2012 IEEE 15th International Conference on Computational Science and Engineering

Applied Lightweight Parallel Multi-Appliance Recognition on Smart Meter

Chin-Feng Lai*, Man Lin†, Yonggang Wen‡, Yi-Wei Ma§, and Jiann-Liang Chen§
*Institute of Computer Science and Information Engineering
National ILan University, I-Lan, Taiwan, Email: cinfon@ieee.org
†Dept. Math, Statistic and Computer Science
St. Francis Xavier University, Antigonish, Canada,
Email:mlin@stfx.ca
‡School of Computer Engineering Nanyang Technological University
Email:ygwen@ntu.edu.sg
§Department of Electrical Engineering
National Taiwan University of Science and Technology, Taipei, Taiwan
Email: yiweimaa@gmail.com and lchen1215@gmail.com

***Abstract*—With the crisis of uprising energy, smart meter development has gained a lot of attention. Along with the popularization of Internet of Things (IoT) and home energy management system, users can identify the electronic device being used with the help of electronic appliance recognition technology in order to improve power usage habits. However, there is a difficulty in multiple electronic appliance recognition which poses as a problem since multiple appliances switching on and off is common in everyday life. Hence this study will discuss simultaneous multi-electronic appliance recognition. Another issue in smart meter development is the difficulty in installation.**

This study solves this problem by proposing a non-invasive smart meter device that also studies the user power usage habits in cases where users are unfamiliar with electronic devices. The system also solves the large data volume processing problem of the current appliance recognition system using a database mechanism, electronic appliance recognition classification, as well as waveform recognition. Other electronic appliance recognition may be power consuming, while this system uses low power low order embedded system chip with high expandability and convenience. Different from past studies, this research considers simultaneous multi-electronic appliance recognition and power usage habits of normal users. The experimental results showed that the total system recognition rate can reach 86.14% with the general daily power usage habits, and the total recognition rate of a single electronic appliance can reach 96.14%, thus proving the feasibility of the proposed system.

***Keywords*-Multi-Appliance Recognition; Smart Meter; Home Energy Management System; Internet of Things;**

I. Introduction

Recently, with the development of Cloud Computing and Internet of things, Smart Home technology enters a new era, the technology industry and research institutions within many countries have worked together on Smart Grids, Cloud Computing Services, and Green Energy. With energy shortage and global warming problems on the brink, the energy shortage has become a main problem in the world. To integrate cloud computing service with smart home technology, this research proposes a parallel multi-electronic appliance recognition system, providing basic energy information for users but also provides the type of appliance within the electronic loop. Household appliance has different states that can be configured with the cloud service provider, which provides more advanced energy control and management in the future therefore influencing the power usage habits of users. The contributions of this research are as follows:

1) **Development and design of smart meter**
This study has developed a smart meter. The extension line of the smart meter was used for simpler installation and lower cost. The screen can show the current information and application status for users.
2) **Implementation of lightweight electronic appliance recognition algorithm**
Most algorithms used for electronic appliance recognition has huge amounts of calculations; an embedded system was used in this case with low operational capability as the core architecture, with low power consumption and cost. The issue is the required calculation and space, therefore, a lightweight electronic appliance recognition algorithm is discussed in this paper.
3) **Parallel multi-electronic appliance recognition**
Presently, with the limit of data samples for electronic appliance recognition, and the inability to identify simultaneous electronic appliances, the electronic appliance research is restrained. Therefore, this study proposes parallel multi-electronic appliance recognition. As the size of the database determines the accuracy of system recognition, how to efficiently process database samples in order to save recognition time is another focus of this study.

