Load Disaggregation of Industrial Machinery Power Consumption Monitoring Using Factorial Hidden Markov Models

Pedro Bandeira de Mello Martins
GreenAnt
Programa de Engenharia Elétrica
COPPE - UFRJ, Brazil
Email: pedro.bandeira@greenant.com.br

Raphael Guimarães Duarte Pinto
GreenAnt
Programa de Planejamento Energético
COPPE - UFRJ, Brazil
Email: raphael@greenant.com.br

Pedro Bittencourt e Silva
GreenAnt
Email: pedro@greenant.com.br

***Abstract*—Non-Intrusive Load Monitoring (NILM) or Load Disaggregation is a set of techniques to identify and monitor loads from readings of aggregated signals from a unique electricity meter on a building. This paper presents a new dataset of industrial electric energy consumption and applies Factorial Hidden Markov Model, a probabilistic machine learning technique, to disaggregate six different industrial machines from a site meter on a factory in Brazil.**

I. Introduction

According to Armel, Gupta et al [1] and Darby [2] a method to control and reduce your energy consumption is to have real-time information about each appliance connected to the grid. Non-intrusive load monitoring (NILM), introduced by Hart in 1992 [3], aims at providing single-appliance power consumption information to household consumers without the need to install intrusive load monitors or appliance-specific sensors. NILM is usually performed using only one meter connected to the main electrical panel in the house. Since then, improvement has been made especially in the residential sector [4], [5], [6], [7].

The industrial sector is the biggest electricity consumer in Brazil, its share corresponds to 33.0% [8] of the entire electricity in the country. Therefore, it is expected that the national energy grid could benefit from energy efficiency programs on industrial plants. Real-time monitoring of machinery power consumption and real-time feedback on the data can give experts insightful information about energy-quality, energy-wastefulness and possibly leverage demand response.

Non-Intrusive Load Monitoring (NILM) techniques in this sector are still not widely researched worldwide [9], [10], nor are publicly available datasets found by the authors until the writing of this paper. In this work, we present a new dataset collected with GreenAnt's energy meters [1] on a poultry feed factory in Minas Gerais, Brazil and show disaggregation on this dataset using Factorial Hidden Markov Models (FHMM) [11].

Section II briefly explains Non-Intrusive Load Monitoring (NILM), while section III shows Factorial Hidden Markov Models (FHMM) technique, used for this analysis. Section IV presents the data collected, giving some background on the factory processes and measurement points. Next, Section V presents the results obtained by performing the experiments on the fore mentioned dataset. Last, Section VI analyzes the results obtained and proposes ideas for future work to be done, following this paper.

[1] http://www.greenant.com.br accessed 2017-12-26

II. Non-Intrusive Load Monitoring

Also known as load disaggregation, NILM can be described as a process of blind-source separation. Introduced by Hart in 1992[3], it aims at estimating individual appliance energy consumption from data of a Low-Voltage Distribution Board (LVDB). Figure 1 shows annotated-events from individual appliances on a whole-building power signal. Hart [3] models each appliance as a finite-state machine (FSM) with two (ON/OFF) or more states which are inferred by event detection and feature extraction in total power consumption from the LVDB.

NILM is considered to be an important feature for energy efficiency programs since it provides information that enables management of energy consumption in the demand side. It provides useful information for controlling and diagnosing different appliances connected to the measured grid, with only one energy reading point.

Zeifman et al. [12] suggest that proper feedback and detailed information can earn consumers up to 18% savings on their electricity consumption. Armel et al. [1] enumerates several benefits of appliance-specific consumption information such as:

- fault detection;
- elucidating behavioral patterns;
- analysis of appliances based on use;
- better data to redesign appliances for energy efficiency;
- improved load forecasting;
- improved economic models to better inform policies and funding allocations;
- changes on label efficiency due to the appliance usage.

