Non Intrusive Load Monitoring (NILM): A State of the Art

Jorge Revuelta Herrero[1(✉)], Álvaro Lozano Murciego[1], Alberto López Barriuso[1], Daniel Hernández de la Iglesia[1], Gabriel Villarrubia González[1], Juan Manuel Corchado Rodríguez[1], and Rita Carreira[2]

[1] University of Salamanca, Plaza de la Merced s/n, 37008 Salamanca, Spain
{jrevuelta,loza,albarriuso,danihiglesias,gvg,corchado}@usal.es
[2] VPS - Virtual Power Solutions, Coimbra, Portugal
rcarreira@vps.energy

Abstract. The recent increase in smart meters installations in households and small bussiness by electric companies has led to interest in monitoring load techniques in order to provide better quality service and get useful information about appliance usage and user consumption behavior. This works summarizes the current state of the art in Non Intrusive Load Monitoring from its beginning, describes the main process followed in the literature to perform this technique and shows current methods and techniques followed nowadays. The possible application of this techniques in the context of ambient intelligence, energy efficiency, occupancy detection are described. This work also points the current challenges in the field and the future lines of research in this broad topic.

Keywords: NILM · ILM · Dissagregation · Ambient intelligence · Load monitoring · HMM · LSTM

1 Introduction

The operating condition of appliances used in such different scopes such as home, industry and commerce cannot be truly determined without the proper monitoring system. The main purpose of load monitoring techniques is to ease the conservation of energy consumption through different approaches like appropriate timing of appliance usage, optimization in their usages and getting rid of unwanted activities producing unnecessary energy consumption. These purposes can be achieved showing to the inhabitants of a house the consumption of each appliance in the sum of the total billing for detect malfunction or excesses in some of them [5]. In addition, it could be possible notify to users of possible savings in their billing deferring their main loads when the price of electricity is low. Contrary to this, Kelly et al. [19] argue in a study that it is not proven yet that these additional feedback lead to savings. Recently there is an evident increase

F. De la Prieta et al. (eds.), *Trends in Cyber-Physical Multi-Agent Systems. The PAAMS Collection - 15th International Conference, PAAMS 2017*,
Advances in Intelligent Systems and Computing 619, DOI 10.1007/978-3-319-61578-3_12

in micro grids and continuous growth of renewable energy facility installation, so to add quality to these saving efforts, more energy measures need to be collected in order to monitor, automate and manage the power system.

In general terms, the load monitoring is the process of identifying and acquiring the load measurement in a power system [1]. This load monitoring will determine the consumption and appliances' status, in order to comprehend the behavior of individual loads in the whole system.

Depending on the approach used to monitor the appliance monitoring it can be *Intrusive Load Monitoring (ILM)* or *Non-Intrusive Load Monitoring (NILM)*:

– **Intrusive Load Monitoring**: This term covers all those approaches that propose to deploy a measurement device for each appliance or load under interest. The need of several measurement devices in the ILM ecosystem makes it expensive and hard to maintain, install and expand. The term intrusive means that the metering device is located in the habitation, close to the appliance being monitored. As mentioned in [37] there are subclassifications depending on the level of intrusion:

  1. *ILM 1* relies on sub-meters that typically measure the consumption, of a zone of the house, placing it at the circuit breaker level.
  2. *ILM 2* uses metering devices placed at plug level, so one device can monitor one or more appliances at the same time.
  3. *ILM 3* uses metering devices placed at appliance level.

  The above explained reasons, led the introduction of a non-intrusive variant of the method with much lower cost.

– **Non-intrusive Load Monitoring**: These approaches consist of processes in which given data coming from the whole house consumption, typically by installing a metering device at panel level which infers what appliances are being used and how much they consume at a given time. The preference of using NILM techniques over ILM ones are mainly due to its cheaper and easier installation, since it only uses one metering device for each energy entrance to the house instead of at least one metering device per room.

