Safety and Reliability – Safe Societies in a Changing World – Haugen et al. (Eds)

Energy efficiency and predictive maintenance applications using smart energy measuring devices

S. Kotsilitis
System Reliability and Industrial Safety Laboratory, National Centre for Scientific Research "Demokritos", Athens, Greece
Department of Information and Communication Systems Engineering, University of the Aegean, Samos, Greece

E.C. Marcoulaki
System Reliability and Industrial Safety Laboratory, National Centre for Scientific Research "Demokritos", Athens, Greece

E. Kalligeros
Department of Information and Communication Systems Engineering, University of the Aegean, Samos, Greece

Y. Mousmoulas
Plegma Labs, Athens, Greece

ABSTRACT: This paper discusses novel technologies for energy efficiency and predictive maintenance using hardware accelerated energy disaggregation. The disaggregation process involves the use of custom designed smart sensors that collect and treat aggregated information on the current and voltage waveforms. The treated data are further on transmitted to the cloud where they are stored and processed to enable the extraction of advanced information on individual device consumption patterns and health status. This information can be extremely useful for the management of electric devices in residential or commercial sites as well as for predictive maintenance in industrial sites. The paper reviews the underlying methodologies, and presents preliminary work and results from data collection in the offices of a software company. The presented work involves the installation of measurement devices and the development of complementary hardware and software. This is part of the ongoing 4-year project PREDIVIS (PREdictive, Disaggregation Intelligent VIS (meaning "power" in Latin)).

1 INTRODUCTION

Nowadays, the ever-growing power demand of industries and households combined with the goals for carbon dioxide emission reduction, have led the communities to take action, by implementing conservation and energy efficiency programs. The first step in energy reduction actions is the rollout of smart meters to monitor energy consumption and the smart grid technologies to distribute the available energy more efficiently, combined with the wide adoption of renewable energy sources.

The energy consumption and carbon emissions are regulated by frameworks and directives, mainly focused on actions by industries in order to minimize their impact on climate change. In most cases these actions are costly and inefficient, and often industries are incapable of adapting new equipment and carbon dioxide emission reduction techniques which leads to increased taxes and fines when goals are not achieved.

Monitoring of energy consumption at appliance level is essential for predicting energy needs and monitoring appliance operation in a household, a building or an industrial system. Energy disaggregation refers to using data analytics and signal processing, to identify specific patterns and to break down electricity consumption to individual appliances. This is usually done in a non-intrusive manner by monitoring the utility connection meter, and has been a field of significant research work for over twenty years. Non-Intrusive Load Monitoring (NILM) is a process where the aggregated electricity consumption is metered at the Grid-consumer connection point, and by analyzing the changes in voltage and current wavelengths tries to identify which appliances are being used at a certain time. Still, NILM technology's main goal is to provide insights into energy consumption at appliance level, mainly to support energy efficiency actions with economic and environmental impact. There are novel techniques using various approaches of NILM for a great number of applications, like safety on industrial environments, device health monitoring and predictive maintenance and demand response applications.

Equipment monitoring on industrial sites is a necessity and most of the time, a costly and complex process. Various industries, monitor their machinery and equipment to prevent malfunctions, minimize danger, service and repair costs, and to increase the overall operating time. NILM techniques could be a cheap alternative to equipment monitoring systems which are costly and require huge and complex installations. Monitoring equipment is vulnerable to failures due to its numerous sensors and measurement devices that are being deployed. NILM is not widely used in industrial and commercial environments because of the complexity of these environments: the great number of similar devices, power factor correction and load balancing equipment, as well as the huge number of harmonics in loads make this process really challenging.

2 TECHNICAL PROBLEM DESCRIPTION

Let a system of N devices. Devices can be of different types (let K denote the number of possible types, e.g., washing machine, PC, monitor, refrigerator, etc.). For each type $k = 1, 2, \dots, K$ of device $n = 1, 2, \dots, N$ there is a set S_k of possible operation states. The assumption here is that there is a mapping between the state of a certain device and its electrical footprint on an aggregated time series. Consequently, the sequence of operational states leaves a string of unique fingerprints on the time series of energy consumption measurements.