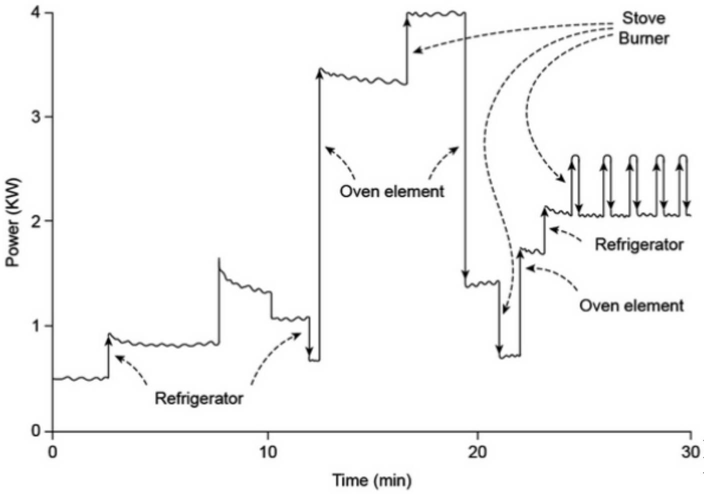


Fig. 1: Whole-building power signal with appliances events annotated. Figure from Hart, 1992 [3].

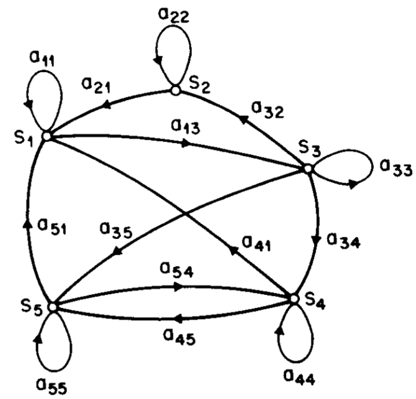


Fig. 2: A Markov chain example. Each state S_n has a probability σ_{nl} to change to the next S_l state. Figure from Rabiner et al. 1989 [14].

Based on the knowledge above, we can formulate the problem as on equation 1, which considers a whole-building signal according to appliance-level consumption.

$$x_t = \sum_{n=1}^{N} x_{n,t} \tag{1}$$

where N is the number of types of equipment, $x_{n,t}$ is the power consumption of equipment n at time t, and x_t is the aggregated signal at time t.

It is also possible to assume that an appliance n has K_n states, and that it can be only at one of the K_n-states at time t, (that is, $\sum_{k=1}^{K_n} z_{t,k}^n = 1$, and $z_{t,k} \in \{0, 1\}$). This appliance n at state k would consume power μ_k^n. Equation 3 express this approach.

$$\begin{aligned} \hat{x}_t &= \sum_{n}^{N} \hat{x}_{n,t} && (2) \\ &= \sum_{n=1}^{N} \sum_{k=1}^{K_n} z_{t,k}^n \mu_k^n && (3) \end{aligned}$$

In short hand, we want to estimate $x_{n,t}$ for the target appliance n – or $z_{t,k}^n \mu_k^n$ if we model its operation as a finite-state machine – at a given time t, from an aggregated x_t signal. Lin et al. [13] reviewed several methods which attempt at solving this problem. This paper will focus on Factorial Hidden Markov Models as first proposed by Kolter et al. [7].

III. Factorial Hidden Markov Models

A probabilistic solution to the problem proposed is developed using Hidden Markov Models (HMM). HMMs are widely used in voice recognition since the 1970's and have been used as a NILM analysis technique by Parson et al. [6]. It assumes that the system has non-observable states.

In Markov chains (figure 2) states are fully observable. However in HMM only the output is observable, so its states are hidden and are a probabilistic function of the output. In other words, the final model is a non-observable stochastic process inside a stochastic process. This technique is generally used on time series processing, where information about the past is considered to be transmitted through a hidden state.

