An Overview of Non-Intrusive Load Monitoring: Approaches, Business Applications, and Challenges

Conference Paper · November 2018

DOI: 10.1109/POWERCON.2018.8601534

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An Overview of Non-Intrusive Load Monitoring: Approaches, Business Applications, and Challenges

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***Abstract*—Load Monitoring (LM) is a fundamental step to implement effective energy management schemes. LM includes Intrusive LM (ILM) and Non-Intrusive LM (NILM). Compared with intrusive approaches, non-intrusive approaches enjoy low cost, easy installation, and promising scalable commercialization potentials. This paper provides a survey of effective NILM system framework and advanced load disaggregation algorithms, reviews load signature models, presents existing datasets and performance metrics, summarizes commercial applications such as demand response, highlights the challenges, and points out future research directions.**

***Index Terms*—NILM Framework; Advanced Disaggregation Algorithms; Load Signature Model; NILM Applications**

I. Introduction

ENERGY conservation and emission reduction has always been a hot topic for the entire society. However, it is still a challenge to persuade individual consumers to save energy due to the lack of detailed energy consumption information. Ref. [1] showed that active energy data feedback to energy users can reduce about 5-20% energy. Real-time Load Monitoring (LM) is considered as a good approach to obtain valuable feedback information and perform energy saving measures, and implement more effective energy management strategies, such as energy efficiency program [2], demand side management, and peak load shedding [3]-[4].In practice, there exists hardware-centric and software-defined approaches to performing LM. For the former, it is easy to obtain the energy usage information of a single device at the expense of high cost associated with hardware materials and labor effort. The later one is called Non-Intrusive Load Monitoring (NILM), which is easy to install and requires no or low maintenance thus scalable.

George W. Hart [5] firstly introduced the concept of NILM in the early 1980s, which is the fundamental of modern NILM system. As an interdisciplinary research topic, NILM has attracted an increasing number of researchers to contribute to its development. Recently, there has been a dramatic increase in the number of papers published on energy disaggregation researches [6] since 2010. Considering the accessibility of data acquisition, most of the research is still focused on residential sectors [6]. Due to the high potential of industrial and commercial use, researchers' attentions have also been drawn in recent years to recognize loads and solve fault detection problems [7]. However, the application of NILM in industrial and commercial building energy detection is still a huge challenge because of its high complexity. Our contributions in this paper focus on the study of framework, applications and challenges of NILM.

Manuscript received April 29, 2018.This work was supported in part by Shenzhen Municipal Science and Technology Innovation Committee (CKCY2017050509590877). Mengemeng Zhuang, Mohammad Shahidehpour, Zuyi Li, are all with the Robert W. Galvin Center for Electricity Innovation and Electrical and Computing Engineering Department at Illinois Institute of Technology, Chicago, IL 606016, USA (email:mzhuang1@hawk.iit.edu, ms@iit.edu , lizu@iit.edu,).

II. Framework of NILM and Key Issues

A. General Framework of NILM

A typical or general framework of NILM includes four steps to implement a practical NILM system as shown in Figure. 1.

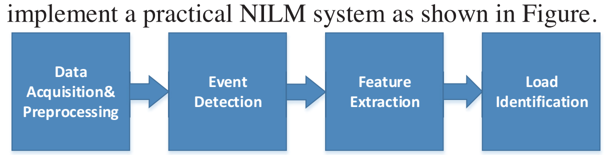

Fig. 1. Typical NILM Framework Procedure

1) Data acquisition and preprocessing

Data acquisition is fundamental and crucial for a NILM system since sampling frequency determines the information types. One example of real power in a period can be seen in Figure.2. Data acquisition systems can be divided into two categories, low frequency (less than 1Hz) and high frequency (kHz to MHz) according to sampling frequencies. Here we compare two different data acquisition meters in NILM.

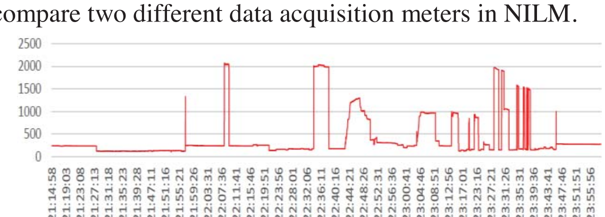

Fig. 2 An example of sampling real power signal

(1) Low frequency energy acquisition meters

From the perspective of scalability, cost is the first consideration, thus low frequency energy acquisition meter is preferred by most industry vendors with the same accuracy

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requirement of identification. In recent years, due to the high cost of obtaining high frequency sampling data, interests of researchers or engineers in industry are drawn to use smart meters to conduct the research [8] since conventional power metrics can be easily obtained via low frequency signals. When designing low rate meters, especially for near real time sampling, sensor is a key technology issue since the sensing precision will have direct effect on data quality. Ref. [9] proposes a near real-time low cost and easy to install low frequency sensor and demonstrates good performance to identify unknown appliances.

(2) High frequency energy acquisition meters

Despite its advantages of low cost and easy deployment, low resolution data is obviously limited in functionality. Hence, in the current literatures, some researchers prefer to adopt high frequency data to study load signature such as current and voltage waveforms, harmonics, and start-up transients. It should be pointed out that it is still a challenge to accurately identify appliances with variable power consumptions even with high frequency data. Ref. [10] adopts a circuit-level measurement approach with high accuracy; however, it is impractical for large scale deployment because of the installation complexity. How to reduce the cost of high frequency energy acquisition meters is becoming a hot topic for research and industry field deployment alike. Ref. [11] proposes a low cost and effective way by designing a powerful and flexible prototype with up to 65 kHz sampling rates and 24 bits amplitude resolution configurable according to user preference.

(3) Data preprocessing

After the data acquisition, periodical raw data is generally normalized or filtered[12]. How to manage and process these data will directly have effect on accuracy, real time and robust of algorithms identification. Ref. [13] introduces a practical energy box: data processing and analysis framework, namely NILM manager, from business application aspects with minimum network bandwidth and automatic energy feature extraction. What's more, in the implementation of NILM, missing readings because of network malfunction is a common problem that requires further research while obtaining raw data.