Another synonym for NILM is the term energy disaggregation, which is a computational technique for estimating the power demand of individual appliances from a single meter which measures the overall demand across several appliances. The main motivations to study NILM in the review proposed in this work are: (1) detailed identification of appliance usage, (2) appliance management, (3) energy theft detection, (4) occupancy detection and (5) lower price level and intrusion compared to intrusive load monitoring. In this work we propose a review over the latest techniques used for NILM and energy disaggregation itself, following the next structure: First of all Sect. 2 summarize the related work about NILM from the beginning of the term to nowadays. Section 3 provides an examination of the process that is followed generally in the literature to achieve load disaggregation in NILM. Section 4 offer a recap of the most common machine learning algorithms used to achieve NILM. Finally Sect. 5 present applications, challenges and future lines of research in the topic.

2 Related Work

Hart first introduced the *Non-intrusive Appliance Load Monitor (NALM)* as a paradigm for a software system capable of analyzing single-point electrical data to obtain information about the energy used by individual appliances [12]. Since then, a number of studies have extended its simple linear model to use other directly sampled quantities to augment and increase the resolving power of the ΔP-ΔQ space [38,43]. This approaches couldn't distinguish appliances that draw similar power and similar operational principles, such as an iron and a hair dryer.

The research of disaggregation techniques based on Fourier harmonics aim to be able to separate more fine grained appliances such as low-load complex devices present in homes, offices and industry [26]. Steady-state monitoring techniques are successfully applied in low event rate generation environments, such as homes and small business [25]. On the other hand, large industrial facilities and companies need more complex approaches due to the high amount of event generation, load balancing and power factor correction [40]. Higher harmonics in the aggregated signal adds another dimension to the classification problem, making possible to distinguish loads with similar ΔP-ΔQ space representation.

The advanced load monitor proposed by Laughtman et al. [25] is capable of recognize individual appliance load based on their transient shapes. This behavior is closely related to the task which the appliance performs. For example, a computer and a light bulb produce turn-on transients different enough that makes possible to perform near real-time classification. For continuously variable loads, Laughtman et al. [25] proposes the analysis of the spectral envelopes. This allows the NILM system to disaggregate loads like VSDs, which draws distorted and pulsatile waveforms leaving characteristic traces not only in real power but in the fifth and seventh harmonic.

In the work proposed by Patel et al. [34] a combination of hardware and software performs the task of household-level current sampling at 1MHz, obtaining features from the electric noise due to appliance usage (above all, turning on and off). Then, a SVM model is supervisedly trained to obtain up to 90% accuracy.

The analysis through this set of techniques require high sampling rate (in the order of kHz sampling rate or more) which makes it hard to apply in real-world environments due to metering limitations. Another drawback is the need of calibrate the prediction models for those houses different enough from the training ones.

The need of new techniques capable of perform appropriately in a wide variety of household and the usage of low-cost devices to retrieve the energy consumption make the methods explained above not valid enough to be introduced into services for end-users. Is for these reasons that lately, new techniques have been proposed with low rate data retrieval from 1 Hz to lower sample rate as 15 min per sample (Makonin supports this approach in its thesis [28]) which tries to apply the latest machine learning and deep learning knowledge to make the best high energy disaggregation process, as explained in the later sections. In the next section we will describe the general pipeline followed in the literature in other to perform Non Intrusive Load Monitoring.

3 NILM Process

NILM is presented as a time series classification problem where we have to detect which appliances are active at a time t and how much each one contributes to the total percentage of consumption. Figure 1 shows a general flowchart that describes the NILM process [49]. Each part of this process is described below.

3.1 Data Acquisition

As highlighted previously, most of NILM approaches pretend to use the data provided by the main smart meter of the household exclusively, but in practice, training with data from single point smart energy meters – in varying degrees – is required in most of the approaches. This will be explained in the following sections.

Regarding to the kind of data collected [28,31], the smart meters measure the alternating current (AC), and therefore the most basics measurements are: voltage (ΔV, measured in Volts: V), current (I, measured in Amperes: A), and apparent power (S, measured in Volt-Amperes: VA) which is the product of current by voltage. There are other measurements derived from the previous ones: real power (P, measured in watts: W) is the transference of energy in the net, regardless of the direction. It is also called power or average power. Note that this is different that the gross transference called apparent power (this is due to power losses in reactive components of a circuit). Another interesting measure is the ratio between the previous ones: power factor (PF), (P/S) or $\cos(\Theta)$ where Θ is the angle between voltage and current, as well as reactive power (Q, measured in volt-ampere-reactive or VAR), which is an usual measure related to the rate at which power is stored and released back by components such as capacitors and inductors. Additionally, there are other advanced measures such as electric characteristic, harmonic distortion [27,46], electromagnetic interference (EMI) and transients. Finally energy consumption is the amount of power consumed

