A LEARNING APPROACH FOR IDENTIFICATION OF REFRIGERATOR LOAD FROM AGGREGATE LOAD SIGNAL

S. Guruprasad, M. Girish Chandra and P. Balamuralidhar

Innovation Labs., TATA Consultancy Services, Bangalore, India
{guruprasad.seshadri, m.gchandra, balamurali.p}@tcs.com

ABSTRACT

Estimation of appliance-specific power consumption from aggregate power signal is an important and challenging problem. The problem is also known as electrical load disaggregation. This paper addresses the problem of identification of refrigerator load, since refrigerators contribute to significant power consumption in domestic scenario. The key idea is to detect *events* corresponding to refrigerator, which are embedded in the aggregate power signal. Firstly, features based on amplitude and duration of events are identified by observation of refrigerator-specific power signal. Secondly, these features are extracted from the aggregate power signal. Thirdly, the extracted features are utilized in both supervised and unsupervised learning schemes to identify regions of activity of refrigerator. Performance of event detection demonstrates the potential of relevant features in both supervised and unsupervised learning frameworks.

***Index Terms*—** Load disaggregation, refrigerator, events, features, supervised, unsupervised, learning.

1. INTRODUCTION

An important goal of future smart grid is to achieve *active* demand-side energy management [1], i.e., to manage the electrical load required by domestic and industrial consumers. Consumption of electricity in households is a significant component of the overall consumption, and it is important for smart grids to exploit information about the distribution of electrical power consumption in households. An important question that needs to be answered is: What is the electrical power consumed by various electrical appliances in a household, and what is the variation of this power consumption over time? In this direction, non-intrusive load monitoring techniques, which provide disaggregated data for different appliances from the composite or aggregate power signal (obtained from smart meters), are emerging as an important component. Consumers can derive benefit from accurate disaggregation results, by obtaining information about the status and energy efficiency of appliances. There are other advantages of load disaggregation as well, from the perspective of end-users to utilities. The accuracy of load disaggregation depends on the number and type of appliances, their load characteristics, their manner of operation, and sampling rate and quantization of power signals. An early description of load disaggregation and a summary of approaches to address the problem was presented in [2]. Approaches based on analysis of active and reactive power [3], analysis of voltage-current trajectories [4], and analysis of harmonic and transient content [5] were proposed for disaggregation. Appliance characteristics are also captured using neural network models [6], and statistical models such as hidden Markov model [7]. A comprehensive summary of various load disaggregation approaches and the emerging trends are discussed in [8], [9] and [10].

Appliances such as refrigerators and cold storages have low power ratings, but tend to be operated over longer durations, leading to significant power consumption. In [11], it has been observed that the contribution of refrigerator to the total power consumption in domestic scenarios is as high as 30-40%. Motivated by this observation, we propose a method in this paper for separating refrigerator power signal from aggregate power signal, by extracting refrigerator-specific features. This is in contrast to the existing approaches which use a common feature set to distinguish between various appliances. The approach presented here uses active power signals at a low sampling rate, which alone are likely to be available for disaggregation rather than voltage and current waveforms at high sampling rates. Importantly, the approach is suitable for learning from labeled data in a supervised manner, and also for learning from unlabeled data in an unsupervised manner.

This paper is organized as follows: Section 2 describes the database used for experiments reported in this paper. The section also discusses the extraction of events and features for identification of refrigerator load. Approaches for learning from the features for classification are discussed in Sec. 3. Classification performance of different learning approaches is discussed in Sec. 4. Conclusions are given in Sec. 5.

2. FEATURES FOR DISAGGREGATING REFRIGERATOR LOAD

2.1. Data set for load disaggregation

The study reported in this paper is conducted using Reference Energy Disaggregation Data Set (REDD) [11]. The database consists of power signals collected from six households, over a period of one month. Power signals from five households are used in this study, since one of the households does not contain refrigerator. Power signals are available in two channels: (a) Plug power signal (PPS) which is collected from individual devices, and (b) meter power signal (MPS) which is the aggregate power signal. In this study, we use the plug power signal (PPS) corresponding to refrigerator. Note that PPS provides the ground truth/reference for the events corresponding to refrigerator. Thus, MPS consists of events due to multiple devices, while PPS consists of events only due to refrigerator. Signals sampled at 0.3 Hz are used in this study.