2) Event detection

In NILM, an event is defined as the change of a signal from an old steady state to a new steady state. Event detection refer to how to detect load switching operation, such as by setting a threshold to obtain on/off changes of equipment. Data points distribution in signal with events can be seen in Figure.3.

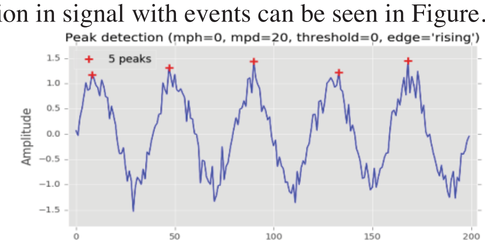

Fig. 3 Data points distribution in signal with events

Recent years, researchers focus on proposing some innovative event-based NILM algorithms [14]–[19]. Ref. [14] presents an event-based algorithm to identify load signatures including trajectories of real, reactive, and distortion power. Ref. [15] compares two novel algorithms, namely, window of margins and shifted sample methods. The result shows that the former method has a higher event detection accuracy. Ref. [16] proposes incorporating power signal information into new event detection metrics for energy disaggregation. Generally, event detection should satisfy some criterial for a practical NILM system; such as automation, simple, fast and robust. Ref. [17] presents a unique window-based approach to automatically identify unknown intermediate process. Ref. [18] proposes a simple and fast event detection approach that detected variable signal in real data environments.

3) Feature extraction

After event detection, load features can be extracted by steady-state[5], transient-state[2] , and other approaches. In the stage of feature extraction, feature selection is a crucial step. We can distinct different appliance according to their signal features. For example, ON/OFF appliances (such as table lamp) are easily recognized in Figure.4 from simple features. However, variable power consumptions appliance (such as washing machine) features are hard to distinguish in Figure.5.

Fig.4 ON/OFF appliance (such as table lamp) signal features

Fig.5 Variable power appliance (such as washing machine) signature features

After the author in[5] pioneers feature selection algorithms and [2] extends and summaries some feature extraction algorithms. Following the work, the researchers in [20]firstly review a comprehensive and systematic feature selection and load feature identification algorithms. Here we do not give more details about feature extraction, readers can refer to the work in [2], [5]and [20]. For the common steady and transient state approaches, there is still no consistent view on which approach is better. For example, steady state methods are better than transient state methods in terms of costs and easy to acquire, but they can easily cause overlapping problems. In comparison, disaggregation algorithms based on transient features can overcome these shortcomings, however, at the expense of high cost hardware. The combinations of two approaches and other features will be wise choices in applications.

4) Load identification

Load identification refers to learning and inference stage[2] of NILM system by means of supervised[2], [21], [22] and unsupervised[23], or semi-supervised[24] learning approaches. For supervised approaches, Ref. [22] presents a supervised load disaggregation algorithm based on event detection, which performs data analysis locally and shows a high promising application. For supervised approach, training is a tough problem because adequately labeled data is generally not available to identify appliance features. To solve training problems in supervised learning, Ref. [24] introduces a self-training approach, which is also named Semi-Supervised Learning (SSL) and proves to be successful in practical applications .The ultimate goal of NILM system is to identify and disaggregate load with unsupervised learning. However, in business applications, especially for the reliability and stability of product development, completely unsupervised learning are not easy to fully realize at the early stage. Here, we give some common learning approaches as references in NILM applications.

(1) Optimization

We first discuss the optimization approaches, and actually the nature of machine learning is fundamentally an optimization approach. This approach matches known power measurements to existing appliance power signals in the database via minimizing the mismatch. Researchers have proposed some common optimization approaches, such as a hybrid programing [8], ALIP (Aided Linear Integer Programming) [25], evolutionary optimization algorithm [26], and validates their research's effectiveness respectively. Optimization methods can gain high identification accuracy, however, an obvious drawback of optimization methods is heavy burden on computing.

(2)Probability statics

Probability theory is a useful approach to solve the problem in power system, such as power planning. Among most researchers focus on the study of Hidden Markov Model (HMM) based models. Ref.[27] firstly proposes probability framework to solve energy disaggregation problem using low frequency data inspired by the success of HMM approaches in identifying network file. Following the work in[27], the authors [28] use probabilistic approach, namely, modified Viterbi algorithm to decompose appliances. Bayesian approach is another common method as well. Ref. [29] adopts an unsupervised bayesian approach to perform load disaggregation. However, the proposed method fails to identify unknown load with high accuracy.

(3) Machine learning /pattern recognition

We then turn to the machine learning/ pattern recognition and approaches. After Hart used P-Q features to recognize appliances [5], most researchers have been focusing on the performance of load disaggregation [2] based on Hart's idea. Ref. [2] has comprehensively analyzed and summarized these common approaches, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Committee Decision Mechanisms (CDM) [30] and so on. The authors in.[31] systemically compared the application of machine learning into NILM from qualitative to quantitative analysis.

(4) Deep learning

Deep learning, as one branch and extending of machine learning, is a hot topic no matter in research or industry field. The readers can refer to [32] on some common deep learning architecture, such as Auto-encoder, Convolutional Neural NETWORK(CNN) and Recurrent Neural Network(RNN). Among auto-encoder proves to be a very powerful unsupervised learning tool to deal with data anomalies, high level, large –scale data problem in NILM [33] . Ref.[34] adopts convolutional neural networks with VI trajectories to automatically exact features and classify appliances. However, the accuracy is not so satisfying.

(5) Graph signal-based and other approaches

As a novel concept, Graph Signal Processing (GSP) technology has proven to be a powerful tool to solve with the problem of data mining and signal processing field in flexibility[35].Different from typical NILM learning approaches, GSP approach has nothing to do with event detection. The researchers [36] firstly propose applying a graph-based signal processing method into energy disaggregation, and the results show this approach has competitive performance compared with HMM approaches. Training is a big problem in conventional load identification learning method, GSP method shows its advantages and good performance to overcome training problems in low frequency sampling environments, which has been verified by these work in [37]–[41]. Besides, NILM researchers also put forward some other approaches based on EMI [10], wavelet design [42],power-spectrum-based approaches[43].

