UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Faculty of Electronic and Computer Engineering

NOVEL FRAMEWORK FOR AUTOMATED APPLIANCE REGISTRATION IN HOME ENERGY MANAGEMENT SYSTEMS

Daphne Tang Hui Zyen

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NOVEL FRAMEWORK FOR AUTOMATED APPLIANCE REGISTRATION IN HOME ENERGY MANAGEMENT SYSTEMS

DAPHNE TANG HUI ZYEN

A thesis submitted
in fulfillment of the requirements for the degree of Master of Science
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2016

DECLARATION

I declare that this thesis entitle "Novel Framework for Automated Appliance Registration in Home Energy Management Systems" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature	:	....
Name	:	....
Date	:	....

APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Master of Science in Electronic Engineering.

Signature	:	....
Supervisor Name	:	....
Date	:	....

DEDICATION

To my beloved parents and siblings

ABSTRACT

Studies in home energy management systems (HEMS) have been focused in improving its monitoring and control capabilities to help user conserve electricity. Depending on its system features, HEMS are shown to be capable of conserving more than 12% electricity annually. As an improvement strategy, appliance recognition technology was later integrated into HEMS to enhance the usability of these systems. Appliance recognition allowed HEMS to identify home appliances based on the unique power signatures of appliances instead of pre-configured plug locations. This meant that the system can identify registered appliances when operated at different outlets around the premise. Such system capability facilitated better study of user behavior and enhances the accuracy of load demand analysis provided to users. With accurate usage statistics, HEMS can thus provide better load demand optimization suggestions/advices. However, time consuming training procedures required for appliance recognition solutions prevents real adaptation of such systems. As a solution, this study applies One-Class Support Vector Machine (OCSVM) for automated reasoning of the HEMS in identifying unregistered appliances to eliminate the manual procedures needed for appliance training. A proposed design of the framework required for automation is also presented in this study. The performance of OCSVM was evaluated with by varying 4 eigenvector based feature extraction methods; namely, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Weighted PCA (WPCA), and Independent Component Analysis (ICA). Evaluation of raw and normalized appliance signatures were also performed during feature extraction stages to study how normalizing data can affect recognition classification accuracy of the OCSVM model. Ten different appliance profiles were used in the experiments and OCSVM was shown to work best with NR-PCA feature extraction method using raw appliance profiles. The method achieved 100% Precision and 83.5% Recall in detecting unregistered appliances through leave-one-out cross validation and acquired an F(1)-score of 97.50%. The result acquired showed strong positive relationship based on analysis of Matthews Correlation Coefficient. Methods used in this study show promising results towards the development of fully automated smart HEMS.

ABSTRAK

Kajian berkenaan dengan sistem pengurusan tenaga rumah (HEMS) telah lama ditumpukan dari segi penambahbaikan fungsi pemantauan dan pengawalan perkakas elektrik demi penjimatan tenaga elektrik. Bergantung kepada ciri-ciri yang ada pada sistem HEMS, ia mampu mengurangkan lebih daripada 12% tenaga elektrik setiap tahun. Bagi meningkatkan lagi kualiti kebolehgunaan sistem tersebut, teknologi pengecaman perkakas elektrik telah disepadukan ke dalam HEMS. Pengecaman perkakas elektrik ini penting untuk mengenal pasti jenis perkakas rumah melalui ciri-ciri isyarat elektrik tersendiri dan bukannya berdasarkan lokasi yang didaftar dalam sistem. Ini bermakna bahawa sistem tersebut boleh mengenal pasti identiti perkakas yang dipasangkan di dalam rumah secara automatik. Keupayaan ini membolehkan sistem HEMS memantau tingkah laku penggunaan sesebuah perkakas elektrik di mana ia akan meningkatkan ketepatan analisis terhadap permintaan beban elektrik yang diperlukan oleh pengguna. Dengan statistik penggunaan yang tepat, HEMS ini boleh memberikan cadangan/nasihat yang bersesuaian dengan cara penggunaan perkakas elektrik. Walaubagaimanapun, pengecaman perkakas elektrik masih tidak digunapakai dalam sistem HEMS komersial hari ini atas sebab masa yang lama diperlukan untuk mendaftar semua perkakas-perkakas elektrik. Dalam kajian ini, kaedah 'One-Class Support Vector Machine' (OCSVM) digunakan untuk mengecam perkakas elektrik yang belum didaftar dalam HEMS sistem secara automatik. Di samping itu, rangka kerja yang diperlukan untuk membenarkan pendaftaran perkakas elektrik rumah ini juga diperkenalkan. Sistem yang dicadangkan tersebut dinilai berdasarkan prestasi OCSVM dalam membezakan sepuluh perkakas elektrik. Empat kaedah penyarian sifat vektor eigen iaitu, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Weighted PCA (WPCA), dan Independent Component Analysis (ICA) digunakan dalam proses penilaian tersebut. Akhir sekali, penilaian juga dilakukan untuk membandingkan penggunaan isyarat elektrik perkakas yang asal dengan isyarat yang diproses menggunakan kaedah penormalan. Sepuluh perkakas elektrik telah digunakan dalam kajian ini dan OCSVM memerolehi keputusan terbaik dengan kaedah NR-PCA. Kaedah ini berjaya mencapai 100% kadar Ketepatan dan 83.5% kadar Pengingatan dalam pengecaman perkakas baru. keputusan ini telah diperolehi melalui cara pengesahan tinggal-luar-satu dan mencatatkan nilai F(1)-skor sebanyak 97.50%. Hasil kajian ini menunjukkan hubungan positif yang kukuh berdasarkan analisis Korelasi Pekali Matthews. Hasil penemuan kajian ini membolehkan pembangunan HEMS pintar yang berfungsi secara automatik.

