Non-Intrusive Load Monitoring and Supplementary Techniques for Home Energy Management

Bahman Naghibi, *Student Member, IEEE,* Sara Deilami, *Member, IEEE*,

Department of Electrical and Computer Engineering, Curtin University, Perth, WA, Australia.

bahman.naghibi@postgrad.curtin.edu.au, s.deilami@curtin.edu.au

***Abstract*- The emerging smart grid technologies and rapid installations of smart meters is encouraging many consumers to implement home energy management systems (HEMSs) in order to decrease their electric utility bills and increase the efficiency of energy consumption. Intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM) are two approaches in the literature for appliance load monitoring (ALM) that make it possible for HEMSs to optimize energy utilization. However, most researchers have addressed NILM as the more practical option. In this paper, three basic methods for NILM are presented and supplementary techniques for improving the accuracy of NILM are discussed and compared. In addition, future research directions and challenges are highlighted.**

***Index Terms*- Non-intrusive load monitoring, load identification, load disaggregation, smart home and smart grid.**

I. INTRODUCTION

The global rapid growth of economic development has dramatically increased electricity energy demands over the last few years. In order to meet this emerging growth, most electric utilities are upgrading their traditional power grids to more sophisticated and self-healing smart grid technologies. It is now possible to monitor and manage residential and commercial buildings and control their electricity energy demands on real-times bases in order to reduce the overall grid efficiency. To do this, power utilities have formulated demand response (DR) programs to merge smart houses with the smart grid. In a smart house, home energy management system (HEMS) can be used to control and coordinate smart appliances, electric vehicles (EVs) and renewable energy resources such as rooftop PV systems and rooftop wind turbines [1-2].

In a smart house, HEMS interacts with all appliances which are connected together with a communication network and performs appliance load monitoring (ALM) to use the energy more efficiently, manage the demand curve and reduce the cost of energy for consumers [1-35]. This can be done using:

- Intrusive load monitoring (ILM) techniques that are relatively accurate but require more equipment and resources.
- Non-intrusive load monitoring (NILM) approaches which are more practical with acceptable accuracy.

The ILM based methods are accurate but relatively expensive and more complicated. For example, they require at least two sensors for every appliance. On the other hand, NILM based approaches have recently attracted more attentions and research focuses as they are more practical for smart grid and house applications. An attractive advantage is that NILM only requires one meter for every building.

This paper discusses NILM methods and gives a survey on supplementary techniques that may be used to improve its performance and accuracy. The remainder of this paper is organized as follows. In Section II, three basic methods of NILM are presented and their characteristics are compared. Section III presents a survey on supplementary techniques that can be utilized for improving the accuracy of NILM followed by the conclusions.

II. NON-INTRUSIVE LOAD MONITORING (NILM) METHODS

NILM is an attractive way to identify individual appliances and determine their energy consumption and operating schedules. Table I presents the main types of appliances that can be identifies by NILM based methods [2]:

- Type-I: ON/OFF appliances with two states such as toaster and usual lamp.
- Type-II: Finite State Machines (FSM) or multi-state appliances such as washing machine and stove burner with repeatable switching pattern.
- Type-III: Continuously Variable Devices (CVD) with no fixed pattern of states such as dimmer lights and power drill.
- Type-IV: Permanent Consumer Devices (PCD) which are active constantly for a long period such as telephone sets and hardwired smoke detector.

Table II presents the most common input data for appliance identification in NILM along with their related reference numbers.

The NILM methods for analyzing the measured data are based on one of the following three main approaches:

1) Steady-state analysis [3-5, 18-20].
2) Transient-state analysis [6, 20-23].
3) Non-traditional appliance features [2-3, 24-27].

The main differences in these analysis approaches for NILM applications are in the way they detect the changes in load identification [20]. The first approach considers stable modes (states) of appliances while the second approach mainly concentrates on the transitional state of appliances power consumption behavior [2]. The last method is based on non-traditional appliance features which is introduced by [21] and pays more attention to the working style and operation of appliances. This section presents detailed analyses and comparison of the above-mentioned data analysis approaches for NILM applications.