B. Key Issue of NILM

For a practical NILM system, the author [28] proposes 6 requirements: the compatibility of feature selection, more than 80% algorithm accuracy, without training, capabilities of near real-time, feasible scalability, and identify various appliance types(ON-OFF types , finite-states, various states, permanent load). Based on these requirements, here, we give some key issues to consider in the NILM research from aspect of applications.

1) Low cost and unsupervised framework

In the industry applications, cost is the first consideration with scalability. How to design cost-effective NILM framework is an open research topic. These include low cost data acquisition, low complexity computing, real time data processing platform and robust load signature model, unsupervised learning inference algorithms in some uncertainty environments. Researchers have put forwarded some valuable NILM frameworks, which can be as reference in the future research. Ref. [44] develops a low cost real-time NILM system based on the System on Chip (SoC) with Field-Programmable Gate Array (FPGA) acceleration through feedback feature. Besides, to solve big data problem, [45] proposes a flexible, distributed ,comprehensive framework, NilmDB, for the storage, transfer, manipulation, and analysis of time-series data. The ultimate goal for NILM is to disaggrate power signal in an unsupervised means. Ref. [46] proposes a fully unsupervised framework with efficient inference algorithms based on NFHMM(Nonparametric Factorial Hidden Markov Models) . Ref. [47] develops a low cost, robust unsupervised learning framework and verify in the small commercial sector.

2) *Load signature model*

Ref. [48] defines Load Signature (LS) as the unique consumption pattern intrinsic to each electrical appliance. How to develop robust LS model based on uncertainty factors is crucial in accuracy improvements of NILM. Hidden Markov Model (HMM) based models are very common approaches. Rent years, researchers are devoted in this area using harmonic[49], data-driven modeling methods [50]-[51]. Ref. [49] develops a robust LS model using odd-order harmonic currents through selecting features such as active power, reactive power, instantaneous current values, and steady state odd order harmonic magnitudes. LS model also seeks for simplify in business applications, the paper[52] develops an innovative and simple load profile modeling approach, which can construct an accurate model by common usage characteristics, and random power variations of different loads. In the future, how to build robust NILM model without known load profile will be an interesting topic.

3) *Robust of disaggregation algorithms*

Various algorithms have been implemented to improve the accuracy of distinctive load features , ranging from basic power analysis [29], harmonic [49], spectrum analysis [53], and wavelet transform analysis [31],[34], to hybrid programing solutions [8] .Accuracy is always the most important evaluation criterion [18] for a practical NILM system. In general, a minimum accuracy of 80–90% is an acceptable range for a good user experience [31]. In the future work, robust of algorithms will be the most important work in improving performance of NILM system, especially for the problems of unknown appliances, similar load behaviors and unknown house energy consumptions. Based on the reviews of unsupervised NILM algorithms [23] .Some more uncommon features have been studied in[54]-[56] in order to improve the robust of algorithms. Ref. [57] proposes an adaptive unsupervised clustering algorithm to detect unknown appliance states. The proposed algorithm shows a good real-time and adaptive aspects performance. Ref. [58] presents an unsupervised algorithm to effectively mitigate the interference of other appliances that have similar load behaviors to electric vehicles.

III. Performance Evaluation

A. *Public Dataset*

In order to evaluate NILM algorithms, a lot of datasets have been published, at least 26 public NILM datasets available until now, the reader can refer to the study in [59]to obtain the details about these datasets. Among, very popular ones are [60]–[65], especially BLUED dataset [62], REDD dataset [65]. BLUED dataset [62] records total load data of one house, without any sub-metered data. The REDD dataset [65] is available at http://redd.csail.mit.edu.

B. *Performance Metrics*

Ref.[59]firstly reviews a comprehensive performance evaluation metrics, which is a good reference on the details of performance metrics. In general, the performance of a typical event-based NILM system can be evaluated in the TABLE I.

TABLE I
Common Performance Metrics for NILM

Symbol	Performance metrics	Equations
RMSE	root-mean-square error	$RMSE=\sqrt{\frac{1}{T}\sum_{t=1}^{T}\lvert\bar{y}_t-\hat{\bar{y}}_t\rvert^2}$
MAE	mean average error	$MAE=\frac{1}{T}\sum_{t=1}^{T}\lvert\bar{y}_t-\hat{\bar{y}}_t\rvert$
D	disaggregation percentage	$D=\frac{\sum_{i=1}^{k}E_i}{E_{tot}}$
TECA	total energy correctly assigned	$TECA=1-\frac{\sum_{t=1}^{T}\sum_{i=1}^{K}\lvert\hat{y}_t^{(i)}-y_t^{(i)}\rvert}{2\sum_{t=1}^{T}\bar{y}_t}$
DE	disaggregation error	$DE=\frac{\sum_{t=1}^{T}\sum_{i=1}^{K}\lvert\hat{y}_t^{(i)}-y_t^{(i)}\rvert^2}{2}$
Acc	accuracy	$Acc=\frac{TP+TN}{\mathrm{TP+FP+TN+FN}}$
P	precision	$P=\frac{TP}{\mathrm{TP+FP}}$
R	recall	$R=\frac{TP}{\mathrm{TP+F}N}$
F_1	F-measure	$F_1=\frac{2\times P\times R}{P+R}$

where $\bar{y}_t$ is original signal, $\hat{\bar{y}}_t$ is the disaggregation signal, E_{tot} is the total energy of original signal, k is appliances signals number and T is sampling number; $\hat{y}_t^{(i)}$ is separated signal, $y_t^{(i)}$ is original signal, TP is the true positive of working appliance, FP is the false positive of working appliance, TN is true negative and FN is the false negative.

In order to solve the problem of the benchmarking algorithms, Ref.[66] proposes a powerful tool: NILMTK-DF, which can change the formats of current datasets. NILMTK includes 6 dataset API, such as REDD [65], AMPds [60], Smart* [67], and so on. The purpose of NILMTK releasing is to help researcher to evaluate the accuracy of their algorithms.

