<table>
<thead>
<tr>
<th><strong>Title</strong></th>
<th>An alternative use of power quality information - load signature studies &amp; applications</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Author(s)</strong></td>
<td>Cheng, JWM; Ng, SKK; Liang, J; Zhong, J</td>
</tr>
<tr>
<td><strong>Citation</strong></td>
<td>The IEEE 15th International Conference on Harmonics and Quality of Power (ICHQP 2012), Hong Kong, 17-20 June 2012. In Proceedings of the 15th ICHQP, 2012, p. 150-155</td>
</tr>
<tr>
<td><strong>Issued Date</strong></td>
<td>2012</td>
</tr>
<tr>
<td><strong>URL</strong></td>
<td><a href="http://hdl.handle.net/10722/153080">http://hdl.handle.net/10722/153080</a></td>
</tr>
<tr>
<td><strong>Rights</strong></td>
<td>International Conference on Harmonics and Quality of Power Proceedings. Copyright © IEEE.; ©2012 IEEE. Personal use of this material is permitted. However, permission to reprint/republish this material for advertising or promotional purposes or for creating new collective works for resale or redistribution to servers or lists, or to reuse any copyrighted component of this work in other works must be obtained from the IEEE.; This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.</td>
</tr>
</tbody>
</table>
Abstract— Electrical appliances have distinct consumption patterns of which can be interpreted as signatures and used for various applications. Based on traditional power quality monitoring techniques, coupled with optimization algorithms and innovative pattern recognition methods and stochastic simulation tools, we are going to demonstrate in this paper how we defined different load signatures systematically, structured a disaggregation framework to identify and track individual appliances, assembled different Monte-Carlo simulators for testing purposes and proposed some innovative applications such as smart metering and equipment health monitoring using different load signatures.

Index Terms—Load signature, smart metering, load disaggregation, power quality, equipment health monitoring, visualization tool.

I. INTRODUCTION

Traditionally, power quality monitoring is always focusing on finding how healthy the electricity service is, in terms of transient and steady state measures [1]-[6]. Voltage and current spikes [7], sags [1], surges/swells [2], unbalance and harmonic distortion [8]-[10] are some of the most notable attributes to describe the power quality of a system while serving its load entities under normal condition and/or subjected to disturbances. Over the years, knowledge and capabilities of monitoring and analyzing power quality attributes have matured and technologies such as sensors and disturbance analyzers are also made available to both electric utilities and industrial users. In the meantime, using the same electrical “signatures” to monitor individual equipment as means of health monitoring [11], fault detection [12]-[14] and usage tracking [15] are also emerging.

In fact, whether the aim is to monitor the behavior of a supply system or the load entities it is serving, the monitored variables are the same, i.e. voltage, current, power and their derivatives. For instance, starting a motor can cause a momentary dip in voltage and surge of the current waveform. Power quality monitoring sees it as a voltage dip that should be kept within some prescribed standards while load signature sees the inrush current wave-shape as a unique signature of the starting-torque and acceleration characteristic. Therefore, the knowledge of interpreting the “signatures” from both camps are interchangeable and of mutual benefits.

This paper is organized as follows. Section II defines the basic concept of load signatures. Based on a multi-feature and multi-algorithm approach, a load disaggregation framework is given in Section III. Section IV provides some Monte Carlo simulation methods designed for testing the performance of different load disaggregation methods and how to automatically construct a load signature database. Section V illustrates a load signature imaging to provide a multi-dimensional scope of visualizing load signatures simultaneously. Section VI presents some potential applications for load signatures such as for smart metering. Section VII discusses some challenges of load signature analysis and provides an insight for future work and finally the conclusion is in VIII.

II. LOAD SIGNATURE FORMS AND DISAGGREGATION ALGORITHMS

Load signatures (LS) are the unique consumption behavior of individual appliances and they can be used to disaggregate a composite load signal. We proposed in our previous papers [16], based on the sampling rate, load signatures can be classified into two levels, namely micro and macro level. The micro level is a detailed view of LS which requires the sampling interval shorter than 1 second (e.g. current waveform). On the contrary, macro level LS refers to data with a sampling interval of longer than 1 second. Traditional load signature studies and disaggregation research mainly focused on macro LS, e.g. real and reactive power (P-Q) [15], [17]. Fig. 1 illustrates the P-Q diagram we derived from an appliances database [16]. Since there may be a large portion of household appliances with similar P-Q characteristics and some appliances are difficult to be distinguished due to noise and feature fluctuation, more sophisticated means and methodology are needed.