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LIST OF ABBREVIATIONS

AC	Alternating Current
ACK	Acknowledge
ADC	Analog to Digital Converter
AEC	Average Energy Consumption
AI	Artificial Intelligence
ANN	Artificial Neural Network
AR	Appliance Recognition
CECU	Communication and Energy Care Units
DC	Direct Current
DTW	Dynamic Time Warping
EC	Edge Counts
ED	Euclidean distance
EEPROM	Electrically Erasable Programmable Read-Only Memory
EMF	Electromagnetic Field
FE	Feature Extraction
FF-AR	Feature Fused Appliance Recognition
FFBE	Frequency Filtered Band Energies
FFT	Fast Fourier Transform
FHMM	Factorial Hidden Markov Model
FN	False Negative
FP	False Positive
GA	Genetic Algorithm
GHG	Green House Gas
GMM	Gaussian Mixture Model
GRA	Grey Relational Analysis
GUI	Graphical User Interface

HEMS	Home Energy Management System
HMM	Hidden Markov Models
HP	Horse Power
HW	Hamming window
IC	Integrated Circuit
ICA	Independent Component Analysis
IFFT	Inverse Fast Fourier Transform
ILM	Intrusive Load Monitoring
IV	Current-Voltage
k-NN	k-Nearest Neighbor
LCD	Liquid Crystal Display
LDA	Linear Discriminant Analysis
LOO-CV	Leave-One-Out Cross Validation
LpO-CV	Leave-p-Out Cross Validation
MAP	Maximum A Posteriori
MCC	Matthew Correlation Coefficient
MCU	Microcontroller
MDL	Multi-Interval Discretization
MFCC	Mel Frequency Cepstral Coefficient
MFNN	Multi-layer Feed-forward Neural Network
MLP	Multilayer Perceptron
NC	Normally Closed
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
NILM	Non-Intrusive Load Monitoring
OCC	One-Class Classification
OCSVM	One-Class Support Vector Machine
P	Real Power
PAN	Personal Area Network
PCC	Pearson Correlation Coefficient
PEC	Percentage Energy Consumption
PLC	Power Line Carrier
Q	Reactive Power
RBF	Radial Basis Function

REDD	Reference Energy Disaggregation Dataset
RMS	Root Mean Square
ROC	Receiver Operating Characteristic
SSR	Solid State Relay
SVD	Singular Value Decomposition
SVM	Support Vector Machines
TFB	Triangular Filter Bank
TN	True Negative
TP	True Positive
WPCA	Weighted Principal Component Analysis

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2	**Daphne H.Z. Tang**, A. Rani Othman, S. S. S. Ranjit, and Yewguan Soo, 2013. Design of a New User Centric Home Energy Management System, 2013, IEEE Conference on Systems, Process & Control (ICSPC), December 2013, pp. 57-61.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Back in the early 80s, home energy monitoring systems were developed with hopes to encourage power saving in domestic homes. Installation of the system allowed detailed monitoring of electrical power consumption within a premise. These systems were designed to provide disaggregated usage data to allow better understanding of power wastages so that users are aware of their expenditures and may learn to conserve electricity.

