Downloaded from http://iran-paper.ir
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid

Towards Non-Intrusive Load Monitoring via Multi-Label Classification

Seyed Mostafa Tabatabaei, Scott Dick, *Member, IEEE*, and Wilsun Xu, *Fellow, IEEE*

***Abstract*-- Demand-side management technology is a key element of the proposed Smart Grid, which will help utilities make more efficient use of their generation assets by reducing consumers' energy demand during peak load periods. However, while some modern appliances can respond to price signals from the utility companies, there is a vast stock of older appliances which cannot. For such appliances, utilities must infer what appliances are operating in a home, given only the power signals on the main feeder to the home (i.e. the home's power consumption must be disaggregated into individual appliances).**

We report on an in-depth investigation of multi-label classification algorithms for disaggregating appliances in a power signal. A systematic review of this research topic shows that this class of algorithms has received little attention in the literature, even though it is arguably a more natural fit to the disaggregation problem than the traditional single-label classifiers used to date. We examine a multi-label meta-classification framework (RA*k*EL), and a bespoke multi-label classification algorithm (ML*k*NN), employing both time-domain and wavelet-domain feature sets. We test these classifiers on two real houses from the Reference Energy Disaggregation Dataset. We found that the multi-label algorithms are effective, and competitive with published results on the datasets.

***Index Terms*—Smart grids, Non-intrusive load monitoring, Machine learning, Blind source separation, Multi-label classifiers**

I. Introduction

RESIDENTIAL customers consume approximately 32% of the total electrical energy produced in Canada [199], and 37% of total production in the United States (the latter is roughly 1.4 *billion* kWh per year) [198]. Thus, residential users must be part of any effort to rein in the growth of power consumption in North America. Numerous authors have suggested that sending a price signal to consumers (via time-of-use or demand pricing, etc.) would be an effective mechanism. However, the current power metering and billing infrastructure (a monthly aggregate bill) is simply inadequate for this task. What is needed is the time-of-use cost of operating the individual appliances in a home. Such detailed feedback would allow the consumer to plan their energy usage in order to reduce their monthly bill, while not suffering an unacceptable disruption to their daily lives. The literature indicates that such feedback can lead to a 10-15 percent saving in energy costs [50], or a savings of about $1.6 billion each year in the Canadian economy. (The *provision* of effective, easy-to-use tools supporting a behavior is known to promote the *adoption* of that behavior [87]). From the utilities' side, meanwhile, formulating demand side management and demand response strategies such as changing the time-of use price schedule or load shedding requires detailed information about the mix of appliances in operation [30]. Load component details are used for both short-term and long-term load prediction, and help to determine when conventional and renewable generation asserts must be added to the power grid [118].

While some modern appliances are equipped to communicate with utilities, older ones have no such capabilities. Thus, the electricity consumption for an appliance must be inferred by monitoring the appliance's power consumption over time. The simplest approach to this monitoring – placing a sensor on the appliance circuit – is an expensive and invasive process, which is unlikely to achieve widespread adoption in North America due to privacy concerns. The alternative is for a utility to disaggregate the electricity load for a home into the individual appliance loads. This well-known problem is referred to as Non-Intrusive Load Monitoring (NILM). Current approaches to NILM require either a database of appliance power signals that a load will be matched against, or training an inductive algorithm to disaggregate the appliances. We have conducted a systematic review of the NILM literature, in order to determine what inductive algorithms have been employed for this problem, and categorize them according to their theoretical foundations and the feature sets they employ. A key finding of this review is that the family of *multi-label* classification algorithms has only ever been applied to NILM by a single research group in the last few years. This in spite of the fact that their fundamental characteristic (predicting a vector of categorical variables instead of a single class) is on its face a better fit to the NILM problem than single-label classifiers. The goal of this paper is thus to explore this new approach to NILM.

We will conduct an extensive experimental investigation of multi-label NILM approaches. The fact that multi-label classifiers have only recently been applied to NILM implies that a number of familiar questions from inductive are once again laid open. The relative merits of supervised versus unsupervised learning (plus the possibility of *semi*-supervised

This work was supported in part by the Natural Sciences and Engineering Research Council of Canada under grant no. RGPIN 262151 and an NSERC Industrial Research Chair.

M. Tabatabaei, S. Dick, and W. Xu are with the Department of Electrical and Computer Engineering, University of Alberta, Edmonton, AB, T6G 1H9 (emails: tabatabaei@ualberta.ca, dick@ece.ualberta.ca, wxu@ualberta.ca).

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid

learning); the feature sets to be employed; the performance measures used to compare different algorithms; all of these questions have previously been investigated for single-label classifiers as applied to NILM. However, they have not been examined in depth for multi-label NILM approaches, and our work is intended to help fill this void. Plainly, we cannot investigate every open question in this paper, and so we focus on comparing two major multi-label approaches to supervised learning. We compare their performance on time-domain and wavelet-domain feature sets, drawn from two real houses from the Reference Energy Disaggregation Dataset (REDD) [125]. We provide performance comparisons against the literature using both specialized NILM metrics (in particular the energy error), and general metrics for multi-label classification (especially the micro-averaging and macro-averaging of the familiar F-measure).

Our contributions in this article are, firstly, a systematic review of the NILM field, from which we build a taxonomy of NILM techniques. Our second contribution is a detailed evaluation of multi-label classifiers, trained in both the time and wavelet feature domains, on the benchmark REDD dataset.

The remainder of this paper is organized as follows. In Section 2, we review related work and essential background on NILM, multi-label classification, time series analysis and wavelet analysis. We discuss our experimental methodology in Section 3, and present our experimental results in Section 4. We offer a summary and discussion of future work in Section 5.

II. Related Work

The technique of non-intrusive load monitoring was first developed by G. Hart at MIT in the 1980s [100]. In this work, appliance signatures were the height of rising and falling edges in the power waveform. Home appliances were divided into three groups of signatures [100]: single state, multi-state, and continuously varying appliances. Fig. 1 depicts examples of each group [157]. Hart proposed both a supervised classification method, as well as a clustering method in the P-Q plane (a plot of active versus reactive power) to identify appliances.

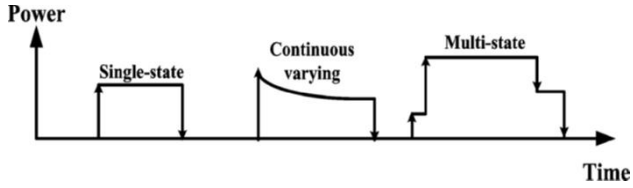

Fig. 1. Different type of appliances [157]

. After Hart's seminal paper, numerous investigations have attempted to improve upon his results, and NILM is now accepted as an important facet of Smart Grid technology. The main differences between published NILM methods are the models and features that they have used for appliance identification. Classification methods such as support vector machines (SVM), *k*-nearest neighbor (*k*-NN), and clustering methods such as *k*-means are commonly applied models in NILM. Active power, reactive power, current and voltage transients and harmonics, duty cycles, and/or combinations thereof are commonly used as features.

A. A Systematic Review of NILM Research

Our objective in reviewing the NILM field is, in general, to identify what avenues in inductive NILM have not been thoroughly investigated. Plainly, this meant that we needed a comprehensive overview of the field, telling us what *has* been done, so that we can infer what has *not*. Systematic reviews [123] are a well-known and respected framework for assembling such an overview. Our research questions for the review are: *Q1: What inductive learning algorithms have been applied to NILM? Q2: What feature sets were employed to develop those classifiers?*

We identified candidate primary research reports from the papers citing Hart's seminal work [100], according to the Google Scholar citation database. We selected this database for its superior coverage; as of March 2016, Google Scholar identifies 954 citations for this paper, while Bing Academic finds 309, and Scopus 554. Our inclusion criterion for these reports were that the paper must propose an inductive learning approach for NILM, and must evaluate it on residential power consumption data. We exclude approaches requiring additional sensors beyond the main power circuit, as the point of non-intrusive monitoring is to avoid burdening the consumer with installing additional sensors in their household. We also exclude studies focused on commercial buildings, as their power consumption characteristics tend to be very different from residential buildings, and thus findings from either class of buildings cannot be assumed to transfer to the other [17]. Finally, we exclude reports whose primary objective is activity identification or privacy preservation rather than appliance identification, as these are not congruent to our objectives in this paper. Since publicly-available benchmark datasets for NILM have only been available in the roughly the last five years, we do not exclude reports that focus on simulated or confidential data. Each candidate report was manually reviewed, and categorized according to our two research questions. From this categorization, we have synthesized taxonomies of algorithms and feature sets in the NILM field.

B. Inductive Learning Algorithms for NILM

We first examine research question Q1, identifying inductive methods used for NILM. Learning algorithms are either supervised or unsupervised. Supervised learning methods require a ground truth of input and output data for each class label to build a prediction model for new unknown data. Thus, supervised NILM methods require labelled instances of each appliance to train the algorithm. This ground truth is collected by recording appliance features with the help of the customer [157] or installing extra sub-meters inside the home [124]. We can further group these algorithms into parametric and non-parametric models. A parametric model assumes that the data has a type of probability distribution with

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid
Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

a finite number of parameters [49, 114, 128, 133, 164], and "fitting" the model consists of determining the parameter values for which the model best matches the training data. Non-parametric models, on the other hand, do not assume a probability distribution a priori; the model is instead induced from the data. Non-parametric models include k-nearest neighbor (k-NN) [18, 20, 21, 32, 78, 83, 86, 98, 179-181, 218, 221], neural networks [23, 34-38, 40, 41, 141, 178, 187, 188, 193, 195, 202]. Deep neural networks are examined in [119, 152]. Support vector machines have been used quite frequently [61, 62, 90, 104, 108-112, 129, 136, 139, 158, 170, 194, 237]. Some researchers have attempted to inductively build a signature database and then match the power signal to it (we view these proposals as distinct from simply querying a predefined signature database) [8, 16, 25, 29, 45, 48, 56, 132, 150, 154, 174, 203, 219]. Decision trees are explored in [22, 77, 93, 147, 163], and hierarchical Bayesian models in [191]. Graph signal processing is employed in [200]. Supervised self-organizing maps are examined in [58, 59, 103], and nonparametric optimization techniques are explored in [10, 79, 80, 137]. Multi-label classification approaches are studied in [12-15] (these will be discussed in-depth in Section II.B).

Combinations of multiple classifiers are often superior to individual ones. NILM researchers have investigated boosted decision trees [6], bagging ensembles of support vector machines and KNN classifiers [126], random forests [126, 155], and a majority-voter meta-classifier using Naives Bayes and KNN base classifiers [145].

Combinatorial search is also a key approach. In addition to deterministic approaches such as integer and regularized linear programming [44, 115], derivative-free search strategies such as ant colony optimization [140], genetic algorithms [66, 68, 213], and differential evolution [101] are employed.

A number of papers compare a multiple learning algorithms when some other aspect of the NILM problem is being manipulated. [151] compares the performance of Naïve Bayes, SMO regression, Br-Trees and MLP when appliance categories are merged into larger groups. [102] compares neural networks, evolutionary neural networks, SVM, and AdaBoost over decision stumps when using shape features of the V-I trajectory as NILM features. [186] investigate how two NILM systems (KNN and Gaussian mixture models) deal with generalizing to appliances that did not appear in the training set (i.e. a covariate shift). [211] explores the Instantaneous- & Memory- Proportional Fit, Gaussian, and Minimum-Mean Squares algorithms along with Markov chains, with or without side information (features beyond just the power signal). [57] explores the use of supervised self-organizing maps, Bayesian inference, support vector machines and finite-state machines trained on shape features of the V-I trajectory. [67] focus on metaheuristics, testing evolutionary algorithms, differential evolution, particle swarm optimization, simulated annealing, cuckoo search, and firefly optimization for NILM. [4] explore the use of powerlets versus an HMM for NILM with extremely low-frequency sampling (one sample per 15-minute interval).