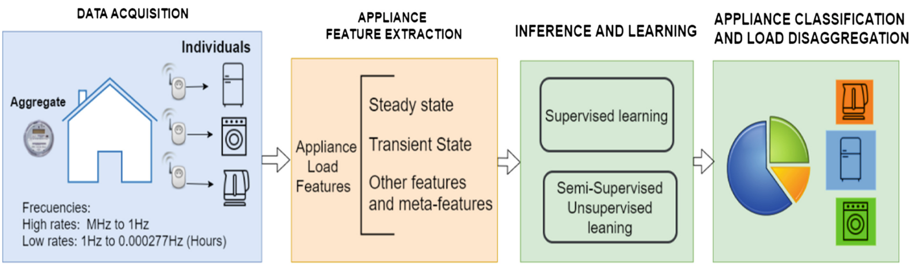

Fig. 1. General pipeline of NILM in literature

over the time (kWh kilowatt-hour). This measure appears in the bill and it is one – actually, the first one – of the main objectives of NILM: disaggregate this total amount to each appliance.

Next to this, it is necessary to emphasize the sampling rate of the data collected, as it determines the type of information that could be extracted from the electrical signals [49]. There are two main groups of data collected based on this criteria [4]:

- **High sampling rate:** The data is collected at a sampling frequency of 1 Hz or more. This kind of data allows to extract some features in the consumption which are only present at these sampling rates. In some cases these very high sampling rates only can be achieved with special hardware.
- **Low sampling rate:** This group includes frequencies of sampling lower than 1 Hz down minutes or even hours. This kind of sampling rate is the most common in the smart meters which can be bought nowadays.

Collected data is stored in remote databases for further feature extraction and processing. In the literature there are several databases of reference in this domain in order to test different algorithms. Some of them are REDD [23], UK-DALE [20], AMPds [29] and others which can be found in this WIKI [47].

3.2 Event Detection and Feature Extraction

After collecting data, the next step is extracting more information about the electrical temporal series in order to obtain features that allow to detect events such as appliance state transitions. Depending on where these features can be extracted, they can be classified as follows [49]:

- **Steady state features:** This features are derived from the steady-sate operation of an appliance. Variations in Real Power (P) and Reactive Power (Q) are commonly used [12] in the steady state to detect the change state events operation of appliances. The number and kind of features that could be extracted will depend on the data sample rating. Features only related to real power can be extracted at a low rate sampling and used to detect appliances with very different power draw characteristics. Features such as current harmonics work better than previous, but they require a high rate sampling to be obtained.
- **Transient state features:** This features are derived from the transient state operation of an appliance. These features are less overlapping between appliances compared to steady state features. However, the major drawback is the high rate sampling required to obtain these features [8]. There are several features such as current spikes, transient response time, repeatable transient power profiles, spectral envelopes, etc.
- **Non traditional features:** These features refer to other new characteristics which are result of the other two kinds of characteristics or other such as time of the day, on/off distribution, use frequency of an appliance and the correlation of usage of multiple appliances [21,48].

3.3 Inference and Learning

Once the features are extracted, it will be necessary to apply methods which determine the appliances that are running at a given time. This techniques can be classified as supervised techniques and semi-supervised or unsupervised methods. The supervised disaggregation methods require individual appliance data to be trained so they can classify the appliances which are working at each moment. Semi-supervised methods need to train a little amount of data at the beginning of the process to perform the classification, and the unsupervised methods can learn from the data collected without previous training data.

Supervised Methods. This kind of methods can be splitted into:

- **Optimization approaches:** They deal with NILM problem as an optimization problem. The extracted features are compared to discover load features stored in a database and to find the closest possible match. These algorithms find the most accurate combination of appliances included in database, which could have caused the output measure. Integer programming [2] and genetic algorithms [3] have been used in this kind of approaches [6].
- **Pattern Recognition approaches:** These approaches are commonly used by researchers in this topic. They can include simple based clustering approach like Hart *et al.* [12], Bayesian approaches [42] – which detect the most likely states of the potential appliances states –, SVMs classifying harmonic features [17], and other approaches like Hidden Markov Models and Artificial Neural Networks [41] – that have demonstrated a great performance due to their ability to introduce temporal and state change information –. Some of this approaches will be explained later. Since the performance of the previous algorithms is dependent of the features extracted, a reference dataset is required in order to evaluate their performance correctly [23].