2.2. Signal preprocessing for event detection

Figure 1(a) shows a segment of plug power signal (PPS) collected from a refrigerator. The meter power signal (MPS) corresponding to the same duration is shown in Fig. 1(c). Similarity between MPS and PPS is observed in those regions where only the refrigerator is operational (along with some appliances which have low and constant

978-1-4799-3080-7/14/$31.00 ©2014 IEEE

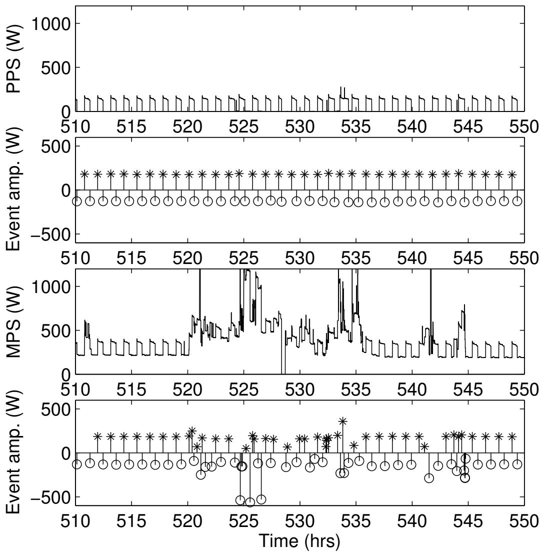

Fig. 1. (a) A segment of refrigerator plug power signal and (b) events detected from the segment. (c) Corresponding segment of meter power signal and (d) the detected events.

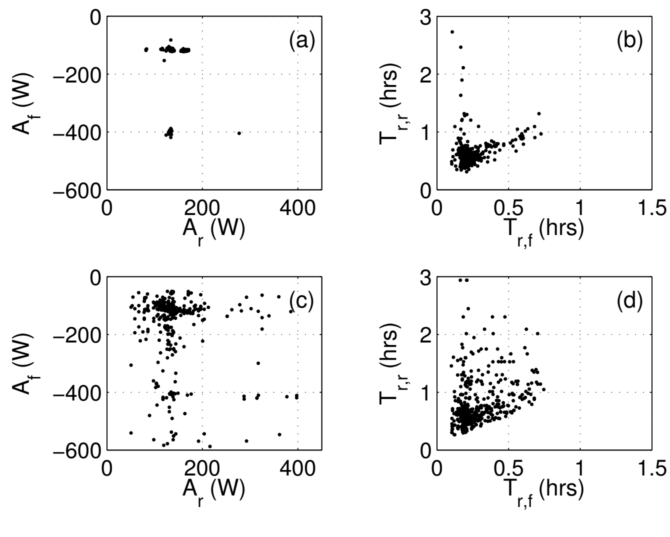

Fig. 2. Scatter plots of features derived from PPS and MPS: (a) Amplitude features and (b) duration features derived from PPS. (c) Amplitude features and (d) duration features derived from MPS.

power). An example of such a region is the time interval 510-520 hrs in Fig. 1. In those regions where high-power appliances are active (such as in the time interval 520-535 hrs), characteristics of refrigerator power signal are masked by those of the high-power appliances. From Figs. 1(a) and (c), we observe that both PPS and MPS are characterized by abrupt increase and decrease in the amplitude of power signal. We denote the abrupt increase and decrease in the amplitude as *events*, which can be classified as rise and fall corresponding to abrupt increase and decrease in the amplitude, respectively. Events are extracted from PPS and MPS as follows:

(a) A five-point median filtering is performed on power signal $s[n]$ to remove spikes and dips in the signal. The output signal is denoted by $x[n]$.

(b) A difference signal $y[n] = x[n] - x[n-N]$ is computed to capture the complete extent of transitions in $x[n]$, which are manifested over a duration of N samples, where N = 3.

(c) Transitions lying within an amplitude range are identified, so as to detect transitions exhibited by refrigerator.

Figures 1(b) and (d) show the events detected from segments of PPS and MPS, respectively. The events in Fig. 1(b) correspond to refrigerator alone, whereas the events in Fig. 1(d) consist of events due to refrigerator, and also of events due to other appliances. The objective is to automatically select the events corresponding to refrigerator, from the set of events detected from MPS. For this purpose, events are translated into features as described below.

Figures 1(a) and (b) indicate that the characteristics of refrigerator power signal can be described by amplitude and duration information. Let A_r denote the amplitude of a given rise event, and A_f denote the amplitude of the succeeding fall event. This information is used to construct the ordered pair (A_r, A_f). Duration information is represented by two features, namely, $T_{r,f}$ and $T_{r,r}$. Here, $T_{r,f}$ denotes the time interval between a rise event and the succeeding fall event, and $T_{r,r}$ denotes the time interval between two successive rise events. Thus, three events are required to construct the ordered pair $(T_{r,f}, T_{r,r})$. These events consist of one fall event occurring between two rise events.

