A Smart Appliance Management System with Current Clustering Algorithm in Home Network

Shih-Yeh Chen[1], Yu-Sheng Lu[2], and Chin-Feng Lai[3]

[1] Master's Program of E-Learning
Taipei Municipal University of Education
No.1, Ai-Guo West Road, Taipei, 10048 Taiwan
me_ya404@hotmail.com
[2] Business Customer Solutions Lab
Chunghwa Telecom Laboratories
No. 12, Lane 551, Min-Tsu Rd. Sec.5, Yang-Mei, Taoyuan 326, Taiwan
yusheng@cht.com.tw
[3] Institute of Computer Science and Information Engineering
National Ilan University
No. 1, Sec1, Shen-lung Road, I-Lan, 260, Taiwan
Cinfon@ieee.org

Abstract. Due to the variety of household electric devices and different power consumption habits of consumers at present, it is a challenge to identify various electric appliances without any presetting. This paper proposed the smart appliance management system for recognizing of electric appliances in home network, which can measure the power consumption of household appliances through a current sensing device. The characteristics and categories of related electric appliances are established, and this system could search the corresponding cluster data and eliminates noise for recognition functionality and error detection mechanism of electric appliances by applying the current clustering algorithm. At the same time, this system integrates household appliance control network services to control them based on users' power consumption plans, thus realizing a bidirectional monitoring service. In practical tests, the system reached a recognition rate of 95%, and could successfully control general household appliances in home network.

Keywords: Appliance Management System, Electric Appliances, Current Clustering Algorithm, Home Network.

1 Introduction

The recently promoted smart meters, such as Google PowerMeter [1] or Microsoft Hohm [2], 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 [3-6]. As a result, users cannot further improve their power consumption habits or avoid the use

Joel J.P.C. Rodrigues et al.: (Eds.): GreeNets 2011, LNICST 51, pp. 13–24, 2012.

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 smart appliance management system with current clustering algorithm in home network, 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 current clustering algorithm 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.

2 Smart Appliance Management System

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

2.1 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 [7-14].

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.

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

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

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

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.

$$\mathrm{p(t)} = \mathrm{v(t)} \times \mathrm{i(t)} \tag{3}$$

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

$$\mathrm{v(t)} = \sqrt{2} \times Vsin(\omega t) \tag{4}$$

$$\mathrm{i(t)} = \sqrt{2} \times Isin(\omega t) \tag{5}$$

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.

$$\mathrm{p(t)} = VI - VIcos(2\omega t) \tag{6}$$

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

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

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(RMS) and power (P), are applied to appliance recognition.

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 01. 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 [15-19], or record data in the electrically-erasable programmable read-only memory (EEPROM).

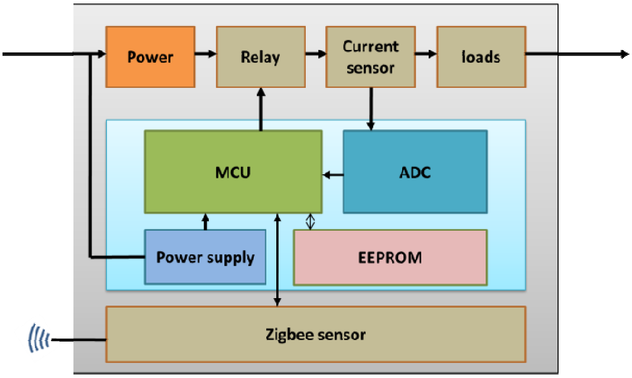

Fig. 1. The design of smart meter

2.1.1 Power Cluster

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 ± 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 current clustering algorithm, the recognition rate of electric appliances can be effectively improved, and abnormal error detection rates caused by noise can be reduced.

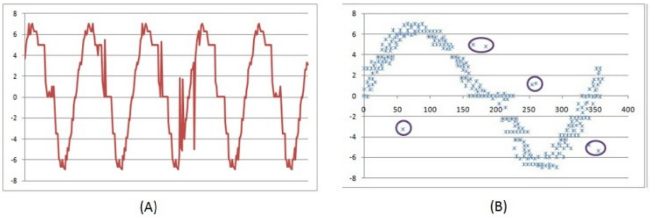

Fig. 2. The clustering distribution of current

In this study, power clustering characteristics were processed using the subtractive clustering method [20] 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.

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

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:

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

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, $\overline{\varepsilon}$ 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.

2.1.2 Appliance Recognition

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 inductorsand capacitors on electric appliances have given rise to current deformations and phase difference relationships, as shown in the following 0.