Semi-supervised and Unsupervised Methods. These methods are highly explored nowadays because they require minimal or no previous information. A lot of companies are interested in these approaches because of their low setup cost, their non intrusiveness and short training phase for load identification algorithms. There are several studies in the literature which use this kind of method to detect loads: In this work [11], authors use steady state features P and Q to cluster the appliances and a matching pursuit to source reconstruction. Other studies – like [39]– focuses on the use a Motif mining approach. This approach uses on/off events and try to identify appliance episode. This method only works for appliances with static episodes of events. In the work [21], the authors have built a probabilistic model using a variation of HMM called Factorial Markov Models (FHMM) and features related to time. Additionally, power consumption of each appliance have been used to model individual models to each appliance. Recently, authors like [15] have developed a method to achieve a fully unsupervised disaggregation. The accuracy obtained from these methods is generally lower than the accuracy obtained with supervised methods in disaggregation, but their easy deployment is highly appealing to the current companies in the sector.

3.4 Appliance Classification and Load Disaggregation

This is the last phase in the NILM process: after completing the load identification, dividing the total consumption among the identified loads is required. Detailed information about the amount of consumption provided by each appliance to the total household consumption will be shown to the user. In addition, information related to the energy price can be provided to inform user about how much every appliance consumption costs.

4 Disaggregation Techniques

This section collects the very latest techniques applied into the energy disaggregation field.

4.1 Autoencoders

NILM and energy disaggregation can be treated as a *denoising* problem. This kind of tasks include removal of grin from an old photo, removal of reverb from an audio or in-filling a part of an image. Energy disaggregation can be treated in the same way, retrieving the clean signal, without the noise produced by other appliances, of the target appliance.

An autoencoder (also named AE) is a neural network which task is reconstruct (rebuild) the input. The key part is that the autoencoder encodes the input to a reduced vector representation and then decodes it for the output. The easiest way to force the network to compress the data representation is having a code layer with a smaller dimension than the input. The behavior of a linear AE with just one hidden layer is equivalent to PCA, thus AEs can be deep and non-linear.

Denoising Autoencoders (dAE) were firstly introduced by Vincent *et al.* [44] tries to recover a clean signal from a noisy one. These are typically trained by artificially corrupting a signal and using it as a the input for the net while the original signal is used as the output of the network.

In NILM, dAEs are used with the aggregated power demand signal as the 'noisy' one to reconstruct and the output is the clean signal of the individual consumption of the target appliance. In the study proposed by Kelly [18] in the use of denoising autoencoders barely reaches an average F1 score of 55%.

4.2 HMM

Hidden Markov Models (HMM) is an approach selected by a broad number of researchers to face NILM [21,28]. This is because they can model time series and represent the unobservable states of that time series. In a HMM the state of the model is hidden (the state is not directly visible to the observer), however, the output is visible and it depends on that hidden state. In NILM the hidden state is the state of all the appliances (each possible combination of theirs possible load states) and the output observed is the aggregate consumption of the household. Each hidden state has a probability distribution related to the all possible outputs and thus, the sequence of outputs provides information about the sequence of the hidden states. Markov property affirm that the conditional probability distribution of hidden states depends only on the value of the immediately previous hidden state and all others previous states have no influence. HMM starts on the premise of that Markov property is holden for a given HMM model. A common HMM can be defined as [28]:

$$\lambda = \{S, O, P_0, A, B\}, \tag{1}$$

where S is the set of possible states, O observations, P_0 initial probabilities, A the transition matrix and B the emission matrix. The total number of states and observations are $K = |S|$ and $N = |O|$ respectively. A defines the probability for state transition from a state to the next state with $K \times K$ matrix where $\sum_i A[i,j] = 1.0$ and B defines the probability for detect a particular observation at the next state with $K \times N$ matrix where $\sum_j B[j,n] = 1.0$. Formally:

$$A[i,j] = p(S_t = j | S_{t-1} = i) \tag{2}$$

$$B[j,n] = p(O_t = n | S_t = j) \tag{3}$$

Algorithms like Viterbi algorithm [45] among others are used to decode the most probable states of the appliances in each moment. This kind of algorithms have a main drawback related to the high complexity in space and time that they present. Given M loads with K internal states (all the loads with the same states for simplicity) the total number of hidden states is k^M so it is a high number of states for a common household monitoring only 10 loads.