IV. Business Applications

The NILM research should not only be focused on theoretical models, but also on the large-scale deployment of these systems in the real world, ultimately open up new opportunities in applications. Here we illustrate some prospective examples. Only considering accuracy of algorithms is not meaningful in practical implementation in residential sector. For example, there is no difference for customers whether the accuracy is 95% or 98%. What is more meaningful is some innovative advanced application and business model based on NILM. Examples in applications may include how to design practical implementation of personalized energy demand management strategies based on power consumption analysis, how to predict the power demand (load forecasting), how to apply management policies, how to avoid overloading over the energy network, and so on. Here we illustrate some potential prospective examples.

A. Smart Energy Data Sharing Platform

From the load characteristics and disaggregation information obtained by the NILM system, an energy data sharing platform can be built to balance the benefits of various entities. Here we list some partners involved in this platform in Figure.6.

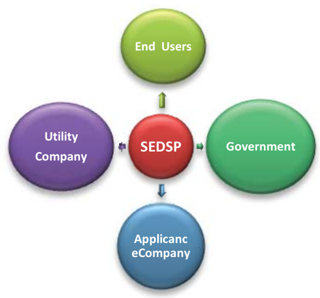

Fig. 6 Smart energy data sharing platform (SEDSP)

1) Utility company benefits

Load disaggregation data via NILM can improve the power load forecasting accuracy and provide a more accurate basic scheme for power system operational planning. In addition, the disaggregated load data can help establish a more accurate load model at the power transmission system level, thereby improving the accuracy of simulation and stability analysis. For the grid operators, these data can be enable to call on flexible demand side resources for demand response and demand shaping to manage uncertainty caused by renewable energy sources. Furthermore, the utility company can estimate demand response potential in some locations from the fine information on the appliance levels.

2) Government benefits

Governments spend billions of dollars on energy efficiency (EE) program every year. However, the feedbacks and effects are not satisfactory. Fortunately, the fine load monitoring through NILM can help the government make wise decisions on EE policies. Energy cost can be reduced through data analysis via NILM, so as to achieve the purpose of energy consumption reduction in a more effective or efficient way.

3) User benefits

Users can detect the power consumption of each appliance via NILM. For those who want to save electricity, they can change and optimize the power consumption plan according to the information provided by NILM. The same information can help users check and eliminate electrical failures. It can also help users to make decision on replacing low-efficiency electrical appliances.

4) Appliance company benefits

Household electricity consumption information can prompt manufactures to speed up the study of high-performance equipment and guide the change of market of household appliances. It can also help relevant departments formulate rational guidelines to improve energy efficiency, reduce pollutants emissions, and mitigate greenhouse effect.

B. Demand Response

Demand Response (DR) is one of most promising solution to accommodate higher renewable energy sources (RES) penetration. However, there still lacks of accurate load models to evaluate DR potential of DR program participants. NILM system can use prior knowledge of appliance load profiles to identify high DR potential appliances, which, when coupled with the control information of different load categories, constitute the basis for accurate DR implementation. One example can be seen in Figure.7.

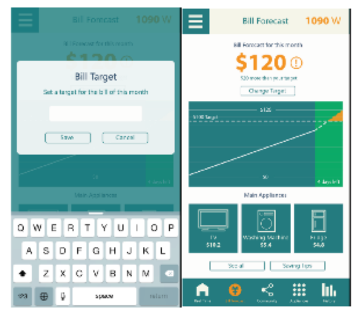

Fig. 7 Personalized energy reduction strategies

In recent years, an increasing number of researchers are devoted to investigating DR based on NILM. Ref. [68] develops a new NILM system for DR based on a comprehensive analysis on the DR requirement from both hardware and software aspects with a more practical load space and a more explicit measuring criterion. Ref. [69] proposes a new pricing model based on NILM that is better than other tariff models by setting different pricing to each group, in order to guide consumers to save as much energy as possible. Ref. [70] presents an intelligent home energy management (HEM) algorithm for managing high power consumption household appliances based on DR analysis at an appliance level. Ref. [71] proposes a novel incentive-based DR program that can be utilized by a service provider (SP) to procure capacity resources from its subscribed customers in terms of load reduction. Ref. [72] provides a practical strategy for load shed verification in residences sector, which promises to greatly simplify trust assumptions required for the deployment of direct control.

C. Microgrid and Smart Home Energy Management

Energy management of microgrid is very important to implement load schedule, demand response, and maximize renewable energy utilization. However, current micro-grid energy management technology focuses on how to control steerable power source, storage energy to manage energy, stochastic, without considering too much the flexibility source of demand side. NILM will provide flexible energy information for microgrid energy management. Ref. [73] shows that NILM can automatically identify load pattern to determine an optimal schedule in off-grid applications. Ref. [74] adopts NILM approach to reveal exact data information about appliances' activities in a hybrid AC-DC microgrid. Ref. [75] presents an improved NILM method to identify Electric Vehicle Battery (EVB) charging in microgrid.

Another important application scenario of NILM is smart home energy management (SHEM).Visualized energy bill information can be easily obtained via the information in the NILM. One application example can be seen in Figure.8. The results of a NILM system can help to identify various loads in a home and detect the condition and use of those loads. Ref. [76] proposes a home energy management system (HEMS) via Bayesian network, which can learn user behavior considering the priority of various home appliances' operation mode. Ref. [77] develops a Smart Home Energy Management System (SHES)to conduct personalized appliances scheduling strategies based on NILM.

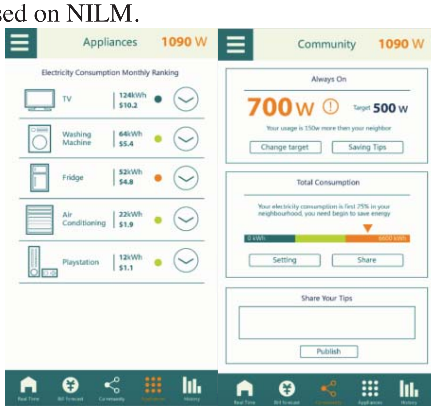

Fig.8 An example of visualized energy bills

D. Personalized Energy Recommendation and Diagnosis

Household occupants can be notified of how much energy each appliance in their homes consumes, and will thus be motivated to take steps to reduce their energy consumption. An example of personalized energy recommendation and diagnose can be seen in Figure.9.