The usual case is that for each time segment, only the total energy consumption is measured and not the individual consumptions of each device. The device fingerprints are therefore mixed up. The disaggregation exercise consists of analyzing the system data in order to unravel the strands of each device, and enable further analysis of the device operation. The disaggregation process is accompanied by information on the operational pattern of each device type, for instance, continuous operation or interrupted, expected duration of each operational state etc.

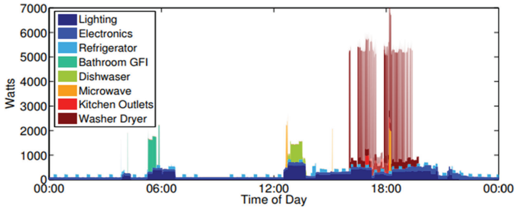

Figure 1. Example of a household total energy consumption from the REDD[1] dataset.

Looking more closely at the device types, it is also possible to extract and make use of more advanced information. Indeed, different device types usually generate slightly different harmonic distortions. The harmonic distortions can be identified if the resolution of the time series is sufficiently high.

3 STATE-OF-THE ART ON ENERGY DISAGGREGATION

Over the past 20 years, there have been many different approaches to addressing the problem of energy disaggregation and the subsequent monitoring of device health.

Since Hart [1] first introduced the concept of Non-Intrusive Appliance Load Monitoring (NIALM) in 1992, numerous techniques have been developed to address the problem. Initial approach was focused on examining a device as a state machine, trying to identify the states and disaggregate the device from the aggregated load. The method could perform well for large loads and devices with a finite number of states that are not always on, with discrete power changes between states.

Since then, other works [5, 6, 7] have proposed different techniques for electrical signature analysis to address the classification problem, with promising results. Such methods include, Support Vector Machines (SVM), Bayesian methods, k-Nearest Neighbors etc. The most common techniques used are Hidden Markov Models and Artificial Neural Networks using supervised, semi-supervised and unsupervised methods [8–12].

Regarding energy disaggregation, the non-intrusive approaches (NILM) promise adequate accuracy with lower installation costs and complexity compared to smart plug-based [2, 12] approaches. NILM methods using steady-state and transient load signatures are further classified according to data time series' measurement frequency. High-frequency [13] methods require custom hardware (high-frequency meters ~10^6 Hz/s) and employ an array of machine learning and pattern recognition methods. Low-frequency methods [14] (1 sec up to 1 hour) apply similar data processing techniques, but are not sufficiently tested to guarantee commercial-grade accuracy. NILM is so far mainly focused on households and small-scale buildings, so there is also the issue of its scalability to commercial buildings or even entire neighborhoods in order to extract useful information for demand response applications, as well as for grid and device health.

The models employed range from least square estimation to Hidden Markov models. Some approaches use Fast Fourier Transform and other transformations to reduce hardware, bandwidth and storage cost. Research in this field focuses on finding the algorithm that increases the accuracy of energy disaggregation in each application case. More recently, new approaches with semi-/un-supervised algorithms are being studied [15]. An emerging research trend is to use IoT based architectures for data capturing and on-board [16] analytics on appliance level to provide energy efficiency solutions. By using IoT devices dedicated to energy monitoring and data manipulation, researchers aim to extract more information by analyzing the electrical characteristics of the appliances in the deployed sites.

At the moment, there is no universal Machine Learning (ML) algorithm that will fit multiple application cases. The specification of the ML algorithms varies with the constraints of each application case. A list of well performing algorithms in different application cases should include Artificial Neural Networks, SVM + kernels, Decision Tree, Random Forests etc. Marking a turning point in the history of Artificial Intelligence, Deep Neural Networks (DNN) are now widely used, e.g., for face recognition on smartphone cameras. Research in this field is ongoing in response to the evolving market interest for improved DNNs. It includes development of new hardware architectures implementing DNNs to improve on the current CPUs and GPUs [17]. Neuromorphic chips have reduced energy consumption and enhanced DNN capabilities in processing the vast volumes of information generated by the IoT [18].

Analyzing data from multiple sensors can provide critical information on each current state of the monitored devices and enable predictions of behavior in the future. The sensors can measure a variety of device/environmental attributes, such as the temperature [19]. Likewise, electrical consumption data, when added to other available device data, can provide significant input to predictive maintenance, and also minimize the data volume that needs to be processed and stored. Approaches to predictive maintenance through electrical consumption data has been made on specific cases.