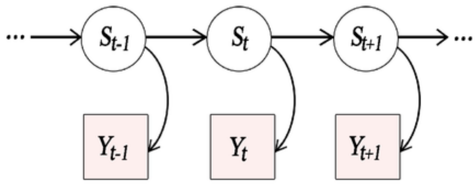
Parson et al. [15] uses iterative Hidden Markov Models to model household's specific appliances. This approach assumes that every step change in the aggregate power is an observation sequence and every appliance state is modelled as a Markov state. It requires a priori knowledge of the appliances' state transition matrix and its power demand to generate a generic model.

This method does not consider possible simultaneous transitions from different individual appliances. In order to address such issue, Kolter et al. [7] considers every observed output as an additive function of different hidden states, a method called by Gharamani and Jordan in 1996[11] Factorial HMM (FHMM). On an FHMM each independent HMM evolves in parallel and represents each monitored device. The aggregated data seen as the observable output is estimated by the combined hidden states and the algorithm models which sequence of Markov hidden states could have produced that output. Figure 3 describes both an HMM and an FHMM models.

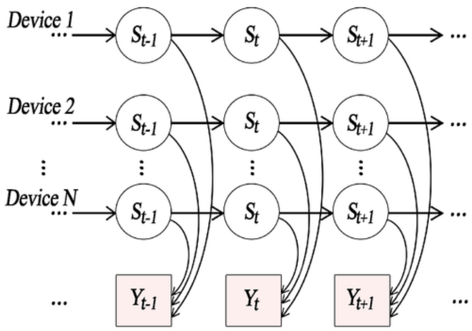
IV. Dataset

Even though there are several publicly available NILM datasets, most of them only include data acquired in residential or light industry environments [17], [18], [19], [20], [21], [22] and only one in a developing country [23]. This dataset, however, contains heavy-machinery data from the Brazilian industrial sector.

The data was collected in a poultry feed factory located in the state of Minas Gerais, Brazil. Its process can be summarized to creating pellets of ration for poultry from corn



(a) A single HMM.



(b) Additive FHMM. Each horizontal flow is an individual HMM. The output is a sum of every hidden state at the same time.

Fig. 3: Comparision between HMM and FHMM. Figures from Paradiso et al. [16].

or soybeans and added nutrients. The factory produces at full-scale over the entire year, thus it has well-behaved usage patterns at any time. It operates from Mondays through Fridays (and occasionally on Saturdays, in case the month's production was not enough) on a daily three-turn shift from 22h to 17h. From 17h to 22h electricity prices are higher, so the factory is closed.

The factory has four different LVDBs under the main medium-voltage distribution board (MVDB). One (1) for lights and administration-related appliances, the second (2) for pelletizing-related machinery, the third (3) for milling-related machinery and the last one (4) for general production-related machinery.

On a first scenario, it was decided to collect single phase (out of three used on the factory) data from the second LVDB (pelletizing-related machinery or LVDB-2) and from the machines connected to it, as it was the most consuming LVDB on the factory. On a national scale, according to Garcia et al. [24] and the Brazilian Energy Balance (BEN) [8], circa 62% of the electricity consumption in foods and beverage industrial sector is destined to electrical motors, being the most important set of electrical appliances on this sector. Hence, all of the measured appliances are horizontal motors on the factory.

This board distributes energy to the most important machines on the factory. Under the second LVDB, there are 3 (three) pairs of motors. The first pair (1) of pelletizers, the second pair (2) of exhaust fans and the third pair (3) of double-pole contactors. Figure 4 shows, in green, which appliances

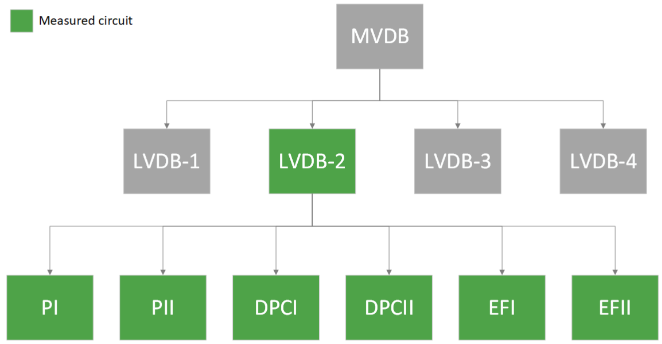


Fig. 4: Diagram of distribution boards and appliances. Measured circuits are shown in green.

