Non-intrusive Appliance Monitoring Now: Effective Data, Generative Modelling and LETE

Chi-Cheng Chuang, Today J. T. Sung, Gu-Yuan Lin, Jimi Y. C. Wen
Networks and Multimedia Institute
Institute for Information Industry
Taipei, TAIWAN
polon, today, guyuan, jimi @nmi.iii.org.tw

Ray-I Chang
Dept of Eng. Science and Ocean Eng.
National Taiwan University
Taipei, TAIWAN
rayichang@ntu.edu.tw

***Abstract*—Monitoring energy consumption at appliance level is a necessary condition for many energy efficient applications. In this paper, we have identified non-intrusive load monitoring (NILM) as a transitional technology, and competing NILM methods must be evaluated not only on performance, but also economical feasibility and user usability of now. Since in the event of maturing an IoT infrastructure, there would be no need for NILM. In this paper, we proposed a NILM for now, a complete solution with novel features: i) pre-processing for effective data, thus more accurate and faster training for user. ii) generative modelling for appliance configuration states, thus without the need for exhaustive training, and iii) LETE algorithm for a simple stateful enhancement. Experiments show the proposed methodology perform well even under only the most simplistic assumptions.**

***Keywords-Energy Management System, Non-Intrusive Load Monitoring, Appliance Monitoring.*;**

I. Introduction

In an effort to become a smarter energy world, the movement towards smart grid infrastructure along with the advances in information communication technologies, there is a need for consumer energy management system. Energy management on the consumer side can be monitoring, planning, control consumer's energy consumption. To reduce waste in energy consumption, building occupants and facilities managers need to better understand how buildings use energy, broken down over space and time through appliance monitoring [1]. Today, however, energy usage statistics are usually available only in the *aggregate* and monthly time resolution or sometimes in 15 minute intervals with the advance metering infrastructure. *Disaggregated* energy usage statistics are more useful than *aggregated* when implementing new efficient energy services, e.g., bill disaggregation, high bill resolution, incentive plan based on individual appliances, bad user usage or appliance operation diagnostics [2].

This ideal paradigm of smarter energy aligns with the developments towards the Internet of Things (IoT) [3], i.e., all things or significant appliances will be connected to the internet with the capability to upload energy usage statistics. There are few obstacles against the disruptive technology of IoT: i) legacy systems, i) cost of communication devices and iii) infrastructure including network protocols to service applications. For *now*, the cost of adding additional sensors to appliance individually is not feasible, economically, for most appliances especially at home. Thus there exists a window of opportunity, before we reach the confirmation stage of IoT for smarter energy applications, to develop a transition technology, viz. the disaggregation of energy usage consumption using algorithms, devices, deployments methods, etc. This dis-aggregating of energy usage is non-intrusive load monitoring (NILM).

There are several approaches on formulating this NILM problem by making different assumptions on the signal properties, environment, application scenario, etc. Here we first make the distinction between NILM and appliance recognition type approaches. These approaches aim to recognize which unknown appliance is operating and does not aim to do disaggregation. Disaggregation is important to reduce cost using less sensors and communication devices. Aggregated load can be analyzed on the transient state or power line noise or the steady-state. Steady-state can also be divided into enveloped-based or harmonic-based. However methods that analyze on the transient or harmonics or noise require a much higher sampling rate from 1 kHz to even 1 MHz, which require either one or both of the following support which are not quite yet the state of the art: i) higher communication bandwidth infrastructure to transmit larger data, ii) additional micro controller chip on the meters to perform more complex NILM. When such a support is ready, NILM is probably not needed.

In additional to monitoring from appliance load, it is also possible other modes of (ambient) signals, such as light, acoustic, vibration, motion, RIFD tags electro-magnetic interference, etc. The assumption for using these multi-modal sensors, is that these ambient sensors are already in everyday house-hold or commercial buildings for various *ubiquitous computing* applications. We do not believe this assumption is a viable candidate as a transitional technology before the full maturation of IoT. Since i) the sensing, computation, network structure required for such ubiquitous sensing is