There are several approaches using HMM and its variants for disaggregation such us Kolter [22], Parsons [33], Johnson [16] and Makonin [30] which deal with the previous problem and they propose different ways to solve it.

4.3 Deep Learning

Deep learning is a term used to refer to a set of machine learning techniques. In the artificial neural networks field it describes networks with many layers. The objective of using this kind of architectures is learning about a hierarchy of features. Studies points that layerwise stacking of feature extraction often yielded better representations (e.g. classification error, quality of samples generated or invariance properties) [7,24].

Each layer processes some kind of input, processes and learns from it, to give a better representation of the data to the next layer's input, exponentially increasing the number of possible state representations [32]. This computational concept is borrowed from the human brain's ability to observe, analyze, learn and make decisions, especially for extremely complex problems. A major advantage of these representations is that they can be invariant to local changes occurred in the input data. Learning from invariant features is a major goal in pattern recognition tasks like those needed in the NILM field.

This kind of deep architectures have succeeded in recent years due to the recent overcome of many problems that prevented the advance of the techniques. Some of major ones are the creation of optimization techniques and architectures and the huge amount of data available in many fields, which are mandatory to successfully train deep networks. Also, the exponential growth of processing power in GPUs with its lowering price tag per processing power make this devices more affordable and usable to train this kind of architectures in shorter periods of time.

The disaggregation process is made through the use of a sliding time window along the input sequence. As such, the first input sequence for the network will be zeros. Then the input window is shifted K samples (where $K >= 0$). If K is less than the length of the network's input layer size, then it will see overlapping input sequences. This behavior allows the net to process same values in several attempts and detect in a better way appliance activation. Onwards, we explain the most recent deep learning architectures applied to energy disaggregation in three major categories named by the neuron and architecture used in each case.

Convolutional Neural Network *CNN.* There are biologically-inspired variants of MLPs. From Hubel and Wiesel's [14] work on cat's visual cortex we know it has a complex arrangement of cells. These are sensitive to subregions of the visual field, called receptive field. The subregions are tiled to cover all the visual field. These cells act as local filters over the input space and are well-suited to exploit the string spatially local correlation present in images.

A feature map is obtained by repeatedly applying a function across subregions of the entire image and by the convolution of the input image with a linear filter, adding a bias term and then applying a nonlinear function.

Convolutional neural nets build a small number of filters, each with a small receptive field, and these filters are duplicated (with shared weights) across the entire input.

There are several kind of convolution neurons depending on the dimension. For the NILM use case, Convolution 1-Dimensional Neurons are applied due to the unidimensional nature of the input time-series dependant data.

Similarly to computer vision tasks, in time series problems we often want to extract a small number of low-level features with a small receptive fields across the entire input.

As proposed in the work of [35] the typical architecture using convolutional layers with increasingly number of filters. Max Pooling layers are also applied in order to give some translation invariance while reducing the number of parameters of the network. The accuracy result is around 84% for all the houses where individual training and testing were applied. This kind of neural network shows better average accuracy results against LSTM Sect. 4.3 architectures.

Long Short Term Memory *LSTM.* This type of neuron was first published by Hochreiter and Schmidhuber in 1997 [13] and have been applied in a broad range of problems with a great success such as handwriting recognition, speech recognition and time-series related classification.

The kind of architecture in which this neurons are applied was designed to solve the vanishing gradient problem, common in typical recurrent neural network architectures. It makes use of gates to have a better control against gradient flow. However, in presence of backpropagation the error loops in the memory and causes an error known as “carousel error”. This issue was fixed with the introduction of peephole connectors, increasing the precision of the network [10]. Also, Gers et al. [9] introduced the called “forget gates” that made possible to the LSTM to learn local self-resets of their memory content that isn't relevant, reducing possible errors due to memory remembrance.