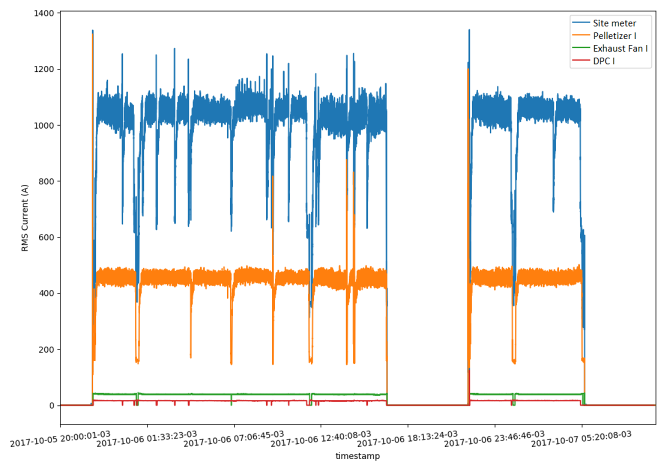


Fig. 5: RMS current on each individual appliance under the site meter.

and boards are measured by the GreenAnt meter[2]. Therefore, there are 7 (seven) GreenAnt meters on the factory measuring LVDB-2 and six appliances, which are:

- Pelletizer I (PI)
- Pelletizer II (PII)
- Double-pole Contactor I (DPCI)
- Double-pole Contator II (DPCII)
- Exhaust Fan I (EFI)
- Exhaust Fan II (EFII)

All machines under this LVDB work at 380 V. Both pelletizer-motors run at a minimum of 1788 RPM using 315 kW of power, while double-pole contactors use 15 kW at a minimum of 1750 RPM and exhaust fans use 45 kW at a minimum of 1775 RPM. As the factory is cyclically producing pellets at full power. Each appliance can be modeled as a three-state machine (OFF, NO LOAD ON, FULL LOAD ON).

The GreenAnt meter samples data at 8 KS/s internally, downsamples it to 1 Hz and sends a package of measurements

[2]http://www.greenant.com.br/en/solutions/ accessed 2017-12-07

every 10 (ten) seconds to an on-site server. Each package includes RMS voltage, RMS current, active power, reactive power, apparent power and active energy. When a remote connection is available the data is then sent to a remote server, where the experiments are performed. For this paper, samples were collected from 2017-10-30 20:54:11 until 2017-11-23 13:06:42, or roughly 24 days of measurements. Figure 5 represents a sample interval of RMS current from those measurements.

The dataset is stored on a remote server and follows NILM Metadata [25] schema for human and machine readable interpretation of the data. This schema also helps by being easily used by the open-source disaggregation solution NILMTK [26], which was used to train the FHMM model on this paper.

V. Results

The collected data presented in section II was divided into three different sets:

- 70% for a training set;
- 15% for a validation set;
- 15% for a test set.

The FHMM model was trained using the implementation available at NILMTK [26]. 200 models were trained, the best was chosen for testing, using the normalized disaggregation error computed over the validation set as the criteria for model selection. Only the active power demand series was used as input to the model, for simplicity.

A. Metrics

In order to validate the trained models, three different metrics were used. Equations 4, 5 and 6 describe them, y represents the target and $\hat{y}$ the predicted signal.