978-0-7695-4914-9/12 $26.00 © 2012 IEEE
DOI 10.1109/ICCSE.2012.57

II. Related Work

A. Smart Meter

At present, smart meter studies follow two directions. The first one is power line design, where the present no-fuse switch general meter used by home users can bear a 50A current supply. This type of design aims at a high power bus, and thus, should be tested by a high-order meter. Another direction is an extension line design, which is also known as the smart socket. Its purposes are: 1) to provide an extension line household appliance control service, including relay control and infrared remote control; 2) to reduce the current sensing range to provide a more complete and safer energy information system; 3) seamless integration with the environment, as a power line meter is difficult to be installed, expandability is worse. Cho et al. [1] designed a Smart Multi-Power Tap (SMPT) for the smart socket in order to obtain positioning information for the context aware system to use in the future. Park et al. [2] conducted data reduction and prediction aiming at the large data volume of a smart meter to reduce the load of data transmission, and validated the accuracy rate. Ye et al. [3] designed a low cost logic circuit with a microprocessor to read, measure, and analyze electronic energy information. They also designed a self-locking loop for when an electronic appliance enters the standby state or approaches the usersset threshold, where the system automatically shuts down the microprocessor and the electronic appliance in order to reduce the electronic energy consumed during the stand-by time. Another type of smart socket provides wired wireless output equipment to export information to the web server, intelligent mobile phone terminal, or computer system. The smart socket, as proposed by Morimoto et al. [4], only provides electronic appliance control and an energy sensor, which information is fed back to the server terminal through Wi-Fi or Ethernet. Thus, the users can remotely view home energy management system information.

B. Appliance Recognition

The main problem of the smart grid is that the users cannot know the status of the devices at home and the service condition [5], [6], which renders it less attractive to users, network service developers, and service providers. Grou [7] proposed fixing an additional electronic appliance data tag to the household appliance plug, and fixed a tag reader into the socket. Thus, the type of electronic appliance could be effectively identified according to the uniqueness of the tag and power usage information could be recorded. The socket has an anticreep mechanism, providing a safe power usage environment for users. Lam et al. [8] drew a V-I diagram for characteristic classification of electronic appliances after normalization of voltage and current of electronic appliances, and created a classification table for subsequent query. Ruzzelli et al. [9] built a RECAP (Recognition of Electronic Appliances and Profiling in Real-Time) system for real-time recognition of individual electronic appliance. The electronic energy eigenvalue was written in the comparison database through a training process, and a neural algorithm was used for recognition and the result was displayed on the user interface terminal. The recognition rate of this method was 84% after validation. Ito et al. [10] designed special electronic energy parameters, analyzed the voltage and current waveforms, and indicated that, as the operational capability of the microprocessor for processing the electronic energy information was limited. Thus, in order to achieve effective recognition and instance, some parameters that were easily calculated and could be used as characteristics should be designed and stored in the database. The data in the database were used for electronic appliance recognition to achieve the recognition effect. Akbar et al. [11] used Fast Fourier Transform to transform the current waveform of time domain into a frequency domain in order to obtain special electronic energy parameters for recognition. Obtaining electronic appliance characteristics from individual socket is difficult for use by common families due to its difficult installation. In this study, only the total current waveforms is required to our system since the proposed recognition approach is adopted to separate each appliance current waveform. Thus this type of information is easily obtained, it is applicable to systems with lightweight operational capability or electronic meters, and is one of the basic sorting parameters used in this study.

C. Cloud Computing Services

Cloud computing aims to apply required services over cloud networks, where users are not required to understand cloud equipments, they are not restricted by cloud control, and service is an extendable network service. However, the cloud computing is divided into three kinds of services, Infrastructure as a Service (IaaS), Platform as a Service (PaaS), Software as a Service (SaaS). Currently, the IaaS prefers grid computing, which is one kind of distributed computing architectures and includes several cloud servers for cloud infrastructures. The PaaS mainly constructs service program development, including the Google and Hadoop systems. A cloud platform is able to be divided into data processing, storage, and a database. The data processing software architecture is focused on MapReduce, which is a distributed program framework that allows service developers to easily compile required services. Hadoop is a PaaS of famous open source codes that has functions to reduce computing time, and is also similar to the Google cloud platform environment. The SaaS is a service application program on the PaaS. Google introduced the concept of web applications, and provides a Google AppEngine, which is compiled using the Python language. The engine SDK, provided by Google, is installed with applications for Google in order to obtain Google Services.