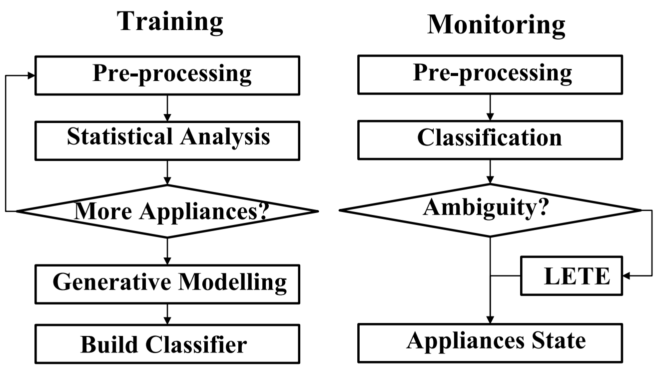

Figure 1: Overview of the proposed methodology for the training stage and the monitoring stage.

essentially a mature IoT infrastructures. Furthermore ii) under such assumptions, appliance of significance would need to be controlled or automated intelligently therefore communication device for the downlink is a necessary condition as well as the uplink. Some methods leverage the knowledge of an given environment, e.g., Jiang et al. proposed to disaggregate specific appliance load under a tree structure [1]. This requires domain experts to customize sensor deployment with specific load distributions, which would not be economically-feasible for most users. Schoofs proposed a niche solution to leverage networked business equipment through LAN network [4].

To attract users to NILM, methodologies should be inexpensive, simple, ready to use and provide the services that are demanded. This paper is structured as follows: in Section II, we present a total solution with the following contributions: i) pre-processing effective data, ii) generative appliance model for simpler training and iii) least effort transition enhancement (LETE) for more accurate and stateful monitoring. Experiments and related work are discussed in Section III and Section IV. We conclude in Section V.

II. Methodology

In this section, we discuss the methodology of the proposed NILM solution as can be seen in Fig. 1(a) and (b) for the training and monitoring stage respectively. In the training stage, the energy usage statistics, namely the load, is pre-processed before the statistical modelling is carried out. An individual appliance model is next computed for all appliances. Finally a statistical generative appliance configuration model is formed using a naïve Bayesian classifier. Pre-processing is also done during the monitoring stage. Classification of the appliance configuration states (ACS) is done next. A Least Effort Transition Enhancement (LETE) algorithm is proposed to solve 'ambiguity' after the classifier.

A. Pre-processing: Effective Data

The objective of pre-processing in the training stage is to train only on 'enough' steady-state load while bypassing transient load, therefore making the training data more effective. The objective of pre-processing in the monitoring is to only classify when there is a transition in steady state there making it more effective, i.e., transients and same steady-states are not classified in monitoring. Computation is not wasted and less messy classified data will be post-processed.

The aggregate load, l_t, can be modelled as a non-stationary signal, and can be decomposed into sequences of transient and steady states. When the aggregated load reaches steady-state conditions, we can assume the load to be a weak stationary process. We assume that the load has reach its steady-state when a large enough window of load data is stationary. We first define an adaptive window, $w_{t-\Omega t+1}(l_t)$, on a sequence of load at time $t \in \mathcal{N}$:

$$w_{t-\Omega t+1}(l_t) = [l_{t-\Omega t+1}, l_{t-\Omega t+2}, \ldots, l_{t-1}, l_t], \qquad (1)$$

and the finite sample distribution, W_t, for the load within the window at at time t:

$$l_\tau \sim W_t \quad \forall \tau \in \mathcal{N}: \quad t - \Omega_t + 1 \leq \tau \geq t. \qquad (2)$$

We form the following hypotheses that the current load value distribution and the test statistics as:

$$H_t^0: \quad l_t \sim W_t = W_{t-1}, \quad \frac{|l_t - \mu(W_{t-1})|}{\sqrt{\mathrm{Var}(W_{t-1})}} \leq \alpha \qquad (3)$$

where α represent the confidence interval. The logic of the adaptive window Ω_t is then defined as for $t > \omega_{min}$:

$$\Omega_t = \begin{cases} \omega_{\text{min}} + 1 & H_{t-1}^0 \text{ is rejected} \\ \Omega_{t-1} + 1 & H_{t-1}^0 \text{ is accepted} \end{cases}, \qquad (4)$$

where ω_{min} denotes the implementation parameter for minimum training window. In the training stage, when $\Omega_{t'}$ is greater than a specified training window ω_{train}, then the load values $w_{t'-\Omega t'+1}(l_{t'})$ are used to train the individual appliance statistical model. In the monitoring stage, when $\Omega_{t'}$ is greater than a specified monitoring window ω_{mon}, then the load values $\mu(w_{t'-\Omega t'+1}(l_{t'}))$ are used for classifier as input.