1) Normalized Disaggregation Error (NDE): It is related to the quality of disaggregation and tries to reduce influence of outliers.

$$\mathrm{NDE} = \frac{\sum_i^N (\hat{y}_i - y_i)^2}{\sum_i^N y_i^2} \tag{4}$$

2) Normalized Signal Aggregated Error (SAE): It is a measurement of discrepancy on energy estimation.

$$\mathrm{SAE} = \frac{|\sum_i^N \hat{y}_i - \sum_i^N y_i|}{\sum_i^N y_i} \tag{5}$$

3) F1 Score: Measurement of test accuracy in binary classification. It considers precision and sensibility of the model against the target. It is related to how well the model correctly classified timestamps on which the appliances were ON and OFF. It can be used as a percentage of time that the machine is correctly detected as turned ON or OFF.

$$\begin{aligned} F_1 &= \frac{2 \cdot \text{true positive}}{2 \cdot \text{true positive} + \text{false negative} + \text{false positive}} \\ &= 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \end{aligned} \tag{6}$$

B. Trained Model Results

The test set aggregate LVDB reading windows were fed into the model after the training and validating, for computing test metrics. Table I shows the results and Figures 6, 7 and 8 display the targets, predictions and inputs.

VI. Conclusion and Future Work

From the results we can assume that:

- Loads which consume a large ratio of total energy consumption on site meters are better disaggregated - as it happens with Pelletizer I and Pelletizer II.
- Binary classification of the time series succeeds on at least 70% of all data points, even on relatively low consumption machinery - such as the Double-Pole Contactors.
- The model was able to identify individual appliances even during moments when where there are more than one of the same equipment on its ON cycle.

It is important to note that only a small window of data was used – only 17 days – for training, as there was a total of 24 days. The next step is to collect more data from the factory and use it to train the model and check if it will improve performance. Also, it is possible that the model overfitted on those particular devices. Therefore, data from more factories should be collected to test inter-factory generalization of the models. As we model every appliance as a motor defined by its speed, power consumption and number of states, it would

TABLE I: Results From the Trained FHMM Model After 200 Rounds of Training and Validation on Test Set.

	PI	PII	DPC I
NDE	0.033241	0.054196	0.259888
SAE	0.026754	0.005615	0.149578
F1 Score	97.06%	96.10%	77.75%

	DPC II	EF I	EF II
NDE	0.336690	0.248441	0.267303
SAE	0.083227	0.145538	0.112474
F1 Score	70.31%	82.46%	89.04%

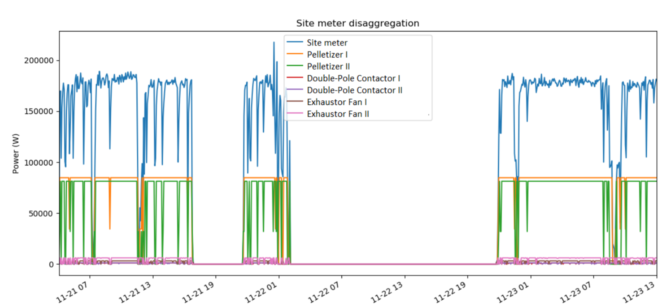


Fig. 6: Disaggregation of all appliances from readings of site meter (blue).

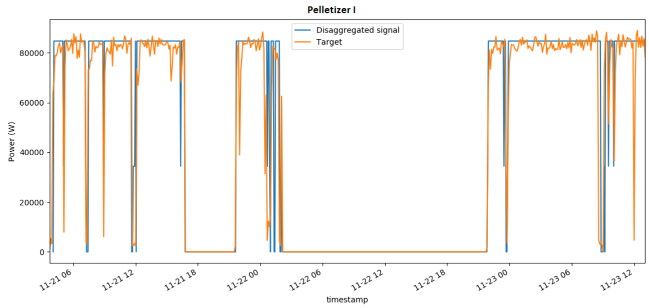


Fig. 7: Disaggregated signal of Pelletizer I from LVDB-2 and its target.