4 PROPOSED APPROACH

4.1 *Description of solution*

Project PREDIVIS aims to develop novel tools for energy disaggregation and monitoring of device operation status, based on real-time pattern recognition/matchmaking of complex energy load data time-series, using hardware acceleration techniques. The proposed approach requires the design, development and implementation of complex algorithms on a reprogrammable Field Programmable Gate Array (FPGA), in order to create a network of distributed agents that performs the majority of the data analysis in real-time, and transmits events, instead of raw data, to a main server.

This project is trying to address the problem of energy Disaggregation on household and commercial/industrial environments. Due to the difference in complexity of the above mentioned two cases that this project is trying to address, we will need to utilize different approaches, algorithms and also fine-tune the sampling frequency needed per case to acquire sufficient data for the disaggregation process. A system like that depends on the specifications of each deployment site, e.g., different sites have different number of devices with different characteristics that might lead us in using completely different data acquisition rate. Typically, a NILM system design involves three main components: Data Acquisition and Storage, Analysis and Classification.

Most of the previous projects were using private generated/produced or open datasets to train models and validate the results and the algorithm efficiency. Previous works are using data collection methods at either High frequency (1 to 10^3 kHz) or Low frequency (10^{-6} to 10^{-3} kHz). The sampling rate may differ from one sample per 15 minutes or more, to a couple of millions per second. This project focuses on High frequency methods using a sampling rate between 8 kHz and 64 kHz to be able to extract more features from the available data to assist the classification process. Sampling rate determines the information that can be extracted from the sampled signals. Consider for example an electrical installation with fundamental power frequency of 5×10^{-2} kHz. Sampling the wavelength with higher sampling rate (8 kHz) fulfilling the Nyquist-Shannon theorem, enables our system to capture up to the 160-th harmonic. By analyzing the different harmonic distortions, we can identify and differentiate the device from the aggregated workload.

Using high frequency sampling rates requires large storage space to store the acquired data and huge bandwidth to transfer the data over the internet to a central powerful unit for further analysis. To minimize storage and bandwidth, some applications are using compression technics or on-site devices to analyze the data. These hardware devices require a great amount of power in order to perform the analysis and usually they are very expensive.

Project PREDIVIS will use a novel technique implementing on site disaggregation to limit bandwidth and storage needed (Figure 2). Using dedicated hardware implemented in FPGA devices will help in decreasing not only the overall bandwidth and storage but also the power consumption needed for the data analysis. Based on the installation,

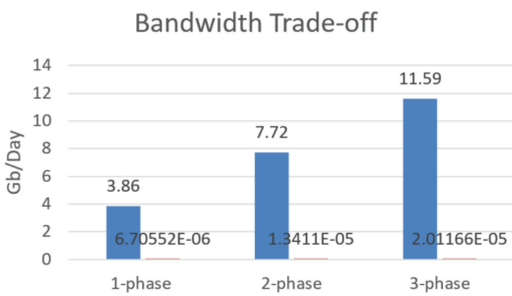

Figure 2. Bandwidth trade-off between raw data transfer and event reporting architecture.

which can be one-, two- or three- phase, the number of electric power transmission data to be used for the disaggregation, will increase proportionally. Note, however, that, the detected events will be more or less the same for each case, despite the number of phases.

For data storage, PREDIVIS will use a small local memory capable of storing the device signatures and a couple of hours of data stream. Aside from the local storage, data like on/off events, total energy consumption and total amount of operation time, anomalies on appliance electric characteristics etc., will be sent to a cloud infrastructure and will be saved in a No-SQL database. Each agent will have the ability to retrain when specific conditions are applied. The system will use adaptive learning techniques to adapt better on new and existing installations by sharing knowledge on already known devices between the employed agents through the central cloud system.

In terms of data analysis, various techniques will be used to extract information from the available data in order to identify:

- Event transitions, when a device is turned on or off. Event-based approaches detect only major changes and anomalies on the energy load time series.
- State transitions, when the device swifts from one state to another (e.g. from full operation to standby and vice versa). State-based approaches also detect the different states of device workload.