The amplitude and duration features are representative of refrigerator characteristics, when they are constructed from the events extracted from PPS. However, the events extracted from MPS are not only due to refrigerator, but also due to other appliances. The events due to refrigerator are embedded among the events due to the other appliances. Hence, we consider different combinations of events detected from MPS, and construct the features from each combination of events in the following manner: For each rise event, three succeeding rise events and three succeeding fall events are identified. In such a case, the number of possible ordered pairs (A_r, A_f) lies between three and eight, and the number of possible ordered pairs $(T_{r,f}, T_{r,r})$ lies between zero and nine. Of these possible ordered pairs, only certain pairs are admissible due to the constraint that $T_{r,f} < T_{r,r}$. The objective now is to identify only those ordered pairs constructed from MPS, which represent the characteristics of refrigerator. Note that the time instants of occurrence of events is associated with the ordered pairs. Thus, given the ordered pairs (or feature points), this association can be used to locate the corresponding events. We now observe the manner in which the amplitude and duration features are reflected in PPS and MPS.

2.3. Manifestation of features in plug and meter data

Figures 2(a) and (b) show the scatter plot of amplitude features and duration features, respectively, extracted from PPS of refrigerator. The scatter plot of amplitude features (Fig. 2(a)) shows two prominent clusters. In most cycles, A_r and A_f have similar values (although $A_r > A_f$). There are some cycles where the rise in amplitude occurs in two steps (like a pedestal), while the fall is abrupt. This leads to a greater magnitude of the fall event, resulting in another cluster. The scatter plot of duration features (Fig. 2(b)) shows one prominent cluster, with variation in both $T_{r,r}$ and $T_{r,f}$. These variations in durations indicate that periodicity/regularity of refrigerator power signal is not a consistent feature. Hence, detection of periodicity in time domain or in spectral domain is not useful in this case.

Figures 2(c) and (d) show the scatter plot of amplitude features and duration features, respectively, extracted from MPS. A comparison of Fig. 2(a) and Fig. 2(c)) indicates that the scatter plot of MPS retains most of the feature points present in the scatter plot of PPS. Also, there are feature points extracted from MPS which are not present in the scatter plots obtained from PPS. This observation is valid for duration features also (Figs. 2(b) and (d)). This is because, the events extracted from MPS represent other appliances in addition to refrigerator. The task of identifying only those feature points from the MPS scatter plots, which correspond to refrigerator, is treated as a classification problem. We now describe approaches for learning from features derived from PPS and MPS.

3. LEARNING FROM FEATURES

In supervised learning scheme, a part of PPS data is used as training data. Here, features extracted from PPS data represent only refrigerator device. In unsupervised scheme, features extracted from MPS data are utilized. In this case, features are influenced by multiple devices. For classification, features extracted from MPS data are used as test data. The ground truth/reference for measuring the performance of classification is derived from PPS data.

3.1. Supervised learning

In this case, features are extracted from PPS, and probability density function (PDF) of the extracted features is modelled as a mixture of Gaussian PDFs. Parameters of the Gaussian PDFs are estimated separately for amplitude and duration features. The number N_c of mixtures is chosen by observing the number of prominent clusters in the features. For amplitude features, $N_c = 2$, while for duration features, $N_c = 1$. Values of mean and variance corresponding to the mixtures are estimated using expectation-maximization algorithm [12]. The mean and variance values are used during the classification stage.

3.2. Unsupervised learning with partial prior knowledge

Electrical characteristics of refrigerators tend to remain similar across most households. However, difference in power ratings can result in a change in values of the extracted features. This results in a change in cluster centers of feature vectors, although the number of prominent clusters remains the same. In such a case, parameters extracted from training data are not capable of generalization over test data. This situation is addressed by using the following prior information from PPS data: (a) Number (N_c) of clusters and (b) bounds on the values of features. Features are extracted from MPS data, and the PDF of features is modelled as a mixture of $N_c + 2$ Gaussian PDFs. The additional two Gaussian PDFs are employed to model the distribution of spurious feature vectors, which are due to devices other than refrigerator. Also, two clusters are merged if the distance between their mean values is lesser than a threshold. This threshold is obtained from the bounds on the values of features. The bounds are also used to hypothesize and eliminate outliers in the features. Of the possible $N_c + 2$ PDFs, parameters corresponding to N_c *prominent* PDFs are retained and used in the classification stage. Here, prominent PDFs are identified on the basis of likelihood of feature points being generated by those PDFs.