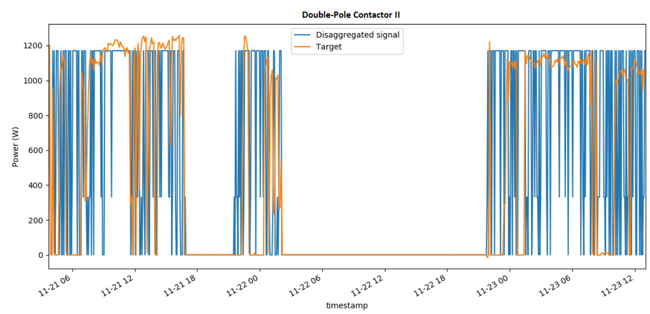


Fig. 8: Disaggregated signal of the second Double-Pole Contactor and its target.

be interesting to also compare how the FHMM models work with motors with same speed, power and number of states working on different industry sectors.

Future work could also aim at trying different techniques for disaggregation using the dataset. Such techniques should include, but not limited to, Convolutional and Recurrent Neural Networks as in Kelly et al. [4] and Graph Signal Processing [27].

As of this paper, the dataset is still under development. Measurements are being taken at other machines and LVDBs in the same factory, as well as at the MVDB circuit. Load disaggregation on heavy-machinery industrial sector could also benefit with a broader dataset, such as one with data from machines of more than one sector – as opposed to one (foods and beverages) – or even more than one country.

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References

[1] K. C. Armel, A. Gupta, G. Shrimali, and A. Albert, "Is disaggregation the holy grail of energy efficiency? the case of electricity," *Energy Policy*, vol. 52, pp. 213–234, 2013.

[2] S. Darby *et al.*, "The effectiveness of feedback on energy consumption," *A Review for DEFRA of the Literature on Metering, Billing and direct Displays*, vol. 486, no. 2006, 2006.

[3] G. W. Hart, "Nonintrusive appliance load monitoring," *Proceedings of the IEEE*, vol. 80, no. 12, pp. 1870–1891, 1992.

[4] J. Kelly and W. Knottenbelt, "Neural nilm: Deep neural networks applied to energy disaggregation," in *Proceedings of the 2Nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments*, ser. BuildSys '15. New York, NY, USA: ACM, 2015, pp. 55–64. [Online]. Available: http://doi.acm.org/10.1145/2821650.2821672

[5] N. Batra, O. Parson, M. Berges, A. Singh, and A. Rogers, "A comparison of non-intrusive load monitoring methods for commercial and residential buildings," *arXiv preprint arXiv:1408.6595*, 2014.

[6] O. Parson, S. Ghosh, M. J. Weal, and A. Rogers, "Non-intrusive load monitoring using prior models of general appliance types." in *AAAi*, 2012.

[7] J. Z. Kolter and T. Jaakkola, "Approximate inference in additive factorial hmms with application to energy disaggregation," in *Proceedings of the Fifteenth International Conference on Artificial Intelligence and Statistics*, ser. Proceedings of Machine Learning Research, N. D. Lawrence and M. Girolami, Eds., vol. 22. La Palma, Canary Islands: PMLR, 21–23 Apr 2012, pp. 1472–1482. [Online]. Available: http://proceedings.mlr.press/v22/zico12.html

[8] "Balanço energético nacional," Empresa de Pesquisa Energética, Ministrio de Minas e Energia, Tech. Rep., 2017.

[9] E. Holmegaard and M. B. Kjærgaard, "Towards nilm for industrial settings," in *Proceedings of the 2015 ACM Sixth International Conference on Future Energy Systems*. ACM, 2015, pp. 207–208.

[10] E. Holmegaard and M. B. Kjaergaard, "Nilm in an industrial setting: A load characterization and algorithm evaluation," in *Smart Computing (SMARTCOMP), 2016 IEEE International Conference on*. IEEE, 2016, pp. 1–8.