4.2 *Description of project*

Project PREDIVIS consists of three main components:

- Agents, which are custom hardware components for data collection, data analysis and load monitoring
- Cloud-based platform for data visualization, storage and NILM assisting mechanisms

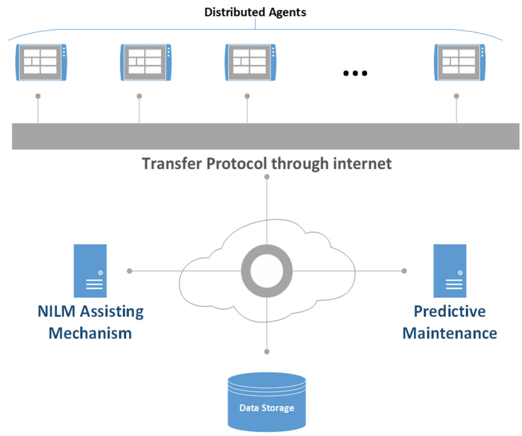

Figure 3. PREDIVIS architecture diagram.

- NILM and Predictive maintenance algorithm suite

The Agents mentioned above are custom hardware implementations using FPGA devices and different Intellectual Property (IP) blocks (e.g., ADC, DSP etc.) to address data collection and analysis on the deployment site. Hardware acceleration of NILM algorithms will help us take the computational load off the cloud infrastructure and minimize the bandwidth needed, as mentioned earlier. Each deployment site is unique, having a different number of N devices with different K states, making the case of using a universal algorithm/approach very challenging. Each device will be able to perform better on its deployment site through adaptive learning techniques, with the assistance of the Central platform and information gathered by other deployed agents with similar site characteristics or identical device types.

The Cloud-based platform will provide data visualization and display information through a friendly User Interface (UI) helping the user get insights on the energy consumption. Acting as a central point for reporting, the platform will complement distributed agents by collecting and analyzing information from each one of them about the deployment site and the site's devices, and will help distributing knowledge between them.

The Cloud platform will also host a NILM suite with several algorithms for analyzing real-time data to determine which algorithm/method is more suitable for that particular site's appliance mix, condition etc. Finally, the predictive maintenance suite will analyze the data and anomalies detected by the agent to help reduce hazardous machinery errors, downtimes and failures.

The consortium of this project comprises the following complementary partners:

- the System Reliability and Industrial Safety Laboratory, National Center for Scientific Research "Demokritos" as a research partner supporting NILM and predictive maintenance analysis.
- Plegma Labs S.A as Enterprise partner in IoT technologies supporting the cloud infrastructure, and the data storage and management.
- the Department of Information and Communication Systems Engineering, University of the Aegean, as a research partner supporting hardware development and data acquisition processes.

Figure 4 depicts the three main stages of this project. The project will run for 4 years and the work is currently at stage one.

4.3 *PREDIVIS technologies breakdown*

The project is a combination of the aforementioned techniques, ranging from hardware blocks to advanced software features. In a nutshell, this project will try to implement hardware designs for data collection using Analog to Digital conversion and Digital Signal Processing techniques, combined with embedded Artificial Intelligence functions and methods. The ability to reprogram over the air an FPGA device, can help each device adapt better to new or pre-installed environments. The software portion of this project includes:

a. the Cloud-based high-level software for data transport and storage,
b. the intelligent adaptive NILM algorithm suite to reprogram and calibrate DNN on agents, and
c. the Predictive maintenance analytics suite combined with statistical models and machine learning algorithms, to predict future failures and stimulate faults.

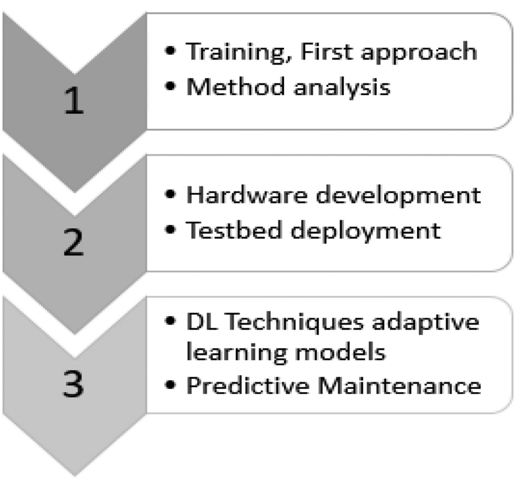

Figure 4. PREDIVIS project stages.

