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A Review of Nonintrusive Load Monitoring and Its Application in Commercial Building

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***Abstract*—Nonintrusive load monitoring (NILM) has been developed for decades in load monitoring and disaggregation. Methods of digital signal processing and statistical modeling have been applied in detecting state change events, extracting the load signatures, identifying individual device load for disaggregation, and parameterizing the transient of devices for diagnosis. In this paper, we discuss the challenges in general NILM system with methods implemented. We focus on models applied in key steps, which are "event detection" and "load recognition". Approaches in residential and commercial buildings are evaluated, where these two typical applications have gained lot attentions recently. The challenges in commercial building are explored and studied, and potential solution and research direction are discussed. It shows that unsolved problems and modern intelligent devices require more sophisticated NILM system in the future.**

I. Introduction

Nonintrusive load monitoring (NILM) has been studied for decades. Traditional techniques of "sub-metering" requires interior wiring to obtain precise measurement on energy consumption on each load; where a nonintrusive method is designed to monitor an electrical circuit that contains a number of devices by measuring the aggregation of all consumes, which is NILM (pioneered by Hart [1]). The research on NILM has gained many research attentions in past twenty years, due to the increasing requirement on electric power monitoring. NILM addresses the "sensor problem" for electrical load monitoring by extracting information about individual loads form a few measurements at a centralized locations. In many applications, this is a very cost-effective tradeoff as a major advantage.

Initial research focuses on devices switch event (ON/OFF) independently. Hart measured the real and reactive powers at 1 Hz sampling rate. The recorded step changes were clustered and classified on a real-reactive power plane. His algorithm is limited in detecting only the isolated ON/OFF events of constant loads. A finite state machine model to handle the multi-sate loads was proposed but no any sequence analysis algorithm. Steven Leeb approached this problem from a different angle, based on the possible pattern of individual load when turning on [2]. He developed an analog spectral envelope (SE) processor, to estimate the real, reactive and harmonic powers at the fundamental frequency. A rudimentary transient detection and classification algorithm was developed to examine power waveforms as desired pattern at multiple time resolutions [3]. It was the first time that Leeb and Norford investigated the feasibility of using NILM for commercial building [4]. Steven Shaw improved the process of calculating digital SE with discrete Fourier transform (DFT) [5]. Approaches concerning the diagnosis were performed by modeling the current waveform with parameter estimation [6], or by analyzing the faults using the power signal [7].

NILM monitors the total load, checking for certain "signatures" which provide information about the activity of the devices which constitute the load [8], [9], [10]. The NILM system estimates the number and status of the individual loads, energy consumption, and other relevant statistics such as time-of-day variations by applying analyses of the current and voltage waveforms. In order to accurately decompose the aggregate load into its components, a model-based approach for describing individual devices and their combination is used. These models suggest that certain signatures which can be detected in the aggregated load to indicate the activities of the separate components. In this paper, we are going to review the nonintrusive load monitor system algorithm applied and the challenges when applying with commercial building. System framework and technical challenges are discussed in Section II. Statistical modeling and data mining algorithms applied in load classification will be explored in Section III. Section IV will focus on challenges and perspective work in commercial building. Conclusion and future work are discussed in Section V.

II. System Framework and Technical Challenges

Electricity has been considered as a medium of energy as well as a medium of information with the widespread networks and mobile terminals. NILM is interested in monitoring individual load, by extracting information from the current and power flows. During the interaction with the loads, electricity inadvertently carries information about the physical nature of loads, which means measured current and power flows embedded information about the characteristics of the loads. NILM uses the carried on information for load disaggregation, fault diagnosis, and system analysis.

A. NILM System Block Diagram

Figure 1 is the system diagram of NILM, which also illustrates the key concepts for each step. There are total 5 steps for a complete NILM application, and the "pre-processing", "event detection", and "load recognition" are key steps.