Table I

Classification of appliance type in NILM

Appliance Type	Appliance Function	Example
Type I	On/Off	Toasters and lamps
Type II	Finite State Machines (FSM)	Washing machine and stove burner
Type III	Continuously Variable Devices (CVD)	Dimmer lights and power drill
Type IV	Permanent Consumer Devices (PCD)	Telephone sets and hardwired smoke detector

Table II

Most common input data for appliance identification in NILM

Input for NILM	Related Reference Number
Current	[3], [4], [5], [6], [7], [1], [8], [9], [10], [11], [12], [13], [14]
Voltage	[3], [5], [6], [1], [9], [10], [11], [12], [13], [14], [15]
Power	[3], [16], [5], [17], [7], [18], [9], [10], [12], [13]
Admittance	[19]
Harmonic	[10], [20]

A. *NILM Methods Based on Steady-State Analysis*

In the steady-state analysis, loads are determined by identifying the times at which changes occur in "electrical power" consumption from a steady state value to another. In [4] load monitoring and appliance determination are mostly based on "current signal" while [19] uses "admittance" for identifying the appliances. Admittance is calculated from the following formula:

$$P_{Norm}(t) = 120^2 Y(t) = \left(\frac{120}{V(t)}\right)^2 P(t) \qquad (1)$$

In Eq. (1), P_{Norm} is normalized power at 120V while $Y(t), V(t)$ and $P(t)$ are the admittance, voltage and power signals, respectively.

Reference [16] uses active ($P(t)$) and reactive ($Q(t)$) power signals for appliance identification (Fig. 1). However, it cannot recognize continuously variable appliances or the appliances which are always on. Reference [20] proposes "harmonic analysis" to identify non-linear loads that overlap ambiguously in the dp-dq plane (Fig. 1). Reference [18] proposed an ad-hoc disaggregation algorithm that can recognize multi-state appliances and uses steady-state analysis because it is cheaper than other approaches. In addition, this reference presents and discusses the experimental for 11 types of appliances.

However, load identification with steady-state analysis has few deficiencies for the following cases which are also mentioned in reference [20]:

- Linear loads may overlap ambiguously in the dp-dq plane.
- Quick sequences of load activation.
- Matchless events which may occur due to the simultaneous load activation.
- Long period of steady-state for some loads.
- New appliances that are not in the data base.

In [5] and [3] other techniques are used to improve the results of steady-state analysis. Event detection and artificial neural network techniques are used after gaining the power signals in [5] to improve the quality of load identification. In the same way [3] utilizes mean-shift clustering algorithm after gaining effective voltage and current and active power in order to increase the accuracy of load identification.

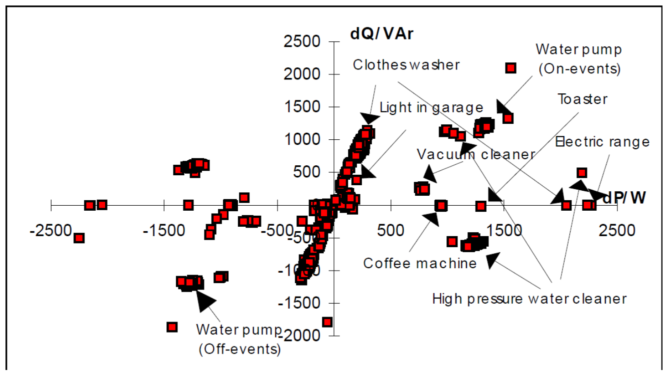

Figure 1. Clusters of appliances based on their active and reactive power measurement [16]

B. *NILM Methods Based on Transient-State Analysis*

In transient analysis, loads are determined by their spectral analysis or high frequency responses. For instance, connecting emitter of high frequency pulses to load of residential network is utilized in [22] and Wavelet analysis is used in [23] to give finer details of signal to improve load identification.

There are some deficiencies for transient analysis which are also mentioned in reference [20] such as:

- Requiring relatively unique and repeatable transient patterns.
- Requiring high sampling frequency.
- Involving complex data bases.
- Effects of network geometry on the measured pulses.

As steady-state analysis and transient analysis have their own advantages and limitations, it is better to combine them or use them with other techniques such as classification or clustering algorithms in order to improve their performance and identification results. In [6] both steady-state analysis and transient analysis are utilized to improve monitoring efficiency. The authors have proposed an innovative function based on "Matrix Pencil" that uses both current and voltage signals to identify electrical loads.