As the basis platform of home automation systems were similar to those of home energy monitoring systems, combination of these two systems were widely implemented and were later known as home management systems (HEMS). Unlike early monitoring systems, HEMS provide additional functionality to control the power supply of the monitored plug outlet. As various advancements were later introduced into HEMS, effects of the advancements were questioned by researchers and various studies were performed to realize the actual impact of these systems when installed in real households.

A meta-review of systems up to 2010 as shown in Figure 1.1 revealed that an average of 4 to 12% of power consumption in a domestic home can be reduced with help from HEMS. While this figure may improve with persistent feedback over time, it also revealed how certain features in HEMS may improve the achievable power savings of these systems (Martinez E., 2010). Nonetheless, such systems still required passive response from users, relying completely on users' actions to modify their behavior in order to conserve power. In this modern world, such actions are often considered troublesome, possibly causing power conservation interests to fade over time.

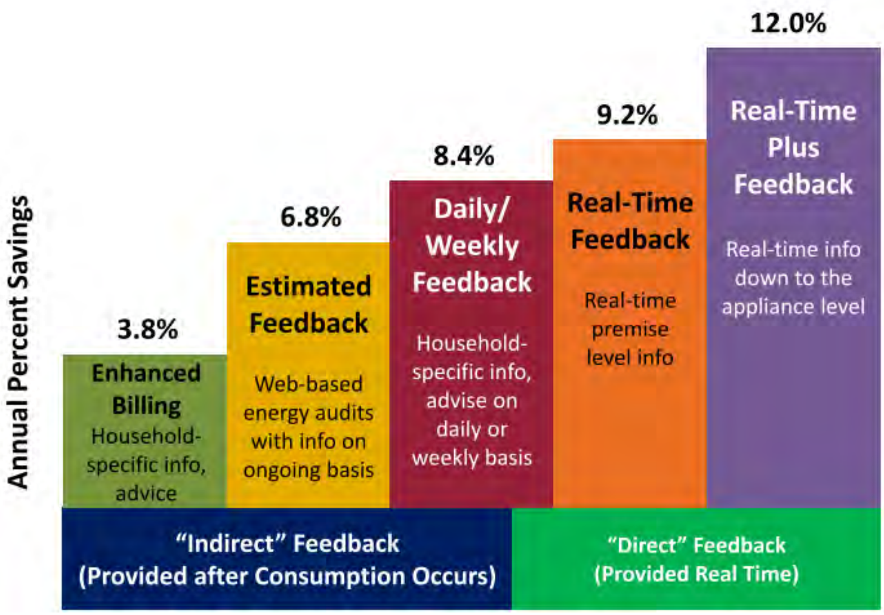


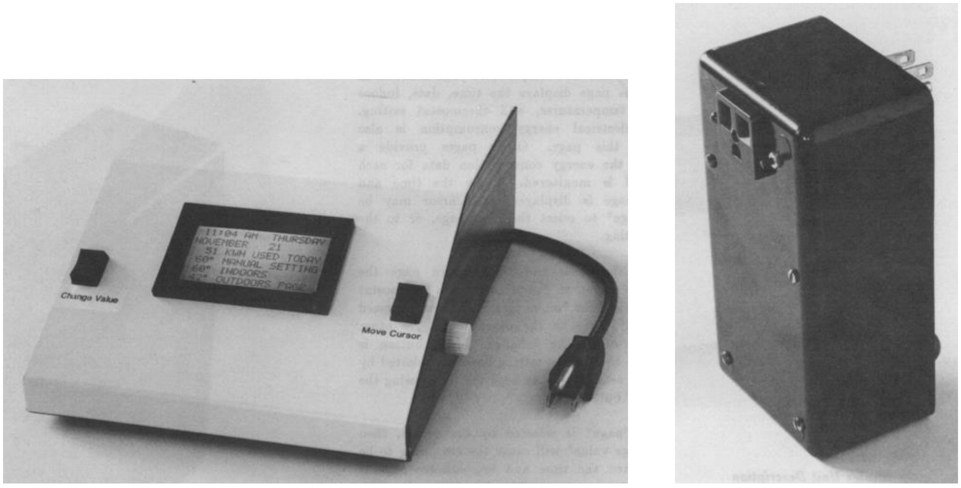
Figure 1.1: Review of annual average household power savings according to HEMS feedback (Martinez E., 2010)