Time series classification algorithms for NILM can be further categorized into three groups: distance-based classification, feature-based classification, and model-based classification. Distance and feature-based classification both work with the actual time series data [122, 204, 228]. Feature based methods such as [157] split the signal into small sequences or windows and then extract features to classify each sequence, while distance based methods use raw sequences directly [71]. Model based methods, on the other hand, convert time-series data into statistical and probabilistic models such as Hidden and Semi- Markov Models, and then identify appliance signature from those models. Symbolic Aggregate approXimation is a related technique in which subsequences of a time series are converted to symbols, and a probabilistic model of the symbols is built [134] Furthermore, within all three groups, there are two possible approaches for developing a classification algorithm. The first approach is to design a whole new algorithm that works with a raw time series, usually by creating a new distance measure for sequential data. The other approach is to design a transformation that turns sequential data into a set of independent feature vectors (e.g. lagged inputs). These feature vectors can then be passed to any standard machine-learning algorithm.

Conventional classification algorithms that work with sequential data usually require a distance metric between two sequences. The selection of a distance (similarity) measure plays a significant role in the quality of the classification algorithm [226]. Euclidean distance is a widely adopted measurement; it requires the two series in comparison to be of equal length [120, 183]. In additions it is sensitive to distortions in time. Distortion in the time axis is common in applications such as speech recognition where speech rates are not constant [189]. Similar problems have been noted in applications such as web logs and biomedical data [33]. Some researchers have tried to overcome the time distortion by pre-processing the acquired signal, however such approaches are not practical in most cases [161]. Thus, elastic similarity measures such as Dynamic Time Warping (DTW) have been employed. [183] describes DTW as a non-linear mapping between two sequences that minimizes the distance between them relative to a cost matrix; it is essentially a relative of the Levenshtein distance for strings. Unlike a Levenshtein distance, however, the cost matrix defines a cost associated with matching one point of the first sequence with one of the second, rather than a fixed cost per *operation*. Although many researchers [1, 9] agree that DTW solves many of the problems of the Euclidean distance, its computational inefficiency limits its adoption [184]. DTW is calculated using dynamic programming, hence has a quadratic time complexity ($O(n*m)$, where n and m are the lengths of the time series). An NILM technique based on Dynamic Time Warping (DTW) is proposed in [69, 127].

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid
Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

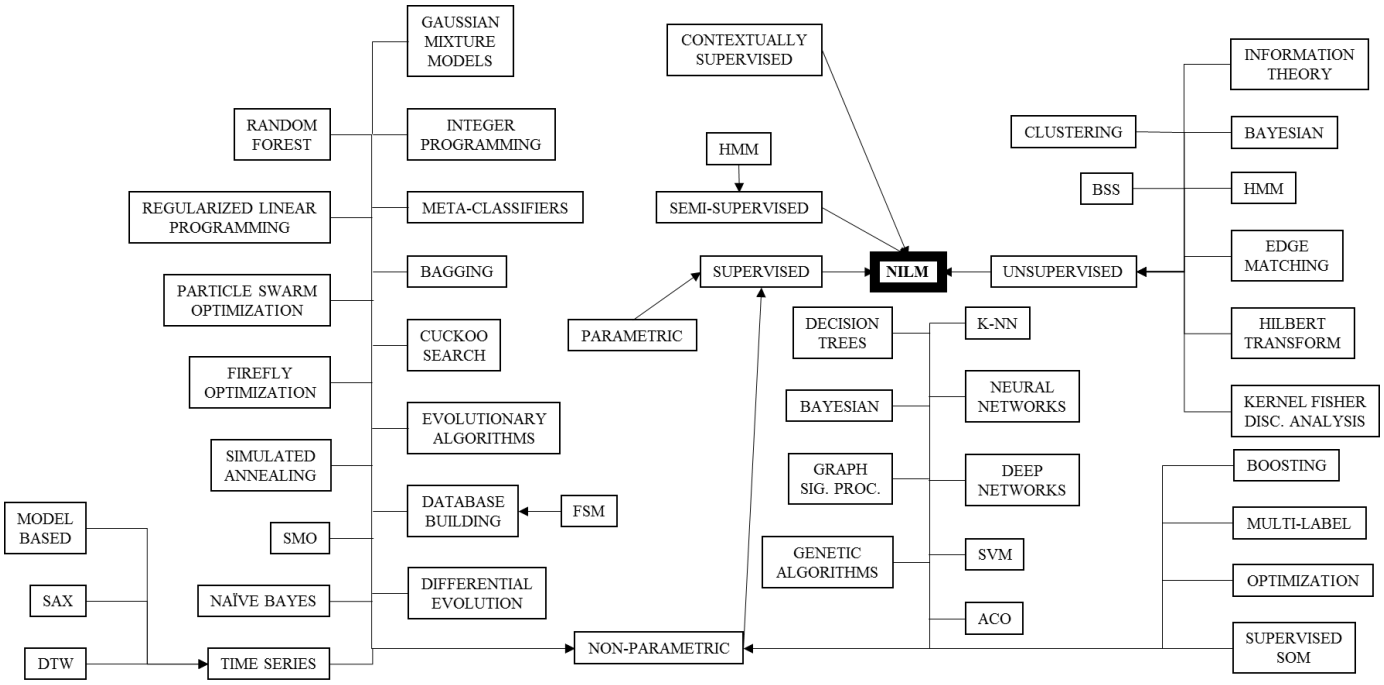

Fig. 2. A semantic network of inductive learning methods for NILM

In contrast, unsupervised learning algorithms discover regularities in measured data, and group data points based on their common properties (proximity in feature space). The main benefit of unsupervised methods is that they do not need a ground truth for training; however, the accuracy of unsupervised methods is generally less than supervised methods. In some investigations, clustering has been used to extract appliance features to build a database of appliances for classification purpose [7, 11, 46, 51, 53, 55, 84, 94, 106, 107, 142, 162, 196]. Clusters were associated with finite state machine models in [217]. Alternatively, clustering has sometimes been used been used to detect groups of similar appliances instead of a single appliance [130]. Statistical methods such as Hidden Markov models [97, 113, 121, 124, 166, 168, 229] [2, 63-65, 81, 97, 116, 121, 131, 144, 148, 159, 165, 167, 169, 173, 185, 190, 224, 233, 236] or Bayesian inference [149, 197, 223, 232]. Rising and falling edges are paired in [95, 210], while the Hilbert transform is used for the same purpose in [91]. Likewise, formulations treating NILM as a blind source separation problem or one of its relatives [82, 206-208, 227] also employ unsupervised learning, as does the information-theoretic analysis in [175] and kernel Fisher discriminant analysis technique in [222].

In real-world deployment scenarios, we expect that ground-truth data will be difficult to come by. Unsupervised learning methods are plainly appropriate for this situation, but it would be desireable to take advantage of the often-greater accuracy of supervised learning. A middle ground between the two exists; *semi*-supervised learning refers to using a small amount of labeled observations to improve the classification of a much larger unlabeled dataset. This idea has been explored for Hidden Markov Models in [19, 135]. Another alternative, *contextual* supervision, uses no actual labels, but associates the unlabeled data wide side-channel information known to be correlated with the actual labels [225]. Our findings for Q1 are presented in Figure 2, a semantic network of the inductive learning approach to NILM in the literature. The directed arrows indicate an "IS-A" (inheritance) relationship between concepts.

C. Feature Sets for NILM

We now examine our results for research question Q2. In our review of inductive NILM methods, we found that a wide variety of features have been evaluated as independent variables for them. First and most obvious are the time series of the actual power measurements; current and voltage, apparent power, active and reactive power, the power phase angle and power factor, have all been employed in NILM, including both steady-state and transient signals. Apparent power (directly measured, or computed from measured current and voltage) is perhaps the single most common feature in NILM research, being used exclusively in [22, 45, 46, 48, 63-69, 71, 75, 80, 81, 88, 91, 95, 97, 115, 116, 128, 131, 132, 142, 144, 152, 159, 165, 167, 169, 173, 175, 181, 190, 191, 197, 200, 211, 224, 231-233]. Edge (event) detection is a common intermediate processing stage for these approaches (e.g. [24, 157]), as well as for papers employing active & reactive power signatures [11, 23, 38, 62, 106, 119, 163, 180, 223]. [156] is one example of a deterministic event-detection scheme, as is [55]. A number of papers fuse the various time series together in different ways; some simply accept the various time series [7, 77, 79, 82, 126, 148, 149, 218, 220, 227], some extract chosen statistical moments [12, 104, 145, 236], some apply time-domain transformations [8, 16, 35, 51, 158, 179, 185, 186, 210].

Beyond the time domain, a number of transforms have been applied to the time series of power readings. Fourier analysis (frequently of the current waveform, but also of other data

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

streams) seems to be the most common, used on its own or in combination with some of the time domain features above [31, 37, 44, 58, 59, 61, 103, 136, 147, 154, 174, 177, 193, 213, 217, 222]. Multiple frequency bands are summarized using information entropy in [26, 27].

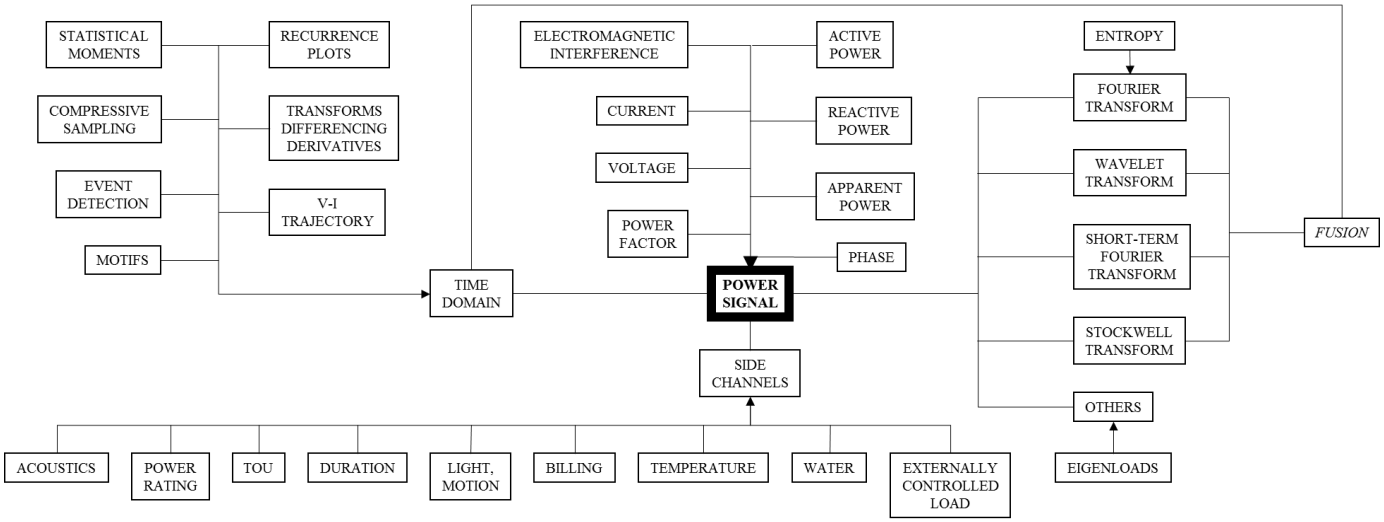

Fig. 3. A semantic network of feature sets used in NILM

Discrete wavelet transforms of the power measurements are also frequently employed, as in [6, 34, 36, 42, 76, 93, 194, 202] [39] The signal is differenced before the DWT is applied in [5]. However, the high frequency transient features extracted from the wavelet transform are not constant across different duty cycles of the same appliance (i.e. they change on each usage of the appliance) so learning algorithms using the raw wavelet coefficients tend not to generalize well.

An oft-cited advantage of wavelet transforms is that they preserve temporal locality in the signal, while the Fourier transform does not. A variation called the short-time Fourier transform attempts to remedy this deficiency; it has been used for NILM in [107-111]. Other complex-valued transforms also attempt time and frequency localization, such as the Stockwell transform [25, 112, 140] and others [53]Combinations of selected transforms are used in [138, 151, 155, 160].

One more feature set cropped up repeatedly: the V-I trajectory is a plot of the instantaneous current and voltage (as an ordered pair) in the current-voltage plane. The time evolution of the current/voltage waveform is thus captured as a (possibly very complex) periodic orbit in this plane. Shape features from this orbit are captured as independent variables in [57, 101, 102].