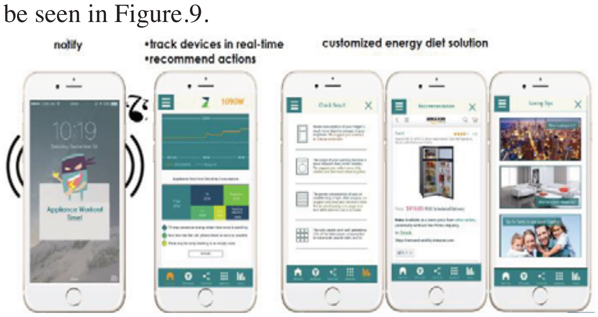

Fig. 9 An example of personalized energy recommendation and diagnose

Load monitoring algorithms are able to determine the time of use for each appliance, and thus can recommend the optimal time of usage when electricity is cheaper or has a lower carbon footprint. Ref. [78] proposes a demand side personalized recommendation system (PRS) by applying NILM system adopting generalized particle filtering algorithms.

NILM can provide important information for diagnostic feedback as a promising technology as well. Ref. [7] presents a case study applying NILM for fault detection and isolation of automated shipboard systems. Ref. [79] presents a robust identification system to recognize winding insulation faults. Ref. [80] adopts harmonic analysis of motor current to track the speed of motors for sensor-less control and proves feasibility of harmonic analysis based on NILM for fault detection and diagnostics.

V. Challenges and Future Work

NILM has been a hot research topic especially with the great advancements of Artificial Intelligence (AI) and sensing technology. However, NILM technology is still facing various challenges no matter in research or in business applications.

For research area, firstly, access to reliable low-cost high frequency sampling data, and the accuracy of NILM algorithm still face great challenging because of some uncertainty factors, such as variable load numbers, type, make, size and user privacy [81]. There will be no universal model that can be used in all end users. In addition, the power consumption of many appliances depends on their own parameter settings. Thus no widely accepted load signatures can be universally used in all appliances, especially in lower power consumption appliances that have similar power characters. NILM is generally easy to detect two-state appliances such as toaster and table lamp. However, it is difficult to recognize some multi-states appliances such as washing machine. It is even more difficult to identify other continuous-state appliances such as dimming light, and constant power appliances such as smoke detector. Also, the ever-increasing number of new appliances will become an obstacle for algorithms accuracy. Most current NILM approaches require off-line training data, and database cannot obtain all the equipment features, so it is not easy to identify unknown new equipment that is not in the database without any labeling. Currently, most research algorithms accuracy are based on some public sample frequency datasets in some developed countries in ideal environments. Until now, there is still no public high frequency public datasets in Asia, especially in China. The researches in these countries face a huge challenge in conducting NILM research in real environments.

For application aspect, firstly, cost is a key factor to commercialize a NILM system. Current most NILM products are very high and hinder the scalability. So how to balance the cost and accuracy of algorithms will be a tough issue needed to explore. And in developing countries, there are few commercial NILM products that can be scalable. Thirdly, still no obviously innovative business model , especially for business to customer （B2C） model. Being lack of trust and interest is a huge challenge to persuade end users to actively participate into energy reduction. Persuasive technology [82] is a promising way since it can establish cognitive trust perception to achieve cost-effective and easy-to-use user engagement through behavioral economics, machine learning, social influence, and interactive design [83].Here we give our design example based on persuasive technology in Figure.10.

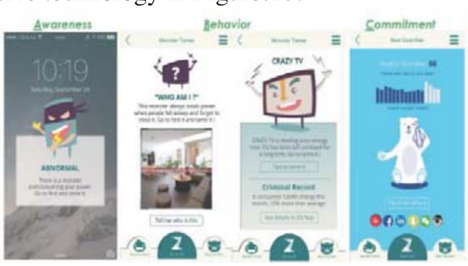

Fig. 10 Case design of NILM based on persuasive technology

Thus we suggest some open research issues as future work.

- Robust and real time NILM learning approaches to deal with unknown loads in unknown houses, identify multi-states load, such as washing machines.
- Develop effective standardizing evaluation matrices and high quality data sets, especially in developing countries.
- Large scale realistic simulators to trace appliances energy model combined with GIS system
- Low cost smart sensor and distributive sensing; data processing (high performance computing); data privacy and security
- Computer-based persuasive energy feedback model.
- Business model innovation integrating with demand side flexible sources in deregulated market environments.

VI. CONCLUSIONS

This paper presented typical framework of NILM system, key issues and performance metrics of NILM implementation. In addition, potential business applications of NILM were discussed in detail, such as smart energy data sharing platform, personalized energy management, equipment diagnoses, and demand response. Furthermore, challenges and futures work of NILM research and applications were summarized. We draw some conclusions:

1) Low cost and robust NILM framework still necessary to explore in order to facilitate the scalability of NILM.

2) From NILM research aspects, robust algorithms to distinctive similar load characteristic between different appliances and load features modeling considering unknown appliances will continue to be hot research topics in the future.

3) From the point of applications, NILM has shown increasingly promising applications, such as energy efficiency, demand response, energy management, and equipment diagnosis. Practical business models based on advanced innovative application of NILM still need to be explored for large-scale NILM deployment.

4) Although three decades since the first NILM proposed, it still faces huge challenges especially in scalability.

ACKNOWLEDGMENT

We express great thanks for the support of Shenzhen Zhidian Energy Company, Shenzhen, China.

REFERENCES

[1] D. Vine, L. Buys, and P. Morris, "The effectiveness of energy feedback for conservation and peak demand: a literature review," *Open J. Energy Effic.*, vol. 02, no. 01, pp. 7–15, 2013.

[2] A. Zoha *et al*., "Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey," *Sensors (Switzerland)*, vol. 12, no. 12, pp. 16838–16866, 2012.

[3] S. Giri and M. Bergés, "An energy estimation framework for event-based methods in non-intrusive load monitoring," *Energy Convers. Manag.*, vol. 90, pp. 488–498, 2015.

[4] C. Liu, A. Akintayo, Z. Jiang, G. P. Henze, and S. Sarkar, "Multivariate exploration of non-intrusive load monitoring via spatiotemporal pattern network," *Appl. Energy*, vol. 211, pp. 1106–1122, 2018.