One of the most common features using the transient shapes of real power was proposed for motor-driven appliances [18], [19]. Harmonics are generally considered as an additional feature and they can be derived from a fast Fourier transformation (FFT). Transient harmonics method was also proposed to detect specific appliances (e.g. multi-mode
appliances) [20]-[24]. Other researchers also used higher order harmonics in the steady-state signals [25], [26], wavelet transform [27], [28] and geometrical features of waveforms [29], [30].

Based on our research works [16], [31], we realized that it is quite challenging to identify individual appliance accurately by only one or two features, particularly if there is a huge amount of appliances and they may have similar features. Furthermore, the identification algorithms (e.g. generic algorithm [32] and integer programming [33]) and pattern recognition (e.g. artificial neural network [25]), could only consider a few features and its performance may vary depending on the feature(s) adopted.

To solve these problems, we developed a multi-feature multi-algorithm platform, in which seven kinds of features are considered whilst both optimization algorithm (Least Residue) and Pattern Recognition (ANN) were integrated to perform load disaggregation as shown in Fig. 2 [16].

The multi-feature approach could enhance the observability of the LS space by taking into account not only the transient and steady-state behaviors but also different features in different domains. These features include: Current Waveform (CW), Active/Reactive power (PQ), Harmonics (HAR), Instantaneous Admittance Waveform (IAW), Instantaneous Power Waveform (IPW), Eigenvalues (EIG) and Switching Transient Waveform (STW) [16].

Different identification/disaggregation algorithms using different feature finally generate a group of solutions / candidates. To consolidating all potential solutions in the pool, we further developed a Committee Decision Mechanism (CDM) to render the best solution [16]. In our study, three kinds of CDM criteria, i.e. Most Common Occurrence (MCO), Least Unified Residue (LUR) and Maximum Likelihood Estimation (MLE) were tested and compared [31].

III. LOAD DISAGGREGATION FRAMEWORK

Fig. 3 shows a framework for load identification and disaggregation. It consists of three functional blocks: 1) Event detection and feature extraction, 2) Load disaggregation and appliance on-off matching, and 3) Application. The disaggregation process is briefly reviewed as below:

1. Event Series: Consisting all the raw recordings of the appliance operation process.
2. Data Acquisition: Capturing the steady-state (at a fixed interval sampling rate) and transient load signals (based on trigger setting).
3. Data Processing: Filtering and normalizing the data.
4. Event Detection: Identifying and setting a triggering threshold to determine whether or not an appliance was switched.
5. Feature Extraction: Extracting multiple features from the detected events.
6. Load Disaggregation: Executing the disaggregation algorithm(s) to identify which appliances are operated.
7. On-off Events matching: Running another set of algorithms to adjust the previous disaggregation results and matching the on-off events based on individual appliance characteristics and minimizing the power mismatch residue.
8. Application: Using the disaggregation results (appliances on-off status) to provide different innovative energy services.

IV. STATISTICAL METHODS

A. Monte Carlo Simulations

Since it is infeasible to conduct thousands of actual trials to examine the load disaggregation capability, we have devised different simulators using Monte Carlo methods to test the disaggregation performance. Three different types of
probabilistic distribution functions for the switching events, namely 1) normally-distributed, 2) evenly-distributed and 3) behavioral-based, were constructed and then used to generate millions of random scenarios [31]. The normally-distributed simulator randomly toggles an appliance to its opposite operating state. The evenly-distributed simulator first randomly selects either an ‘on’ or ‘off’ state and then randomly switch an appropriate appliance according to the selected state. Both simulators treat all appliances indistinguishably. The behavioral-distributed simulator is a more sophisticated one that requires the classification of appliances into different types and the expected operating periods. Random switching is then performed to emulate the corresponding behavior. The number of simultaneously operating appliances as shown in Fig. 4 helps indicate one of the key characteristics of different random switching profiles [31]. The accuracy of the proposed disaggregation framework could achieve above 90% using these simulators as test case.

V. MULTI-FEATURE PROJECTION – LOAD SIGNATURE IMAGING

Load signatures process many features. Most often we look at the variations with respect to time, i.e., a number of time series. However, as described earlier, some of the features and characteristics are in different domains and/or the projection of one variable onto another sub-space, e.g., voltage-current, real and reactive power and frequency domain etc. It is difficult to see all these features in a 2-dimensional space simultaneously. As such, we devised and proposed a Load Signature Imaging (LSI) layout that can display a snapshot of many detectable features onto a 2-dimensional screen for examination as shown in Fig. 5 [35].