B. Generative Models

The main objective here is to train each appliance once only, which we define as non-exhaustive training, i.e., without the need to train all the different combinations. This can increase the user-acceptability greatly by decreasing the training effort on the user. We propose a statistical model, $y_t^n(s^n) \sim Y^n(s^n)$, for the apparent power of $n-$th appliance with 3 operation states $s^n = \{0, 1, 2\}$.[1] The statistical model of steady-state appliance load can be written as:

$$y_t^n(s^n) \sim Y^n(s^n) = \begin{cases} 0 & s^n = 0 \\ x_t^n \sim X^n & s^n = 1 \\ x_t'^n \sim X'^n & s^n = 2, \end{cases} \qquad (5)$$

[1]The proposed method can be generalized for higher dimension feature space and similarly for appliance with more than 3-states.

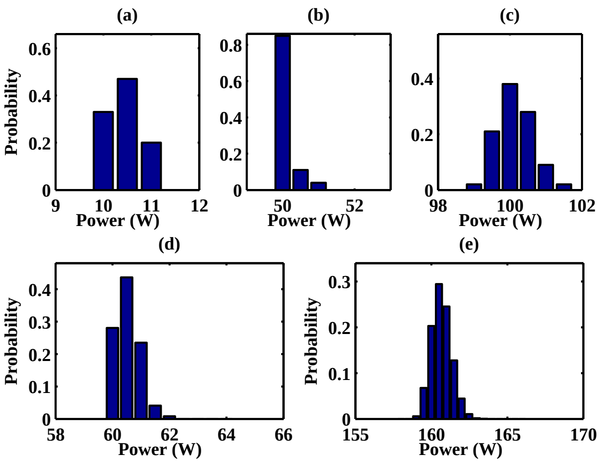

Figure 2: Load distribution of (a) appliance 1, (b) appliance 2 (c) appliance 3, state 2, (d) appliance 1 and appliance 2 and (e) appliance 1 and appliance 2 and appliance 3.

Distribution X^n can be trained by either forming an empirical distribution or some common probability distribution[2] and their parameters can be estimated. We now define a vector, the appliance configuration state (ACS), $\mathbf{s}$, for N total appliances:

$$\mathbf{s} = [s^1, s^2, \ldots, s^N]^{\mathrm{T}} \tag{6}$$

then the total aggregated load can be written as:

$$l_t(\mathbf{s}) = \sum_{n=1}^{N} y_t^n(s^n). \tag{7}$$

Assuming each appliance load is independent with respect to ACS, the distribution of the total aggregate load for a given ACS can be written as:

$$L(\mathbf{s}) = \Upsilon_{n=1}^{N} Y^n(s^n), \tag{8}$$

where Υ denotes the cumulative convolution operator. For example if

$$\mathbf{s} = [1\ 1\ 2\ 0\ 0\ \ldots\ 0]^{\mathrm{T}}, \tag{9}$$

total load can be written as

$$l_t(\mathbf{s}) = x_t^1 +_t^2 + x_t^{'3} + 0 + \ldots + 0, \tag{10}$$

thus the distribution of the the total load for this ACS can be written as:

$$L(\mathbf{s}) = X^1 * X^2 * X^{'3}, \tag{11}$$

where $*$ denotes the convolution operator. An illustration of (11) can be seen in Fig. 2. The load distribution of appliance 1, 2 and 3 are shown in Fig. 2(a), (b) and (c) respectively. The load distribution of the ACS, $\mathbf{s} = [1\ 1\ 0\ 0\ \ldots\ 0]^{\mathrm{T}}$ is next shown in Fig. 2(d) as the convolution on load distribution appliance 1 (Fig. 2(a)) and 2 (Fig. 2(b)). The load distribution of the ACS, $\mathbf{s} = [1\ 1\ 2\ 0\ \ldots\ 0]^{\mathrm{T}}$ is then shown in Fig. 2(e) as the convolution on the load distribution of the ACS, $\mathbf{s} = [1\ 1\ 0\ 0 \ldots\ 0]^{\mathrm{T}}$ (Fig. 2(d))and appliance 3 Fig. 2(c)). Therefore, in the proposed method, only N training on each individual appliance is required, different combinations are generated by convolution of individual distributions, instead of total combination of 2^n or more for exhaustive training. In the monitoring stage, each steady state value can be evaluated in a simple Bayesian sense i.e.