[5] G. W. Hart, "Nonintrusive appliance load monitoring," in *Proceedings of the IEEE*, 1992, vol. 80, no. 12, pp. 1870–1891.

[6] Y. F. Wong, Y. Ahmet Sekercioglu, T. Drummond, and V. S. Wong, "Recent approaches to non-intrusive load monitoring techniques in residential settings," *IEEE Symp. Comput. Intell. Appl. Smart Grid, CIASG*, pp. 73–79, 2013.

[7] J. C. Nation *et al*., "Nonintrusive monitoring for shipboard fault detection," *SAS 2017 - 2017 IEEE Sensors Appl. Symp. Proc.*, 2017.

[8] W. Kong, Z. Y. Dong, D. J. Hill, F. Luo, and Y. Xu, "Improving non-intrusive load monitoring efficiency via a hybrid programming method," *IEEE Trans. Ind. Informatics*, vol. 12, pp. 2148–2157, 2016.

[9] F. Rossier, P. Lang, and J. Hennebert, "Near real-time appliance recognition using low frequency monitoring and active learning methods," *Energy Procedia*, vol. 122, pp. 691–696, 2017.

[10] A. Marchiori and D. Hakkarinen, "Circuit-level load monitoring for household energy management," *Pervasive Comput.*, vol. 10, no. 1, pp. 40–48, 2011.

[11] A. Adabi, P. Manovi, and P. Mantey, "Cost-effective instrumentation via NILM to support a residential energy management system," in *IEEE International Conference on Consumer Electronics (ICCE)*, 2016, pp. 107–110.

[12] D. Egarter, V. P. Bhuvana, and W. Elmenreich, "PALDi: Online load disaggregation via particle filtering," *IEEE Trans. Instrum. Meas.*, vol. 64, no. 2, pp. 467–477, 2015.

[13] J. S. Donnal, J. Paris, and S. B. Leeb, "Energy applications for an energy box," *IEEE Internet of Things Journal*, vol. 3, no. 5, pp. 787–795, 2016.

[14] J. Alcala, J. Urena, A. Hernandez, and D. Gualda, "Event-based energy disaggregation algorithm for activity monitoring from a single-point sensor," *IEEE Trans. Instrum. Meas.*, vol. 66, no. 10, pp. 2615–2626, 2017.

[15] H. a D. Azzini, R. Torquato, and L. C. P. Silva, "Event detection methods for nonintrusive load monitoring," in *IEEE PES General Meeting | Conference & Exposition*, 2014, pp. 1–5.

[16] D. Benitez, K. D. Anderson, M. E. Bergest, A. Ocneanut, D. Benitez, and J. M. P. Moura, "Event detection for non intrusive load monitoring," in *Annual Conference on IEEE Industrial Electronics Society*, 2012, pp. 3312–3317.

[17] M. Dong, P. C. M. Meira, W. Xu, and W. Freitas, "An event window based load monitoring technique for smart meters," *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 787–796, 2012.

[18] M. N. Meziane, P. Ravier, and G. Lamarque, "High accuracy event detection for non-intrusive load monitoring," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2017, pp. 2152–2156.

[19] C. C. Yang, C. S. Soh, and V. V. Yap, "Comparative study of event detection methods for nonintrusive appliance load monitoring," in *International Conference on Applied Energy*, 2014, pp. 1840–1843.

[20] N. Sadeghianpourhamami, J. Ruyssinck, D. Deschrijver, T. Dhaene, and C. Develder, "Comprehensive feature selection for appliance classification in NILM," *Energy Build.*, vol. 151, pp. 98–106, 2017.

[21] M. Azaza and F. Wallin, "Supervised household's loads pattern recognition," *IEEE Electr. Power Energy Conf.*, pp. 1–5, 2016.

[22] M. Nardello, M. Rossi, and D. Brunelli, "A low-cost smart sensor for non intrusive load monitoring applications," in *IEEE International Symposium on Industrial Electronics*, 2017, pp. 1362–1368.

[23] R. Bonfigli, S. Squartini, M. Fagiani, and F. Piazza, "Unsupervised algorithms for non-intrusive load monitoring: An up-to-date overview," in *IEEE 15th International Conference on Environment and Electrical Engineering (EEEIC)*, 2015.

[24] K. S. Barsim and B. Yang, "Toward a semi-supervised non-intrusive load monitoring system for event-based energy disaggregation," in *IEEE Global Conference on Signal and Information Processing(GlobalSIP)*, 2015, pp. 58–62.

[25] M. Z. A. Bhotto, S. Makonin, and I. V. Bajić, "Load disaggregation based on aided linear integer programming," *IEEE Trans. Circuits Syst. II Express Briefs*, vol. 64, no. 7, pp. 792–796, 2017.

[26] A. S. and W. E. Dominik Egarter, "Evolving non-intrusive load monitoring," in *16th European Conference on the Applications of Evolutionary Computation*, 2013.

[27] H. Kim, M. Marwah, M. F. Arlitt, G. Lyon, and J. Han, "Unsupervised disaggregation of low frequency power measurements," in *Proceedings of the SIAM Conference on Data Mining*, 2011, pp. 747–758.

[28] M. Zeifman, "Disaggregation of home energy display data using probabilistic approach," *IEEE Trans. Consum. Electron.*, vol. 58, no. 1, pp. 23–31, 2012.

[29] K. Srinivasarengan, Y. G. Goutam, M. G. Chandra, and S. Kadhe, "A framework for non intrusive load monitoring using bayesian inference," in *International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing*, 2013, pp. 427–432.

[30] J. Liang, S. K. K. Ng, G. Kendall, and J. W. M. Cheng, "Load signature study-part II: Disaggregation framework, simulation, and applications," *IEEE Trans. Power Deliv.*, vol. 25, no. 2, pp. 561–569, 2010.

[31] C. Nalmpantis and D. Vrakas, "Machine learning approaches for non-intrusive load monitoring: from qualitative to quantitative comparation," *Artif. Intell. Rev.*, 2018.

[32] G. Ian, Y. Bengio, and A. Courville, *Deep learning*. 2016.

