustering distribution of current

In this study, power clustering characteristics were processed using the subtractive clustering method [26] in the neural algorithm. The main concept of the subtractive clustering method is to regard all data points as potential center points and select clustering standards according to the density of the surrounding data points. This method is independent of the complexity of the system dimension, but is proportional to the data amount. Here, it is supposed that M is the power group, and r_a is the influence distance of the center point of the clustering group and is a positive constant. The potential value P_i (Eq. 8) of the sampling point group M_i can be calculated, which represents the potential of this point becoming the clustering center point.

$$P_i = \sum_{j=1}^n \exp\left(-\frac{\|M_i - M_j\|^2}{\frac{r_a^2}{4}}\right) \quad (8)$$

After all potential values P of the sampling points are calculated, the M_{c1} with the highest potential value is selected as the first clustering center point. The potential values of the other points then need to be modified, as per the following Eq. 9:

$$P_i = P_i - P_{c1} \exp\left(-\frac{\|M_i - M_j\|^2}{\frac{r_b^2}{4}}\right) \quad (9)$$

wherein r_b is a value to be set in order to avoid getting too close to the last clustering center point M_{c1} . It needs to be greater than r_a , and its value is generally recommended as 1.5 times that of r_a . After this process is repeated, the sampling point group M can be divided into subgroups, wherein, $\bar{\varepsilon}$ and $\underline{\varepsilon}$ are the upper and lower limit ratios of the potential value, which are defined in this study as 0.5 and 0.15, respectively.

3.3.3. Appliance Recognition Bundle

In this study, each household appliance was regarded as an RLC circuit, and each had different power characteristics under different operating states. Through the previous study of the power characteristics of household appliances, they can be identified mainly based on the four parameters of I(RMS), power (P), current and voltage phase shift angle, and the distortion power factor. I(RMS) and power (P) were introduced in the last section, and here, the definitions of current and voltage phase shift angles and distortion power factor are

introduced.

In an ideal AC circuit, the voltage and current should have the same phase angle, but in actual circuits, the effects of inductors and capacitors on electric appliances have given rise to current deformations and phase difference relationships, as shown in the following 0.

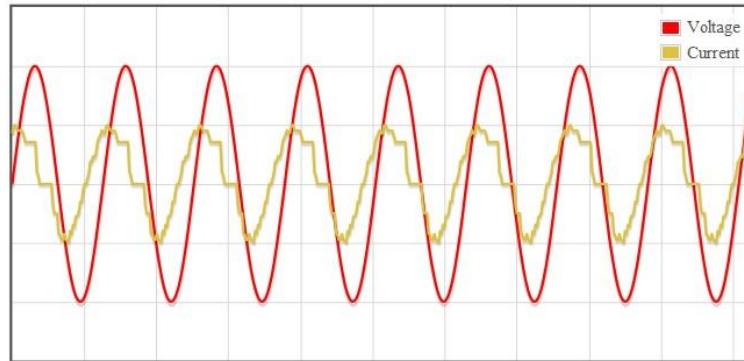


Fig. 6. The example of current deformations and phase difference relationships

The so-called distortion power factor (DPF) (Eq. 10) is defined.

$$\text{DPF} = \frac{1}{\sqrt{1+\text{THD}_i^2}} = \frac{I_{1,\text{rms}}}{I_{\text{rms}}} \quad (10)$$

THD_i is the total harmonic distortion of the load current, $I_{1,\text{rms}}$ is the fundamental component of the current, and I_{rms} is the total current. After returning to the original waveform through the DPF, the deviation angle ω can be discovered according to the following Eq. 11:

$$|P| = |S| \cos \omega \quad (11)$$

where S is the apparent power. When the electric appliance first joins the HEM system, the system will record and study its characteristics, and then create model data. Users need to input data for different models of this appliance, such as name, brand, power usage, and so on, so as to provide enough information for the database. Later, when the electric appliance is restarted, the system will compare its characteristics with those of the model.

3.3.3.1. Comparison programs of power characteristics

The system establishes a factor queue of the various eigenvalues in sequence. After the factor queue of eigenvalues is ready, when data from new electric appliances are generated, they are input into the search system. Searched results are obtained and saved as a database. Each element within it is built with the same structure, which records the device model, device importance, video description, and power characteristics. The structure of the power characteristics is comprised of four parameters, namely the power cluster value, the angular position of the peak value of the sine wave interval, the delayed value of the sine wave interval, and the displacement value of the state power. Afterwards the retriever performs the corresponding operation of the database from the factor queue based on the factor properties. Cases of factor operations are as follows.