III. Overall Architecture

This study implements a smart meter with a parallel multi-electronic appliance recognition function. Its system structure, as shown in Fig. 1, consists of a hardware layer, a data process layer, and a recognition layer. The smart home and smart grid domains are covered by the application derived from this meter system. The hardware layer is the hardware design layer of a smart meter, which is in charge of processing electronic energy signals, including complete electronic energy signal waveform extraction, waveform correction and regulation. The data process layer is the advanced data processing part inside the STM32, and includes internal current waveform extraction, noise reduction, and state detection. The recognition layer is the core method of this paper, and includes a waveform recognition algorithm, database creation, and segmentation, it is in charge of calculating and classifying the electronic energy characteristics of the data process layer.

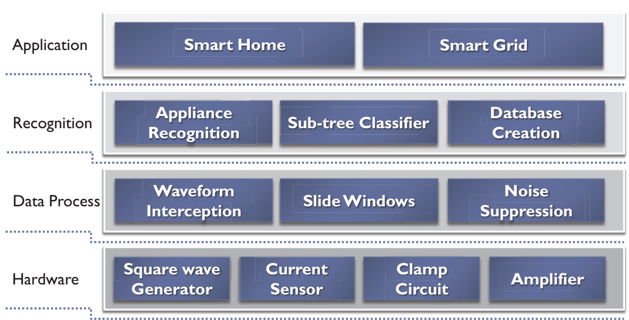

Figure 1. Proposed System Architecture

A. Electronic Energy Data Processing Method

In order to accurately capture the waveform of a surge current and avoid different power frequencies under energy policies of different countries, this study uses a transformer in the Hardware layer to normalize the waveform extraction. Waveform extraction is a type of electronic energy extraction, the goal is to achieve real-time electronic energy information acquisition and to improve the recognition rate. The signal processing aims at electronic appliance state detection and noise processing, thus, two mechanisms are designed in the Data Process layer, which are state detection and noise reduction. State detection in the Recognition layer provides an appropriate recognition time point for electronic appliance recognition, which is important as the time of electronic appliance recognition will influence the accuracy of recognition as the time needed for electronic appliance recognition is higher than signal sampling, there will be extra electronic energy consumption if the electronic appliances recognition is activated in turn. Therefore, in order to have a accurate recognition with low energy consumption, this study analyzes the electronic energy information of electronic appliance state change. Household appliances are divided into three states: Steady, Transient, and Close. An electronic appliance turns into transient state when it is switched on or in the status switching process, therefore, the presently approximate state of the electronic appliance can be obtained by capturing the transient information.

B. Waveform Recognition Algorithm

The electronic appliance recognition algorithm used in this study is a waveform recognition algorithm, which is used for recognizing the variations and similarities of waveforms or this method is the commonly used method of Distance Measure, and is mostly applied to electrocardiography (ECG), speech recognition, and pattern recognition domains. This study uses a waveform recognition algorithm to analyze instantaneous value of a current, where the major difference between the current and the aforesaid speech recognition is spatial compression. The Euclidean distance is the most fundamental part of distance measurement, as well as the basis of implementation of multiple distance algorithms, the discussed information is the range difference between two sets in Euclidean space as the basis of measurement. If there are two finite data sets in a p-dimensional Euclidean space, $A = \{a_1, a_2, \ldots, a_n\} \subset R^p$ and $B = \{b_1, b_2, \ldots, b_n\} \subset R^p$, the equation of Euclidean distance is defined as follow.

$$dist(A, B) = [(a_1 - b_1)^2 + (a_2 - b_2)^2 + ... + (a_n - b_n)^2]^{1/2} \tag{1}$$

As the Euclidean distance has not processed the time axis, there will be system recognition error as a result of displacement and noise, which renders it inapplicable to accurate electronic appliance recognition.