Several other feature sets appear occasionally in NILM research. [134] takes the time series of apparent power, and then selects converts sub-sequences of it into symbols. A probabilistic model is then built for the symbol sequence. [219] creates a sparse-matrix representation of the current waveform. [96] uses electromagnetic interference conducted by the powerline as appliance signatures; different appliances have been shown to generate distinctive interference patterns. [176] uses recurrence plots (a visualization of autocorrelation in a time series after a delay embedding) to recognize appliances, distinctive power usage then maps to distinctive patterns in the recurrence plot. [60, 75] extract finite-state-machine models from current waveforms; and then extract statistical features from those FSMs as the independent variables for NILM. [3] computes the S-transform, then plots its magnitude against time and frequency (with both quantized to form a square matrix). A PCA analysis is then done, and the resulting eigenvectors are considered the orthonormal basis ("eigenloads") for the appliance signature space. [47] explores random filtering and random demodulation of the current waveform. These are essentially undersampling approaches that allow for signal reconstruction even after sub-Nyquist sampling. [72] decompose a power signal into "powerlets." Each appliance is represented as a mixture of ARX models, and many short sequences of observations from these mixutres are identified. Powerlets are the minimal set of those sequences that represent the dataset; a bespoke subset selection algorithm is used to find them. Shapelets [172] are similar, in that each shapelet is a small subsequence of a time series. However, shapelets are used only in labeled time series, because the selection criteria for a shapelet is that it maximizes the information gain with respect to the label sequence.

While the focus of our review is on NILM methods that only require access to the main power feeder of the house, we do need to acknowledge the extensive research in using side-channel information to augment the main signal. Commonly (although not exclusively), these works focus on sensors that are already widely deployed in households. Variables such as time of use and duration of use for a given rising/falling edge pair can obviously be inferred just from the main power sensor and a time signal [70]; dependencies between appliances, however, would require expert knowledge [2], so their combination cannot just be automatically inferred [121]. The power rating of an appliance may be found in its manual – but this assumes a very precise identification of the appliance

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid
Downloaded from http://iran-archive.com
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

[206-208]. A household's monthly power bill, and disaggregated power signals from homes with similar monthly usage and demographics, however, would be available to a utility [18]. Exterior temperature is also obviously available [225]. [196] suggest exploiting power and water meters, and light and motion sensors for NILM; the latter is part of most home security systems. Voltage fluctuations alone are used in [85]. However, the method requires that one reference load in the building be under the analyst's control, to act as a reference signal by switching a known power draw at known times.

Given the momentum behind adopting the "Internet of Things," future NILM researchers may well have a plethora of sensors to employ (e.g. the smart thermostat is often mooted as the central consumer-side hub for demand-response pricing schemes [99]). Given the widespread interest in voice-command interfaces (Apple's Siri, Microsoft's Cortona, Amazon's Echo) those sensors will obviously include audio pickups, so the acoustic noise produced by an appliance could be used in NILM [171, 237]. Our findings for Q2 are again summarized in a semantic network in Figure 3, Again, arrows indicate an "IS-A" relationship, while plain lines edges generally indicate a functional relationship (i.e. a transform being applied). The two exceptions are when feature sets are being fused together; when side-channel information is added to the power signal, and for the "Fusion" concept. This latter represents a many-to-many relationship in which several feature domains can be combined together.

Considering all the sources of information used in NILM, and the extensive progress made in appliance identification, it is fairly clear that this technology can now be used to infer human behaviours within a private home. This matter is outside the scope of our review, but we will note that the idea of behaviour fingerprinting, possible socially acceptable uses for it (health & safety monitoring of live-at-home seniors, for instance), the security and privacy concerns raised by this technology, and the development of privacy-preserving NILM approaches, have all received considerable attention in the NILM literature.

D. NILM as a Multi-Label Classification Problem

The classifier algorithms we have discussed are single-label approaches, in which instances are mapped to one element of a set of class labels L. The classification problem is termed binary when L contains two elements, or multi-class when there are more. More generally, we could map instances to a vector of labels; these are termed multi-*label* classifiers.

Multi-label classification was initially developed for automatic text categorization and medical diagnosis. However, a number of other prediction tasks can also be conveniently described as multi-label problems [215]. For example, articles on medical science can belong to both a science and a health category; genes may be associated with multiple diseases [54, 73]; images can belong to many categories depending on their content [28, 234]; a movie can belong to e.g. the action, crime, thriller, and drama genres [105]; an email message can be tagged as both work and research project [146, 153]. Clearly, traditional binary and multi-class problems both can be posed as special cases of the multi-label problem [230].

The two main approaches to creating multi-label classifiers are problem transformation and algorithm adaptation [214]. Problem transformation maps a multi-label problem to an equivalent single-label problem, solved by single-label classifiers. E.g. the Label Power set (LP) maps each element of the power set of L to a new label, and trains a single-label classifier on the LP labels. This is conceptually simple, but leads to a large set of LP labels, most of which are rarely encountered. RA*k*EL (RAndom *k*-labELsets), is an improved version of LP. The RAkEL algorithm draws a subset of LP labels of size k without replacement and constructs an LP classifier for it. Many of these classifiers are combined in an ensemble [216]. Algorithm adaptation refers to modifying existing algorithms to handle multi-label problems. E.g. ML*k*NN is a multi-label learning approach derived from the popular *k*-Nearest Neighbor (*k*NN) algorithm [230]. ML*k*NN finds the label set for a given test instance using the maximum a posteriori (MAP) technique [52], based on prior and posterior probabilities of the k nearest neighbor instances.

In general, NILM can reasonably be considered a multi-label problem. At each sample instant, the power draw is almost always associated with a mixture of appliances. Each appliance is furthermore an independent "concept" that can occur simultaneously with others. Multi-label classification method was first explored in NILM in [12]. Power draw at each sample instant, and its change over sliding windows, were used to disaggregate three specific appliances.

E. Delay Coordinate Embedding

A dynamical system consists of a state space and a map defining transitions between states. These describe the system at any given time, including (for a deterministic system) its future evolution under known inputs [117]. Assuming the system is dissipative, over time the system state will converge to a specific subset of states, known as an attractor [192]. In a time series, the state of the underlying system that generated it cannot be measured directly. A time series is only a sequence of measurements, forming a nonlinear projection of a d-dimensional state trajectory. In order to forecast the evolution of a time series, we need to reverse this projection (or find a mapping that is equivalent to doing so). This *state space reconstruction*, is commonly done via delay embedding. The idea is to transform the time series into a multi-dimensional time-lagged state space. We concatenate the current observation and a number of past observations (lags) into a "delay vector." If the number of lags is sufficient, then this embedding space is equivalent to the actual state space. Hence, we can forecast the next observation using the current delay vector. This also implies that the delay vectors may be used as feature vectors in any standard machine learning algorithm, which can be trained to forecast the time series [117].

The key step in a delay embedding is to find the "best" dimensionality m and time delay τ; there are only heuristic guidelines to findings these parameters in the literature[117]. In this research, the time-delayed mutual information method

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

determines the time delay, and the method of false nearest neighbors determines the dimensionality.

F. Discrete Wavelet Transform

A times series tends to contain a great deal of redundancy, which increases the complexity of the resulting models, and may make them less accurate. One solution is to transform the data to a less-redundant form, which is also better-suited for pattern recognition techniques [235]. The Fourier transform and Discrete Wavelet Transform (DWT) are examples of such aproaches. We favor DWT as it has the multi-resolution and time-frequency localization properties. DWT analyzes the signal at different frequency bands with different resolutions; it decomposes the signal into a coarse approximation and fine detail at different levels of decomposition. Approximation coefficients represent the large-scale, low-frequency components of the signal, while detail coefficients are small-scale, high-frequency components.

Dimensionality reduction in DWT is accomplished by selecting certain coefficients to retain, and discarding the others. This potentially makes a wavelet-domain classifier algorithm both faster and more accurate, as the discarded coefficients should be principally noise. The problem is how to select these coefficients; again, we must rely on heuristic criteria to do so.

Wavelet feature selection method fall into two categories: supervised and unsupervised method [92]. Unsupervised feature selection methods try to find the optimum set of coefficients with maximum similarity to the original data while minimizing the number of coefficients. Supervised features extraction evaluates the performance of coefficients based on class separability. Good quality class separation means maximum separation between classes and minimum data variation inside each class. We focus on unsupervised methods, as class separability in NILM is not a straightforward concept.

The simplest criterion for selecting DWT coefficients is simply to keep the first few and discard the rest. The first DWT coefficients tend to have higher standard deviations, contain more of the signal energy, and carry more information [74]. A more insightful method is to evaluate how similar coefficient sequences in different decomposition levels are to the original signal, by measuring how much energy from the original signal is preserved. Although increasing the decomposition level reduces the data dimensionality more, similarity to the original sequence usually decreases [143]. The amount of energy contained in a signal $x(t)$ is expressed as:

$$\mathrm{E}_{\mathrm{x(t)}} = \int |x(t)|^2 \, dt \qquad (6)$$

The energy content of a signal can be calculated from the DWT coefficients using Parseval's theorem [212]. DWT coefficients x_j^n quantify the amount of energy associated with level of decomposition, n. The total amount of energy contained in the signal is equal to the sum of the energy in all coefficients [92]:

$$E^n = \sum_{j=1}^{M_n} \left(x_j^n\right)^2 \qquad (7)$$

where M_n coefficients are available in the level.

The Haar wavelet is the simplest wavelet transform. It is a series of averaging and differencing operations on a discrete time function. Haar wavelets are popular because of their simplicity and interpretable output. The wavelet is defined as [209]:

$$\Psi_{Haar}(\mathrm{u}) = \begin{cases} -1 & -0.5 < u \le 0 \\ 1 & 0 < u \le 0.5 \\ 0 & otherwise \end{cases} \qquad (8)$$

Haar wavelets are not continuous, and so cannot smoothly follow a continuous signal, although this characteristic is beneficial when studying signals with sharp transitions. Moreover, it is a two element wide wavelet, which reduces its resolution. Haar wavelets are widely used in time series analysis and stream data mining [43, 89, 201, 205].

III. Methodology

A. Datasets

We evaluate our proposed multi-label classifiers on two of the houses (specifically, House 1 and House 3) monitored in the REDD dataset, which collects both whole-house and circuit-level power consumption at 1Hz and 0.33Hz, respectively. House 1 and house 3 have been selected for the tests because data are collected for a longer period of time for these houses. Furthermore, both active and reactive power can be determined for house 3 (via current and voltage measurements), while only active power is available for house 1. The circuit-level data allows us to assign labels to the power signal; we do so in any sample instant where the power consumption is greater than 10W. Plainly, we are assuming that circuits will usually map to a limited group of appliances; for the larger appliances, this is plainly true. Results from the existing literature also indicate that the Bath GFI and Outlet circuits are reasonably predictable, although the Kitchen Outlet circuit seems to be exceptionally difficult.The dataset is available at http://redd.csail.mit.edu [125].

B. Delay Embedding, Wavelet Feature Extraction

Our time domain experiments are conducted on a delay embedding of the power time series (active & reactive power in House 3, active power in House 1). Using the methods described in Section II.E, we find that House 1 is best embedded with 8 dimensions and a delay of 32 seconds, while House 3 requires 18 dimensions and a delay of 95 seconds. We label each delay coordinate with all of the circuits active at the chronologically latest lag in the delay vector

Four our wavelet-domain experiments, we use the Haar wavelet to transform the power time series. In selecting our wavelet coefficients, we set a goal of retaining at least 95% of

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

the signal energy. In REDD House 3, only one circuit (Bath GFI) drops below 95% retained energy at decomposition level 3, and so we employ those coefficients. In House 1, again only 1 appliance drops below the 95% threshold at level 3, but that one is the oven – a high-draw appliance with short, frequent duty cycles when in use. It seems unwise to allow this appliance to have less than 95% retained energy, and so we select decomposition level 2 for this dataset. Each vector of wavelet coefficients is labeled with appliances active at the temporal center of the wavelet.