$$\max_{\mathbf{s}}\{p[L(\mathbf{s})|\mu(w_{t'-\Omega t'+1}(l_{t'}))]\}. \tag{12}$$

C. Least effort transition enhancement

We proposed an heuristic module: Least Effort Transition Enhancement (LETE). When there are more than one candidate ACS that score a relatively significant likelihood in the generative model, e.g.,

$$\operatorname*{diff}_{\star=c_1,c_2} p[L(\mathbf{s}^\star)|\mu(w_{t'-\Omega t'+1}(l_{t'}))] < p_\sigma \tag{13}$$

The rational behind this is: it is less likely to have a sudden transition of many appliance at once, i.e., many switching on and off of appliances. Thus the hypothesis is that the *less* the effort in the transition from the previous ACS to the candidate ACS, the *more likely* the candidate ACS. Let us define the ACS transition, $\Delta\mathbf{s}^c$, for candidate, $c \in \mathcal{C}$, with respect to the previous ACS as

$$\Delta\mathbf{s}^c = \mathbf{s}_{t-1} \oplus \mathbf{s}_t^c, \tag{14}$$

where $\oplus$ denotes the XOR or exclusive disjunction operator. The estimated effort can then be calculated as

$$\min_{c\in\mathcal{C}}\{\epsilon\Delta\mathbf{s}\}, \tag{15}$$

where $\epsilon = [1\ 1\ \ldots\ 1]$. Other weights can be chosen that reflect the effort more realistically, e.g., switching off the fridge is less likely than the TV. This module is heuristic because we do not formulate a probability model for an given ACS transition, i.e., we can only minimize effort but cannot maximize posterior probability. The weights are also chosen heuristically, without the need for training. Training would defeat the purpose of advantages of the training only N-times on each individual appliance using generative modelling.

III. Experiments

In this section, we discuss the experiment setup and results. Load data are collected by a power meter EZ-RP-15 [3]at 1 Hz sampling rate and transmitted via the Zigbee protocol and processed by a PC. Each individual appliance model is found during the training stage. The three different appliance sets and the total number of reference ACS transitions collected are shown in Table I. A reference script for different ACS are generated randomly for all the

[2]i.e., a Gaussian distribution, a Rayliegh distribution, etc.

[3]www.joseph-tech.com.tw

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Table I: APPLIANCE SETS FOR TESTING. NUMBER (#) OF s DENOTES THE NUMBER OF DIFFERENT STATES TESTED.

Set / # of s	appliances
1 / (70)	Desk lamp (24W), adjustable lamp (170W), tungsten light bulb (100W), tungsten light bulb (160W), fan (50W), Halogen light bulb (250W)
2 / (71)	Desk lamp (24W), fan (40W), tungsten light bulb (40W), tungsten light bulb (60 W), tungsten light bulb (200W), Halogen light bulb (230W), LCD monitor (12W)
3 / (101)	Refrigerator (120W), laptop (40W), tungsten light bulb (100W), tungsten light bulb (180W), Halogen light bulb (400W), Halogen light bulb (500W), computer server (230W)

appliances except for the computer server and refrigerator, where we manually placed, to better reflected actual practise in everyday life. The computer server is on for the first two-thirds and the refrigerator is on for last two-thirds of the total configurations. This script is carried out and the load is measured and stored. The performance is evaluated using word recognition rate (WRR) [5]:

$$\text{WRR} = \frac{M_R - E_I - E_D - E_S}{M_R}, \tag{16}$$

where M_R is total number of reference ACS, E_S is the number of substituted appliance states in classified ACS, E_D is the number of appliance states from the reference ACS deleted in the classified ACS, and E_I is the number of appliance states inserted in the classified ACS not appearing in the reference ACS.