C. Dynamic Time Warping

The waveform recognition algorithm used in this study is Dynamic Time Correction or Dynamic Time Warping (DTW), which is a common algorithm for discovering the similarities between two time dependent series, and as the characteristic of dynamic programming (DP) is usually used in speech recognition, the characteristic of speech recognition is the scaling of time axis, and the DTW can compare the waveform similarity between two sets in different matrix lengths.

If two sets $Q = \{q_1, q_2, ..., q_{n-1}, q_n\}$ and $U = \{u_1, u_2, ..., u_{m-1}, u_m\}$ are given, a $n * m$ distance matrix D is created, where the matrix $D(i, j)$ is the distance between q_i and u_j, i.e. all $D(i, j) = d(q_i, u_j)$, and the warping path (W) in matrix D represents the coincidence relation between Q and U, as defined by Eq. 2.

$$W = \{w_1, w_2, ..., w_k\}, \max(m, n) \leq K < m + n - 1 \tag{2}$$

The limits to warping path are as listed below:

- **Boundary conditions:** $w_1 = (1,1)$ and $w_k = (m,n)$, i.e. the start and end of warping path are a clinodiagonal path.
- **Continuity:** if $w_k = (a,b)$, $w_{k-1} = (a',b')$ meets $a - a' \leq 1$ and $b - b' \leq 1$, i.e. the available direction of warping path must be the adjacent matrix, including adjacent bevel matrix.
- **Monotonicity:** if $w_k = (a,b)$, $w_{k-1} = (a',b')$ meets $a - a' \leq 0$ and $b - b' \leq 0$, i.e. this warping path must go in the single direction of the time series.

As shown in Fig. 2, the left waveform (Sample Data) is the sampled electronic energy information, and the lower waveform is the electronic lamp sample in comparison database, as the two path matrices match each other completely, it is warped to a bevel linear path.

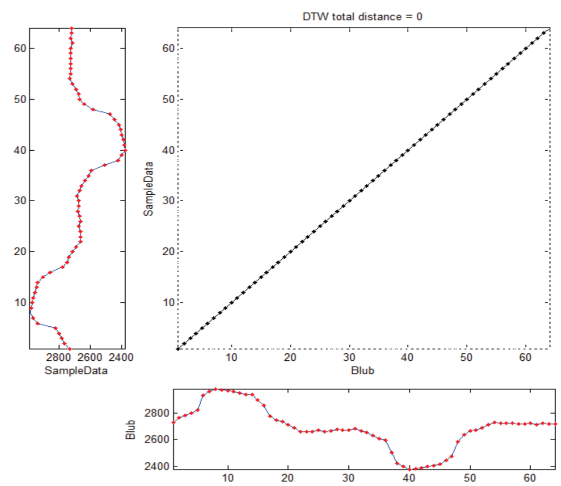

Figure 2. The Distance Schematic of DTW Lamp Identification

The DTW length is defined as the minimum warping cost of a slant path, as shown in Eq. 3.

$$DTW(Q,U) = \min \left\{ \sqrt{\sum_{k=1}^{K} w_k / 2} \right\} \quad (3)$$

The time complexity for calculating DTW distance is about $O(mn)$, namely, the time complexity of equidistant DTW calculation is $O(n^2)$; therefore, many studies have optimized this algorithm, and the Path Constraints [24] can reduce the time complexity to $O(n)$ by limiting the warped boundary in matrix D. Another method is local path constraint [25], where the warp angle in matrix D is limited to $-27° - 45° - 63°$. This method supports a jumping processing, which provides better path calculation instead of counting the noise in the total DTW distance, the optimal path of DTW distance will go $-27°$ and $-63°$, as possible, in order to obtain a shorter distance, with the fundamental purpose reducing the calculation load while limiting the reasonable image path.

IV. System Implementation and Result Analysis

This study uses the following five electronic appliances as the analytic data set, as shown in Table 1, including a circulation fan, a notebook computer, an LCD screen, a table lamp, and a hot melt gun.