Signals of the voltage, current, real power, and power factor are measured in the first stage of NILM system. The typical measurement error dues to the meter inconsistencies - different meter could yield different value for same device. The real power and power factor show 10%-20% difference,

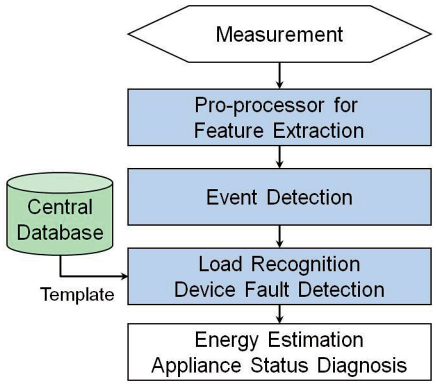

Fig. 1. NILM system block diagram.

given claimed accuracy of 3% [11]. Digital signal processing techniques have been widely used in analyzing signals and the sample rate becomes a key issue. The sample rate of 120 Hz is enough to reconstruct the signal as the electricity is a low frequency sinusoid signal (no more than 60 Hz). When considering harmonics, a higher sample rate might be necessary. Quantization error during A/D convert is introduced by the digital meter [12]. The noise in measured signal also play an important role, including color noise introduced by variable speed device (VSD, or variable frequency device, VFD) [4], [13], [14]; and white noise by constant load [8], [13]. Moreover, there might exist information loss due to raw data compression in most commercial sensors [15].

Measured signals are processed for de-noising, quantizing, and extracting features in the "pre-processing" step. Reactive power, spectral envelop, and higher harmonics are calculated as load signatures for individual device. The transient waveform is also extracted as a feature during the device turn-on, depending on the specific window length. Signal sensitivity is important in this stage, which is affected by resolution and dynamic range. Actually these two are competing parameters, which means that we can only find a good trade-off of designed or selected parameters [12]. Another problem in this stage is the device inconsistence: devices change their behaviors with time, such as malfunction, decay, etc [15].

Event detection is applied to capture the changes in the extracted features, such as power signal or transient waveform, according to the the specific time scales and pre-defined thresholds. There are two major challenges in this step, which are definition of events and parameter selection. The detected events might be caused by ON/OFF change, transient of states, and continuous variable. This requires extra information to support the detection. The threshold setting and the window size are also critical. Each combination of parameters selection leads to similar effects - including some devices but excluding others, depending on detailed applications [16] [15].

Pattern recognition algorithms are designed to identify individual load with extracted features associated with each event. Classic algorithms using an off-line training schema, developed a "Load Signature Library" in the database (Figure 1) as the training result and would be used in the testing. Due to the specific sampling rate, particular window size, etc., this trained signature library is highly related to the equipment used to obtained the measurements, the empirical factors selected, and to some degree the individual devices used in data acquisition. This requires the disaggregation model be robust when applying in different sets of devices, especially for the application of residential building as the variation is large across manufactures. The long-term decay of devices have big impact on the off-line model robustness. Finally, individual device energy consumption can be estimated according to identified and disaggregated individual load. The accuracy is mainly affect by event detection, load classification, and load average power consumption from the database.

Practical NILM system varies a lot according to specific applications, including residential building, commercial building, and transportation unit. Residential building may be the most critical one concern about the intrusion on the house, which meet the advantages of NILM. Privacy is always the problem, especially when NILM system can disaggregate the load usage in a building without knowing the number and classes of appliance in the building. The type and brand of residential device vary a lot, which require the NILM should be robust. The challenges in commercial building are most due to high event density and large range of dynamic load, which requires the NILM system has high sampling rate and can handle the trade-off between resolution and measure range. Moreover, different kinds of commercial buildings, such as shopping mall, office building, hospital, etc., will have very unique characteristics on the load, and it requires an application-oriented NILM. NILM in transportation unit (such as ship) is a very special application filed requiring high reliability on load status detection and fault detection.

B. Electric Load and Data Pre-processing

Power (instantaneous power) on an AC circuit is a complex quantity which can be computed as $P(t) = v(t)i(t) = V_m \sin(\omega t) I_m \sin(\omega t - \phi)$. ϕ is the phase lag between voltage and current, which determines the power factor $\cos(\phi)$ (equals to the ratio between real and apparent power). The power factor and the reactive power fully characterize the electrical system and can be studied by NILM.