We first test the performance of with and without pre-processing for different waiting times. The waiting time for without preprocessing is the training time, but with pre-processing the waiting time is the sum of the training time and transient bypassing time. It can be seen that in Fig. 3(a) with pre-processing, the performance is greatly improved for shorter waiting times. For a 90 % WRR, the waiting time is reduced approximately from 90 seconds to 30 seconds with pre-processing and for a 95 % WRR, the waiting time is reduced approximately from 2 minutes toward 1 minute. For waiting times over 3 minutes, the two methods are the same, i.e., the effect transients on the appliance model is negligible.

We next test the performance of LETE for $p_\sigma = 0.1$ and $p_\sigma = 0.5$. It can be seen in Fig. 3(a) that LETE with $p_\sigma = 0.1$ does not make a significant difference in appliance set 1 or in appliance set 2, where LETE correctly corrects one substation error. In the case of relatively constant load appliances sets, 1 and 2, LETE with $p_\sigma = 0.5$ mistakenly corrects too many ACS of a lower likelihood. Since $p_\sigma = 0.5$ allows the difference of likelihood of competing candidate ACS up to 0.5, which might allow LETE to mistakenly determine the transition of the higher likelihood of the candidate ACS to be of *too much effort*. However for a more load varying appliance set 3, LETE with $p_\sigma = 0.5$ outperforms

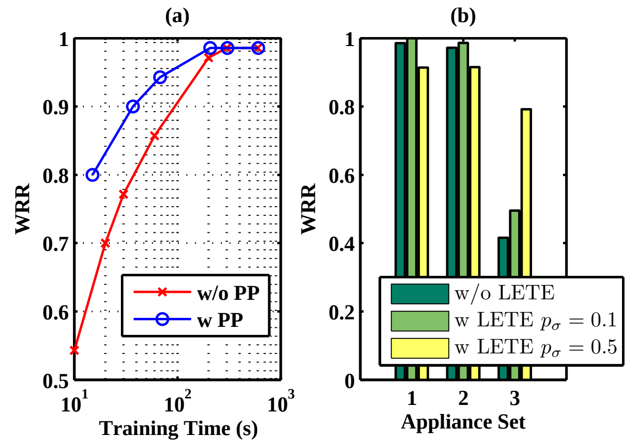

Figure 3: (a) WRR for different waiting times for with and without pre-processing on appliance set 1. (b) WRR for different appliance sets with and without LETE.

LETE with $p_\sigma = 0.1$ and without LETE greatly. Since LETE with $p_\sigma = 0.5$ allows higher likelihood discrepancies, it allows the hypothesis of least effort to work more. Thus this resulted a more stateful classifier, which can handle load varying appliances better. There is a performance tradeoff for the selection of p_σ, depending on the assumption of appliances being monitored.

IV. RELATED WORK

Recent interests in industry show towards improving building energy monitoring. Several startups, such as Tendril and EnergyHub, etc., provide detailed power measurements of selected individual loads. While this approach is useful in observing a few loads at high fidelity, it is neither practical nor cost-effective when full coverage of many appliances is desired.

An appliance recognition approach distinguishs the difference between a variety of appliances by individual appliance properties. Ito et al. [6] proposed several feature parameters, such as average, peak, crest factor, form factor, etc., to characterize the power waveform of individual appliance. They applied nearest neighbors method to recognize which appliance was in use. Kato et al. applied one-class SVM to classify appliance state based on individual current and voltage [7]. However they do not solve problem of one meter to monitoring multiple appliances problem.