Table I
The list of Electrical Experiment

Data Type	Multi-Column			
Fan	Close	Weak	Medium	Strong
Notebook	Close	Power saving	High performance	N/A
LCD Monitor	Close	Open	N/A	N/A
Bulb	Close	Open	N/A	N/A
Hot-melt gun	Close	Open	N/A	N/A

The correctness evaluation method of data mining is used for data verification in this study. In the test for parallel multi-electronic appliance recognition, this study randomly extracts different electronic appliance combinations and uses the electronic appliance recognition algorithm adopted in this study to identify the electronic appliances.

The precision (p) and recall (r) of this recognition system can be determined by the aforesaid four states. The precision means ”taking the information of real electronic appliance a out of the set of all the types identified as electronic appliance a”, higher precision means lower misrecognition rate. And TP, FP and FN means: True Positive, False Positive, and False Negative.

$$p = TP/(TP + FP) \quad (4)$$

The recall represents the ”ratio of samples of actual electronic appliance a identified as electronic appliance a”, this study uses recall as the basis of recognition rate in the sample space.

$$r = TP/(TP + FN) \quad (5)$$

A. Two random electronic appliances

Two of the four electronic appliances are randomly selected for recognition at this stage, this study conducts 174 times of electronic appliance recognition process, and the results are analyzed in Fig. 3. The evaluation method is binary classification, namely, it is TP when two electronic appliances are completely recognized, and FN on the contrary. It is observed that the states of the notebook computer and circulation fan are worse. According to analysis, the current waveform and amplitude of a circulation fan in a moderate state are slightly different from the circulation fan in a weak state, only may be the first cause for the circulation fan misrecognition.

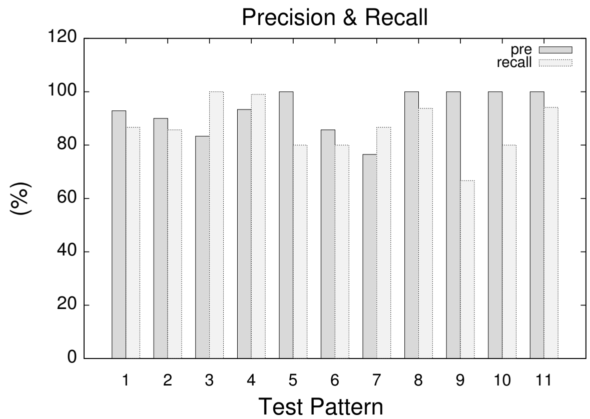

Figure 3. The Precision and Recall of combination of Two Electrical

The electronic appliance recognition used at this stage simultaneously identifies two electronic appliances and the overall recognition rate is 86.21%, in order to analyze the causes influencing the overall system recognition rate, and the individual recognition rate is also an interesting result of this paper. Therefore, the aforesaid data set is used to analyze a single electronic appliance. It is observed in Fig. 4 that the recognition rate of the bulb of the table lamp is 98.68%, and the recall accuracy is 100%. However, the recognition rate and precision of notebook computer are 78.94%; whereas, the recognition rate of the combination of two electronic appliances is only 66.66%. Thus, it is inferred that the notebook computer is the first cause influencing the overall recognition rate, and this study will analyze individual waveforms of the notebook computer in the future.