[11] Z. Ghahramani and M. I. Jordan, "Factorial hidden markov models," in *Advances in Neural Information Processing Systems*, 1996, pp. 472–478.

[12] M. Zeifman and K. Roth, "Nonintrusive appliance load monitoring: Review and outlook," *IEEE transactions on Consumer Electronics*, vol. 57, no. 1, 2011.

[13] Y.-H. Lin and M.-S. Tsai, "Development of an improved time–frequency analysis-based nonintrusive load monitor for load demand identification," *IEEE Transactions on Instrumentation and Measurement*, vol. 63, no. 6, pp. 1470–1483, 2014.

[14] L. R. Rabiner, "A tutorial on hidden markov models and selected applications in speech recognition," *Proceedings of the IEEE*, vol. 77, no. 2, pp. 257–286, 1989.

[15] O. Parson, S. Ghosh, M. Weal, and A. Rogers, "Using hidden markov models for iterative non-intrusive appliance monitoring," 2011.

[16] F. Paradiso, F. Paganelli, D. Giuli, and S. Capobianco, "Context-based energy disaggregation in smart homes," *Future Internet*, vol. 8, no. 1, 2016.

[17] 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*, vol. 25, no. Citeseer, 2011, pp. 59–62.

[18] M. Kahl, A. U. Haq, T. Kriechbaumer, and H.-A. Jacobsen, "Whited-a worldwide household and industry transient energy data set," in *Workshop on Non-Intrusive Load Monitoring (NILM), 2016 Proceedings of the 3rd International*, 2016.

[19] K. Anderson, A. Ocneanu, D. Benitez, D. Carlson, A. Rowe, and M. Berges, "BLUED: a fully labeled public dataset for Event-Based Non-Intrusive load monitoring research," in *Proceedings of the 2nd KDD Workshop on Data Mining Applications in Sustainability (SustKDD)*, Beijing, China, Aug. 2012.

[20] A. Monacchi, D. Egarter, W. Elmenreich, S. D'Alessandro, and A. M. Tonello, "Greend: an energy consumption dataset of households in italy and austria," in *Smart Grid Communications (SmartGridComm), 2014 IEEE International Conference on*. IEEE, 2014, pp. 511–516.

[21] J. Kelly and W. Knottenbelt, “The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes,” vol. 2, no. 150007, 2015.

[22] M. Gulati, S. Sundar Ram, and A. Singh, “An in depth study into using emi signatures for appliance identification,” in *Proceedings of the First ACM International Conference on Embedded Systems For Energy-Efficient Buildings*. ACM, 2014.

[23] N. Batra, M. Gulati, A. Singh, and M. B. Srivastava, “It’s different: Insights into home energy consumption in india,” in *Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings*, ser. BuildSys’13. New York, NY, USA: ACM, 2013, pp. 3:1–3:8. [Online]. Available: http://doi.acm.org/10.1145/2528282.2528293

[24] A. G. P. Garcia, A. S. Szklo, R. Schaeffer, and M. A. McNeil, “Energy-efficiency standards for electric motors in brazilian industry,” *Energy Policy*, vol. 35, no. 6, pp. 3424–3439, 2007.

[25] J. Kelly and W. Knottenbelt, “Metadata for Energy Disaggregation,” in *The 2nd IEEE International Workshop on Consumer Devices and Systems (CDS 2014)*, Västerås, Sweden, Jul. 2014.

[26] N. Batra, J. Kelly, O. Parson, H. Dutta, W. Knottenbelt, A. Rogers, A. Singh, and M. Srivastava, “NILMTK: An Open Source Toolkit for Non-intrusive Load Monitoring,” *ArXiv e-prints*, Apr. 2014.

[27] K. He, L. Stankovic, J. Liao, and V. Stankovic, “Non-intrusive load disaggregation using graph signal processing,” *IEEE Transactions on Smart Grid*, 2017.