The Operation of power characteristics: The same power characteristics of the database are compared to eliminate elements with overlarge differences in the power characteristics of the database. Here, a set of appliance-matching algorithms is presented, which is a modified algorithm based on the Boyer-Moore algorithm. It is assumed that the system regularly captures the clustering power of every section of the electric appliance in both the first D1 seconds and the last D1 seconds as the identification standard, and that the system will capture the currently measured power clustering in the first D1 seconds as the eigenvalue of power clustering for the first identification. The system compares each phase of the power clustering in the first D1 seconds with the power clustering list obtained through the first phase of screening as a comparison target. If M1 videos are successfully identified as being related, then the following electric quantity clustering data are identified with the M1 elements in the last D1 seconds as the samples and the rest may be deduced by analogy, until a complete power model is identified and the identification algorithm is completed, as shown in 0.

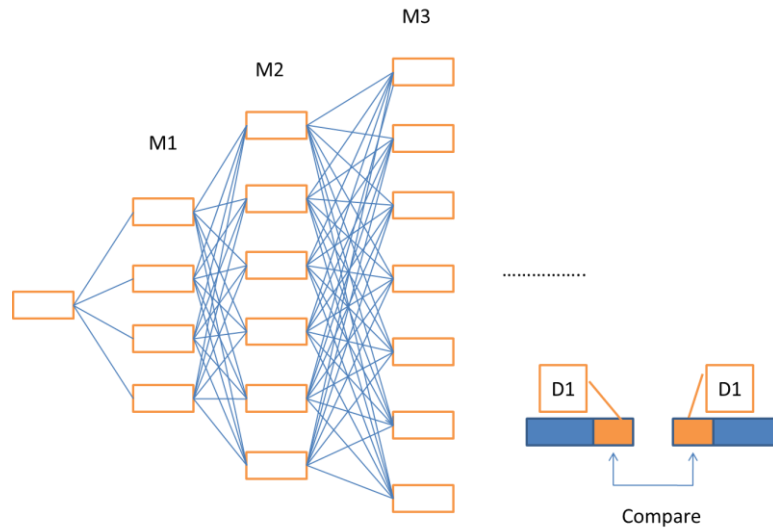


Fig. 7. Comparison programs of power characteristics

Suppose that there are M electric appliance models. It takes $2M * T_1(D1)$ to find the electric power models with a beginning and ending of $D1$, respectively, and $T_2(D1)$ to identify and compare the $D1$. The total time consumption is as Eq. 12:

$$T(M) = 2M * T_1(D1) + M1 * T_2(D1) + M1M2 * T_2(D1) + M1M2M3 * T_2(D1) + \dots \quad (12)$$

By analogy, suppose that the same amount of models is successfully identified each time, and that $M1 = M2 \dots = n$, it is simplified as Eq. 13:

$$T(M) = 2M * T_1(D1) + nT_2(D1) * (nm - 1)/(n - 1) \quad (13)$$

When the operation corresponding to each factor is completed, an index array will be obtained. The index array records the element index in the database and continuously inputs the structural sequence of this device into the operating queue in sequence. The system

shows the operating queue as the electric appliance being used, and the continuous control commands may also collect device models from this operating queue.

3.3.4. Context aware bundle

This bundle detects the regional context, such as temperature and humidity, whether there are human activities or not, and so on, and then transmits the results to the server through a network so as to be available for relevant people and other programs. It is mainly divided into four steps.

3.3.4.1. Information collection

When users interact with the device, data will be collected. The system submits the collected amount of environmental parameters and related information of the interactive devices (such as UPnP, Bluetooth, infrared, ZigBee, etc.) to the learning system for information analysis, so as to produce effective information. Furthermore, useful information can be integrated with other information once again to form new information. The detailed degree of users' behavioral patterns expressed by the information depends on the integration degree; that is, users' ongoing behaviors can be more accurately described according to the information with a higher integration degree.

3.3.4.2. Information analysis

Information analysis aims to determine users' behavioral patterns represented by the information. Upon receipt of the information and after analysis, the system will divide interactive information into two groups. The first group is information on further behavioral patterns after interaction with the device. The second group is information on user dissatisfaction with the environment or the response time after implementation of the operation. Information analysis integrates the synthetic information in the information collection stage, and then sorts out and strengthens the programs that can be judged by the command reasoning system.