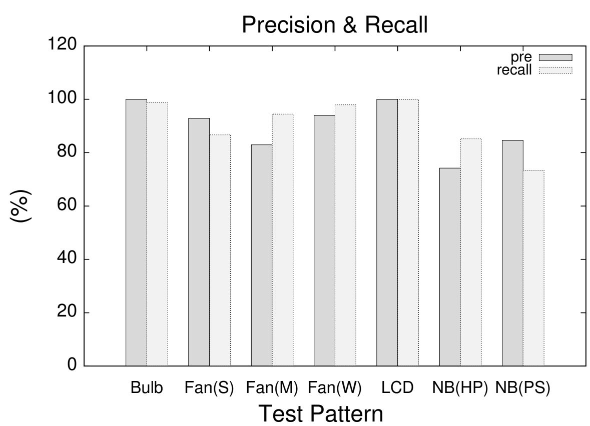

Figure 4. The Precision and Recall of Single in Two Electrical

B. *Recognition of three random electronic appliances*

This stage verifies the influence of the differences in waveforms of multiple electronic appliances on the algorithm, where the combination of random electronic appliances will from two to five, the number of combined samples is 96 groups. The subtree classification mechanism mentioned in the recognition system architecture will be used at this stage. The original current characteristics are classified to three level subtrees according to the pre-stage current data, then the per level subtree is indexed in the appliances database. It will reduce the recognition time through the appliances database. As shown in Fig. 5, the number of tests for the fourth group of electronic appliances is larger than that for other groups, and it is observed in the data that the recognition rate of the hot melt gun is worse than other electronic appliances. However, the second group of data shows the recognition rate of the hot melt gun is almost 100%. After several data comparisons and analyses, it is found that, although the hot melt gun has no state switching in the electronic appliance appearance, the heating stage is divided into low temperature, moderate temperature, and high temperature stages, which is not considered at the initial learning stage. Not distinguishing the three stages can result in misrecognition of the system. The total electronic appliance recognition rate can be maintained at 100% at the moderate temperature stage, which is why the second group of data is more accurate than the fourth group. The heating and high temperature stages actually result in system misrecognition in our new test that test for five appliances.

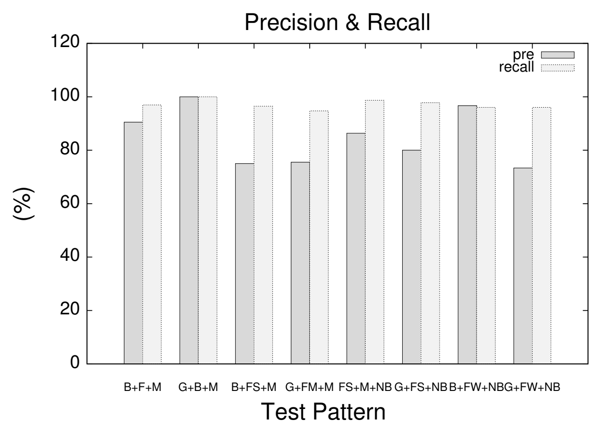

Figure 5. The Precision and Recall of Three Electrical

As shown in Fig. 6, The hot melt gun recognition rate influences the total recognition rate of the entire sample space. Therefore, the single electronic appliance recognition rate is studied, as based on various electronic appliance combinations, and found that the total recognition rate of single electronic appliance is almost 90% with the misrecognition rate of the hot melt gun and table lamp being relatively high. The precision of the table lamp and the recall of the hot melt gun are lower, according to the TN and TP in the table lamp, the hot melt gun may be misrecognized as table lamp when the hot melt gun is in a low temperature heating state, thus, the precision and recall of combination of the table lamp and hot melt gun are low.

