High frequency energy disaggregation sampling and analysis towards predictive maintenance applications

S. Kotsilitis[1,2,3], E. C. Marcoulaki[1], E. Kalligeros[2]

[1] System Reliability and Industrial Safety Laboratory, National Centre for Scientific Research "Demokritos", Athens, Greece. E-mail: skotsilits@ipta.demokritos.gr, emarcoulaki@ipta.demokritos.gr

[2] Department of Information and Communication Systems Engineering, University of the Aegean, Samos, Greece E-mail: kalliger@aegean.gr

[3] Plegma Labs S. A., Athens, Greece

This paper presents the progress of the PREDIVIS project, on the development of a novel energy disaggregation hardware/software tool towards energy efficiency, anomaly detection and predictive maintenance. The PREDIVIS project involves the use of an edge-cloud hybrid computing architecture, hardware accelerated algorithms, machine/deep learning, and big data approaches for the analysis of high frequency electrical loads. The project will deliver an advanced and innovative solution for energy disaggregation intended for industrial applications, commercial buildings and households. A main scope of the project is to address the problem of predictive maintenance by providing a cost-efficient solution with industry 4.0 features.

Keywords: Embedded systems, energy monitoring, energy analytics, energy disaggregation, internet of things, Edge computing, device health monitoring.

1. Introduction

Nowadays, the advances in technologies like IoT, smart-grid, big data and communications are leading towards the fourth industrial revolution. Industry 4.0 is transforming traditional domains into digital domains with smart manufacturing being the first target into transitioning to the new standards. Domains that are being transformed through the fourth industrial revolution are oil and gas, chemical industry, energy, healthcare, smart-cities etc. The transformation taking place aims to deliver smart features to reduce the complexity and improve system efficiency by optimizing different process of manufacturing, logistics etc.

Cyber Physical Systems (CPSs) are transformed from using traditional monitoring systems to use advanced features like remote monitoring, advanced diagnosis, additional services like process optimization etc. New capabilities are being developed like remote control, services, diagnosis, condition monitoring system health structural health etc. Energy disaggregation provides a cost-effective way to monitor the energy consumption through a single point of measurement.

Equipment and machinery monitoring on industrial sites is a costly and complex process. Multi sensor systems are deployed to monitor machinery operation by analyzing different points such as oil debris, motor vibration, response time etc. to prevent malfunctions, minimize safety issues, repair costs and down times due to damages or deterioration of components. Non-Intrusive Load monitoring (NILM) techniques could offer a cost alternative to equipment monitoring by providing advance insights on machinery operation especially for electromechanical equipment. Industrial application of NILM is a challenging field due to the large loads that need analysis and the huge number of harmonics presented.

The amount of data produced by monitoring CPSs through various systems has led the development of new techniques towards predictive and preventive maintenance. NILM methods can help in updating old machinery equipment to help the transition of small and medium sized businesses towards industry 4.0 features [5, 6]. Numerous techniques for Predictive maintenance have been developed harnessing the power of data, Machine learning and artificial intelligent. These approaches are providing useful solutions towards predictive and preventive maintenance.

This paper is organized as follows. Section 2 reviews the state of the art on predictive maintenance. Section 3 presents the different domains involved in this work. Section 4 describes the problem of high frequency energy sampling and the signal disaggregation. Section 5 presents the proposed approach. Section 6 presents a case study on energy analysis towards fault detection.

2. Predictive maintenance

In general, maintenance is being grouped in three categories Run to Failure, preventive and predictive maintenance. Run to failure

Proceedings of the 29th European Safety and Reliability Conference.
Edited by Michael Beer and Enrico Zio

Published by Research Publishing, Singapore.
ISBN: 978-981-11-2724-3; doi:10.3850/978-981-11-2724-3_0892-cd

maintenance is performed after a failure of a component or a device, this is the least effective but most adopted technique nowadays. This technique is costly as the downtime associated with the failure is larger compared to planned actions to prevent a failure. Preventive maintenance (PvM) is the process where maintenance actions are planned based on a schedule. This technique is targeting to prevent failures by scheduling actions to replace or repair components and equipment. Usually, failures are prevented but there is a large waste of resources and unnecessary actions leading to waste of resources and components.