3.3. Fully unsupervised case

In this case, no prior information about the number of clusters or bounds on the values of features is available. Events are detected from MPS data according to the steps given in Sec. 2.2. No features are extracted, and all the detected events are hypothesized as refrigerator-specific events. The goal is to observe the effect of events due to devices other than refrigerator.

4. EXPERIMENTS AND RESULTS

4.1. Classification of MPS features

Features obtained from MPS data are grouped into two classes, namely C_1 and C_2. The class C_1 consists of features that are hypothesized to represent refrigerator, and C_2 consists of features that are hypothesized as not representing refrigerator. Features that satisfy the following condition are assigned to C_1: $(\mu_{i,j} - K\sigma_{i,j}) \leq x \leq (\mu_{i,j} + K\sigma_{i,j})$, $i = 1, ..., N_c$, $j = 1, ..., d$, where d denotes the dimension of feature vectors, and x denotes the value of feature along j^{th} dimension. The parameters $\mu_{i,j}$ and $\sigma_{i,j}$ represent the i^{th} PDF and the j^{th} dimension of feature vector. Here, $d = 2$, and the value of K is chosen as 3, so as to retain the same feature regions in the MPS data as those in the PPS data. Classification is performed for two cases: (a) When the parameters $\mu_{i,j}$ and $\sigma_{i,j}$ are obtained from PPS data using supervised learning (Sec. 3.1), and (b) when the parameters are obtained from MPS data using unsupervised learning (Sec. 3.2). After classification of features of MPS data, the features assigned to class C_1 are used to locate the associated events. If a feature is correctly assigned to C_1, then the associated events in MPS data are true refrigerator-specific events. Thus the performance of classification of features can be measured in terms of the number of refrigerator-specific events correctly detected from MPS data. In the fully unsupervised case (Sec. 3.3), all the detected events are hypothesized as refrigerator-specific events.

The rise and fall events corresponding to refrigerator are marked from PPS, and these events are denoted as reference events. Events from MPS hypothesized as refrigerator-specific events are compared to the reference events. An event hypothesized from MPS is considered as a correctly detected event, if its deviation from a reference event is less than one minute. Let

$N_1 =$ number of reference events, detected from PPS,
$N_2 =$ total number of events hypothesized from MPS, and
$N_3 =$ number of correctly detected refrigerator-specific events from MPS.

Precision (P) and recall (R) are given by $P = \frac{N_3}{N_2}$, and $R = \frac{N_3}{N_1}$. Higher the value of P, smaller is the number of false positives. Higher the value of R, smaller is the number of missed detections.

4.2. Discussion

Figure 3 shows the performance of the three approaches discussed in Sec. 3 for the task of event detection, in terms of precision and recall measures. In this figure, S denotes the supervised learning approach (Sec. 3.1), UP denotes the unsupervised learning approach with partial prior knowledge (Sec. 3.2), and U denotes the fully unsupervised learning approach (Sec. 3.3). From Figs. 3(a) and (c), it is observed that the supervised approach has the best precision (97% and 91% for amplitude and duration features, respectively) for both amplitude and duration features. The fully unsupervised approach has the best recall (least missed detections) among the three approaches (Figs. 3(b) and (d)). This is because the events are hypothesized without imposing constraints on features, resulting in lesser number

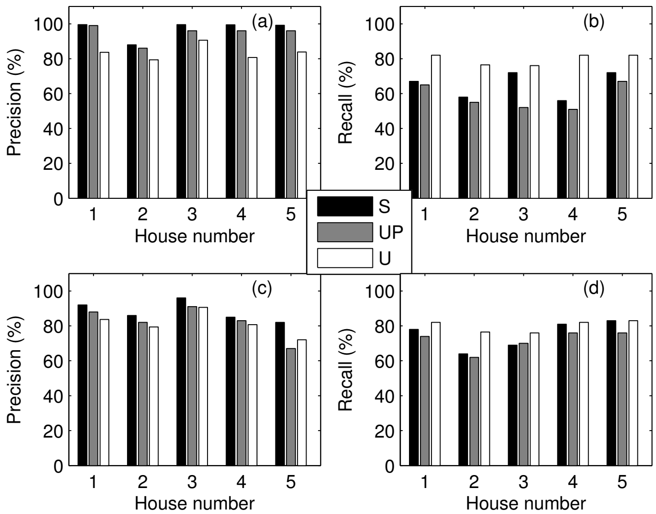

Fig. 3. Performance of event detection. (a) Precision and (b) recall obtained from amplitude features. (c) Precision and (d) recall obtained from duration features. Legend: S - supervised, UP - unsupervised with partial prior knowledge, and U - fully unsupervised.