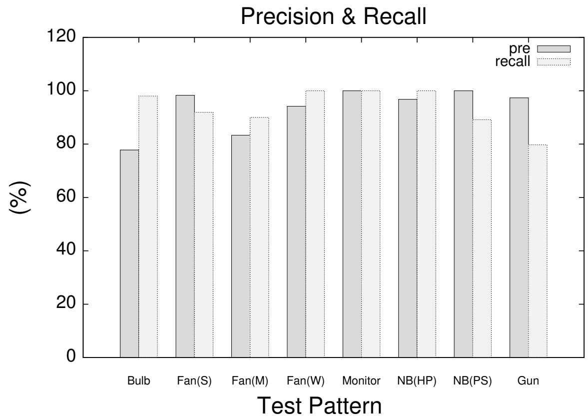

Figure 6. The Precision and Recall of Single in Three Electrical

V. CONCLUSION

This research proposes a smart meter which extends the line smart meter designed to provide a simpler installation method for convenience and expandability for Smart Home applications. This study also proposes a lightweight electronic appliance recognition method for this specific design. The average recognition rate of a single appliance can reach up to 96.14%, where parallel multi-electronic appliance recognition does not consider power usage conditions and recognition rate can reach 84.14%, hence confirming the possibility of a lightweight electronic appliance recognition system to lower the computing capability of an embedded system. The parallel multi-electronic appliance recognition system proposed in this study aims at the training part, which is usually neglected in electronic appliance recognition. This study also proposes a current waveform merging mechanism to provide the rapid creation of a recognition sample database. Finally, the subtree classification mechanism is used to cut the database parent tree into several cluster subtrees, thus, obtaining the computing time of a recognition algorithm and its spatial balance point.

ACKNOWLEDGMENT

The authors would like to thank the editor and the anonymous referees. This work was supported in part by the Nation Science Council of Taiwan, R.O.C., under contract NSC 101-2628-E-197-001-MY3, 101-2219-E-197-004 and 101MG07.

REFERENCES

[1] H. S. Cho, M. Hahn, T. Kato and T. Yamazaki, Simple and robust method for detecting the electrical appliances using markers and programmable logic devices, *In Proc. of the IEEE 13th International Symposium on Consumer Electronic*, pp. 334-338, 2009.

[2] S. Park, H. Kim, H. Moon, J. Heo, and S.Yoon, Concurrent Simulation Platform for Energy-Aware Smart Metering Systems, *IEEE Transactions on Consumer Electronics*, Vol. 56, No. 3, pp. 1918-1926, 2010.

[3] Y. Yingcong, L. Binqiao, G. Jing and S. Yehui, A Design of Smart Energy-saving Power Module, *In Proc. of the IEEE Conference on Industrial Electronics and Applications*, pp. 898-902, 2010.

[4] N. Morimoto, M. Tanaka, T. Akehi, M. Yoshida, H. Yoshimizu, M. Takiyamada and Y. Kamimura , The Design and Implementation of a Smart Tap for Policy-based Power Management, *In Proc. of the IEEE Consumer Communications and Networking Conference*, pp. 280-284, 2012.

[5] M. Qiu, H. Su, M. Chen, Z. Ming, and L. T. Yang, Balance of Security Strength and Energy for a PMU Monitoring System in Smart Grid. IEEE Transactions on Smart Grid, Vol. 2, No. 4, pp. 715-723, Nov. 2011.

[6] H. Su, M. Qiu, and H. Wang, Secure Wireless Communication System for Smart Grid with Rechargeable Electric Vehicles, IEEE Communication Magazine, Vol. 50, No. 8, pp.62-68, Aug. 2012.

[7] John La Grou, John La Grou plugs smart power outlets http://www.ted.com/talks/john_la_grou_plugs_smart_power_outlets_1.html, retrieved on July 2012.

[8] H.Y. Lam, G.S.K. Fung, and W.K. Lee, A Novel Method to Construct Taxonomy of Electrical Appliances Based on Load Signatures, *IEEE Transactions on Consumer Electronics*, Vol. 53, No. 2, pp. 654-660, 2007.

[9] A.G. Ruzzelli, G.M.P. O'Hare, A. Schoofs and C. Nicolas, Real-Time Recognition and Profiling of Appliances through a Single Electricity Sensor, *In Proceedings of the IEEE Communications Society Conference on Sensor Mesh and Ad Hoc Communications and Networks* , pp.1 - 9, 2010.

[10] M. Ito, R. Uda, S. Ichimura, K. Tago, T. Hoshi and Y. Matsushita,A method of appliance detection based on features of power waveform, *In Proceedings of the International Symposium on Applications and the Internet*, pp. 291 - 294, 2004.

[11] M. Akbar and D.Z.A. Khan, Modified nonintrusive appliance load monitoring for nonlinear devices, *In Proc. of the IEEE International Multitopic Conference*, pp. 1 - 5, 2007.