C. NILM Methods based on Non-Traditional Appliance Features

If the small fluctuations in power signal and consumption of appliances are neglected, then the power signal can be considered as combination of triangles and rectangles (Fig. 2).

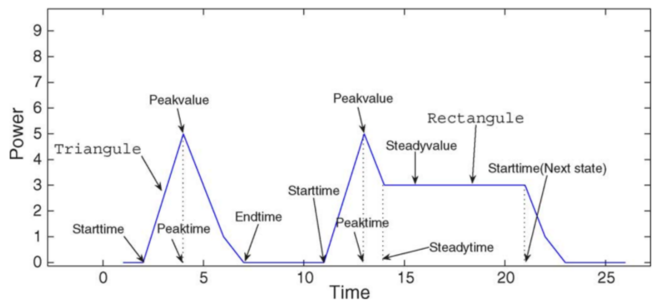

Figure 2. Diagram of two unit graph for combined triangles and rectangles representation of power signal [3]

As illustrated in Fig. 2, rectangle unit can be define by considering “peak-value”, “peak-time”, “start-time”, “steady-power”, “steady-time” and “end-time” while the triangles can be define by “peak-time”, “peak-value”, “start-time” and “end-time”. Considering the work style of appliances we can further categorize them for load identification. References [3, 24-27] have considered non-traditional features in their investigation. The bold advantage of this method is that training and supervision is not required [2].

Another approach to improve the precision of load disaggregation is to use supplementary techniques. There are two methodologies for learning and inference in NILM; supervised and unsupervised learning approaches. The supervised learning approaches encompass optimization methods and pattern recognition. The unsupervised learning approaches are less complicated and more applicable because supervised training is usually more costly and requires more human effort [2].

III. Supplementary Techniques for Load Disaggregation

This section investigates recent publications and research to improve and update the compression of learning algorithms for load disaggregation presented in reference [2]. The load disaggregation classification is illustrated in Table III. In [7] after selecting candidate events based on generic signatures, authentic events of these appliances are identified using a weight-based clustering method. After that an association algorithm is used in order to estimate appliances’ operation cycles which are used to determine electric signatures.

A fuzzy clustering analysis algorithm along with fuzzy pattern recognition is used in [17] to identify appliances. The results indicate this approach can accurately identify main loads. However, it can’t identify similar appliances with the same power signatures.

In [1] a NILM based on time-frequency analysis is considered as three system components. In the first system (the data acquisition system), a low-pass filter on current and voltage signal is used and the signal is digitized to be analyzable with the second system which is ST-based transient feature extraction. The second system (the multi-resolution scheme) is designed to captures transient responses of the undetermined appliances, especially when they are simultaneously energized. Finally in the third system (the load identification system), a complex search algorithm is formulated as a modified 0-1 multi-dimensional knapsack problem which is solved using ant colony optimization.

Table III
Classification of load disaggregation algorithms

Learning Algorithm	**Features Steady-State/ Transient**	**Accuracy [%]**	**Training Supervised/ Unsupervised**	**Online/ Offline**	**Scalability**	**Appliance Types**
SVM [28-31]	Both	75–98	Supervised	Online	Yes	I, II, III, IV
Bayes [27, 28, 32]	Steady-State	80–99	Supervised	Both	No	I, II
HMM [26, 33, 34]	Steady-State	75–95	Both	Offline	No	I, II
Neural Networks [9-12, 30, 35]	Both	80–97	Supervised	Online	Yes	I, II, III
KNN [19, 36, 37]	Both	70–90	Supervised	Both	Yes	I, II
Optimization [1, 24, 25, 38, 39]	Both	60–97	Supervised	Offline	No	I, II
Fuzzy Clustering [17]	Transient	N/A	Supervised	Online	Yes	I
Weight-based clustering and Association Algorithm [7]	Transient	87-99	Unsupervised	Offline	Yes	I, II
k-NNR and AIA [8]	Transient	95-99	Supervised	Offline	Yes	I, II
BP-ANN and AIA [8]	Transient	95-99	Supervised	Offline	Yes	I, II

In addition, reference [1] presents some experimental results to show feasibility of the proposed strategy. However, the authors have made some assumptions that need to be investigated in the future studies, such as restrictions on the total number of appliances and the time invariant nature of the nonlinear appliances. Another limitation of this approach is that data collection should be performed for every appliance in advance.