5 GENERATION OF DATA SETS

In order to develop and test different energy disaggregation methods and optimize the efficiency of PREDIVIS project, a variety of datasets will be used. These involve open High Frequency public datasets as well as privately generated data. Some of the public sets that we intend to use are the REDD [2] (2011), the Blued [3] (2012), and the UK-DALE [4] (2015). These datasets relate mainly to residential applications.

The private datasets will contain data from office sites and from industrial sites. Regarding the former, a set of measuring devices is currently installed at offices of a typical software SME. Figure 3 shows the layout of the company offices. The site is connected to the electricity grid through a three-phase power supply. Note that, three-phase data have entirely different characteristics compared to single or two-phase data and this will be considered during the analysis stages.

The installed measuring devices collect data logs from the main power circuitry connector, as well as from individual devices. The main power data involve the aggregated electric current and voltage waveforms, and these are measured at both low and high-frequency rates. The electric power of individual devices is monitored using one smart plug per device.

Seventeen (17) different entities are monitored, ranging from lighting to air-condition units. These include multiple devices of the same appliance type, for example 9 monitors and 3 laptops.

5.1 *Monitoring devices setup*

This section presents the employed technical equipment towards the generation of the dataset described above.

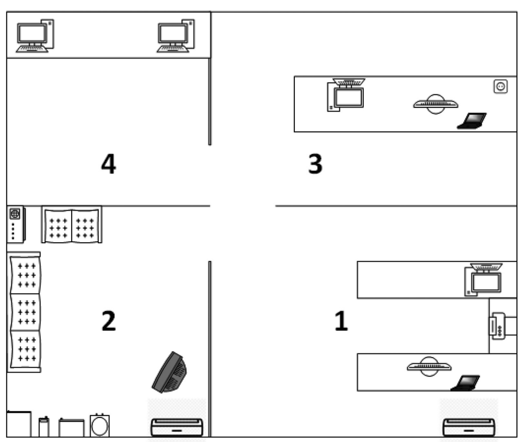

Figure 5. Plegma labs headquarters installation.

For the main power supply, the authors developed a custom implementation using (a) a set of voltage and electric current converters for the measurements, (b) an Analog to Digital Converter (ADC) and (c) an ARM based single board computer for data treatment. In particular:

a. The current sensors used for this project are current transformers with 1:1800 turn ratio with rated input of 100 Amperes to 50 milliamperes output. For the voltage sensing, in-house implemented voltage transformers have been used.
b. The employed ADS is the ADS 131E08 by Texas Instruments, which is capable of sampling simultaneously eight different channels. The number of available channels allows the measuring of electric current and voltage for each of the three phases, leaving two channels free for additional analog sensors (e.g. for temperature, humidity, luminosity etc.). The sampling frequency can range from 1 kHz up to 64 kHz. For the needs of the PREDIVIS project, data are collected at the maximum resolution. In the future, the analysis will indicate whether lower are sufficient (to reduce the sensor consumption) without losing on the quality of results.
c. The arm single board computer is a Raspberry Pi 3 by Raspberry Pi Foundation which receives data from the ADC through serial peripheral interface (SPI) communication.

In order to verify the data collected through the above custom implementation, a widely used industrial grade energy meter/analyzer is also connected to the system. The selected device is the BFM136 produced by SATEC ltd (see Table 1).

For the recording of individual devices' data, a Z-wave based system is implemented. The system uses two different types of smart-pugs, namely the Wall Plug by Fibaro and the Smart Switch 6 by Aeotec. Each plug is monitored continuously at the interval of 5 seconds or less, using a Z-wave USB adapter. The adapter is the Z-Stick S2 by Aeotec (see Table 1).

The two sets of measuring devices are accompanied by appropriate software components developed by the authors. These include:

Table 1. Devices used in the case study.

Metering device	Number
BFM136	1
100 A High Accuracy Current Sensors	3
ADS136E08 with RPi	1
100 A:50 mA Current Sensors	3
Voltage Sensors	3
Fibaro Wall Plug	4
Aeotec Smart Switch 6	13

a. a No-SQL database to store the data locally. The chosen format for the recorded data is in the form of time—voltage—current triplets. These follow a key-value format, with UNIX timestamp for the time.
b. a custom interface is herein implemented to collect and transmit the data and visualize the current and voltage waveforms. The data are sent over the internet to Plegma's cloud infrastructure.