C. Experimental Design and Performance Metrics

For our experiments, we employ a chronologically ordered single-split design, with the training examples all earlier in time than the test examples; this is a commonly used in time series forecasting. Multi-label classification requires slightly different evaluation measures than those used in traditional single-label classification [215]. They are based on averaging traditional classification metrics over the different labels. Evaluation measures can be calculated using either macro-averaging and micro-averaging. Macro-averaging takes the mean of a measure computed for individual classes, making it more sensitive to classes with few examples. Micro-averaging aggregates all the classes into one contingency matrix. This tends to emphasize overall classification performance [182]. In this article, we select the F-measure as the base measure, as it is commonly used in NILM studies.

In addition to the F-measure and its usual competitors, the NILM field also employs an additional measure called the energy error. The idea is to measure how closely the energy consumption of an appliance matches the energy consumption assigned to that appliance by a NILM technique. The problem, of course, is to translate a predicted label into predicted power consumption. Plainly, this cannot be done precisely, as labels can be associated with single-state, multi-state, or continuously varying appliances. Our approach is to assign each occurrence of each label the *average* power consumption of the appliance during a duty cycle. The total predicted energy is the sum of predicted energies for each label assigned to that sample instant. The *energy error* is the difference between the total predicted energy, and the total actual energy consumed by each active appliance in that sample instant. In the literature, one usually finds that relative energy error is reported:

$$error = \frac{\left| \left(\sum_{i=1}^{k} p_{ave,i} \right) - \left(\sum_{i=1}^{k} p_{actual,i} \right) \right|}{\left(\sum_{i=1}^{k} p_{actual,i} \right)} \qquad (1)$$

where *error* is the relative energy error, $p_{ave,i}$ is the average predicted power for appliance i (i=1,2,…,k), and $p_{actual,i}$ is the actual power consumed by appliance i at that sample instant.

IV. Experimental Results

Table I presents our results on all four classifiers for House 3 of the REDD dataset. We find that there is not much difference between RA*k*EL (using the SVM base classifier) or ML*k*NN. The performance of the classification methods is by some measures superior in the wavelet domain, and by others superior in the time domain. It is impossible to select one as the best method just from these overall results.

Table II presents our results for House 1 of REDD, with RA*k*EL again using the SVM base classifier. dataset lacks reactive power measurements, which made appliance detection more challenging. From the results, it can be concluded that ML*k*NN classification in time domain has better performance among multi-label classification methods.

A. Circuit-Level Evaluation

In this section, we analyze our experimental results at the level of individual appliances. We are interested in determining which methods accurately detect more appliances, and especially the large appliances that consume the most power.

TABLE I
Evaluation of Multi-Label Classification on REDD, House 3

	Micro F-measure	Macro F-measure
RAkEL (Time domain)	0.923	0.492
MLkNN (Time domain)	0.921	0.471
RAkEL (Wavelet domain)	0.959	0.455
MLkNN (Wavelet domain)	0.943	0.472

TABLE II
Evaluation of Multi-Label Classification on REDD House 1

	Micro F-measure	Macro F-measure
RAkEL (Time domain)	0.587	0.393
MLkNN (Time domain)	0.776	0.619
RAkEL (Wavelet domain)	0.763	0.430
MLkNN (Wavelet domain)	0.597	0.524

We present the results for our classifiers on REDD House 3 in Table III. The results are quite mixed, with no one method standing out as performing the best across all appliances. All methods recognized the electronics well, and all utterly failed in detecting the furnace. Upon further examination of the house 3 dataset, we found that measurements of the houses in REDD was done in the beginning of summer, therefore the furnace rarely appears in the dataset. Furthermore most of those few occurences are in the early (training) portion of the dataset; during the period covered by the test set, the furnace has only been used for a few minutes.

The performance of our classifiers on REDD house 1 is presented in Table IV. For this house, the time-domain ML*k*NN was superior to the other methods on all appliances except the microwave.

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Downloaded from http://iranpaper.ir
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

TABLE III
Circuit-Level Performance on REDD, House 3

	RAkEL (Time domain)		MLkNN (Time domain)		RAkEL (Wavelet domain)		MLkNN (Wavelet domain)	
	F-measure	Energy Error	F-measure	Energy Error	F-measure	Energy Error	F-measure	Energy Error
Electronics	1.0	0.009	1.0	0.009	1.0	0.009	1.0	0.009
Furnace	0.001	0.954	0	0.456	0	0.322	0	0.469
Washer dryer	0.947	0.105	0.989	0.027	0.97	0.050	0.98	0.046
Microwave	0.377	0.759	0.628	0.012	0	1.0	0.15	6.267
Bath GFI	0.627	0.344	0.430	0.813	0.76	0.011	0.59	0.305
Kitchen outlet	0.017	0.983	0.133	0.824	0	1.000	0.12	0.898

TABLE IV
Circuit-Level Performance on REDD, House 1

	RAkEL (Time domain)		MLkNN (Time domain)		RAkEL (Wavelet domain)		MLkNN (Wavelet domain)	
	F-measure	Energy Error	F-measure	Energy Error	F-measure	Energy Error	F-measure	Energy Error
Oven	0	1.0	0.31	0.607	0.01	0.937	0.01	0.956
Refrigerator	0.92	0.070	0.94	0.019	0.93	0.059	0.65	1.023
Light	0.39	0.437	0.79	0.149	0.72	0.856	0.56	0.472
Microwave	0.52	0.031	0.09	10.413	0.54	0.434	0.54	0.110
Bath GFI	0	1.00	0.53	0.443	0	1.0	0.39	0.510
Outlet	0	1.00	0.77	0.193	0	1.0	0.68	0.366
Washer	0.92	0.145	0.90	0.093	0.80	0.025	0.84	0.112

B. Comparison with Previous Results on REDD

We now compare our proposed methods with previous results from the literature on REDD. These prior results only measure performance on individual appliances; overall classification or energy error measures are not available.

[124] uses a Factorial Hidden Markov Model to identify appliances in a home, after which AFAMAP convex optimization was used to estimate the appliances (states) from the model. The precision, recall, and F-measure of their method was determined for each appliance. As noted above, none of our classifiers offered consistently superior results on all of these appliances. We thus make the (arbitrary) choice to compare the results of [124] with our time-domain MLkNN classifier (see Table V). While our method was superior on some of the appliances (notably electronics and the washer/dryer), the FHMM method was superior on others.

The method in [229] decomposes a set of appliance models into groups of appliances whose power signals overlap, and then disaggregates each group using the Viterbi algorithm. This method is evaluated on certain appliances from House 1 of REDD, and compared against a Bayesian classifier using the F-measure. The results for both methods, as well as our time-domain MLkNN classifier are presented in Table VI.

TABLE V
Comparison with [124] on REDD

	MLkNN (Time domain)			Factorial HMM [10]		
Appliance	Prec.	Recall	F-measure	Prec.	Recall	F-measure
Electronics	1.0	1.0	1.0	0.416	0.008	0.016
Furnace	0	0	0	0.917	0.708	0.799
Washer/Dryer	0.998	0.981	0.989	0.988	0.736	0.844
Microwave	0.612	0.645	0.628	0.975	0.661	0.788
Bath GFI	0.294	0.802	0.430	0.827	0.708	0.763
Kitchen Outlet	0.587	0.075	0.133	0.452	0.16	0.236

TABLE VI
Comparison with [229] on REDD

Appliance	Proposed MLkNN in time domain	Bayesian method in [18]	Proposed method in [18]
	F-measure	F-measure	F-measure
Oven	0.31	0.8	0.908
Refrigerator	0.94	0.859	0.831
Microwave	0.09	0.775	0.899
Bath GFI	0.53	0.753	0.927
Outlet	0.77	0.409	0.84

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid

Table VII
Comparison with [19] and [16] on REDD

	Proposed method		Results in [168]			Results in [166]		
Appliance	RAkEL	MLkNN	No training	Aggregate training	Sub -metered training	No training	Aggregate training	Sub-metered training
Refrigerator	0.07	0.019	0.550	0.150	0.140	0.380	0.210	0.550
Washer- dryer	0.145	0.093	4.280	0.280	0.240	34.690	0.550	0.710
Microwave	0.031	10.413	0.540	0.220	0.100	0.630	0.530	0.380

HMM along with EM clustering and the Viterbi algorithm has been used to identify a few appliances from REDD in [168] and [166]. The idea of their research is to further develop the Factorial HMM method in [124]. They have evaluated their method by calculating the energy consumption error on a few appliances, averaged across multiple houses in REDD. Table VII shows the results of their two published articles, which we compare to our results on those appliances in House 1. For *just* these three appliances, the time-domain RA*k*EL classifier has better performance than the time-domain ML*k*NN, due to the poor result observed on the microwave. Both RA*k*EL and ML*k*NN performed better than the methods from [166, 168] on the refrigerator and washer, and RA*k*EL was also superior on the microwave.

V. Summary and Future Work

In this paper, we have conducted the most in-depth study of multi-label classification for NILM that exists in the literature. We examined two different multi-label classification methods, applying them to both time-domain and wavelet-domain feature sets. We evaluated our methods on two real houses studied in the REDD dataset. Comparisons against the existing literature on the latter two datasets revealed that our multi-label classifiers were competitive with the existing literature; while our classifiers were not consistently superior to the existing methods, they were also not consistently inferior. Thus, the principal conclusion of this work must be that multi-label classification is a plausible approach for NILM.

Future work in this topic will involve further exploration of multi-label classifiers for NILM. In particular, we will investigate semi-supervised multi-label classification, a class of algorithms that has not previously been examined for NILM. Semi-supervised algorithms require only a small number of labelled training examples in a larger corpus of unlabelled ones. This may be a lower-cost approach to NILM, while still offering superior accuracy to unsupervised algorithms.

VI. References

[1] J. Aach and G. M. Church, "Aligning gene expression time series with time warping algorithms," *Bioinformatics*, vol. 17, pp. 495-508, 2001.
[2] K. A. Agyeman, *et al.*, "Real-Time Recognition Non-Intrusive Electrical Appliance Monitoring Algorithm for a Residential Building Energy Management System," *Energies*, vol. 8, pp. 9029-9048, 2015.
[3] H. Ahmadi and J. R. Marti, "Load Decomposition at Smart Meters Level Using Eigenloads Approach," *IEEE T. Pow Syst.*, vol. 30, pp. 3425-3436, 2015.
[4] M. Al Abassi, *et al.*, "SSGMI Greenely Report Energy disaggregation with low resolution data," presented at the Swedish Study Group Mathematics in Industry, Djursholm, Swden, 2015.
[5] S. Alshareef, "Analysis and Techniques for Non-Intrusive Appliance Load Monitoring," M.Sc. Thesis, Elec. Comp. Eng., Univ. Ont. Inst. Tech., Oshawa, ON, Canada, 2014.
[6] S. Alshareef and W. G. Morsi, "Application of wavelet-based ensemble tree classifier for non-intrusive load monitoring," presented at the IEEE Elec. Power Ener. COnf., London, ON, Canada, 2015.
[7] K. D. Anderson, "Non-Intrusive Load Monitoring: Disaggregation of Energy by Unsupervised Power Consumption Clustering," Ph.D. Dissertation, Electrical & Comp. Eng., Carnegie Mellon Univ., Pittsburgh, PA, USA, 2014.
[8] A. S. Ardeleanu and C. Donciu, "Nonintrusive load detection algorithm based on variations in power consumption," presented at the Int. C. Elec. Power & ENg., Iasi, 2012.
[9] Z. Bar-Joseph, *et al.*, "A new approach to analyzing gene expression time series data," in *Proceedings of the sixth annual international conference on Computational biology*, 2002, pp. 39-48.
[10] M. Baranski and A. Voss, "Genetic algorithm for pattern detection in NIALM systems," *2004 Ieee International Conference on Systems, Man & Cybernetics, Vols 1-7*, pp. 3462-3468, 2004.
[11] K. S. Barsim, *et al.*, "Unsupervised Adaptive Event Detection for Building-Level Energy Disaggregation," presented at the Pow. Ener. Stud. Summ., Stuttgart, Germany, 2015.
[12] K. Basu, *et al.*, "Load identification from power recordings at meter panel in residential households," in *Electrical Machines (ICEM), 2012 XXth International Conference on*, 2012, pp. 2098-2104.
[13] K. Basu, *et al.*, "Residential appliance identification and future usage prediction from smart meter," presented at the Ann. C. IEEE Ind. Elec. Soc., Vienna, Austria, 2013.
[14] K. Basu, *et al.*, "Nonintrusive Load Monitoring: A Temporal Multilabel Classification Approach," *IEEE T. Industrial Informatics*, vol. 11, pp. 262-270, 2015.