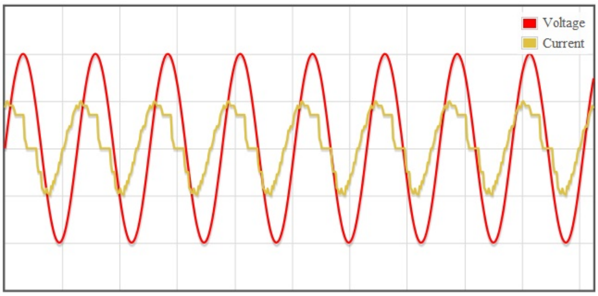

Fig. 3. The example of current deformations and phase difference relationships

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

$$\mathrm{DPF} = \frac{1}{\sqrt{1+\mathrm{THD}_i^2}} = \frac{I_{1,\mathrm{rms}}}{I_{\mathrm{rms}}} \tag{10}$$

$\mathrm{THD_i}$ is the total harmonic distortion of the load current, $I_{1,\mathrm{rms}}$ is the fundamental component of the current, and Irms 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:

$$|\mathrm{P}| = |\mathrm{S}| \cos \omega \tag{11}$$

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.

2.1.2.1 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 M1videos 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.

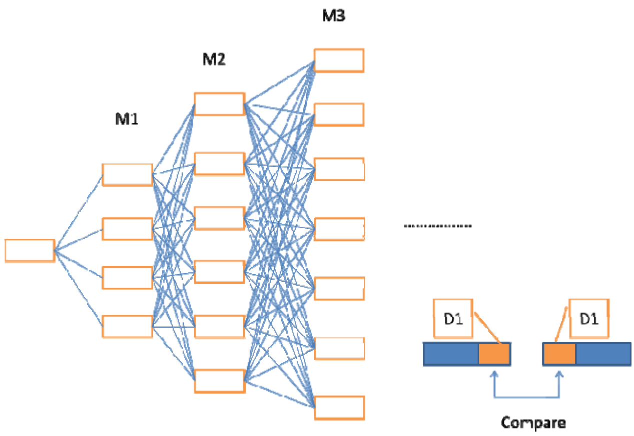

Fig. 4. Comparison programs of power characteristics

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:

$$\mathrm{T(M)} = 2\mathrm{M} * \mathrm{T1(D1)} + \mathrm{M1} * \mathrm{T2(D1)} + \mathrm{M1M2} * \mathrm{T2(D1)} \\ + \mathrm{M1M2M3} * \mathrm{T2(D1)} + \cdots \tag{12}$$

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

$$\mathrm{T(M)} = 2\mathrm{M} * \mathrm{T1(D1)} + \mathrm{nT2(D1)} * (\mathrm{nm} - 1)/(\mathrm{n} - 1) \tag{13}$$

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.

2.1.3 Context Aware Service

This service 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.

2.1.3.1 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.

2.1.3.2 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 Result and Analysis

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

3.1 Implementation

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

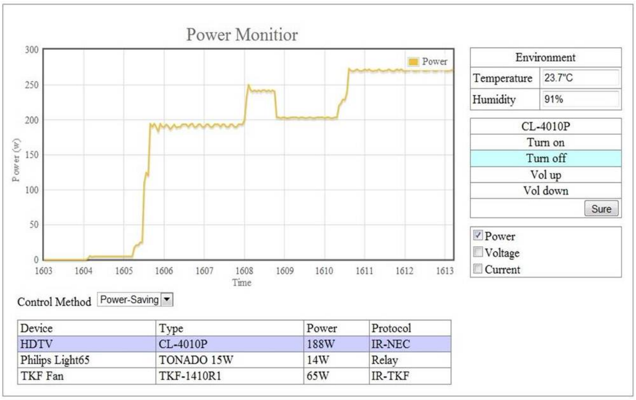

Fig. 5. The user interface of the system

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.

3.2 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.

3.2.1 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:

$$F = \frac{\text{Recognition time}}{\text{Sampling time}} * 100\% \tag{22}$$

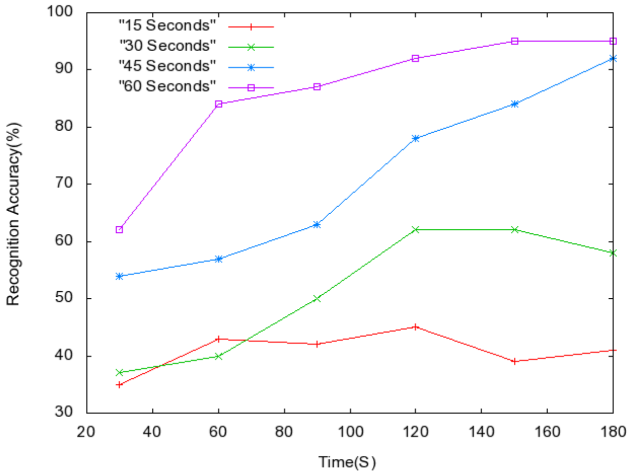

Fig. 6. Relation between recognition accuracy and recognition time

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%.

3.2.2 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.