In the NILM field, LSTM based architectures have been successfully applied in energy disaggregation like the work presented by [18,35] reaching up to 80% precision score in different houses and appliances as their work show, a little worse performant than convolutional networks.

5 Applications and Challenges

Finally we will show some of the most interesting application of NILM and their related challenges:

- **Detailed bill information:** The most widespread application, which tries to provide more information to the user in order to obtain energy savings and reductions in its bill. The main objective is achieving the best accuracy. Researchers are searching a way to compare the disaggregation present in the market.
- **Demand response application:** Other interesting use case is the detection of potential consumers of demand response programs by utility electricity companies. The detection of deferrable loads or inactivity periods in the energy consumption of their consumers can target them for a possible demand response program.
- **Ambient intelligence:** The load monitoring enables other sensing approaches without the need of include new sensors in the household.
- **Occupancy detection:** Linked with the previous point, it would be possible infer the presence or absence in household by the power consumption. This is an interesting point for companies to offer extra services without deploy any sensor platform, in the same way this may involve an intrusion into the privacy of thousands of users of the electric network.
- **New companies services:** Thanks to this, load monitoring companies are offering new services like show the current billing amount from the beginning of the billing period to the current time. Also other services like [36] offer real time information about appliances switched on and provide reminders, for example, to switch off certain appliances before leave home.
- **Illegal load detections:** Other useful application of NILM its the detection of anomalous loads in household which can be used to report possible energy thefts in public and private buildings.

NILM is and will be a intense subject of study in the following years as the use of smart grids, demand response programs and other energy-consumption and metering approaches are more and more spread into end user applications. The arrival of new techniques as explained in this work accelerate this spreading process.

Acknowledgments. This work has been supported by the European Commission H2020 MSCA-RISE-2014: Marie Skłodowska-Curie project DREAM-GO Enabling Demand Response for short and real-time Efficient And Market Based Smart Grid Operation - An intelligent and real-time simulation approach ref 641794.

References

1. Abubakar, I., et al.: Application of load monitoring in appliances energy management a review. Renew. Sustain. Energy Rev. **67**, 235–245 (2017). doi:10.1016/j.rser.2016.09.064. ISSN: 18790690
2. Bhotto, M.Z.A., Makonin, S., Bajic, I.: Load disaggregation based on aided linear integer programming. IEEE Trans. Circuits Syst. II Express Briefs 1 (2016). doi:10.1109/TCSII.2016.2603479. ISSN: 1549-7747
3. Baranski, M., Voss, J.: Genetic algorithm for pattern detection in NIALM systems. In: IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No.04CH37583), pp. 3462–3468. IEEE (2004). doi:10.1109/ICSMC.2004.1400878. ISBN: 0-7803-8567-5
4. Basu, K., Hably, A., Debusschere, V., Bacha, S., Driven, G.J., Ovalle, A.: A comparative study of low sampling non intrusive load dis-aggregation. In: IECON Proceedings (Industrial Electronics Conference), pp. 5137–5142 (2016). doi:10.1109/IECON.2016.7793294
5. Darby, S.: The effectiveness of feedback on energy consumption a review for DEFRA of the literature on metering, billing and direct displays. In: Environmental Change Institute University of Oxford, 22 April, pp. 1–21 (2006). doi:10.4236/ojee.2013.21002. http://www.citeulike.org/user/cblock/article/4123593. ISSN: 2169-2637
6. Egarter, D., Sobe, A., Elmenreich, W.: Non-intrusive load monitoring, pp. 4–6. Springer, Heidelberg (2013). doi:10.1109/5.192069. ISBN: 1424409462
7. Erhan, D., et al.: Why does unsupervised pre-training help deep learning? J. Mach. Learn. Res. **11**, 625–660 (2010). ISSN: 1533-7928
8. Figueiredo, M.B., De Almeida, A., Ribeiro, B.: An experimental study on electrical signature identification of non-intrusive load monitoring (NILM) systems. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 6594. PART 2, pp. 31–40. Springer, Heidelberg (2011). doi:10.1007/978-3-642-20267-4_4. ISBN: 9783642202667
9. Gers, F.A.: J Urgen Schmidhuber, and Fred Cummins. Learning to Forget: Continual Prediction with LSTM (1999)
10. Gers, F.A., Schraudolph, N.N., Schmidhuber, J.: Learning precise timing with LSTM recurrent networks. J. Mach. Learn. Res. **3**, 115–143 (2002)
11. Gonçalves, H., et al.: Unsupervised disaggregation of appliances using aggregated consumption data. In: Environmental Engineering (2011)
12. Hart, G.W.: Nonintrusive appliance load monitoring. Proc. IEEE **80**(12), 1870–1891 (1992). ISSN: 15582256

13. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural Comput. **9**(8), 1735–1780 (1997). doi:10.1162/neco.1997.9.8.1735. ISSN: 0899-7667
14. Hubel, D.H., Wiesel, T.N.: Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. J. Physiol. **160**(1), 106–154 (1962). doi:10.1113/jphysiol.1962.sp006837. ISSN: 00223751
15. Jia, R., Gao, Y., Spanos, C.J.: A fully unsupervised nonintrusive load monitoring framework. In: 2015 IEEE International Conference on Smart Grid Communications, SmartGridComm 2015, pp. 872–878 (2016). doi:10.1109/SmartGridComm.2015.7436411
16. Johnson, M.J., Willsky, A.S.: Bayesian nonparametric hidden semi-Markov models. J. Mach. Learn. Res. **14**, 673–701 (2013)
17. Kato, T., Cho, H.S., Lee, D., Toyomura, T., Yamazaki, T.: Appliance recognition from electric current signals for information-energy integrated network in home environments. In: Mokhtari, M., Khalil, I., Bauchet, J., Zhang, D., Nugent, C. (eds.) Ambient Assistive Health and Wellness Management in the Heart of the City, ICOST 2009. LNCS, vol. 5597, pp. 150–157. Springer, Heidelberg (2009). doi:10.1007/978-3-642-02868-7_19
18. Kelly, J.D.: Disaggregation of domestic smart meter energy data, August 2016
19. Kelly, J., Knottenbelt, W.: Does disaggregated electricity feedback reduce domestic electricity consumption? A systematic review of the literature (2016). arXiv:1605.00962
20. Kelly, J., Knottenbelt, W.: The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes. Sci. Data **2**, 150007 (2015). doi:10.1038/sdata.2015.7
21. Kim, H., Marwah, M., Arlitt, M., Lyon, G., Han, J.: Unsupervised disaggregation of low frequency power measurements. In: Proceedings of the 2011 SIAM International Conference on Data Mining, pp. 747–758 (2011). doi:10.1137/1.9781611972818.64
22. Kolter, Z., Jaakkola, T., Kolter, J.Z.: Approximate inference in additive factorial HMMs with application to energy disaggregation. In: Proceedings of the International Conference on Artificial Intelligence and Statistics, pp. 1472–1482 (2012). http://people.csail.mit.edu/kolter/lib/exe/fetch.php?media=pubs:kolter-aistats12.pdf
23. Kolter, J.Z., Johnson, M.J.: REDD : a public data set for energy disaggregation research. In: SustKDD Workshop, vol. 1, pp. 1–6 (2011)
24. Larochelle, H., et al.: Exploring strategies for training deep neural networks. J. Mach. Learn. Res. **10**, 1–40 (2009). ISSN: 1533-7928
25. Laughman, C., et al.: Power signature analysis. IEEE Power Energy Mag. **1**(2), 56–63 (2003). doi:10.1109/MPAE.2003.1192027. ISSN: 15407977
26. Lee, K.D.: Electric load information system based on non-intrusive power monitoring (2003)
27. Lee, K.D., et al.: Estimation of variable-speed-drive power consumption from harmonic content. IEEE Trans. Energy Convers. **20**(3), 566–574 (2005). ISSN: 08858969
28. Makonin, S.: Real-time embedded low-frequency load disaggregation. pp. 1–121, August 2014
29. Makonin, S., et al.: Electricity, water, and natural gas consumption of a residential house in Canada from 2012 to 2014. Sci. Data **3**(160037), 1–12 (2016)