of missed events. However, the fully unsupervised approach also has least precision for both features, indicating greater rate of false acceptance (Figs. 3(a) and (c)). The precision of the unsupervised learning approach with partial prior knowledge (95% and 86% for amplitude and duration features, respectively) is close to that of the supervised approach, and better than that of the fully unsupervised approach (84% and 83% for amplitude and duration features, respectively). Precision is more important than recall in the context of load disaggregation, since, high precision can help identify refrigerator-only regions accurately. The missed out events are likely to be in the regions where refrigerator signal faces interference from signals due to other devices. Once the refrigerator-only regions are identified with high precision (low false acceptance), events in those regions can be used to reconstruct the refrigerator power signal, and also estimate the power consumption of refrigerator in those regions.

5. CONCLUSION

This paper presents an approach for disaggregation of refrigerator power signal from the aggregate power signal. The approach is based on extraction of amplitude and duration features specific to refrigerator. Approaches based on supervised and unsupervised learning are proposed, for classification of features derived from aggregate load data. The unsupervised learning approach (with partial prior knowledge) is particularly suited to the situation where electrical characteristics of appliances within a given category are similar, but feature values tend to vary. This approach has low incidence of false acceptance, resulting in reliable identification of refrigerator-only regions. The events in refrigerator-only regions can be used to estimate the power consumption of refrigerator in those regions, and to estimate power consumption in other regions also. The method has a formal basis, and is scalable to a larger number of households. The framework presented is valid for other appliances also, particularly if the appliance characteristics can be expressed in terms of events and suitable features.

6. REFERENCES

[1] Saima Aman, Yogesh Simmhan, and Victor K. Prasanna, "Energy management systems: State of the art and emerging trends," *IEEE Communications Magazine*, vol. 51, no. 1, pp. 114–119, Jan. 2013.

[2] G. W. Hart, "Nonintrusive appliance load monitoring," *Proc. IEEE*, vol. 80, no. 12, pp. 1870–1891, Dec. 1992.

[3] F. Sultanem, "Using appliances signatures for monitoring residential loads at meter panel level," *IEEE Trans. Power Del.*, vol. 6, no. 4, pp. 1380–1385, Oct. 1991.

[4] H. Y. Lam, G. S. K. Fung, and W. K. Lee, "A novel method to construct taxonomy of electrical appliances based on load signatures," *IEEE Trans. Consum. Electron.*, vol. 53, no. 2, pp. 653–660, May 2007.

[5] C. Laughman, K. Lee, R. Cox, S. Shaw, S. Leeb, L. Norford, and P. Armstrong, "Power signature analysis," *IEEE Power Energy Mag.*, vol. 1, no. 2, pp. 56–63, Apr. 2003.

[6] D. Srinivasan, W. S. Ng, and A. C. Liew, "Neural-network-based signature recognition for harmonic source identification," *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 398–405, Jan. 2006.

[7] H. Kim, M. Marwah, M. Arlitt, G. Lyon, and J. Han, "Unsupervised disaggregation of low frequency power measurements," in *Proc. SIAM Conference on Data Mining*, Mesa, AZ, USA, Apr. 2011.

[8] Jian Liang, Simon K. K. Ng, Gail Kendall, and John W. M. Cheng, "Load Signature Study-Part I: Basic Concept, Structure, and Methodology," *IEEE Trans. Power Del.*, vol. 25, no. 2, pp. 551–560, Apr. 2010.

[9] Jian Liang, Simon K. K. Ng, Gail Kendall, and John W. M. Cheng, "Load Signature Study-Part II: Disaggregation Framework, Simulation, and Applications," *IEEE Trans. Power Del.*, vol. 25, no. 2, pp. 561–569, Apr. 2010.

[10] Saima Aman, Yogesh Simmhan, and Viktor K. Prasanna, "Energy management systems: state of the art and emerging trends," *IEEE Communications Magazine*, vol. 51, no. 1, pp. 114–119, 2013.

[11] J. Zico Kolter and Matthew J. Johnson, "REDD: A public data set for energy disaggregation research," in *Proc. SustKDD Workshop on Data Mining Applications in Sustainability*, San Diego, CA, USA, Aug. 2011.

[12] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *J. Royal Statistical Soc., Ser. B*, vol. 39, no. 1, pp. 1–38, 1977.