In [8] an adaptive NILM system is developed based on current signal in order to keep track of each appliance energy consumption. Transient feature extraction methods with two recognizers based on Back-Propagation Artificial Neural Network (BP-ANN) and K-Nearest Neighbor Rule (k-NNR) are utilized in order to identify appliances and different operation statuses. In order to improve the identification performance for new appliances, Artificial Immune Algorithm (AIA) with the fisher criterion is employed. The overall recognition rate is estimated to be higher than 95% for all experiments. However, simultaneously energized or de-energized appliances are not considered in this system.

Both [9] and [10] have utilized artificial neural network with transient-state analysis. In [9], the power spectrum of wavelet transform coefficients (WTCs) is calculated in various scales by Parseval's theorem in order to reduce the number of WTCs representing load transient signals. Also back-propagation classification system is utilized for artificial neural network construction and load identification. Similarly [11] utilizes an ANN to identify multiple simultaneous loads. This approach is robust to various operational modes, power consumption changes and voltage variations. In order to improve recognition accuracy, Particle Swarm Optimization (PSO) is utilized for optimizing parameters of the training algorithms. Table III summarized the results of our survey including a comparison between different techniques.

IV. CONCLUSION

This paper presents and compares three methods for NILM in addition to a few recent supplementary techniques for improving the appliance load monitoring accuracy. In general, NILM is cheaper and more applicable than ILM for load disaggregation. Steady-state analysis, transient analysis and non-traditional appliance features are three basic approaches that can be used for NILM and are summarized in Section II. The supplementary techniques are essential to improve the accuracy of NILM and are discussed and compared in Section III. However, none of these set of algorithms could recognize all appliances accurately particularly appliances that are energized for a long time or their power is variable with no fixed pattern of states. Therefore, in the future more research should be done for finding a suitable set of techniques and features for NILM. In addition using of similar database for different techniques can make it possible to compare different techniques more accurately in the future.

REFERENCES

[1] L. Yu-Hsiu and T. Men-Shen, "Development of an Improved Time--Frequency Analysis-Based Nonintrusive Load Monitor for Load Demand Identification," Instrumentation and Measurement, IEEE Transactions on, vol. 63, pp. 1470-1483, 2014.

[2]. A. Zoha, A. Gluhak, M. A. Imran, and S. Rajasegarar, "Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey," Sensors, vol. 12, pp. 16838-16866, 2012.

[3] W. Zhenyu and Z. Guilin, "Residential Appliances Identification and Monitoring by a Nonintrusive Method," Smart Grid, IEEE Transactions on, vol. 3, pp. 80-92, 2012.

[4] F. Sultanem, "Using appliance signatures for monitoring residential loads at meter panel level," Power Delivery, IEEE Transactions on, vol. 6, pp. 1380-1385, 1991.

[5] T. Bier, D. Abdeslam, J. Merckle, and D. Benyoucef, "Smart meter systems detection & classification using artificial neural networks," in IECON 2012-38th Annual Conference on IEEE Industrial Electronics Society, 2012, pp. 3324-3329.

[6] H. Najmeddine, K. El Khamlichi Drissi, C. Pasquier, C. Faure, K. Kerroum, T. Jouannet, M. Michou, and A. Diop, "Smart metering by using “Matrix Pencil”," in Environment and Electrical Engineering (EEEIC), 2010 9th International Conference on, 2010, pp. 238-241.

[7] D. Ming, P. C. M. Meira, X. Wilsun, and C. Y. Chung, "Non-Intrusive Signature Extraction for Major Residential Loads," Smart Grid, IEEE Transactions on, vol. 4, pp. 1421-1430, 2013.

[8] M.-S. Tsai and Y.-H. Lin, "Modern development of an Adaptive Non-Intrusive Appliance Load Monitoring system in electricity energy conservation," Applied Energy, vol. 96, pp. 55-73, 2012.

[9] C. Hsueh-Hsien, L. Kuo-Lung, S. Yi-Ching, and L. Wei-Jen, "Power-Spectrum-Based Wavelet Transform for Nonintrusive Demand Monitoring and Load Identification," Industry Applications, IEEE Transactions on, vol. 50, pp. 2081-2089, 2014.