Generally the non-sinusoidal current introduces new higher frequency components having integer multiples of the fundamental frequency. Different appliances with a non-sinusoidal current draw have different harmonic characteristics, which can turn out to be useful for disaggregation. There is another interesting observation happened in higher harmonics, which is spectral components that are not integer multiples of the voltage frequency, called inter-harmonics [17]. The inter-harmonics are typically caused by either a periodically varying load or a frequency difference in the inverter of a VSD [14]. This so called "load imbalance" can be used in diagnosis.

Beside constant linear load, research on multi-state appliances was performed using finite-state machine models [18]. The widely used intelligent devices such as VSD/ VFD consume the electrical load in a continuously varying way, which makes the disaggregation and monitor tasks more complicated and difficult. The continually varying load may also interfere other load and reduce the detection accuracy. There are three classes of device models from the NILM perspective:

1) ON/OFF (Two-state): Devices such as light bulbs, are either on or off at any given moment.

2) Multi-state: Devices such as washing machines, with distinct types of ON states, e.g., fill, rinse, spin, etc.
3) Continuously variable: Devices such as variable-speed fan, with a continuous range of ON states.

All the features discussed before, can be calculated with voltage and current signals and used in load classification & disaggregation. The amount of information we can obtain from the signal determines how accurate the NILM model can be, which is related to the sampling rate and the signal precessing method. The sampling rate is decided by the interested load signatures. For example, the v-section of the turn-on transient of an instant-start fluorescent lamp falls in millisecond time solution [3], [4], which requires a sampling rate above 1 KHz. When considering the harmonics in 5^{th}, 7^{th}, or even higher to 20^{th}, the sampling rate might go to 8 KHz. The pre-processing on the measured signals includes denoising and re-sampling. Re-sampling requires filter bank and down-samples the signal to set up frequencies according to the multi-rate sampling tree structure. Denoising method is to find a good approximation of the signal and increase the accuracy of event detection. The major concern in pre-processing is to minimize the information lose, as the information is not computed from the raw values and cannot be obtained with the down-sampled data is lost.

III. Pattern Recognition Challenges

The feature used in recognizing the load class rises a very critical problem for either feature extraction and load recognition, which is when it is a proper time. This relates to detect a change in the signal, which could be a power jump due to a change in the consumption or a transient signal caused by a device or group of devices at any given time. We will discuss this "event detection" in the following section.

A. Event Detection

All events can be treated as the result of state change of the device, which could be due to: a) a state change for one or more devices; b) noise; c) part of the normal operation of a continuous load device without being a state transition. Signal processing algorithms have been developed for clear and robust event detection. Early method applied filters to smooth out small or erratic variations in the total power signal and extract separate parts for load recognition. The filtered signal consists of distinct rectangular shapes where each increase or decrease in demand is more likely to represent a significant state change. When the number of devices increase or the dynamic range gets larger, filtering the signal to extract rectangular shapes as events becomes impossible and unreliable. Late, a probabilistic model is widely applied to detect the power change for event detection [16], [19], [20].

Before implementing edge detection algorithm,"denoising" needs to be applied to filter the signal and mask rapid power oscillations for clear edge transition. Median filter, linear smoothing, and total variation regularization are three most used algorithms, which preserves edges while removing noise under certain conditions. The median filter is a nonlinear digital filtering technique, which is widely used in digital image processing. The disadvantage of this method is it smoothes away edges to a greater or lesser degree when reducing noise. Total variation regularization or total variation denoising (TVD) was first discussed [21]. The principle behind is that signals with excessive and possibly spurious detail have high total variation, that is, the integral of the absolute gradient of the signal is high. This method removes noise and preserves important details such as edges in the signal, even at low SNR.