The original work on NILM was done by George W. Hart [8], grouped appliance events in the real/reactive power space and built a finite state machine to infer the operating status of appliances according to the power difference between two steady-state periods. Laughman et al. discuss the two limiting assumptions used in Hart's method [9]: i) different loads of interest must exhibit unique signatures. ii) load composition is determined by steady-state power consumption only. Assumption 1 typically hold for homes or small offices, however as there are more appliance in a

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total load it gets harder to satisfy assumption i). Laughman et al. then proposed to use higher harmonics in the aggregate current signal to distinguish loads with overlapping clusters in the real/reactive signature space [9]. Lee et al. proposed to use signature correlations in harmonic content to estimate appliances with variable speed drive [10]. This relaxes assumption ii) described by laughman et al. Kushiro et al. attached sensors to a distribution board and employed wavelet transform on current waveform to obtain frequency domain features and utilized pattern matching method to identify the operating status of those target appliances which performed well in recognizing the operating status of appliances with irregular load [11]. Patel et al. measured the electrical noise delivered via power lines to detect the states change of appliances [12]. Such noise is generated by the fast switching of relatively high currents. They employed Fast Fourier Transform (FFT) on the measured noise to separate the component of frequencies and adopt SVM to classify the appliance's state. These frequency/harmonic approaches require higher sampling rate which would require additional hardware to process inside the meter or increase the communication bandwidth greatly.

Jiang et. al proposed a method based on the assumption that the fundamental structure of residential and commercial electrical power flow can be modelled as a load tree. It branches through several levels transformers, bus bars, panels, breakers, power strips, receptacles to individual appliances and within those appliances to various subsystems [1]. Jung and Sawides proposed a method for estimating the power consumption breakdown per appliance inside a home assuming simple ON/OFF appliance state information is available [13]. Schoofs et al. presented NetBem, a novel energy monitoring technique ad hoc to office buildings, capturing the contribution of networked business equipment to a power load through the LAN [4]. The above method are based on the assumption of extra information based on domain knowledge sensor deployment, which would restrict the universality of methods to be used in the real world.

Gupta et al. and Rowe et al. both relied on the fact that most modern consumer electronics and fluorescent lighting employ switch mode power supplies which continuously generate high frequency electromagnetic interference during operation that propagates throughout a homes power wiring which can be measured via electromagnetic sensors [14] [15]. Kim et al. proposed ViridiScope, a finegrained power monitoring system that uses ambient signals from magnetic, light, and acoustic sensors placed near appliances to estimate power consumption [16]. Schoofs et al. proposed a system to automate electricity data annotation leveraging cheap wireless sensor nodes. Characteristic sensory stimuli captured by sensor nodes placed next to appliances are translated into appliance operating state and correlated to the electricity data, autonomously generating the annotation of electricity data with appliance activity [4]. These approaches are base on different mode of sensors which is still far from commercialization.

We now discuss two similar approaches to our work, namely i) super-second sampling so no additional hardware is needed in existing meters or increased communication requirements. ii) non-exhaustive training, i.e., appliance configuration are generated instead of trained, for better user acceptance. Marchiori et al. proposed two methods for NILM, i) a heuristic approach which process individual appliance models into peak points in a feature space and then generated appliance configuration models in a simple vector addition sense therefore uncertainty is measured by distance not probability, and ii) a Bayesian approach which require training of randomly generated different configurations, therefore a semi-exhausitive training is needed. In our proposed non-heuristic generative modelling, the uncertainty based on probability. Ruzzelli et al. presented a plug-and-play tool identify consumption of individual appliances using a neural network (NN). Although a NN require much more training effort than a simple statistical appliance model proposed in our work, Ruzzelli et al. championed NN over a simpler Bayesian type of classifier to incorporate different state or parameter variations. In our work, the proposed LETE improves a simple Bayesian classifier by giving it a *sense of states*. It is to the knowledge of the authors, this work is also the first to study the acceleration of training.

V. Conclusion and Future Work

Monitoring energy consumption at appliance level is a necessary condition for many energy efficient applications. In this paper, we have identified non-intrusive load monitoring (NILM) as a transitional technology, and competing NILM methods must be evaluated not only on performance, but also economical feasibility and user usability of now. Since in the event of maturing an IoT infrastructure, there would be no need for NILM. In this paper, we proposed a NILM for now, a complete solution with novel features: i) pre-processing for effective data, thus more accurate and faster training for user. ii) generative modelling for appliance configuration states, thus without the need for exhaustive training, and iii) LETE algorithm for a simple stateful enhancement. Experiments show the proposed methodology perform well even under only the most simplistic assumptions. The next step in our research is to convert appliance configuration states into human activities, therefore enabling value-added services for energy efficiency, comfort and convenience.

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 ISBN: 978-1-61208-136-6