[10] C. Hsueh-Hsien, C. Kun-Long, T. Yuan-Pin, and L. Wei-Jen, "A New Measurement Method for Power Signatures of Nonintrusive Demand Monitoring and Load Identification," Industry Applications, IEEE Transactions on, vol. 48, pp. 764-771, 2012.

[11] C. Hsueh-Hsien, L. Lung-Shu, C. Nanming, and L. Wei-Jen, "Particle-Swarm-Optimization-Based Nonintrusive Demand Monitoring and Load Identification in Smart Meters," Industry Applications, IEEE Transactions on, vol. 49, pp. 2229-2236, 2013.

[12] A. G. Ruzzelli, C. Nicolas, A. Schoofs, and G. M. P. O'Hare, "Real-Time Recognition and Profiling of Appliances through a Single Electricity Sensor," in Sensor Mesh and Ad Hoc Communications and Networks (SECON), 2010 7th Annual IEEE Communications Society Conference on, 2010, pp. 1-9.

[13] M. Figueiredo, A. de Almeida, and B. Ribeiro, "An Experimental Study on Electrical Signature Identification of Non-Intrusive Load Monitoring (NILM) Systems," in Adaptive and Natural Computing Algorithms. vol. 6594, A. Dobnikar, U. Lotrič, and B. Šter, Eds., ed: Springer Berlin Heidelberg, 2011, pp. 31-40.

[14] H. Y. Lam, G. S. K. Fung, and W. K. Lee, "A Novel Method to Construct Taxonomy Electrical Appliances Based on Load Signaturesof," Consumer Electronics, IEEE Transactions on, vol. 53, pp. 653-660, 2007.

[15] S. Gupta, M. S. Reynolds, and S. N. Patel, "ElectriSense: single-point sensing using EMI for electrical event detection and classification in the home," in Proceedings of the 12th ACM international conference on Ubiquitous computing, 2010, pp. 139-148.

[16] H. Pihala, Non-intrusive appliance load monitoring system based on a modern kWh-meter: Technical Research Centre of Finland, 1998.

[17] Y. Gao and H. Yang, "Non-Intrusive Load Identification by Fuzzy Cluster Analysis Based on Active Power," in Power and Energy Engineering Conference (APPEEC), 2012 Asia-Pacific, 2012, pp. 1-4.

[18] P. Ducange, F. Marcelloni, and M. Antonelli, "A Novel Approach Based on Finite-State Machines with Fuzzy Transitions for Nonintrusive Home Appliance Monitoring," Industrial Informatics, IEEE Transactions on, vol. 10, pp. 1185-1197, 2014.

[19] G. W. Hart, "Nonintrusive appliance load monitoring," Proceedings of the IEEE, vol. 80, pp. 1870-1891, 1992.

[20] H. Najmeddine, K. El Khamlichi Drissi, C. Pasquier, C. Faure, K. Kerroum, A. Diop, T. Jouannet, and M. Michou, "State of art on load monitoring methods," in Power and Energy Conference, 2008. PECon 2008. IEEE 2nd International, 2008, pp. 1256-1258.

[21] Z. Wang and G. Zheng, "Residential appliances identification and monitoring by a nonintrusive method," Smart Grid, IEEE Transactions on, vol. 3, pp. 80-92, 2012.

[22] M. Deschizeau, P. Bertrand, A. Anglade, and M. Grimaldi, "A new method for detailed electric consumption of domestic appliances," in Energy efficiency in household appliances and lighting, ed: Springer, 2001, pp. 419-427.

[23] L. Cristaldi, A. Monti, and F. Ponci, "Three-phase Load Signature," in Sixth International Workshop on Power Definitions and Measurements under Non-Sinusoidal Conditions, Milano, 2003.

[24] L. Jian, S. K. K. Ng, G. Kendall, and J. W. M. Cheng, "Load Signature Study—Part I: Basic Concept, Structure, and Methodology," Power Delivery, IEEE Transactions on, vol. 25, pp. 551-560, 2010.

[25] K. Suzuki, S. Inagaki, T. Suzuki, H. Nakamura, and K. Ito, "Nonintrusive appliance load monitoring based on integer programming," in SICE Annual Conference, 2008, 2008, pp. 2742-2747.