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid
Downloaded from http://iran-archive.com
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

[15] K. Basu, *et al.*, "Time series distance-based methods for non-intrusive load monitoring in residential buildings," *Energy and Buildings*, vol. 96, pp. 109-117, 2015.
[16] N. Batra, *et al.*, "INDiC: Improved Non-intrusive Load Monitoring Using Load Division and Calibration," presented at the Int. C. Mach. Learn. Apps. , Miami, FL, USA, 2013.
[17] N. Batra, *et al.* (2014, A comparison of non-intrusive load monitoring methods for commercial and residential buildings. *arXiv 1408.6595v1*.
[18] N. Batra, *et al.* (2015, Neighbourhood NILM: A Big-data Approach to Household Energy Disaggregation. *arXiv 1511.02900*.
[19] C. Beckel, *et al.*, "The eco data set and the performance of non-intrusive load monitoring algorithms," presented at the ACM C. Embedded Systems for Energy-Efficient Buildings, Memphis, TN, USA, 2014.
[20] M. Berges, *et al.*, "User-Centered Nonintrusive Electricity Load Monitoring for Residential Buildings," *Journal of Computing in Civil Engineering*, vol. 25, pp. 471-480, Nov-Dec 2011.
[21] M. E. Berges, *et al.*, "Enhancing electricity audits in residential buildings with nonintrusive load monitoring," *Journal of industrial ecology*, vol. 14, pp. 844-858, 2010.
[22] S. Bhattacharjee, *et al.*, "Appliance Classification using Energy Disaggregation in Smart Homes," presented at the Int. C. Comp. Power, Ener., Inf., Comm. , Chennai, INdia, 2014.
[23] T. Bier, *et al.*, "Smart meter systems detection & classification using artificial neural networks," presented at the Ann. C. IEEE Ind. Elec. Soc., Montreal, QC, Canada, 2012.
[24] T. Bier, *et al.*, "Smart meter systems measurements for the verification of the detection & classification algorithms," presented at the IECON, VIenna, Austria, 2013.
[25] V. P. Borin, *et al.*, "A novel approach for home appliances identification using Vector Projection Length and Stockwell Transform," presented at the IEEE Braz. & South. Pow. Elec. Conf. , Fortaleza, Brazil, 2015.
[26] A. S. Bouhouras, *et al.*, "Load signatures improvement through the determination of a spectral distribution coefficient for load identification," presented at the Int. C. Eur. Ener. Mkt., Florence, Italy, 2012.
[27] A. S. Bouhouras, *et al.*, "Development of distinct load signatures for higher efficiency of NILM algorithms," *Elec. Pow. Syst. Res.*, vol. 117, pp. 163-171, 2014.
[28] M. R. Boutell, *et al.*, "Learning multi-label scene classification," *Pattern Recognition*, vol. 37, pp. 1757-1771, 2004.
[29] R. Breed and J. Delport, "Non-intrusive load monitoring of residential appliances," in *Proceedings of the 7th Domestic Use of Energy Conference*, 2001.
[30] A. Capasso, *et al.*, "A bottom-up approach to residential load modeling," *Power Systems, IEEE Transactions on*, vol. 9, pp. 957-964, 1994.
[31] K. Chahine and K. E.-K. Drissi, "A Novel Feature Extraction Method for Nonintrusive Appliance Load Monitoring," *App. Comp. Int. Soft. Comp.*, p. 7pp., 2013.
[32] K. Chahine, *et al.*, "Electric Load Disaggregation in Smart Metering Using a Novel Feature Extraction Method and Supervised Classification," *Impact of Integrated Clean Energy on the Future of the Mediterranean Environment*, vol. 6, pp. 627-632, 2011.
[33] S. Chan, *et al.*, "Mining emerging substrings," in *Database Systems for Advanced Applications, 2003.(DASFAA 2003). Proceedings. Eighth International Conference on*, 2003, pp. 119-126.
[34] H.-H. Chang, "Non-Intrusive Demand Monitoring and Load Identification for Energy Management Systems Based on Transient Feature Analyses," *Energies*, vol. 5, pp. 4569-4589, 2012.
[35] H.-H. Chang, *et al.*, "Feature extraction based hellinger distance algorithm for non-intrusive aging load identification in residential buildings," presented at the Ann. Mtng. IEEE Ind. Apps. Soc., Addison, TX, USA, 2015.
[36] H.-H. Chang, *et al.*, "Energy spectrum-based wavelet transform for non-intrusive demand monitoring and load identification," presented at the Ann. Mtng. Ind. Apps. Soc., Lake Buena Vista, FL, USA, 2013.
[37] H.-H. Chang, *et al.*, "Particle-Swarm-Optimization-Based Nonintrusive Demand Monitoring and Load Identification in Smart Meters," *IEEE T. Ind. Apps.*, vol. 49, pp. 2229-2236, 2013.
[38] H.-H. Chang, *et al.*, "A Non-Intrusive Load Monitoring System Using an Embedded System for Applications to Unbalanced Residential Distribution Systems," *Energy Procedia*, vol. 61, pp. 146-150, 2014.
[39] H. Chang, *et al.*, "Power Spectrum-Based Wavelet Transform for Non-Intrusive Demand Monitoring and Load Identification," *IEEE Transactions on Industry Applications*, To appear.
[40] H. H. Chang, *et al.*, "A New Measurement Method for Power Signatures of Nonintrusive Demand Monitoring and Load Identification," *Ieee Transactions on Industry Applications*, vol. 48, pp. 764-771, Mar-Apr 2012.
[41] H. H. Chang, *et al.*, "Load identification in nonintrusive load monitoring using steady-state and turn-on transient energy algorithms," presented at the Int. C. Computer Supported Cooperative Work in Design, Shanghai, China, 2010.
[42] K. L. Chen, *et al.*, "A new transient feature extraction method of power signatures for Nonintrusive Load Monitoring Systems," presented at the IEEE Int. Wkshp. App. Meas. Pow. Syst., Aachen, Germany, 2013.
[43] C. L. Chentan Gupta, Song Wang, Abhay Mehta, "Non-Dyadic Haar Wavelets for Streaming and Sensor Data," *26th International Conference on Data Engineering (ICDE), IEEE*, pp. 569-580, 2010.
[44] J. T. Chiang, *et al.*, "Load disaggregation using harmonic analysis and regularized optimization," presented at the Asia-Pac. Sig. Inf. Proc. Assoc. Ann. Summ. C., Hollywood, CA, USA, 2012.
[45] P.-A. Chou, *et al.*, "Automatic appliance classification for non-intrusive load monitoring," presented at the POWERCON, Auckland, New Zealand, 2012.
[46] P. A. Chou and R. I. Chang, "Unsupervised Adaptive Non-Intrusive Load Monitoring System," presented at the IEEE Int. C. Syst. Man Cyber., Manchester, UK, 2013.
[47] M. Clark and L. Lampe, "Single-channel compressive sampling of electrical data for non-intrusive load monitoring,"

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid
Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

presented at the IEEE Glob. C. Sig. Inf. Proc., Orlando, FL, USA, 2015.
[48] R. Cox, *et al.*, "Transient event detection for nonintrusive load monitoring and demand side management using voltage distortion," *APEC 2006: Twenty-First Annual IEEE Applied Power Electronics Conference and Exposition, Vols 1-3*, pp. 1751-1757, 2006.
[49] R. W. Cox, *et al.*, "Using the non-intrusive load monitor for shipboard supervisory control," *2007 IEEE Electric Ship Technologies Symposium*, pp. 523-530, 2007.
[50] S. Darby, "The effectiveness of feedback on energy consumption," *A Review for DEFRA of the Literature on Metering, Billing and direct Displays*, vol. 486, 2006.
[51] G. De Poli, "SELF-LEARNING ALGORITHM FOR ENERGY DISAGGREGATION," TESI DI LAUREA, Dipartimento di Ingegneria dell'Informazione, UNIVERSIT`A DI PADOVA, Padova, Italy, 2012.
[52] M. H. DeGroot, *Optimal statistical decisions* vol. 82: Wiley-Interscience, 2005.
[53] H. G. C. P. Dinesh, *et al.*, "Individual Power Profile Estimation of Residential Appliances Using Low Frequency Smart Meter Data," presented at the IEEE Int. C. Ind. Inf. Syst., Peradeniya, Sri Lanka, 2015.
[54] S. Diplaris, *et al.*, "Protein classification with multiple algorithms," in *Advances in Informatics*, ed: Springer, 2005, pp. 448-456.
[55] M. Dong, *et al.*, "Non-Intrusive Signature Extraction for Major Residential Loads," *Smart Grid, IEEE Transactions on*, vol. 4, pp. 1421-1430, 2013.
[56] S. Drenker and A. Kader, "Nonintrusive monitoring of electric loads," *Ieee Computer Applications in Power*, vol. 12, pp. 47-51, Oct 1999.
[57] L. Du, "Advanced Classification and Identification of Plugged-In Electric Loads," Ph.D. Dissertation, Elec. & Comp. Eng., Georgia Inst. Tech., Atlanta, GA, USA, 2013.
[58] L. Du, *et al.*, "Self-organizing classification and identification of miscellaneous electric loads," presented at the Pow. Ener. Soc. Gen. Mtng., San Diego, CA, USA, 2012.
[59] L. Du, *et al.*, "Nonintrusive, Self-Organizing, and Probabilistic Classification and Identification of Plugged-In Electric Loads," *IEEE T. Smart Grid*, vol. 4, pp. 1371-1380, 2013.
[60] L. Du, *et al.*, "Feature Extraction for Load Identification Using Long-Term Operating Waveforms," *IEEE T. Smart Grid*, vol. 6, pp. 819-826, 2015.
[61] L. Du, *et al.*, "Support vector machine based methods for non-intrusive identification of miscellaneous electric loads," presented at the IECON, Montreal, QC, 2012.
[62] L. Dufour, *et al.*, "A non-intrusive model to predict the flexible energy in a residential building," presented at the Wireless Comm. Netw. Conf. Wkshps, New Orleans, LA, USA, 2015.
[63] D. Egarter, *et al.*, "Appliance State Estimation based on Particle Filtering," presented at the ACM BuildSys, Rome, Italy, 2013.
[64] D. Egarter, *et al.*, "PALDi: Online Load Disaggregation via Particle Filtering," *IEEE T. Instr. Meas.*, vol. 64, pp. 467-477, 2015.
[65] D. Egarter and W. Elmenreich, "Autonomous Load Disaggregation Approach based on Active Power Measurements," presented at the IEEE Int. C. Perv. Comp. Wkshps., St. Louis, MO, USA, 2015.
[66] D. Egarter and W. Elmenreich, "EvoNILM: evolutionary appliance detection for miscellaneous household appliances," in *Gen. Evol. Comp. Conf.*, Amsterdam, The Netherlands, 2013, pp. 1537-1544.
[67] D. Egarter and W. Elmenreich, "Load Disaggregation with Metaheuristic Optimization," presented at the Energieinformatik, Karlsruhe, Germany, 2015.
[68] D. Egarter, *et al.*, "Evolving Non-Intrusive Load Monitoring," *Lec. Notes. Comp. Sci.*, vol. 7835, pp. 182-191, 2013.
[69] G. Elafoudi, *et al.*, "Power disaggregation of domestic smart meter readings using dynamic time warping," presented at the Int. Symp. Comm. Cont. Sig. Proc., Athens, Greece, 2014.
[70] C. Elbe and Schmautzer, "Appliance-Specific Usage Patterns for Load Disaggregation Methods," presented at the Internationale Energiewirtschaftstagung an der TU Wien, 2013.
[71] C. Elbe and E. Schmautzer, "APPLIANCE-SPECIFIC ENERGY CONSUMPTION FEEDBACK FOR DOMESTIC CONSUMERS USING LOAD DISAGGREGATION METHODS," presented at the Int. C. Elec. Dist., Stockholm, Sweden, 2013.
[72] E. Elhamifar and S. Sastry, "Energy Disaggregation via Learning 'Powerlets' and Sparse Coding," presented at the AAAI C. Art. Int., Austin, TX, USA, 2015.
[73] A. Elisseeff and J. Weston, "A kernel method for multi-labelled classification," in *Advances in neural information processing systems*, 2001, pp. 681-687.
[74] J. M. Fadili and E. T. Bullmore, "Wavelet-based approaches for multiple hypothesis testing in activation mapping of functional magnetic resonance images of the human brain," in *Optical Science and Technology, SPIE's 48th Annual Meeting*, 2003, pp. 405-416.
[75] Y. C. Fan, *et al.*, "Efficient Time Series Disaggregation for Non-intrusive Appliance Load Monitoring," presented at the Int. C. Ubiq. Int. Comp. & Aut. Trust. Comp., Fukuoka, 2012.
[76] F.-J. Ferrández-Pastor, *et al.*, "Using Wavelet Transform to Disaggregate Electrical Power Consumption into the Major End-Uses," in *Ubiquitous Computing and Ambient Intelligence. Personalisation and User Adapted Services*, R. Hervas, *et al.*, Eds., ed Basel: Springer International Publishing, 2014, pp. 272-279.
[77] P. Ferrez and P. Roduit, "Non-Intrusive Appliance Load Curve Disaggregation for Service Development," presented at the IEEE Int. Ener. COnf., Dubrovnik, Croatia, 2014.
[78] M. Figueiredo, *et al.*, "Home electrical signal disaggregation for non-intrusive load monitoring (NILM) systems," *Neurocomputing*, vol. 96, pp. 66-73, Nov 1 2012.
[79] M. Figueiredo, *et al.*, "Analysis of trends in seasonal electrical energy consumption via non-negative tensor factorization," *Neurocomputing*, vol. 170, pp. 318-327, 2015.
[80] M. Figueiredo, *et al.*, "Electrical Signal Source Separation Via Nonnegative Tensor Factorization Using On