All the devices reported in Table 2 are measured through the smart-plug installation. The two main monitoring devices are currently polled in 3 second (BFM136) intervals, as well as with frequency of 8 kHz (custom implementation). The main monitoring devices are measuring the three-phase installation as follows:

Table 2. Measuring devices and entities.

Entity	Measuring device	Room No
Main	BFM136 & ADS with RPi	Electricity board
Water cooler	Fibaro Wall plug	2
Microwave	Fibaro Wall plug	2
Coffee maker	Fibaro Wall plug	2
Refrigerator	Fibaro Wall plug	2
Work station 1 desktop with 2 monitors	Aeotec Smart Switch 6	1
Work station 2 laptop with 1 monitor	Aeotec Smart Switch 6	4
Work station 3 1 desktop with 2 monitors	Aeotec Smart Switch 6	3
Work station 4 1 high load desktop with 2 monitors	Aeotec Smart Switch 6	4
1 Monitor	Aeotec Smart Switch 6	3
1 Laptop	Aeotec Smart Switch 6	3
1 TV monitor	Aeotec Smart Switch 6	2
1 Router	Aeotec Smart Switch 6	2
1 Printer	Aeotec Smart Switch 6	1
Guest plug 1	Aeotec Smart Switch 6	1 or 3
Guest plug 2	Aeotec Smart Switch 6	1 or 3
2 Air-condition Units	Aeotec Smart Switch 6	1, 2

- Phase 1 lights for rooms 1, 2, 3 and 4,
- Phase 2 sockets of rooms 1 and 2,
- Phase 3 sockets of rooms 3 and 4.

5.2 *Future steps*

Due to the differentiation of the two cases this project is trying to address, it is necessary to be able to simulate different events and scenarios to test its efficiency. The two cases are divided in two major categories residential and industrial/commercial. In order to test the efficiency of the utilized algorithm on specific cases and validate our data different devices will be simulated on variable working states.

The collected data allow us to test different approaches of NILM, based on either high or low frequency data. This project is trying also to address the problem of device health monitoring, and predictive maintenance. In order to have sufficient data for the third phase of the project where a Predictive Maintenance suite will be implemented, we will tamper some specific days of the data from the devices, with different methods (e.g. leaving the fridge door open, turning devices on and off, modifying thermal loads etc.).

Additional data will be generated to see how the disaggregation mechanisms work, to test their ability to distinguish the anomalies produced and match them to the device or entity appropriately. More similar sites will follow so that the final dataset has adequate variety to allow the development of widely applicable algorithms and tools.

6 CONCLUSIONS

In this paper, we reviewed the fundamentals of NILM systems and the energy disaggregation problem. A novel technique is proposed to address this problem that will be applicable to the energy efficiency and predictive maintenance.

Recent works indicate that energy disaggregation is an active field, and there are a lot of different approaches to address it. Even, however, the most advanced methods have not achieved adequate results to be reliable for deployment on a large scale. The problem, therefore, is still open and the potential benefits of disaggregation, in terms of its ability to support end-users and utilities, cannot be fully exploited.

The project PREDIVIS presented here proposes a novel approach with custom hardware implementation of measuring devices. The combination of software and hardware modules can address the problem of data bandwidth and storage size. Adequate information on predictive maintenance can be obtained by combining electric consumption data with other monitoring data.

The availability of relevant and reliable data is crucial for the development of the disaggregation tools. For this reason, the project starts with the generation of datasets for residential, commercial and industrial energy use patterns. The collected residential and commercial data will be combined with publicly available datasets. For commercial and industrial environments, the lack of public datasets makes it a more challenging process.

Once the datasets are fixed, the main work involves the development of energy disaggregation algorithms, the design of data collection and smart on-site devices for hardware accelerated analysis. With continuous monitoring it is possible to produce useful information about the device and machinery health. Monitoring the full cycle of operation could support energy efficiency and predictive maintenance applications, by detecting abnormalities, predicting total operating time of components etc. The current approach could thus detect early-stage device malfunction in industrial sites, supported by energy consumption evidence as well as other sensor data (e.g. temperature). The project considers, at a later stage, the development of decision support systems for industrial, commercial and large residential sites. The success of non-intrusive electric load monitoring on predictive maintenance could provide a much cheaper alternative as compared to complex and expensive monitoring equipment.

ACKNOWLEDGEMENTS

Author SK acknowledges financial support through the Programme of Industrial Scholarships of the Stavros Niarchos Foundation.