Generalized likelihood ratio (GLR) detection was proposed by Basseville [22], which discussed the problem of on-line detection of model change with the simplest case: jumps in mean. The main idea is to design a detector which can detect a single jump as quickly as possible in an on-line framework, in order to allow the detection of near successive jumps. The GLR detection using log-likelihood ratio test is

$$\Lambda_n(r) = \frac{\mu_1 - \mu_0}{\sigma^2} \sum_{k=r}^{n} (y_k - \mu_0 - \frac{\mu_1 - \mu_0}{2}) = \frac{1}{\sigma^2} S_r^n(\mu_0, \nu),$$

where $S_r^n = \nu \sum_{k=r}^{n} (y_k - \mu_0 - \frac{\nu}{2})$ and $\nu = \mu_1 - \mu_0$ (the jump magnitude by assuming a constant signal μ_n with additive white noise $\epsilon_n \sim \mathcal{N}(0, \sigma^2)$). The GLR detector is to find out the jump of μ_n where the jumps in the mean occur at unknown time instants with unknown jump level. In NILM, event detection is a problem of on-line detection of such jumps appears at any power change due to state change. For observation sequence $y_n = \mu_n + \epsilon_n$, where the jump happens in time r, the hypothesis is

$$\mu_n = \begin{cases} \mu_0 & \text{if } n < r - 1 \\ \mu_1 & \text{if } n \geq r \end{cases}$$

This likelihood ratio test $\Lambda_n(r)$ is performed to estimate the jump time r by assuming knowing the two mean. The detection of jump time r is still a multiple hypotheses testing problem, as we need to find a maximum likelihood ratio among detection window $0 \leq r \leq n$. The detector determines when $\Lambda_n(r) = \max_{0 \leq r \leq n} S_r^n(\mu_0, \nu) > \lambda$, where λ is the set threshold. The μ_0 is known by calculating the recursive coefficients and μ_1 is unknown. The likelihood ratio test becomes a double maximization $\max_{0 \leq r \leq n} \max_{\nu} S_r^n(\mu_0, \nu) \gtrless_{H_0}^{H_1} \lambda$.

Luo et al. [23] developed a modified GLR tester to study important parameters for a reliable GLR detector. There are four parameters need to be trained for a given application:

1) the length of the pre-event averaging window;
2) the length of the detection window;
3) the threshold for the detection statistic;
4) the standard deviation of the power data.

Selection the parameters can follow a prior experience or expert knowledge, turning the parameters based on the trained data, or automatically adjusting the parameters online. The first two parameters varies to sampling rate and can be determined by specific application and training data, where the threshold and standard deviation might need to be adjusted online.

Setting equipment based non-zero minimum expected jump can reduce the false alarm, especially with low SNR. Resetting the detector after an event can avoid producing alarm continuously using sliding pre-event mean window before the window past the event. This may reduce extra work to determine exact jump time by purging the pre-event mean window when an alarm first occurs and refilling it with new data. The denoising techniques also impacts the GLR output. Almost all parameters are affected by the sampling rate, which means that applying single rate for GLR detector inevitably involves a conflict between sensitivity and robustness. Using GLR detector on different sample rate for same data might increase the accuracy of jump time detection.

B. Load Signatures

At each detected event, the load signatures need to be extracted for device classification and load disaggregation. When getting more understanding on the physical characteristics, many load signatures have been extracted. Sophisticated NILM system also considers scalability, such as the high event rate, load balance, and power factor correction happened in large commercial building. Building management system wants real-time monitoring proposes another challenge for NILM system.

A 2D signature space is set up representing the magnitude and sign in real and reactive power, which is called the P-Q plane. This process of detecting steady-state changes was studied for a commercial version in [24], which described a five-step process for load disaggregation through detecting the aggregated power changes. The limitation of using a 2D space are quite clear: lacking of capability to handle large number and variety of loads; the estimate accuracy is affected by the GLR detector highly and not reliable; and it is an off-line detecting and classifying system.