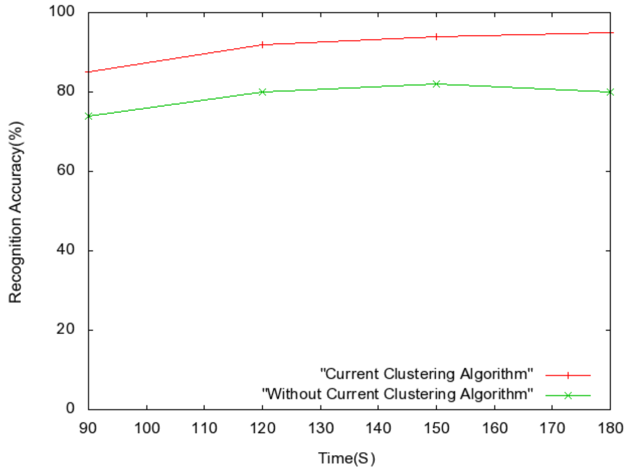

Fig. 7. Relation between recognition accuracy and the current clustering algorithm

4 Concluding Remarks

In this study, a smart appliance management system with current clustering algorithm in home network was presented. It measured power information through a smart 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.

References

[1] Google Inc., Save energy. Save money. Make a difference (March 2011)
[2] Microsoft Corp., How energy efficient is your home? (March 2011)
[3] Ye, Y., Li, B., Gao, J., Sun, Y.: A design of smart energy-saving power module. In: Proc. of the 2010 5th IEEE Conference on Industrial Electronics and Applications, Taichung, pp. 898–902 (June 2010)
[4] Serra, H., Correia, J., Gano, A.J., de Campos, A.M., Teixeira, I.: Domestic power consumption measurement and automatic home appliance detection. In: Proc. of International Workshop on Intelligent Signal Processing, Faro, Portugal, pp. 128–132 (September 2005)
[5] Cho, H.S., Yamazaki, T., Hahn, M.: Determining location of appliances from multi-hop tree structures of power strip type smart meters. IEEE Transactions on Consumer Electronics 55(4), 2314–2322 (2009)
[6] Tajika, Y., Saito, T., Teramoto, K., Oosaka, N., Isshiki, M.: Networked home appliance system using Bluetooth technology integrating appliance control/monitoring with Internet service. IEEE Transactions on Consumer Electronics 49(4), 1043–1048 (2003)
[7] Han, D.M., Lim, J.H.: Design and implementation of smart home energy management systems based on ZigBee. IEEE Transactions on Consumer Electronics 56(3), 1417–1425 (2010)
[8] Han, D.M., Lim, J.H.: Smart home energy management system using IEEE 802.15.4 and ZigBee. IEEE Transactions on Consumer Electronics 56(3), 1403–1410 (2010)
[9] Bennett, C., Highfill, D.: Networking AMI Smart Meters. In: Proc. of IEEE Energy 2030 Conference, Atlanta, GA, pp. 1–8 (November 2008)
[10] Liu, J., Zhao, B., Wang, J., Zhu, Y., Hu, J.: Application of power line communication in smart power Consumption. In: Proc. of IEEE International Symposium on Power Line Communications and Its Applications, Rio de Janeiro, pp. 303–307 (March 2010)
[11] Son, Y.S., Pulkkinen, T., Moon, K.D., Kim, C.: Home energy management system based on power line communication. IEEE Transactions on Consumer Electronics 56(3), 1380–1386 (2010)
[12] Lien, C.H., Bai, Y.W., Chen, H.C., Hung, C.H.: Home appliance energy monitoring and controlling based on Power Line Communication. In: Proc. of Digest of Technical Papers International Conference on Consumer Electronics, Las Vegas, NV, pp. 1–2 (January 2009)
[13] Jahn, M., Jentsch, M., Prause, C.R., Pramudianto, F., Al-Akkad, A., Reiners, R.: The Energy Aware Smart Home. In: Proc. of 5th International Conference on Future Information Technology, Busan, pp. 1–8 (May 2010)
[14] Capone, A., Barros, M., Hrasnica, H., Tompros, S.: A New Architecture for Reduction of Energy Consumption of Home Appliances. In: TOWARDS eENVIRONMENT, European Conference of the Czech Presidency of the Council of the EU (2009)
[15] Heo, J., Hong, C.S., Kang, S.B., Jeon, S.S.: Design and Implementation of Control Mechanism for Standby Power Reduction. IEEE Transactions on Consumer Electronics 54(1), 179–185 (2008)
[16] Sundramoorthy, V., Liu, Q., Cooper, G., Linge, N., Cooper, J.: DEHEMS: A user-driven domestic energy monitoring system. In: Proc. of Internet of Things, Tokyo, November 29-December 1, pp. 1–8 (2010)
[17] Park, S., Kim, H., Moon, H., Heo, J., Yoon, S.: Concurrent simulation platform for energy-aware smart metering systems. IEEE Transactions on Consumer Electronics 56(3), 1918–1926 (2010)

[18] Park, W.K., Han, I., Park, K.R.: ZigBee based Dynamic Control Scheme for Multiple Legacy IR Controllable Digital Consumer Devices. IEEE Transactions on Consumer Electronics 53, 172–177 (2007)
[19] Min, C., Gonzalez, S., Leung, V., Qian, Z., Ming, L.: A 2G-RFID-based e-healthcare system. IEEE Wireless Communications 17, 37–43 (2010)
[20] Chiu, S.L.: Fuzzy model identification based on cluster estimation. Journal of Intelligent and Fuzzy Systems 2, 267–278 (1994)