Predictive maintenance (PdM) is the process where maintenance is performed based on estimations of health status of equipment [1]. Various methods are being used ranging from visual inspection to automated processes using signal processing, pattern recognition physical modelling, empirical data approaches etc. [2]. The method is mainly based on indicators collected from different sensors or observations and the detection of failures is based on historical data, human defined parameters and statistical methods [3]. Machine Learning (ML) [4] seems like the most suitable technique to deal with the multi dimension problems where numerous variables of physical values need to be processed e.g. flow, pressure, voltage, temperature etc. [5].

Most of these systems are based on the deployment of multiple sensors and harvesting of the data produced by already deployed sensors on different devices. Harnessing the power of IoT and big data to provide predictive analytics and anomaly/ abnormal behaviour detection [6]. Main

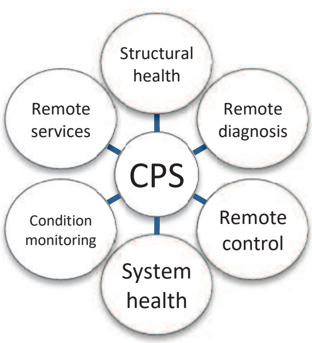

Figure 1 CPS systems and peripheral systems

scope is to adapt predictive maintenance policies according to real-time data and algorithms to combine with the preventive analytics policies to achieve optimal results and maximise the overall working time of equipment.

For instance, the Motor Current Signature Analysis (MCSA) technique uses the electrical current harmonics in order to detect anomalies in motor operation [7]. MCSA is monitoring the frequency spectrum of the current and analyses it to diagnose faults in the stator, rotor or bearing. MCSA is frequently combined with vibration analysis to provide enhanced PdM features. Other techniques targeted for motor equipment are the Current Signature Analysis (CSA), the Voltage Signature Analysis (VSA), and the Extended Park's Vector Approach (EPVA) [8-9].

2.1 *Non-intrusive monitoring*

Non-intrusive monitoring is refereeing to the technique where sensors are being deployed to monitor a device without requiring physical integration with the device. Another advantage of non-intrusive monitoring is the ability to retrofit and reduce installation costs. Numerous devices can be developed to monitor, vibration, power, structural health, physical corrosion etc.

The benefits of non-intrusive monitoring are mainly focused on the low-cost of equipment compared to intrusive systems and ease of installation without requiring any downtime or highly trained personnel.

With the advances in IoT and wireless technologies the field of energy monitoring as a source to predict faults on machinery equipment is becoming more and more attractive towards predictive maintenance and energy efficiency.

2.2 *Machinery health monitoring*

There are numerous techniques for machinery monitoring and diagnostics developed utilizing different techniques for data acquisition, different sets of data and analysis methods. Analysis techniques ranging from statistical pattern recognition [10] to ML and Neural Networks (NN) [11] in the later years. Continuous monitoring is essential to reduce faults and unpredicted downtime and increase overall productivity. Predictive maintenance via signal processing for fault diagnosis using wavelet transform and fuzzy neural networks can detect early stage faults [13]. Neural network techniques utilizing feed forward networks with backpropagation have reached classification accuracy of possible faults up to 99.3% [12].

2.3 *Maintenance in Industry 4.0*

Industry 4.0 is the combination of data and advances in automation that is transforming CPSs to intelligent systems to increase efficiency and productivity. Predictive maintenance is a main feature of the term Industry 4.0 based on large volumes of data collected from various sensors and multiple locations in order to reduce costs for maintenance and downtime of assets and as well as increase asset availability and overall work time. Different methods and sensors have been developed to assist the process, sensing different variables sensors to monitor temperature, energy consumption, vibration etc. are being deployed [13].