Spectral envelope estimator computes the real power $P_k(t) = \frac{1}{T}\int_{t-T}^{t} i_a(s)V\cos(k\frac{2\pi}{T}(s))ds$ and reactive power $Q_k(t) = \frac{1}{T}\int_{t-T}^{t} i_a(s)V\sin(k\frac{2\pi}{T}(s))ds$ with sampled voltage signal V and current signal i_a. The harmonic index k is a nonnegative integer and T is the period of the utility line cycle. Using the spectral envelop estimator as a load signature, especially during the transient event was firstly developed by Leeb et al. in [2], [3], [4]. Spectral envelops can loosely interpreted as the slowly varying envelops of real & reactive power and of harmonic content [3], which makes it feasible for not strictly periodic waveforms and a potential good signature. Moreover, Leeb et. al use segments with substantial variation of a start-up signal as signature, which are denoted as "v-sections" [2], [3], [4]. As the v-sections carry the characteristic shapes associated with the loads, the event detector will be able to identify the pattern of v-sections and the transients as long as each of the v-section shapes are not overlapped.

Many loads draw distorted, such as nonsinusoidal currents produced by office equipment (e.g., computers), or actively controlled industrial equipment (e.g., variable speed fans). This is due to their inherent physical characteristics or using power electronics. The introduced higher harmonics in the aggregate current signal can be used to distinguish loads. Let $k = 3, 5, 7, \ldots$ in $P_k(t)$ AND $Q_k(t)$, we can calculate the 3^{rd}, 5^{th}, and 7^{th} harmonics. The sample rate needs to be 8,000 Hz or higher to get current waveforms for higher harmonics [4], [12]. Commercial application confirms that there is information can be used for NILM up to 20^{th} harmonics [25]. Using a phase-locked short-time Fourier transform to calculate the harmonic contents was discussed in [8].

A V-I trajectories (normalized voltage and current) of a wide range of loads were developed and evaluated in [26]. Trajectories under start-up and steady-state conditions were found to be classified with eigenfunction decomposition or feature-based analysis. V-I trajectory was explored with shape features extraction on complex loads, including mixture of resistive, inductive loads and slightly nonlinear loads. Studying on V-I trajectories of modern intelligent devices was carried on [27], such as CD player, desktop PC, etc.

C. Load Recognition

Load signatures have been studied for NILM for a long time, while there is still no a single load signature can work for any device under any circumstance. The limitation of load signature requires more sophisticated classification algorithm to recognize loads in an accurate and robust way. Classification algorithms were studied for load recognition was first proposed by Hart [28]. In the early stage, most efforts focused on clustering the steady-state power, to separate different device as well to estimate the energy consumption. Clustering with L_2 distance classifier was used in [28], [29], [24], [30].

Machine learning and data mining algorithms were developed and applied in NILM lately. Neural network such as Multilayer Perceptron (MLP), Radial Basis Function network, Back Propagation, Learning Vector Quantization, and Support Vector Machines, were widely used [31], [32], [33], [34], [35]. Neural network approaches were also examined such as self-adapting artificial neural network [36], and fuzzy neural network with fuzzy sets [37]. Method from optimization view to solve the combination of current signals were also studied, using linear combination [38], and genetic algorithm [39]. Using Neural Network in combination with genetic programming and turn-on transient energy analysis was tried in [40].

Finite State Machine (FSM) model was proposed by Hart [28], where a dynamic programming with Viterbi algorithm was used to predict state transition. A probabilistic FSM was discussed [18]. Smart grid supported NILM uses clustering to disaggregate load, and applies genetic algorithm based FSM for a precise prediction on load consumption [41]. When transient event was successfully detected, vector based analyses using L_2 distance were applied a lot, including polynomial discrimination [2], match filter and transversal filter [4], projection to orthonomal basis [30], curve fitting with parameter estimate (L_1 distance) [42], spectral coefficients [43], linear combination on classifiers [44], dynamic time warping [35], and discriminative sparse coding [45].

Researchers who focus on developing novel load signature applied well developed classifier (K-Nearest Neighbor) and and obtained good results [20], [46]. Maximum Likelihood with Gaussian random vector was studied by Lee [30] firstly. Hidden Markov Model (HMM) and Factorial HMM were developed with load signatures for load prediction and disaggregation [47], [48], [49]. Study on the operational pattern as side information was found in [50], which monitor the continuous changes in the device mode of operation compressed along the time axis. The operational pattern increases the accuracy of load prediction but this model lacks of robustness. Voting methods were also studied to combine various load signatures and matching algorithms. A voting method called

Committee Decision Mechanism was applied with three approaches including Most Common Occurrence, Least Unified Residue, and Maximum Likelihood Estimation by Liang et al. [9], [10]. They studied classification algorithms includes least residue, integer programming, genetic algorithm, artificial neural network, where large variation between classifiers is required by the hybrid methods for a successful voting [10].