REFERENCES

[1] Hart, G.W. (1992). Nonintrusive appliance load monitoring. *Proceedings of the IEEE*, 80(12), 1870–1891.

[2] Kolter, J.Z., & Johnson, M.J. (2011, August). REDD: A public data set for energy disaggregation research. In Workshop on Data Mining Applications in Sustainability (SIGKDD), San Diego, CA (Vol. 25, pp. 59–62).

[3] Filip, A. (2011). BLUED: A fully labeled public dataset for event-based non-intrusive load monitoring research. In 2nd Workshop on Data Mining Applications in Sustainability (SustKDD) (p. 2012).

[4] Kelly, J., & Knottenbelt, W. (2015). The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes. Scientific data, 2, 150007.

[5] Kolter, J.Z., Batra, S., & Ng, A.Y. (2010). Energy disaggregation via discriminative sparse coding. In Advances in Neural Information Processing Systems (pp. 1153–1161).

[6] Barsim, K.S., Streubel, R., & Yang, B. (2014, June). An approach for unsupervised non-intrusive load monitoring of residential appliances. In Proceedings of the 2nd International Workshop on Non-Intrusive Load Monitoring.
[7] Bochao Zhao, Lina Stankovic, and Senior Member. On a Training-Less Solution for Non-Intrusive Appliance Load Monitoring Using Graph Signal Processing. IEEE Transactions on Smart Grid, 4, 2016.
[8] Bonfigli, R., Principi, E., Fagiani, M., Severini, M., Squartini, S., & Piazza, F. (2017). Non-intrusive load monitoring by using active and reactive power in additive Factorial Hidden Markov Models. *Applied Energy*, 208, 1590–1607.
[9] Beckel, C., Kleiminger, W., Cicchetti, R., Staake, T., & Santini, S. (2014, November). The ECO data set and the performance of non-intrusive load monitoring algorithms. In Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings (pp. 80–89). ACM.
[10] Li, G.A.O., Bo, Y.I.N., & ZHU, Z.C. (2017). Load Identification of Non-intrusive Load-monitoring System Based on Time-frequency Analysis and PSO-SVM. DEStech Transactions on Engineering and Technology Research, (EETA 2017).
[11] Shaw, S.R., Leeb, S.B., Norford, L.K., & Cox, R.W. (2008). Nonintrusive load monitoring and diagnostics in power systems. *IEEE Transactions on Instrumentation and Measurement*, 57(7), 1445–1454.
[12] Ridi, A., & Hennebert, J. (2014). Hidden Markov Models for ILM appliance identification. *Procedia Computer Science*, 32, 1010–1015.
[13] Bouhouras, A.S., Milioudis, A.N., & Labridis, D.P. (2014). Development of distinct load signatures for higher efficiency of NILM algorithms. Electric Power Systems Research, 117, 163–171.
[14] Liao, J., Elafoudi, G., Stankovic, L., & Stankovic, V. (2014, June). Power disaggregation for low-sampling rate data. In 2nd International Non-intrusive Appliance Load Monitoring Workshop, Austin, TX.
[15] Liu, B., Luan, W., & Yu, Y. (2016). A Fully Unsupervised Appliance Modelling Framework for NILM. In Proceedings of the 3rd international workshop on NILM.
[16] Villani, C., Balsamo, D., Brunelli, D., & Benini, L. (2015, May). Ultra-low power sensor for autonomous non-invasive voltage measurement in IoT solutions for energy efficiency. In SPIE Microtechnologies (pp. 95172I-95172I). International Society for Optics and Photonics.
[17] Knag, P., Kim, J.K., Chen, T., & Zhang, Z. (2015). A sparse coding neural network ASIC with on-chip learning for feature extraction and encoding. *IEEE Journal of Solid-State Circuits*, 50(4), 1070–1079.
[18] Sharma, H., Park, J., Amaro, E., Thwaites, B., Kotha, P., Gupta, A. & Esmaeilzadeh, H. (2016). Dnnweaver: From high-level deep network models to fpga acceleration. In the Workshop on Cognitive Architectures.
[19] Daily, J., & Peterson, J. (2017). Predictive Maintenance: How Big Data Analysis Can Improve Maintenance. In Supply Chain Integration Challenges in Commercial Aerospace (pp. 267–278). Springer International Publishing.