30. Makonin, S., et al.: Exploiting HMM sparsity to perform online realtime nonintrusive load monitoring. IEEE Trans. Smart Grid **PP**(99), 2575–2585 (2015). doi:10.1109/TSG.2015.2494592. ISSN: 19493053
31. Mehta, V.K.: Principles of Electronics, p. 792. Prentice Hall, Upper Saddle River (1980). ISBN: 0130344060
32. Najafabadi, M.M., et al.: Deep learning applications and challenges in big data analytics. J. Big Data **2**(1), 1 (2015). doi:10.1186/s40537-014-0007-7. ISSN: 2196-1115
33. Parson, O., et al.: Non-intrusive load monitoring using prior models of general appliance types. In: Proceedings of the 26th AAAI Conference on Artificial Intelligence, Toronto, pp. 356–362 (2012). ISBN: 9781577355687
34. Patel, S.N., 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). In: LNCS, vol. 4717, pp. 271–288. Springer, Heidelberg (2007). ISBN: 9783540748526
35. Paulo, P.: Applications of deep learning techniques on NILM (2016)
36. PG&E energy efficiency gains using behavior – Bidgely Blog. http://www.bidgely.com/blog/pge-pilot-yields-7-7-energy-savings/. Accessed 13 Feb 2017
37. Ridi, A., Gisler, C., Hennebert, J.: A survey on intrusive load monitoring for appliance recognition. In: Proceedings - International Conference on Pattern Recognition, pp. 3702–3707 (2014). doi:10.1109/ICPR.2014.636. ISSN: 10514651
38. Roos, J.G., et al.: Using neural networks for non-intrusive monitoring of industrial electrical loads. In: Instrumentation and Measurement Technology Conference (IMTC 1994). Conference Proceedings. 10th Anniversary. Advanced Technologies in I & M, pp. 1115–1118. IEEE (1994)
39. Shao, H., Tech, V., Marwah, M.: A temporal motif mining approach to unsupervised energy disaggregation. In: 1st International Workshop on Non-Intrusive Load Monitoring, pp. 1–2 (2012). ISBN: 9781577356158
40. Shaw, S.R., et al.: Instrumentation for high performance nonintrusive electrical load monitoring. J. Solar Energy Eng. **120**(3), 224 (1998). doi:10.1115/1.2888073. ISSN: 01996231
41. Srinivasan, D., Ng, W.S., Liew, A.C.: Neural-network-based signature recognition for harmonic source identification. IEEE Trans. Power Deliv. **21**(1), 398–405 (2006). doi:10.1109/TPWRD.2005.852370. ISSN: 0885-8977
42. Srinivasarengan, K., et al.: A framework for non intrusive load monitoring using Bayesian inference. In: 2013 Seventh International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing, July 2013, pp. 427–432. IEEE (2013). doi:10.1109/IMIS.2013.78. ISBN: 978-0-7695-4974-3
43. Sultanem, F.: Using appliance signatures for monitoring residential loads at meter panel level. IEEE Trans. Power Deliv. **6**(4), 1380–1385 (1991). ISSN: 19374208
44. Vincent, P., Larochelle, H., Bengio, Y., Manzagol, P.-A.: Extracting and composing robust features with denoising autoencoders. In: Proceedings of the 25th International Conference on Machine Learning - ICML 2008, pp. 1096–1103 (2008). doi:10.1145/1390156.1390294. ISBN: 9781605582054, ISSN: 1605582050
45. Viterbi, A.: Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. IEEE Trans. Inf. Theor. **13**(2), 260–269 (1967). doi:10.1109/TIT.1967.1054010. ISSN: 0018-9448
46. Wichakool, W., et al.: Modeling and estimating current harmonics of variable electronic loads. IEEE Trans. Power Electron. **24**(12), 2803–2811 (2009). ISSN: 08858993
47. Wiki NILM Databases. http://wiki.nilm.eu/index.php?title=NILM_dataset. Accessed 09 Feb 2017

48. Zeifman, M.: Disaggregation of home energy display data using probabilistic approach. IEEE Trans. Consum. Electron. **58**(1), 23–31 (2012). doi:10.1109/TCE.2012.6170051. ISSN: 00983063
49. Zoha, A., et al.: Non-intrusive load monitoring approaches for disaggregated energy sensing: a survey. Sensors (Switzerland) **12**(12), 16838–16866 (2012)