D. Fault Detection and Diagnosis Application

The detection and diagnosis of faults with NILM relies on the correlation of electrical power signal and exogenous variables with clear physical meaning such as as airflow or motor speed. Norford and Leeb [4] showed that a poorly tuned chiller controller could be seen in the electrical signal measured at the HVAC service entry. Learning either the electric power or the electromechanical dynamics during turn on of HVAC for diagnosis was discussed in [7]. Transient analysis for diagnosis was studied in [8] by exploring the relationship between the electrical transient and the physics of the load. Moreover, load consumption change (most increase) can be used for fault detection such as the failure of flexible couplings and the presence of leaks in cycling system [51]. Details in diagnostics with NILM will not be discussed further.

IV. NILM in Commercial Buildings

Commercial buildings occupy about 35% of total electricity consumption in the U.S., and it is expected to encounter an increase of 40% from 2010 to 2030 [52]. They also have around 40% impact on load shape and peak electricity [53]. It becomes necessary and important to understand and monitor the usage of electricity in commercial buildings either for building control system or smart power grid system.

A. Typical Challenges

Challenges on applying NILM in commercial building major lie in the scalability. Large number of device and type, high event density, and large dynamic power range are key issues. The equipment density in commercial buildings (office) is about 40 units/$1000ft^2$ [54], which means we may face 1000 miscellaneous equipments in a medium office. The turn-off rate is around 70% for about half of the total devices, major are the integrated computer systems, monitors, scanners, and printers [54]. It is not surprisingly to find high rate of simultaneously happened events, which introduces big ambiguity in event detection algorithm no matter how accurate the GLR detector is.

The load dynamics and signature variation make it very hard to find a robust recognition model for individual device. Power range varies from watts to thousand watts for a single device. The high dynamic power range reduces the signal resolution, and rises two competing parameters requiring application specific optimization [12]. This situation will be aggravated when SNR gets smaller. Moreover, noise introduced by individual device will aggregated in the master meter, which may overwhelms the power jump of small load device.

Due to the large demand of HVAC in the commercial buildings, various frequency devices are widely applied. Modern intelligent HVAC system involves many continuously various load device. All these bring big trouble for NILM to accurately track the varying load from the aggregated signal, especially when the behavior pattern is unknown. When the number gets larger, it is almost impossible to track individual load correctly. The color noise generated by the VSD is another problem for the signal process algorithms of NILM system.

Beside the challenges we discussed before, the high occurrence rate of faults, which is due to the large number of devices and high usage of loads, makes it hard for NILM to separate regular load recognition from anomaly detection. It is hard to tell the difference between slight irregular transient and normal variation for a same device, especially when the variation is large. Finally, different types of commercial buildings may have different electricity usage profile [55] and different challenges. For example, the lighting takes big percentage in office but there is almost no lighting in cinema. This indicates that an application-oriented solution for commercial buildings might be a feasible way for NILM application.

B. Perspective Solutions

All the problems discussed before can be grouped into two major challenges: reliable event detection and accurate load recognition. Generally the electrical system dynamics changes due to the continuous load or VFD, where the system dynamics includes power consumption and the harmonics and the noise level. The interaction of loads under same meter may change the system dynamics, and it will be worse with simultaneously happened events. It requires a enhanced GLR detector.