[26] H. Kim, M. Marwah, M. F. Arlitt, G. Lyon, and J. Han, "Unsupervised Disaggregation of Low Frequency Power Measurements," in SDM, 2011, pp. 747-758.

[27] M. Zeifman, "Disaggregation of home energy display data using probabilistic approach," Consumer Electronics, IEEE Transactions on, vol. 58, pp. 23-31, 2012.

[28] L. Gu-yuan, L. Shih-chiang, J. Y. J. Hsu, and J. Wan-rong, "Applying power meters for appliance recognition on the electric panel," in Industrial Electronics and Applications (ICIEA), 2010 the 5th IEEE Conference on, 2010, pp. 2254-2259.

[29] T. Kato, H. S. Cho, D. Lee, T. Toyomura, and T. Yamazaki, "Appliance recognition from electric current signals for information-energy integrated network in home environments," in Ambient Assistive Health and Wellness Management in the Heart of the City, ed: Springer, 2009, pp. 150-157.

[30] D. Srinivasan, W. S. Ng, and A. C. Liew, "Neural-network-based signature recognition for harmonic source identification," Power Delivery, IEEE Transactions on, vol. 21, pp. 398-405, 2006.

[31] S. N. Patel, T. Robertson, J. A. Kientz, M. S. Reynolds, and G. D. Abowd, At the flick of a switch: Detecting and classifying unique electrical events on the residential power line (nominated for the best paper award): Springer, 2007.

[32] A. Marchiori, D. Hakkarinen, H. Qi, and L. Earle, "Circuit-Level Load Monitoring for Household Energy Management," Pervasive Computing, IEEE, vol. 10, pp. 40-48, 2011.

[33] J. Z. Kolter and T. Jaakkola, "Approximate inference in additive factorial hmms with application to energy disaggregation," in International Conference on Artificial Intelligence and Statistics, 2012, pp. 1472-1482.

[34] M. J. Johnson and A. S. Willsky, "Bayesian nonparametric hidden semi-Markov models," The Journal of Machine Learning Research, vol. 14, pp. 673-701, 2013.

[35] W. Chan, A. So, and L. Lai, "Wavelet feature vectors for neural network based harmonics load recognition," 2000.

[36] M. Berges, E. Goldman, H. S. Matthews, L. Soibelman, and K. Anderson, "User-centered nonintrusive electricity load monitoring for residential buildings," Journal of Computing in Civil Engineering, vol. 25, pp. 471-480, 2011.

[37] T. Saitoh, T. Osaki, R. Konishi, and K. Sugahara, "Current sensor based home appliance and state of appliance recognition," Sice Jcmsi, vol. 3, pp. 86-93, 2010.

[38] M. Baranski and J. Voss, "Nonintrusive appliance load monitoring based on an optical sensor," in Power Tech Conference Proceedings, 2003 IEEE Bologna, 2003, p. 8 pp. Vol.4.

[39] M. Baranski and J. Voss, "Genetic algorithm for pattern detection in NIALM systems," in Systems, Man and Cybernetics, 2004 IEEE International Conference on, 2004, pp. 3462-3468 vol.4.

Bahman Naghibi received his Bachelor degree in Electronic Engineering from Islamic Azad, Fasa, Iran and Master of Science in Information Technology (IT) Engineering and Management from Amirkabir University of Technology, Tehran, Iran in 2006 and 2013, respectively. He has five years of industry experience. Currently, he is working towards a PhD degree in Electrical and Computer Engineering at Curtin University, WA, Australia.

Sara Deilami received her B.S. degree in Electrical Engineering from Islamic Azad University, Tehran, Iran and her M.S. and PhD degrees in Electrical and Computer Engineering from Curtin University, WA, Australia in 2000, 2011 and 2014, respectively. She was awarded a Curtin University Postgraduate Scholarship (CUPS) and an Australian Postgraduate Award (APA) scholarship in 2010 and 2011, respectively. She has nine years of industry experience. Currently, she is a Faculty Member at the Electrical and Computer Engineering Department, Curtin University, Perth, WA, Australia. Dr. Deilami is a member of IEEE and the co-chair of the IEEE PES-PELS WA chapter.