[33] C. Fan, F. Xiao, Y. Zhao, and J. Wang, "Analytical investigation of autoencoder-based methods for unsupervised anomaly detection in building energy data," *Appl. Energy*, vol. 211, pp. 1123–1135, 2018.

[34] L. De Baets, J. Ruyssinck, C. Develder, T. Dhaene, and D. Deschrijver, "Appliance classification using VI trajectories and convolutional neural networks," *Energy Build.*, vol. 158, pp. 32–36, 2018.

[35] S. Chen, R. Varma, A. Singh, and J. Kovačević, "Signal representations on graphs: tools and applications," *arXiv:1512.05406,* pp. 1–27.

[36] V. Stankovic, J. Liao, and L. Stankovic, "A graph-based signal processing approach for low-rate energy disaggregation," in *IEEE Symposium Series on Computational Intelligence for Engineering Solutions, Proceedings*, 2014.

[37] B. Zhao, L. Stankovic, and V. Stankovic, "On a training-less solution for non-intrusive appliance load monitoring using graph signal processing," *IEEE Access*, vol. 4, pp. 1784–1799, 2016.

[38] D. Whfkqltxhv *et al.*, "Non-intrusive load monitoring based on graph signal processing," in *Recent Development in Control,Automation& Power Engineering(RDCAPE)*, 2017, vol. 3, pp. 18–21.

[39] K. He, L. Stankovic, J. Liao, and V. Stankovic, "Non-intrusive load disaggregation using graph signal processing," in *IEEE Transactions on Smart Grid*, 2018, vol. 9, no. 3, pp. 1739–1747.

[40] B. Zhao, L. Stankovic, and V. Stankovic, "Blind non-intrusive appliance load monitoring using graph-based signal processing," *2015 IEEE Glob. Conf. Signal Inf. Process. Glob. 2015*, pp. 68–72, 2016.

[41] X. F. Liu, M. Y. Zhai, and Z. Y. Xie, "A graph-based signal processing approach for non-intrusive load disaggregation," *Proc. 2017 Int. Conf. Wirel. Commun. Signal Process. Networking, WiSPNET 2017*, vol. 2018–Janua, pp. 780–785, 2018.

[42] J. M. Gillis, S. M. Alshareef, and W. G. Morsi, "Nonintrusive load monitoring using wavelet design and machine learning," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 320–328, 2016.

[43] H. H. Chang, K. L. Lian, Y. C. Su, and W. J. Lee, "Power-spectrum-based wavelet transform for nonintrusive demand monitoring and load identification," *IEEE Trans. Ind. Appl.*, vol. 50, no. 3, pp. 2081–2089, 2014.

[44] T. K. Nguyen, E. Dekneuvel, G. Jacquemod, B. Nicolle, O. Zammit, and V. C. Nguyen, "Development of a real-time non-intrusive appliance load monitoring system: An application level model," *Int. J. Electr. Power Energy Syst.*, vol. 90, pp. 168–180, 2017.

[45] J. Paris, J. S. Donnal, and S. B. Leeb, "NilmDB: The non-intrusive load monitor database," *IEEE Trans. Smart Grid*, vol. 5, no. 5, pp. 2459–2467, 2014.

[46] R. Jia, Y. Gao, and C. J. Spanos, "A fully unsupervised non-intrusive load monitoring framework," in *IEEE International Conference on Smart Grid Communications (SmartGridComm)*, 2015, pp. 872–878.

[47] S. Mostafavi, J. Troxler, R. W. Cox, and N. Carolina, "An unsupervised approach for disaggregating major loads in small commercial buildings," in *IEEE Energy Conversion Congress and Exposition (ECCE),* 2017, pp. 1575–1581.

[48] J. Liang, S. K. K. Ng, G. Kendall, and J. W. M. Cheng, "Load signature study-part I: Basic concept, structure, and methodology," *IEEE Trans. Power Deliv.*, vol. 25, no. 2, pp. 551–560, 2010.

[49] A. S. Bouhouras, M. Vaggos, N. Poulakis, and G. C. Christoforidis, "Load signatures enhancement via odd-order harmonic currents," in *IEEE 16th International Conference on Environment and Electrical Engineering(EEEIC)*, 2016.

[50] S. Welikala, C. Dinesh, R. I. Godaliyadda, M. P. B. Ekanayake, and J. Ekanayake, "Robust Non-Intrusive Load Monitoring (NILM) with unknown loads," in *IEEE International Conference on Information and Automation for Sustainability: Interoperable Sustainable Smart Systems for Next Generation, ICIAfS*, 2016.

[51] L. Wang, R. Kubichek, and X. Zhou, "Adaptive learning based data-driven models for predicting hourly building energy use," *Energy Build.*, vol. 159, pp. 454–461, 2018.

[52] S. Barker, S. Kalra, D. Irwin, and P. Shenoy, "Empirical characterization and modeling of electrical loads in smart homes," in *International Green Computing Conference Proceedings, IGCC*, 2013.

[53] D. F. Teshome, T. D. Huang, and K. L. S. Member, "Distinctive load feature extraction based on Fryze ' s time-domain power theory," *IEEE Power Energy Technol. Syst. J.*, vol. 3, no. 2, pp. 60–70, 2016.

[54] E. J. Aladesanmi, "Non-intrusive load monitoring and identification for energy management system using computational intelligence approach," University of Cape Town, 2015.

[55] A. L. Wang, B. X. Chen, C. G. Wang, and D. D. Hua, "Non-intrusive load monitoring algorithm based on features of V–I trajectory," *Electr. Power Syst. Res.*, vol. 157, pp. 134–144, 2018.

[56] Y. Lin and M. Tsai, "Non-intrusive load monitoring by novel neuro-fuzzy classification considering uncertainties," *IEEE Trans. Smart Grid*, vol. 5, no. 5, pp. 2376–2384, 2014.

[57] P. A. Chou and R. I. Chang, "Unsupervised adaptive non-intrusive load monitoring system," in *IEEE International Conference on Systems, Man, and Cybernetics, SMC*, 2013, pp. 3180–3185.