Let's consider detecting a change in a dynamic system: a process y_t having condition distribution in time t is $P(y_t \epsilon dy | y_{t-1}, \ldots, y_0) = p_\theta(y|y_{t-1}, \ldots, y_0)dy$, where θ represents an unknown parameter. When change happened in time t, the distribution of process change not only the mean (as we discussed in section III-A but also the variance). The prototype problem in state space becomes:

$$\begin{cases} X_{t+1} = FX_t + GU_t + V_{t+1} \\ Y_{t+1} = HX_t + JU_t + W_{t+1} \end{cases}$$

where U_t is the input, and (V, W) are noise. Then the process $y_t = (Y_t, U_t)$ and $\theta = (H, F, G, J, cov(V, M))$ can be used to describe the system.

Detecting the change of distribution parameter θ off-line can be done with GLR test with maximizing the likelihood of the data to the hypothesis H_1 (change happened). We need to be careful that the hypothesis H_1 is not reduced to a single distribution but a set of distributions, which requires local asymptotic analysis or large deviations asymptotic analysis [56], [57]. From the on-line point of view, the GLR detector need to do a double maximization on likelihood of new distributions and the jump time. It needs to minimize the detection delay based on a fixed false alarm rate [56]. Alan Willsky studied this problem from a purely state space system, using detection with the multiple filter structure and the residual-based structure [58].

Using adaptive noise cancelation to redue the noise level might be another feasible way to enhance GLR detector. Adaptive inverse system can help to model continuous loads. When looking into the meaning of "event", it reminds us that it is the result of state change of the device and can be defined as a known startup transient shape, or any suitable condition, such as a specific harmonics. Verifying the detected events by features can be another way for a reliable event detection.

Extracting more orthogonal "features" may increase the model discriminability on different classes of load, especially for simultaneously happened loads. To increase the model degree of freedom within a period is essential to ensure the possibility of complete load disaggregation. Higher harmonics (as up to 40^{th}) or projecting the signal to orthonomal bases (eigenvectors or wavelets) are feasible ways. Modeling the consecutive v-sections with a transition matrix, might enhance the recognition accuracy especially for the superimposed v-sections from different loads. Fusion methods can improve the system performance with finite load signatures.

Another perspective direction is blind source separation, such as independent component analysis, non-negative matrix factorization, or compressive sensing. Compressive sensing is to construct a underdetermined linear system of equations $Ax = b$, where it has large $||x||_0 =$ number of zeros of x, and matrix $A \in R^{m\times n}$ with $m < n$ [59], [60]. It requires no additional information on x, where we are interested in those x that have structure with many zeros. Typically x can be represented by sparse linear combinations of certain building blocks (e.g., a basis). The signal x can be recovered with no information loss. This suggests that the power signal b can be disaggregated with a sparse linear combinations.

Involving the continuous changes in the appliance mode of operation compressed along the time axis can help to distinguish same type of device running under different operational pattern. The operational behavior is relative constant in commercial building. The synergetic relationship that could exist between the building commissioning process and the training for NILM algorithms, which was studied in [61]. Taking advantage of the commissioning process to facilitate the NILM technology with individual electrical load profiles and equipment health indicators was discussed for residential building in [61]. From a practical view, adding sensors to detect events, or using sub-meter in HVAC system can significantly increase NILM performance and yield a commercial solution. Using acoustic and light sensor for event was studied for residential building [62]. Adding extra sensors to detect individual device ON/OFF for NILM was explored in [63].

V. Conclusion and Future Work

Monitoring electric loads using a nonintrusive way with low cost gets a lot attentions recently. It provides information in load disaggregation, state monitoring, and fault detection and diagnostics. Key challenges are event detection, signature extraction and recognition, transient detection, and load decomposition. NILM involves many technologies such as signal processing, machine learning, and statistical modeling. The results can be linked to a proper electrical, mechanical, or thermal model of the system, for energy usage optimization, electric load control, and fault diagnosis.

Successful models have been developed for residential building but there are still limitations when applying in commercial buildings. Simultaneously happened events, low SNR, color noise, and large system dynamics are major challenges in generating a robust and accurate NILM system in a complicated environment. The information of the power systems will be the key in meeting the challenges posed by the fledgling information society. This requires the integration of data-driven model with physics-based knowledge. Open problems such as state estimation of multi-stage load, continuously variable load tracking, real-time load processing, and new load identification require more effort in developing sophisticated NILM models.

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