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid

Site Measurements in a Smart Home," *IEEE T. Instr Meas.*, vol. 63, pp. 364-373, 2014.
[81] M. Figueiredo, *et al.*, "On the Optimization of Appliance Loads Inferred by Probabilistic Models," presented at the NILM Wkshp, Austin, TX, USA, 2014.
[82] M. Figueiredo, *et al.*, "On the Regularization Parameter Selection for Sparse Code Learning in Electrical Source Separation," *Lec. Notes. Comp. Sci.*, vol. 7824, pp. 277-286, 2013.
[83] M. B. Figueiredo, *et al.*, "An experimental study on electrical signature identification of non-intrusive load monitoring (nilm) systems," in *Adaptive and Natural Computing Algorithms*, ed: Springer, 2011, pp. 31-40.
[84] M. B. Figueiredo, *et al.*, "Extracting Features from an Electrical Signal of a Non-Intrusive Load Monitoring System," *Intelligent Data Engineering and Automated Learning - Ideal 2010*, vol. 6283, pp. 210-217, 2010.
[85] A. Filippi, *et al.*, "Voltage only multi-appliance power disaggregation," presented at the IEEE Int. Ener. Conf. Ex., Florence, Italy, 2012.
[86] M. Fitta, *et al.*, "Exploring Techniques for Monitoring Electric Power Consumption in Households," in *UBICOMM 2010, The Fourth International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies*, 2010, pp. 471-477.
[87] B. J. Fogg, *Persuasive Technology: Using Computers to Change What We Think and Do* San Francisco, CA, USA: Morgan Kaufmann, 2002.
[88] S. Frank, *et al.*, "Extracting Operating Modes from Building Electrical Load Data," in *Green Technologies Conference (IEEE-Green), 2011 IEEE*, 2011, pp. 1-6.
[89] A. W.-c. F. Franky Kin-Pong Chan, Clement Yu, "Haar Wavelets for Efficient Similarity search of Time Series: With and Without Time Wraping," *IEEE Transaction on Knowledge and Data Engineering*, vol. 15, p. 20, 2003.
[90] J. Froehlich, *et al.*, "Disaggregated End-Use Energy Sensing for the Smart Grid," *Ieee Pervasive Computing*, vol. 10, pp. 28-39, Jan-Mar 2011.
[91] A. Gabaldón, *et al.*, "Disaggregation of the electric loads of small customers through the application of the Hilbert transform," *Ener. Eff.*, vol. 7, pp. 711-728, 2014.
[92] R. X. Gao and R. Yan, *Wavelets: Theory and Applications for Manufacturing*: Springer US, 2010.
[93] J. M. Gillis, *et al.*, "Nonintrusive Load Monitoring Using Wavelet Design and Machine Learning," *IEEE T. Smart Grid*, vol. 7, pp. 320-328, 2016.
[94] H. Goncalves, *et al.*, "Unsupervised disaggregation of appliances using aggregated consumption data," in *The 1st KDD Workshop on Data Mining Applications in Sustainability (SustKDD)*, 2011.
[95] M. Gonzalez, *et al.*, "A load identification method for residential building applications," presented at the IEEE Int. C. Ind. Tech., Athens, Greece, 2012.
[96] M. Gulati, *et al.*, "An In Depth Study into Using EMI Signatures for Appliance Identification," presented at the ACM BuildSys, Memphis, TN, USA, 2014.
[97] Z. Guo, *et al.*, "Home appliance load modeling from aggregated smart meter data," *IEEE T. Power Systems*, vol. 30, pp. 254-262, 2015.
[98] S. Gupta, *et al.*, "ElectriSense: Single-Point Sensing Using EMI for Electrical Event Detection and Classification in the Home," *Ubicomp 2010: Proceedings of the 2010 Acm Conference on Ubiquitous Computing*, pp. 139-148, 2010.
[99] D. J. Hammerstrom, *et al.*, "Pacific Northwest GridWise Testbed Demonstration Projects. Part I: Olympic Penninsula Project," Pacific Northwest National Laboratory, Richland, WA, USA2007.
[100] G. W. Hart, "Nonintrusive appliance load monitoring," *Proceedings of the IEEE*, vol. 80, pp. 1870-1891, 1992.
[101] T. Hassan, "Bi-level characterization of manual setup residential non-intrusive demand disaggregation using enhanced differential evolution," presented at the Int. Wkshp NILM, 2012.
[102] T. Hassan, *et al.*, "An Empirical Investigation of V-I Trajectory Based Load Signatures for Non-Intrusive Load Monitoring," *IEEE T. Smart Grid*, vol. 5, pp. 870-878, 2014.
[103] D. He, *et al.*, "Incorporating Non-Intrusive Load Monitoring Into Building Level Demand Response," *IEEE T. Smart Grid*, vol. 4, pp. 1870-1877, 2013.
[104] G. Hoogsteen, *et al.*, "Non-intrusive appliance recognition," presented at the IEEE PES Int. C. Inn. Smart Grid Tech., Berlin, Germany, 2012.
[105] X.-S. Hua and G.-J. Qi, "Online multi-label active annotation: towards large-scale content-based video search," in *Proceedings of the 16th ACM international conference on Multimedia*, 2008, pp. 141-150.
[106] F. Jazizadeh, *et al.*, "Unsupervised Clustering of Residential Electricity Consumption Measurements for Facilitated User-Centric Non-Intrusive Load Monitoring," presented at the Int. C. Comp. Civ. Build. Eng., Orlando, FL, USA, 2014.
[107] F. Jazizadeh, *et al.*, "An unsupervised hierarchical clustering based heuristic algorithm for facilitated training of electricity consumption disaggregation systems," *Advanced Engineering Informatics*, vol. 28, pp. 311-326, 2014.
[108] L. Jiang, *et al.*, "Power Load Event Detection and Classification Based on Edge Symbol Analysis and Support Vector Machine " *Applied Computational Intelligence and Soft Computing*, pp. 742461:1-10, 2012.
[109] L. Jiang, *et al.*, "An Approach of Household Power Appliance Monitoring Based on Machine Learning," presented at the Int. C. Intell. Comp. Tech. Aut., Zhangjiajie, Hunan, China, 2012.
[110] L. Jiang, *et al.*, "Automatic power load event detection and appliance classification based on power harmonic features in nonintrusive appliance load monitoring," presented at the IEEE C. Ind. Elec. Apps., Melbourne, VIC, Australia, 2013.
[111] L. Jiang, *et al.*, "Intelligent electrical appliance event recognition using multi-load decomposition," *Advanced Materials Research*, vol. 805-806, pp. 1039-1045, 2013.
[112] Y. Jimenez, *et al.*, "Feature extraction for nonintrusive load monitoring based on S-Transform," presented at the Power Syst. Conf., Clemson, SC, USA, 2014.
[113] M. J. Johnson and A. S. Willsky, "Bayesian nonparametric hidden semi-markov models," *J. Machine Learning Research*, vol. 14, pp. 673-701, 2013.
[114] D. Jung, *et al.*, "Tracking Appliance Usage Information in Residential Settings Using Off-the-Shelf Low-