3.3.4.3. Context reasoning

0 (A) shows the process of the basic framework of the reasoning system, which is implemented on the premise of completing data collection and data analysis. After data such as environmental parameters, interactive information of devices and behavioral patterns are obtained from the reasoning system, if the reasoning system cannot find corresponding records from previous learning experiences, it will introduce these data into the learning system; otherwise, it will begin to implement its work. The reasoning system will judge every possible context according to a standard. This standard gives priority to the information in accordance with its accuracy and integration degree. In the flowchart of context generation shown in **0 (B)**, if a possible context has a higher priority, then this context will be decided and implemented, while other contexts with a lower priority will not be adopted because of insufficient information.

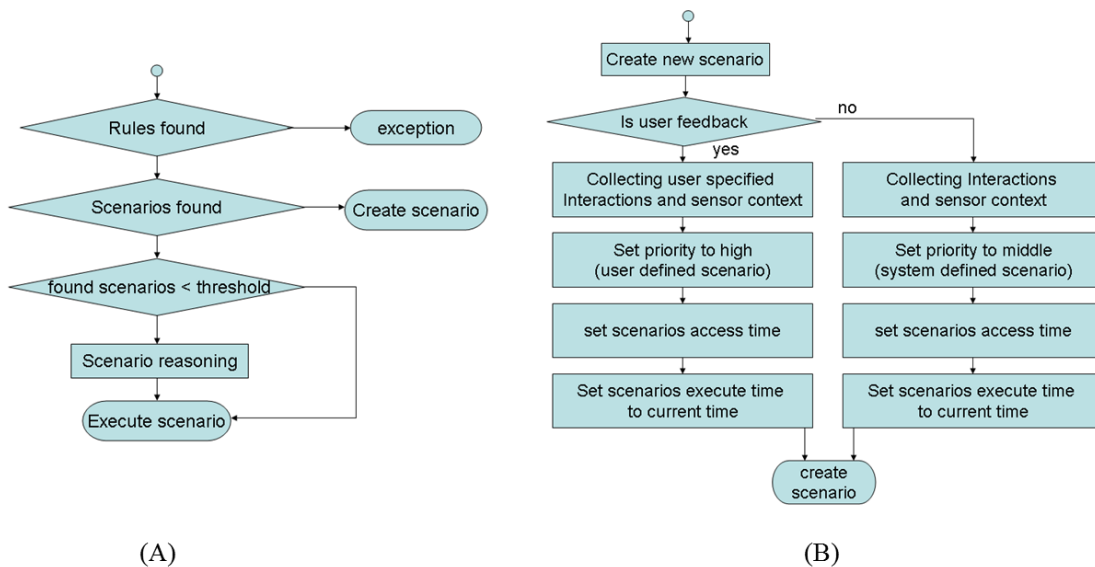


Fig. 8. Process of the reasoning system (A), and Flowchart of context generation (B)

3.3.4.4. Users' feedback:

After the implementation of corresponding assistance programs, the system waits for the users' responses as to whether the assistance helps to achieve the desired functions, and then transmits these responses to the learning system. The learning system updates the regulations in response to this information, which then enhances intelligence and other subsequent work. The priority of all possible contexts forecast by the reasoning system is given in accordance with the accuracy and integration degree of the information, but user feedback will either enhance or reduce the priority. At this stage, the priority of the implemented contexts is adjusted after prediction.

3.4 ZigBee Control Module

To integrate existing electric appliances without changing the general control model of household appliances, a ZigBee control module was responsible for receiving the commands issued by the energy management platform and for converting these commands to the command formats of the corresponding devices, where it could then control the household appliances through a ZigBee-to-IR [27] framework. The ZigBee control module is shown in the following 0:

This module is composed of a group of IR transmission signals, a relay control and a ZigBee receiving module. An infrared remote controller transmits data using a modulated manner, that is, the data and carrier frequency at a certain frequency are taken as the AND. In this way, the transmitting efficiency can be improved and power consumption can be reduced. In this study, infrared signals could be decoded through a Linux infrared remote control kit developed for the Linux platform, and by using an infrared receiver connected to a PC via RS232, and the host computer could also be remotely controlled to do specific actions. The function of each button is recorded, and then its data are input to the ZigBee control module. When the control module receives a signal, the packet is analyzed to find the corresponding control command units, so as to issue control and achieve an integrated control service of household appliances.