Within the same screen, we were able to show the 1-cycle waveforms of a typical household appliance – refrigerator. Of course, the merits of such a detailed analysis may not be justified for a typical household refrigerator. However, for an expensive HVAC compressor or mission-critical equipment, such a visualization tool for identifying the complex nature of the load signature may be justifiable.
VI. APPLICATIONS IN SMART METERING

Load signatures analysis can find many applications. An artist’s rendition of a futuristic energy billing layout is shown in Fig. 6. Once the equipment signature is identified, we can then track and compare its performance against its own historical data for trending and life-expectancy estimate. We can also sample different appliances in many flats and then compared the load signatures among them. For heaters, washing machines and air-conditioners, the disaggregation accuracy was quite promising from a trial we conducted as shown in Fig. 7 [36]. As such, the owner or user of the equipment can use such information to gauge the value of replacement, repair or let it run until its useful life.

Similar signatures among different appliances;
- Inactive appliances, e.g. stand-by units;
- Database assembly and updates;
- Disaggregation accuracy; and
- Accurate signature database assembly.

In essence, high-consumption (power hungry) equipment are easy to detect and track, e.g. water tanks, air-conditioners etc. Their disaggregation accuracy are 100% (>100 W). Similar appliances and resistive loads are more difficult to identify. The way to define disaggregation accuracy also needs to be well defined [16], [38]. In time, particularly with the deployment of more electronic smart meters and ever increasing connectivity and processing power, these technical challenges may be overcome. Perhaps the greatest challenge is the value and business opportunities derived from such an endeavor.

VIII. CONCLUSION

Power quality monitoring has always been focusing on examining what the supply system is performing. Various features under such an examination can in fact be used as signatures to reflect the operating and health conditions of the load entities. In our experiences with load signature studies, derived from the knowledge of power quality monitoring and assessment, it was found that load disaggregation is possible but the needs for high sampling rate and computing power are also inevitable. However, with the emerging trend of more smart meters and smart grid deployment around the world, it is foreseeable that the smart metering applications based on different load signature patterns will likely to expand.

IX. ACKNOWLEDGMENT

The authors would like to acknowledge the management of CLP Research Institute (CLP-RI) in supporting the initiative of the load signature research, particularly Dr. Gail E. Kendall (retired Managing Director of CLP-RI). We also like to express our gratitude to the initial work led by Prof. Felix F. Wu and Mr. W. K. Lee of the University of Hong Kong and continuous advices provided by Mr. C. C. Ngan of CLP-RI.
X. References


---

John W M Cheng (M’99) received the B.Eng. from the University of Saskatchewan, M.Eng. and Ph.D. from McGill University. He is currently the Manager of Technology Research & Deployment of CLP Holdings based in Hong Kong. His research interests include load signature studies, Monte Carlo simulations, renewable energy technologies and smart grid applications. He is a P.Eng registered in Ontario and a member of HKIE, CIIGRE and IERE.

Simon K. K. Ng received the B.Eng. (Hons.) and M.Phil. degrees in electrical engineering from The University of Hong Kong, Hong Kong, China, in 2005 and 2007, respectively. He is currently pursuing the Ph.D. degree of power systems in the same institution. He was a Modeling Specialist with the CLP Research Institute Ltd. from 2008 to 2009. His main research activities include load signature analysis and load modeling.

Jian Liang received the B.Eng. and M.Eng. degrees from Tsinghua University, Beijing, China and the Ph.D. degree from The Chinese University of Hong Kong. He is currently the Senior Associate in Group Operations – New Energy of CLP Holdings based in Hong Kong. His areas of interests include the technical and commercial research of new energy technologies. He
is a Chartered Scientist registered in UK and a member of the Energy Institute and China New Energy Chamber of Commerce.

**Jin Zhong** (M’05, SM’10) received the B.Sc. degree from Tsinghua University, Beijing, China, the M.Sc. degree from China Electric Power Research Institute, Beijing, and the Ph.D degree from Chalmers University of Technology, Gothenburg, Sweden, in 2003. At present, she is an Associate Professor in the Department of Electrical and Electronic Engineering of the University of Hong Kong. Her areas of interest are power system operation, electricity sector deregulation, ancillary service pricing, and smart grid.