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

Frequency Meters," *2012 49th Acm/Edac/Ieee Design Automation Conference (Dac)*, pp. 163-168, 2012.
[115] S. J. Kang, *et al.*, "Cost effective disaggregation mechanism for the NIALM system," *Int. J. Smart Grid Clean Ener.*, vol. 2, pp. 364-370, 2013.
[116] Z. Kang, *et al.*, "Virtual Power Sensing Based on a Multiple-Hypothesis Sequential Test," presented at the IEEE Int. C. Smart Grid Comm., Vancouver, BC, Canada, 2013.
[117] H. Kantz and T. Schreiber, *Nonlinear time series analysis* vol. 7: Cambridge University Press, 2003.
[118] G. Kats and E. Capital, *Green building costs and financial benefits*: Massachusetts Technology Collaborative Boston, MA, 2003.
[119] J. Kelly and W. Knottenbelt, "Neural NILM: Deep Neural Networks Applied to Energy Disaggregation," presented at the ACM BuildSys, Seoul, South Korea, 2015.
[120] E. Keogh and S. Kasetty, "On the need for time series data mining benchmarks: a survey and empirical demonstration," *Data Mining and Knowledge Discovery*, vol. 7, pp. 349-371, 2003.
[121] H. S. Kim, "Unsupervised disaggregation of low frequency power measurements," University of Illinois, 2012.
[122] Y. Kim, *et al.*, "ViridiScope: design and implementation of a fine grained power monitoring system for homes," in *Proceedings of the 11th international conference on Ubiquitous computing*, 2009, pp. 245-254.
[123] B. Kitchenham, "Procedures for Performing Systematic Reviews," Keele University, Keele, UK2004.
[124] J. Z. Kolter and T. Jaakkola, "Approximate Inference in Additive Factorial HMMs with Application to Energy Disaggregation," in *International Conference on Artificial Intelligence and Statistics*, 2012.
[125] J. Z. Kolter and M. J. Johnson, "REDD: A public data set for energy disaggregation research," in *Workshop on Data Mining Applications in Sustainability (SIGKDD), San Diego, CA*, 2011.
[126] O. Kramer, *et al.*, "Nonintrusive Appliance Load Monitoring with Bagging Classifiers," *LOGIC JOURNAL OF IGPL*, vol. 23, pp. 359-368, 2015.
[127] F. Kupzog, *et al.*, "Automatic electric load identification in self-configuring microgrids," in *AFRICON, 2009. AFRICON '09.*, 2009, pp. 1-5.
[128] F. Laasch, *et al.*, "Event detection using adaptive thresholds for non-intrusive load monitoring," presented at the Baden-Württemberg Symp. Inf. Comm. Syst., Konstanz, Germany, 2015.
[129] Y. X. Lai, *et al.*, "Multiappliance recognition system with hybrid SVM/GMM classifier in ubiquitous smart home," *Information Sciences*, vol. 230, pp. 39-55, 2013.
[130] H. Y. Lam, *et al.*, "A novel method to construct taxonomy of electrical appliances based on load signatures," *Ieee Transactions on Consumer Electronics*, vol. 53, pp. 653-660, May 2007.
[131] H. Lange, "Disaggregation by State Inference A Probabilistic Framework For Non-Intrusive Load Monitoring," M.Sc. Thesis, Computer Science & Engineering, Aalto University, Berlin, Germany, 2015.
[132] X. C. Le, *et al.*, "l1-Norm minimization based algorithm for non-intrusive load monitoring," presented at the IEEE Int. C. Perv. Comp. Comm. Wkshps., St. Louis, MO, USA, 2015.
[133] K. D. Lee, *et al.*, "Estimation of variable-speed-drive power consumption from harmonic content," *Ieee Transactions on Energy Conversion*, vol. 20, pp. 566-574, Sep 2005.
[134] D. Li, *et al.*, "Profiling Household Appliance Electricity Usage with N-Gram Language Modeling," presented at the IEEE Int. C. Ind. Tech., Taipei, Taiwan, 2016.
[135] D. Li, *et al.*, "Disaggregating household loads via semi-supervised multi-label classification," presented at the Ann. C. North American Fuzzy Information Processing Society, Redmond, WA, USA, 2015.
[136] J. Li, *et al.*, "Power decomposition based on SVM regression," presented at the Int. C. Model. Ident., Cont., Wuhan, Hubei, China, 2012.
[137] J. Liang, *et al.*, "Load Signature Study—Part II: Disaggregation Framework, Simulation, and Applications," *Power Delivery, IEEE Transactions on*, vol. 25, pp. 561-569, 2010.
[138] A. C. S. Lima, *et al.*, "Noninvasive monitoring of residential loads," presented at the IEEE PES Int. C. Ex. Innov. Smart Grid Tech. Eur., Berlin, Germany, 2012.
[139] Y.-H. Lin and M.-S. Tsai, "Applications of hierarchical support vector machines for identifying load operation in nonintrusive load monitoring systems," in *Intelligent Control and Automation (WCICA), 2011 9th World Congress on*, 2011, pp. 688-693.
[140] Y.-H. Lin and M.-S. Tsai, "Development of an Improved Time–Frequency Analysis-Based Nonintrusive Load Monitor for Load Demand Identification," *IEEE T. Instr. Meas.*, vol. 63, pp. 1470-1483, 2014.
[141] Y.-H. Lin and M.-S. Tsai, "A novel feature extraction method for the development of nonintrusive load monitoring system based on BP-ANN," in *Computer Communication Control and Automation (3CA), 2010 International Symposium on*, 2010, pp. 215-218.
[142] T. Liu, *et al.*, "A Generic Energy Disaggregation Approach: What and When Electrical Appliances are Used," presented at the IEEE Int. C. Data Min. Wkshp., Atlantic City, NJ, USA, 2015.
[143] Y. Liu, "Dimensionality reduction and main component extraction of mass spectrometry cancer data," *Knowledge-Based Systems*, vol. 26, pp. 207-215, 2012.
[144] R. Łukaszewski, *et al.*, "Methods of Electrical Appliances Identification in Systems Monitoring Electrical Energy Consumption," presented at the IEEE Int. C. Int. Data Acq. Adv. Comp. Syst., Berlin, Germany, 2013.
[145] L. Lulu, *et al.*, "Electric Load Signature Analysis for Home Energy Monitoring System," *Int. J. Fuzz. Log. Int. Syst.*, vol. 12, pp. 193-197, 2012.
[146] X. Luo and A. N. Zincir-Heywood, "Evaluation of two systems on multi-class multi-label document classification," in *Foundations of Intelligent Systems*, ed: Springer, 2005, pp. 161-169.
[147] J. Maitre, *et al.*, "Efficient Appliances Recognition in Smart Homes Based on Active and Reactive Power, Fast Fourier Transform and Decision Trees," presented at the AAAI Workshops, Austin, TX, USA, 2015.

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

[148] S. Makonin, "Real-time embedded low-frequency load disaggregation," Ph.D. Dissertation, Computing Science, Simon Fraser Univ., Vancoiuver, BC, Canada, 2014.
[149] S. Makonin, *et al.*, "AMPds: A public dataset for load disaggregation and eco-feedback research," presented at the Elec. Pow. Ener. Conf., Halifax, NS, Canada, 2013.
[150] M. L. Marceau and R. Zmeureanu, "Nonintrusive load disaggregation computer program to estimate the energy consumption of major end uses in residential buildings," *Energy Conversion and Management*, vol. 41, pp. 1389-1403, Sep 2000.
[151] M. Mathis, *et al.*, "Improving the Recognition Performance of NIALM Algorithms through Technical Labeling," presented at the IEEE Int. C. Embed. Ubiq. Comp., Milano, Italy, 2014.
[152] L. Mauch and B. Yang, "A new approach for supervised power disaggregation by using a deep recurrent LSTM network," presented at the IEEE Glob. C. Sig. Inf. Proc., Orlando, FL, USA, 2015.
[153] A. McCallum, "Multi-label text classification with a mixture model trained by EM," in *AAAI'99 Workshop on Text Learning*, 1999, pp. 1-7.
[154] P. Meehan, *et al.*, "An Efficient, Scalable Time-Frequency Method for Tracking Energy Usage of Domestic Appliances Using a Two-Step Classification Algorithm," *Energies*, vol. 7, pp. 7041-7066, 2014.
[155] J. Mei, *et al.*, "Random Forest Based Adaptive Non-Intrusive Load Identification," presented at the Int. J. C. Neur. Net. , Beijing, China, 2014.
[156] A. N. Milioudis, *et al.*, "Event detection for load disaggregation in Smart Metering," presented at the IEEE PES C. Innov. Smart Grid Tech. Eur., Lyngby, Denmark, 2013.
[157] D. Ming, *et al.*, "An Event Window Based Load Monitoring Technique for Smart Meters," *Smart Grid, IEEE Transactions on*, vol. 3, pp. 787-796, 2012.
[158] M. Mittelsdorf, *et al.*, "Submeter based Training of Multi-class Support Vector Machines for Appliance Recognition in Home Electricity Consumption Data.," presented at the SMARTGREENS, Aachen, Germany, 2013.
[159] J. A. Mueller, *et al.*, "Hidden Markov models for nonintrusive appliance load monitoring," presented at the N. Am. POw. Symp., Pullman, WA, USA, 2014.
[160] H. Nakajima, *et al.*, "The state estimation of existing home appliances using signal analysis technique," presented at the SICE Ann. Conf., Sapporo, Japan, 2014.
[161] J. Nerbonne, *et al.*, "Comparison and classification of dialects," in *Proceedings of the ninth conference on European chapter of the Association for Computational Linguistics*, 1999, pp. 281-282.
[162] S. K. Ng, *et al.*, "Automatic appliance load signature identification by statistical clustering," presented at the Int. C. Advances in Power System Control, Operation & Management, London, UK, 2009.
[163] M. Nguyen, *et al.*, "A Novel Feature Extraction and Classification Algorithm Based on Power Components Using Single-point Monitoring for NILM," presented at the Canad. C. Elec. Comp. Eng., Halifax, NS, Canada, 2015.
[164] J. Paris, *et al.*, "Scalability of Non-Intrusive Load Monitoring for Shipboard Applications," presented at the ASNE Day, National Harbor, MD, USA, 2009.
[165] O. Parson, "Unsupervised Training Methods for Non-intrusive Appliance Load Monitoring from Smart Meter Data," Ph.D. Dissertation, Electronics & Computer Science, Univ, Southampton, Southampton, UK, 2014.
[166] O. Parson, *et al.*, "Non-Intrusive Load Monitoring Using Prior Models of General Appliance Types," presented at the Conference on Artificial Intelligence (AAAI-12), Toronto, Canada, 2012.
[167] O. Parson, *et al.*, "An unsupervised training method for non-intrusive appliance load monitoring," *Artificial Intelligence*, vol. 217, pp. 1-19, 2014.
[168] O. Parson, *et al.*, "Using hidden markov models for iterative non-intrusive appliance monitoring," presented at the Neural Information Processing Systems Workshop on Machine Learning for Sustainability, Sierra Nevada, Spain, 2011.
[169] O. Parson, *et al.*, "A Scalable Non-intrusive Load Monitoring System for Fridge-Freezer Energy Efficiency Estimation," presented at the NILM Wkshps, Austin, TX, USA, 2014.
[170] S. N. Patel, *et al.*, "At the flick of a switch: Detecting and classifying unique electrical events on the residential power line - (Nominated for the best paper award)," *UbiComp 2007: Ubiquitous Computing, Proceedings*, vol. 4717, pp. 271-288, 2007.
[171] N. Pathak, *et al.*, "Acoustic based appliance state identifications for fine-grained energy analytics," presented at the IEEE Int. C. Perv. Comp. Comm St. Louis, MO, USA, 2015.
[172] O. P. Patri, *et al.*, "Extracting discriminative features for event-based electricity disaggregation," presented at the IEEE C. Technologies for Sustainability, Portland, OR, USA, 2014.
[173] S. Pattem, "Unsupervised Disaggregation for Non-intrusive Load Monitoring," presented at the Int. C. Mach. Learn. App., Boca Raton, FL, USA, 2012.
[174] O. Pezeshkfar, "Low Cost Framework for Non-Intrusive Load Monitoring (NILM) to Monitor Human Behavioral Pattern," M.S. Thesis, Electrical and Computer Engineering Department, University of Missouri-Columbia, Columbia, MO, USA, 2013.
[175] M. Pöchacker, *et al.*, "Proficiency of Power Values for Load Disaggregation," *IEEE T. Instr. Meas.*, vol. 65, pp. 46-55, 2016.
[176] F. Popescu, *et al.*, "Recurrence Plot Analysis for characterization of appliance load signature," presented at the Int. C. Comm., Bucharest, Romania, 2014.
[177] R. S. Prasad and S. Semwal, "A simplified new procedure for identification of appliances in smart meter applications," presented at the IEEE Int. Syst. Conf., Orlando, FL, USA, 2013.
[178] A. Prudenzi, "A neuron nets based procedure for identifying domestic appliances pattern-of-use from energy recordings at meter panel.," presented at the 2002 Ieee Power Engineering Society Winter Meeting, Vols 1 and 2, Conference Proceedings, 2002.