[58] A. Munshi and Y. A.-R. I. Mohamed, "Unsupervised non-intrusive extraction of electrical vehicle charging load patterns," *IEEE Trans. Ind. Informatics*, pp. 1–13, 2018.

[59] L. Pereira and N. Nunes, "Performance evaluation in non-intrusive load monitoring: Datasets, metrics, and tools-A review," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, pp. 1–17, 2018.

[60] S. Makonin, F. Popowich, L. Bartram, B. Gill, and I. V. Bajić, "AMPds: A public dataset for load disaggregation and eco-feedback research," *IEEE Electr. Power Energy Conf. EPEC*, pp. 1–6, 2013.
[61] M. Kahl, A. Haq, and T. Kriechbaumer, "Whited-a worldwide household and industry transient energy data set," in *3rd International Workshop on Non-Intrusive Load Monitoring*, 2016.
[62] K. Anderson, A. F. Ocneanu, D. Benitez, D. Carlson, A. Rowe, and M. Bergés, "BLUED : A fully labeled public dataset for event-based Non-Intrusive Load Monitoring research," in *2nd KDD Workshop on Data Mining Applications in Sustainability (SustKDD)*, 2012.
[63] S. Makonin, Z. J. Wang, and C. Tumpach, "RAE: The rainforest automation energy dataset for smart grid meter data analysis," *data*, vol. 3, no. 1:8, pp. 1–9, 2018.
[64] M. Maasoumy, K. Poolla, B. M. Sanandaji, and A. S. Vincentelli, "BERDS - Berkeley energy disaggregation data set," in *Workshop on Big Learning at the Conference on Neural Information Processing Systems (NIPS)*, 2013.
[65] J. Z. Kolter and M. J. Johnson, "REDD : A public data set for energy disaggregation research," in *Workshop on Data Mining Applications in Sustainability (SIGKDD), San Diego, CA,* 2011, vol. 25, pp. 59–62.
[66] J. Kelly *et al*., "Demo Abstract: NILMTK v0.2: A non-intrusive load monitoring toolkit for large scale data sets," in *1st ACM International Conference on Embedded Systems For Energy-Efficient Buildings,* 2014.
[67] S. Barker, A. Mishra, D. Irwin, E. Cecchet, P. Shenoy, and J. Albrecht, "Smart*: An open data set and tools for enabling research in sustainable homes," in *SustKDD*, 2012.
[68] D. He, W. Lin, N. Liu, R. G. Harley, and T. G. Habetler, "Incorporating non-intrusive load monitoring into building level demand response," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1870–1877, 2013.
[69] C. Lin and Z. Wang, "A new DSM energy-pricing model based on load monitoring system," in *Proceedings of the 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce, AIMSEC*, 2011, pp. 3650–3653.
[70] M. Pipattanasomporn, M. Kuzlu, S. Rahman, S. Member, M. Kuzlu, and S. Rahman, "An algorithm for intelligent home energy management and demand response analysis," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2166–2173, 2012.
[71] M. Yu, S. H. Hong, and J. B. Kim, "Incentive-based demand response approach for aggregated demand side participation," in *IEEE International Conference on Smart Grid Communications, SmartGridComm*, 2016, pp. 51–56.
[72] D. C. Bergman, D. Jin, J. P. Juen, N. Tanaka, C. A. Gunter, and A. K. Wright, "Non-intrusive load shed verification," *IEEE Pervasive Comput*., vol. 10, no. 1, pp. 49–57, 2011.
[73] A. A. Zaidi, T. Zia, and F. Kupzog, "Automated demand side management in microgrids using load recognition," in *IEEE International Conference on Industrial Informatics (INDIN)*, 2010, pp. 774–779.
[74] Z. Huang, T. Zhu, Y. Gu, and Y. Li, "Shepherd: Sharing energy for privacy preserving in hybrid aC-dC microgrids," in *Proceedings of the Seventh International Conference on Future Energy Systems*, 2016, pp. 202–211.
[75] P. Zhang, C. Zhou, B. G. Stewart, D. M. Hepburn, W. Zhou, and J. Yu, "An improved non-intrusive load monitoring method for recognition of electric vehicle battery charging load," *Energy Procedia*, vol. 12, pp. 104–112, 2011.
[76] T. Shoji, W. Hirohashi, Y. Fujimoto, Y. Amano, S. Tanabe, and Y. Hayashi, "Personalized energy management systems for home appliances based on bayesian networks," *J. Int. Counc. Electr. Eng*., vol. 5, no. 1, pp. 64–69, 2015.
[77] T. Liu, Y. Liu, Y. Che, S. Chen, Z. Xu, and Y. Duan, "SHE: Smart home energy management system for appliance identification and personalized scheduling," in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*, 2014, pp. 247–250.
[78] F. Luo, G. Ranzi, W. Kong, Z. Y. Dong, S. Wang, and J. Zhao, "Non-intrusive energy saving appliance recommender system for smart grid residential users," *IET Gener. Transm. Distrib*., vol. 11, no. 7, pp. 1786–1793, 2017.
[79] S. Das, P. Purkait, C. Koley, and S. Chakravorti, "Performance of a load-immune classifier for robust identification of minor faults in induction motor stator winding," *IEEE Trans. Dielectr. Electr. Insul*., vol. 21, no. 1, pp. 33–44, 2014.
[80] U. A. Orji *et al*., "Fault detection and diagnostics for non-intrusive monitoring using motor harmonics," in *Proceedings of the 25th IEEE Applied Power Electronics Conference and Exposition (APEC)*, 2010, pp. 1547–1554.
[81] A. Haq and H.-A. Jacobsen, "Prospects of appliance-level load monitoring in off-the-shelf energy monitors: a technical review," *Energies*, vol. 11, no. 1, pp. 189–211, 2018.
[82] W. N. W. Ahmad and N. M. Ali, "Trust perceptions in using persuasive technologies," in *3rd International Conference on Computer and Information Sciences*, 2016, pp. 49–53.
[83] A. Emeakaroha, C. S. Ang, Y. Yan, and T. Hopthrow, "A persuasive feedback support system for energy conservation and carbon emission reduction in campus residential buildings," *Energy Build*., vol. 82, pp. 719–732, 2014.

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