Statistics by the World Nuclear Association records that electricity production caters up to approximately 37% of greenhouse gas (GHG) emitted into the atmosphere. This contributes to a release of around 10 gigatonnes of GHG from electricity production alone; with expected increase in electricity production of up to 14% by 2035 (Anon n.d., 2015). Out of the total electricity produced, 40% of it is used to power residential and commercial buildings. GHG affects the earth atmosphere whereby high concentration of it depletes the ozone layer, resulting in global warming. By instilling power conservation awareness at a domestic level, its effects could be spread widely across all line of work.

HEMS address these issues by providing power consumption feedback to users and helping users identify wastages while offering advises to conserve power.

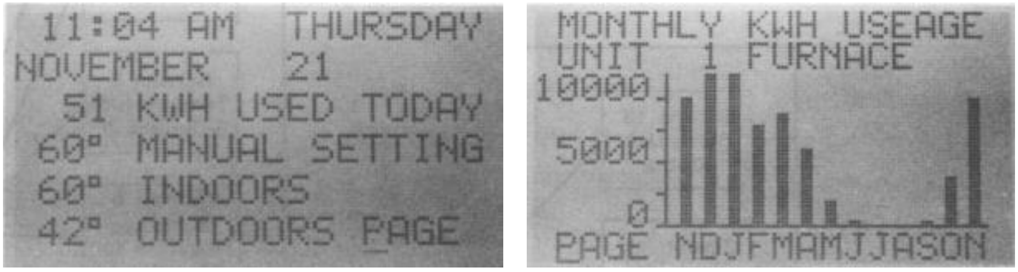
1.2 Background

The earliest HEMS was developed using master-slave protocols through power-line carrier (PLC) communication where the master unit can be plugged into any outlet in the house while the slave units were installed as intermediates between the appliances and the power outlet (Hunt et al., 1986). Power consumption data were updated every 10 minutes and may be observed through the master unit in form of daily and monthly bar graphs or in tabular formats. The slave units were designed with relays and can be commanded through PLC by the master unit to turn on or off its load. To reduce cost, only the master unit is built with non-volatile memory to store all consumption data even during power outages.



(a) Master Unit (b) Slave unit

Figure 1.2: Hunt's master and slave energy monitoring design



(a) Time and temperature (b) Monthly bar graph

Figure 1.3: Energy usage display in Hunt's master unit

Back then, researchers were more concerned with development costs and there were various technological limitations to improving the systems design. The flourishing of inexpensive Internet and wireless technologies today allows realization of various design ideas by system researchers to create and command conclusive studies on factors affecting the reliability of these systems in real-life situations. Rapid advancement in sensornet (networked sensors) research from the past decade has allowed more comprehensive understanding toward underlying problems of past HEMS designs to create systems that are more deployable into real-life scenarios.

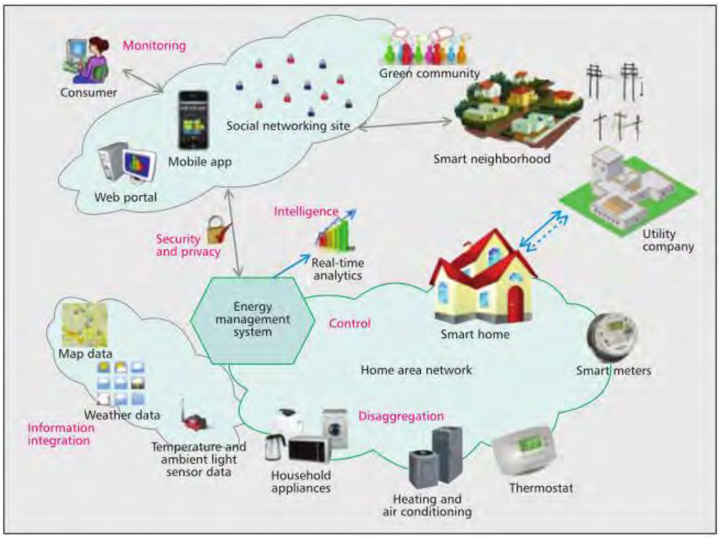


Figure 1.4: Energy management system in a smart grid (Aman, 2013)