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid
Downloaded from http://iran-archive.com
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24

[179] D. Rahayu, *et al.*, "Learning to be energy-wise: Discriminative methods for load disaggregation," presented at the Int. C. Future Energy Syst., Madrid, Spain, 2012.
[180] S. Rahimi, "Usage Monitoring of Electrical Devices in a Smart Home," M.Sc. Thesis, Department of Systems and Computer Engineering, Carleton University, Ottawa, ON, Canada, 2012.
[181] S. Rahimi, *et al.*, "Nonintrusive load monitoring of electrical devices in health smart homes," presented at the IEEE Int C. Instr. Meas. Tech., Graz, 2012.
[182] R. Rak, *et al.*, "Multi-label associative classification of medical documents from medline," in *Machine Learning and Applications, 2005. Proceedings. Fourth International Conference on*, 2005, p. 8 pp.
[183] C. A. Ratanamahatana and E. Keogh, "Everything you know about dynamic time warping is wrong," in *Third Workshop on Mining Temporal and Sequential Data*, 2004, pp. 22-25.
[184] C. A. Ratanamahatana and E. Keogh, "Making time-series classification more accurate using learned constraints," in *Proceedings of SIAM international conference on data mining*, 2004, pp. 11-22.
[185] A. Ridi, *et al.*, "Appliance and State Recognition using Hidden Markov Models," presented at the Int. C. Data Sci. Adv. Anal. , Shanghai, China, 2014.
[186] A. Ridi, *et al.*, "Unseen Appliances Identification," *Lec. Notes. Comp. Sci.*, vol. 8259, pp. 75-82, 2013.
[187] J. G. Roos, *et al.*, "Using Neural Networks for Non-Intrusive Monitoring of Industrial Electrical Loads," *10th Anniversary, Imtc/94 - Advanced Technologies in I & M, Conference Proceedings, Vols 1-3 and Supplement*, pp. 1115-1118, 1994.
[188] A. G. Ruzzelli, *et al.*, "Real-time recognition and profiling of appliances through a single electricity sensor," in *Sensor Mesh and Ad Hoc Communications and Networks (SECON), 2010 7th Annual IEEE Communications Society Conference on*, 2010, pp. 1-9.
[189] H. Sakoe and S. Chiba, "Dynamic programming algorithm optimization for spoken word recognition," *Acoustics, Speech and Signal Processing, IEEE Transactions on*, vol. 26, pp. 43-49, 1978.
[190] A. Sankara, "Energy disaggregation in NIALM using hidden
Markov models," M.Sc. Thesis, Computer Science, Missouri University of Sci & Tech., Rolla, MO, USA, 2015.
[191] M. Sanquer, *et al.*, "Hierarchical Bayesian learning for electrical transient classification," presented at the Int. C. Acous. Sp. Sig. Proc., Vancouver, BC, Canada, 2013.
[192] T. Sauer, *et al.*, "Embedology," *Journal of Statistical Physics*, vol. 65, pp. 579-616, 1991.
[193] S. Semwal, *et al.*, "Group control and identification of residential appliances using a nonintrusive method," *Turk J Elec Eng & Comp Sci*, vol. 23, pp. 1805-1816, 2015.
[194] M. Singh, *et al.*, "Residential Load Signature Analysis for Their Segregation Using Wavelet—SVM," in *Power Electronics and Renewable Energy Systems: Proceedings of ICPERES 2014*, C. Kamalakannan, *et al.*, Eds., ed New Delhi: Springer India, 2015, pp. 863-871.
[195] D. Srinivasan, *et al.*, "Neural-network-based signature recognition for harmonic source identification," *Ieee Transactions on Power Delivery*, vol. 21, pp. 398-405, Jan 2006.
[196] V. Srinivasan, *et al.*, "FixtureFinder: Discovering the Existence of Electrical and Water Fixtures," presented at the Int. C. Inf. Proc. Sens. Net., Philadelphia, PA, USA, 2013.
[197] K. Srinivasarengan, *et al.*, "A Framework for Non Intrusive Load Monitoring Using Bayesian Inference," presented at the Int. C. Innov. Mob. Intern. Svcs. Ubiq. Comp., Taichung, Taiwan, 2013.
[198] Staff. (2012, April 26). *Electricity Explained: Use of Electricity*. Available: http://www.eia.gov/energyexplained/index.cfm?page=electricity_use
[199] Staff, "Energy Statistics Handbook," vol. Q4, S. Canada, Ed., ed. Ottawa, 2009, pp. Table 8.7-1.
[200] V. Stankovic, *et al.*, "A graph-based signal processing approach for low-rate energy disaggregation," presented at the IEEE Symp. Comp. Int. Eng. Sol., Orlando, FL, USA, 2014.
[201] A. N. Su Chen, "Dynamic Nonuniform Data Aproximation in Databases with Haar Wavelet," *Journal of Computer*, vol. 2, pp. 67-76, 2007.
[202] Y.-C. Su, *et al.*, "Feature Selection of Non-intrusive Load Monitoring System Using STFT and Wavelet Transform," in *e-Business Engineering (ICEBE), 2011 IEEE 8th International Conference on*, 2011, pp. 293-298.
[203] F. Sultanem, "Using Appliance Signatures for Monitoring Residential Loads at Meter Panel Level," *Ieee Transactions on Power Delivery*, vol. 6, pp. 1380-1385, Oct 1991.
[204] K. Suzuki, *et al.*, "Nonintrusive Appliance Load Monitoring Based on Integer Programming," *2008 Proceedings of Sice Annual Conference, Vols 1-7*, pp. 2626-2631, 2008.
[205] X. Z. Tan Minsheng, Wang Lei, "Voronoi Tessellation based Haar Wavelet Data Compression for Sensor Network," *International Conference on Wireless Communications, Networking and Mobile Computing, WiCOM*, pp. 1-4, 2006.
[206] G. Tang, *et al.*, "A Distributed and Scalable Approach to Semi-Intrusive Load Monitoring," *IEEE T. Par. Dist. Syst.*, To Appear.
[207] G. Tang, *et al.*, "A simple and robust approach to energy disaggregation in the presence of outliers," *Sust. Comp.: Inf. and Syst.*, vol. 9, pp. 8-19, 2016.
[208] G. Tang, *et al.*, "A simple model-driven approach to energy disaggregation," presented at the IEEE Int. C. Smart Grid Comm., Venice, Italy, 2014.
[209] Q. L. Tao Li, Shenghuo Zhu, Mitsunori Ogihara, "A survey on wavelet applications in data mining," *SIGKDD Explorations*, vol. 4, pp. 49-68, 2003.
[210] G. M. Tina, *et al.*, "Web interactive non intrusive load disaggregation system for active demand in smart grids," *EAI Endorsed Transactions on Energy Web*, vol. 1, pp. 1-9, 2014.
[211] A. T. V. Tomas, "Inference methods for nonintrusive load monitoring applications," Ph.D. Dissertation, Elec. & Comp. Eng., Tecnico Lisboa, Lisbon, Portugal, 2014.

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Downloaded from http://iranpaper.ir
http://www.itrans24.com/landing1.html
سفارش ترجمه این مقاله
آنلاین: www.trans24.ir
تماس: (۰۲۱) ۴۰-۶۶۵۷۲۲۳۸
trans24
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2584581, IEEE Transactions on Smart Grid

[212] C. Torrence and G. P. Compo, "A practical guide to wavelet analysis," *Bulletin of the American Meteorological society*, vol. 79, pp. 61-78, 1998.
[213] K. N. Trung, *et al.*, "Event Detection and Disaggregation Algorithms for NIALM System," presented at the Int. NILM Wkshp., Austin, TX, USA, 2014.
[214] G. Tsoumakas and I. Katakis, "Multi-label classification: An overview," *International Journal of Data Warehousing and Mining (IJDWM)*, vol. 3, pp. 1-13, 2007.
[215] G. Tsoumakas, *et al.*, "Mining multi-label data," in *Data mining and knowledge discovery handbook*, ed: Springer, 2010, pp. 667-685.
[216] G. Tsoumakas and I. Vlahavas, "Random k-labelsets: An ensemble method for multilabel classification," in *Machine Learning: ECML 2007*, ed: Springer, 2007, pp. 406-417.
[217] E. Vogiatzis, *et al.*, "Real-time and low cost energy disaggregation of coarse meter data," presented at the IEEE PES Innov. Smart Grid Tech. Eur., Copenhagen, Denmark, 2013.
[218] X. Wang, *et al.*, "An online load identification algorithm for non-intrusive load monitoring in homes," presented at the IEEE Int. C. Int. Sesnors, Sensor Nets., Inf. Proc., Melbourne, Australia, 2013.
[219] Y. Wang, *et al.*, "Compressive sampling for non-intrusive appliance load monitoring (NALM) using current waveforms," presented at the IASTED Int. C. Sig. Proc. Patt. Rec. Apps., Crete, Greece, 2012.
[220] Z. Wang and G. Zheng, "Residential Appliances Identification and Monitoring by a Nonintrusive Method," *Smart Grid, IEEE Transactions on*, vol. 3, pp. 80-92, 2012.
[221] M. Weiss, *et al.*, "Leveraging smart meter data to recognize home appliances," *2012 Ieee International Conference on Pervasive Computing and Communications (Percom)*, pp. 190-197, 2012.
[222] B. Wild, *et al.*, "A new unsupervised event detector for non-intrusive load monitoring," presented at the IEEE Glob. C. Sig. Inf. Proc., Orlando, FL, 2015.
[223] V. S. Wong, *et al.*, "A fast multiple appliance detection algorithm for non-intrusive load monitoring," presented at the IEEE Symp. Comp. Int. Apps. Smart Grid, Singapore, 2013.
[224] Y. F. Wong, *et al.*, "Real-time load disaggregation algorithm using particle-based distribution truncation with state occupancy model," *ELECTRONICS LETTERS*, vol. 50, pp. 697-699, 2014.
[225] M. Wytock and J. Z. Kolter, "Contextually Supervised Source Separation with Application to Energy Disaggregation," presented at the AAAI C. Art. Int., Quebec City, QC, Canada, 2014.
[226] Z. Xing, *et al.*, "A brief survey on sequence classification," *ACM SIGKDD Explorations Newsletter*, vol. 12, pp. 40-48, 2010.
[227] Z. You, *et al.*, "An inference framework for detection of home appliance activation from voltage measurements," presented at the IEEE Int. C. Acou. Sp. Sig. Proc., Florence, Italy, 2014.
[228] Y. X. Yu, *et al.*, "Non-Intrusive Method for On-Line Power Load Decomposition," *2008 China International Conference on Electricity Distribution, Vols 1 and 2*, pp. 100-107, 2009.
[229] M. Zeifman, "Disaggregation of Home Energy Display Data Using Probabilistic Approach," *Ieee Transactions on Consumer Electronics*, vol. 58, pp. 23-31, Feb 2012.
[230] M.-L. Zhang and Z.-H. Zhou, "ML-KNN: A lazy learning approach to multi-label learning," *Pattern Recognition*, vol. 40, pp. 2038-2048, 2007.
[231] M. Zhong, *et al.* (2014, Interleaved Factorial Non-Homogeneous Hidden Markov Models for Energy Disaggregation. *arXiv 1406.7665v1*.
[232] M. Zhong, *et al.*, "Latent Bayesian melding for integrating individual and population models," presented at the Adv. Neur. Inf. Proc. Syst., Montreal, QC, Canada, 2015.
[233] M. Zhong, *et al.*, "Signal Aggregate Constraints in Additive Factorial HMMs, with Application to Energy Disaggregation," presented at the Neur. Inf. Proc. Syst., Montreal, QC, Canada, 2014.
[234] Z.-H. Zhou and M.-L. Zhang, "Multi-instance multi-label learning with application to scene classification," in *Advances in Neural Information Processing Systems*, 2006, pp. 1609-1616.
[235] M. Zhu, "Feature Extraction and Dimension Reduction with Applications to Classification and the Analysis of Co-occurrence Data," Stanford University, Palo Alto, CA, USA, 2001.
[236] A. Zoha, *et al.*, "Low-power appliance monitoring using Factorial Hidden Markov Models," presented at the IEEE Int. C. Int. Sens. Sens. Nets. Inf. Proc. , Melbourne, Australia, 2013.
[237] A. Zoha, *et al.*, "Acoustic and device feature fusion for load recognition," presented at the IEEE Int. C. Int. Syst., Sofia, Bulgaria, 2012.

Seyed Mostafa Tabatabaei received the B.Sc. degree in electrical engineering from the Isfahan University of Technology, Isfahan, Iran, in 2008, and two M.Sc. degrees in electrical engineering (energy systems) from the Amirkabir University of Technology, Tehran, Iran and the University of Alberta, Edmonton, Canada in 2011 and 2014, respectively. His research interests include Smart Grid, Power Quality and Energy Saving.

Scott Dick (M'02) received the B.Sc. and M.Sc. in Computer Science, and the Ph.D. in Computer Science and Engineering in 1997, 1999, and 2002, respectively, all from the University of South Florida, Tampa, FL, USA. He is currently an Associate Professor of Electrical and Computer Engineering at the University of Alberta. His research interests are in computational intelligence, machine learning, and data mining. He is the chair of the IEEE CIS Fuzzy Systems Technical Committee Task Force on Complex Fuzzy Sets and Logic.

Wilsun Xu (M'90-SM'95-F'05) obtained the Ph.D. degree in Electrical and Computer Engineering from the University of British Columbia, Vancouver, in 1989. Currently, he is a NSERC/iCORE Industrial Research Chair Professor at the University of Alberta. His current main research interests are power quality and power disturbance analytics.

1949-3053 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.