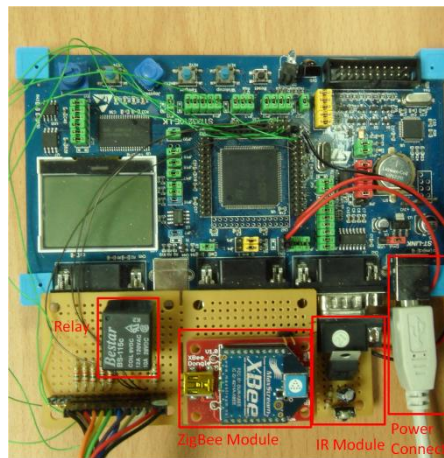


Fig. 9. ZigBee Control Module

4. Result and Analysis

This section introduces the results achieved in this study and experimental analysis according to this system.

4.1. Implementation

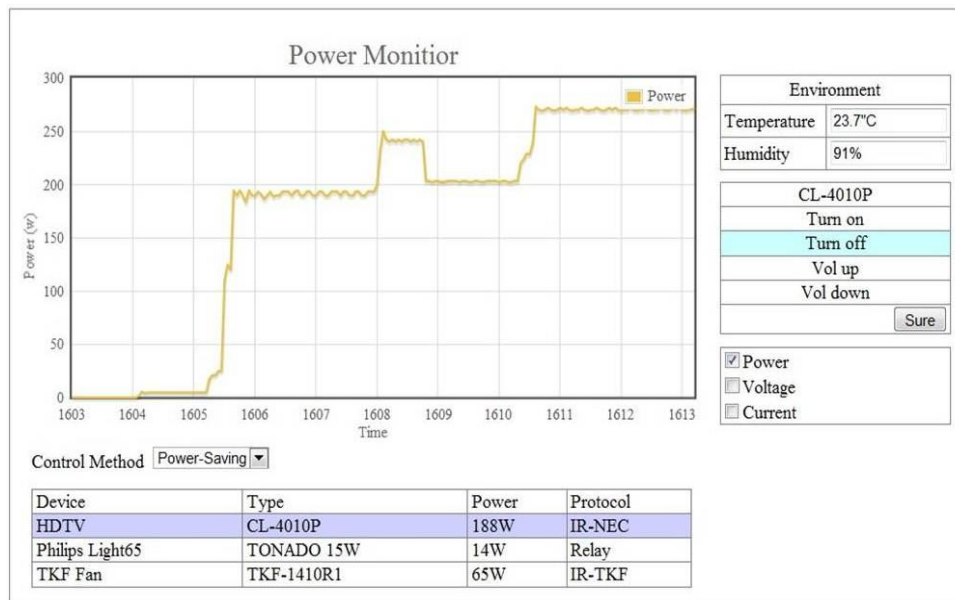


Fig. 10. The User Interface of the System

The result interface achieved in this study is shown in the following 0. This study was mainly used to measure the power consumption of general household appliances and to identify electric appliances, as well as allow users to remotely inquire about related information through the Internet. The measured information was comprised of the household temperature and humidity measured by sensors in the surrounding environment, which could simultaneously display the power, voltage and current information. The general relay

controls and IR controls of a television and an electric fan were completed in the electric control section. The control method section was divided into user-controls, power-saving, content-awareness and planning. User-control was defined as all electric appliances that are self-controlled by users, and power-saving was defined as an automatic shutoff to the power supply when a standby state was detected. Content-awareness was defined as the automation of controls in electric appliances based on environmental information and historical user information. The planning section was defined as the user input of scheduled power consumption, and then allowing the system to decide the schedule the electric appliances according to the electricity price and necessity.

4.2. Experiments and analysis

In this study, a total of 40 different household appliances were used for experimental analysis. During the experiment, at most six electric appliances were randomly started for identification analysis, and there were 30 experiments in each stage.

4.2.1. Relation between recognition accuracy and recognition time

In this experiment, the recognition accuracy was studied mainly based on the sampling time and recognition time, and the accuracy rate was defined as:

$$F = \frac{\text{Recognition time}}{\text{Sampling time}} * 100\% \quad (22)$$

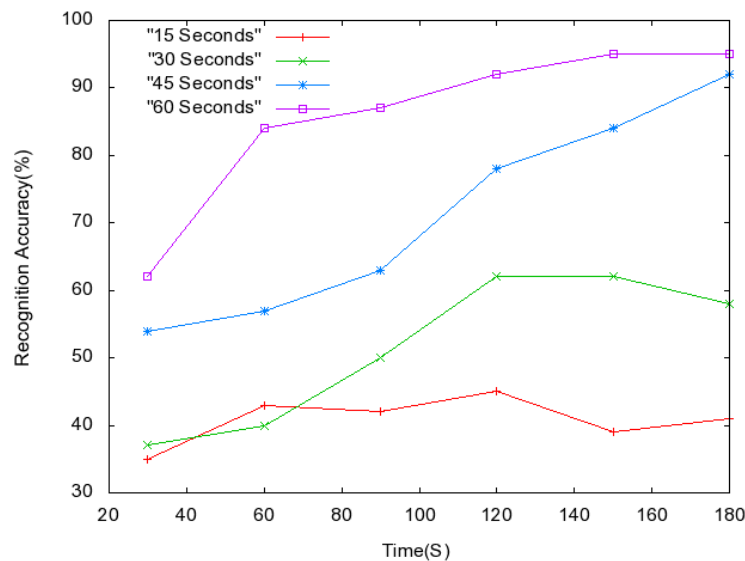


Fig. 11. Relation between recognition accuracy and recognition time

As can be seen from the experimental results, **0**, when the sampling time was insufficient (15 S), the sample would be incompletely established, resulting in recognition difficulties. Even if the recognition time was extended, it was still difficult to increase the recognition rate, while too short of recognition time would also cause recognition difficulties. As can be seen from the experimental results, the best sampling time was 60 seconds. When the recognition time reached 120 seconds, the recognition accuracy was 92%, and this could reach as high as 95%.

4.2.2. Relation between recognition accuracy and the current clustering algorithm

In this experiment, **0**, the effect of the current clustering algorithm on the system recognition rate was analyzed. An experiment is performed with a sampling time of 60 seconds and a recognition time of 90, 120, 150, and 180 seconds, respectively. The experimental results are shown in the following figure. As can be seen from the experimental results, the recognition accuracy rate was approximately 91.5% on average using the current clustering algorithm, and 79% on average without the current clustering algorithm, due to the effect of noise on data collection, sampling and identification.

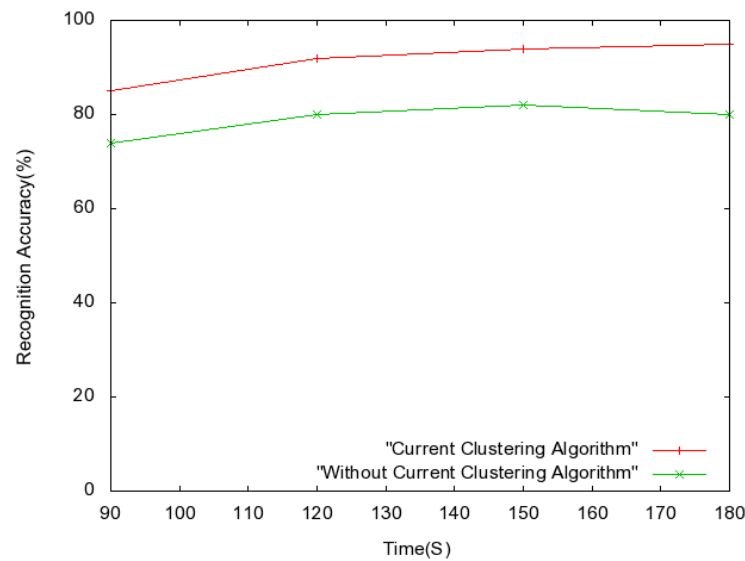


Fig. 12. Relation between recognition accuracy and the current clustering algorithm

4.2.3. Relation between recognition accuracy and recognition number

Table 1. Relation between recognition accuracy and recognition number

Number of electric appliance	1	2	3	4	5	6
recognition accuracy	100%	97%	95%	88%	90%	91%

Another concern was whether increasing the number of electric appliances would affect recognition accuracy, so the detection of different numbers of electric appliances was investigated. The experimental results are listed in the following Table 1. When there was one electric appliance, the recognition rate was 100%, but when there were two or more electric appliances, the recognition rate was reduced due to the effect of capacitors and inductors in series. This will be a target of subsequent studies in the future.

5. Concluding Remarks

In this study, a set of HEMS for the interconnection and sensing of various household appliances was presented. It measured power information through a power meter and transmitted the data back to the management platform via wireless transmission. It allowed

users to realize the currently used electric appliances and their power consumptions through the identification of the devices, and provided corresponding control interfaces for the users to remotely control household appliances. It established content-aware service functions with the help of context information sensors and user habits, and its recognition rate reached as high as 95% with the aid of the current clustering algorithm and the establishment of identification samples. In the future, research will be mainly engaged in establishing the planning control model matched with cloud services, so as to expand the scope of recognition and the obtainment of identification samples.

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