The IoT is the main factor that helps industry to advance to the new standards of industry 4.0. CPS are equipped with sensors, actuators and other components that are part of the IoT ecosystem. The IoT is composed of "Things" with embedded or integrated technologies to sense, collect, process and transfer data to fill a purpose. The ultimate target of the vast amount of data captured by the devices is to analyse and act according to them [14]

The vice versa communication flow of IoT devices can assist the exchange of different and heterogenous machinery equipment data that compose a production line. The new capabilities developed in the context of Industry 4.0 are mainly IoT use cases that assist in tackling different problems. IoT devices are assisting in domains like structural health monitoring, track and trace, system health, remote services, control and diagnosis, condition monitoring etc.

The all growing computational power of IoT devices can be harnessed to assist edge and fog computing architectures to provide Industry 4.0 features by retrofitting into outdated CPSs. Distributed architectures are becoming more attractive by the advances in hardware level components [15].

3. Energy Disaggregation

Energy disaggregation first introduced in the 90's by Hart [16], is the process where an aggregated energy signal is decomposed into separate signals produced by each device's workload. IoT technologies and the rollout of smart energy meters helped the domain to bloom in the recent years. Energy disaggregation is mainly focused on households due to the simplicity of the problem (lower order of harmonics), data availability and the development of smart grid technologies.

Energy disaggregation via NILM promised adequate accuracy with lower installation costs and complexity. Different methods and approaches have been proposed to address the problem. Data sampling is divided in two categories low and high frequency. Low frequency techniques are using data collected in the orders of seconds up to minutes and analyse the power consumed to predict the devices used, whereas high frequency techniques are using data sampled in the order of kHz or MHz [17]. The sampling method defines the analysis steps as different features are available or can be constructed via data processing [18-19].

The most used techniques for energy disaggregation are Hidden Markov Models, Graph Signal Processing, Machine Learning (SVM, Knn etc) techniques and in the later years Neural Networks like RNN, LSTM [20] etc. These methods are producing pretty accurate results up to 95.6% but there is no evidence on the ability to generalize the problem and the lack of a universal approach or method to fit multiple installations or different sites with different devices.

Energy disaggregation nowadays is mainly using the traditional Cloud computing architecture where data sampled from smart meters or sophisticated energy monitoring devices are analysed. The analysis takes place on the cloud where models have been trained with all available data. In the later years there are approaches where analysis is being made on premise to reduce data volumes exchanged.

4. Problem description

The majority of systems for monitoring and diagnosis of Cyber Physical Systems (CPSs) are based on observations and assumptions of subject matter experts on the field and industry domain. These models are tailormade for a specific application and installation characteristics making impossible to apply them on a large scale. Additionally, these systems are hard to maintain, upgrade and verify the ability to predict with adequate accuracy possible faults and deterioration of equipment. Data driven approaches are the main alternative with promising results on large scale deployment and prediction accuracy.

Let $\boldsymbol{X}$ denote a device comprised of N components so that $\boldsymbol{X}$ becomes $\boldsymbol{X}=\{x_1, x_2..., x_N\}$. Each component x_i of device $\boldsymbol{X}$ has a unique energy fingerprint, different working characteristics and a specific timing for operation status change according to the work schedule. The disaggregation exercise consists of analysing the system data in order to unravel the strands of each device to enable further analysis of the device operation.

At a given time, each component x_i has its own energy load characteristics, which are part of the aggregated energy consumption of the device. Let $S(t)$ denote the aggregated load of $\boldsymbol{X}$ at time t:

$$S(t) = \sum_{i=1}^{N} p_i(t) \quad (1)$$

Where $p_i(t)$ is the power of x_i at time t, i.e. the product of the voltage and electric current wavelength fingerprint of x_i at time t. The component power depends on the operation state and status of the device $\boldsymbol{X}$ over time.

During energy disaggregation S is analysis into its component signals $p_i(t)$, so that we can monitor the operation of each device component and the overall health of the device. Note that, each component x_i has different deterioration rate according to its function and production characteristics.

5. Proposed approach

The PREDIVIS project will deliver smart sensor technologies with sampling, data analytics, hardware acceleration, and communication capabilities. In this paper we present the development of the PREDIVIS project [21-22] and the architecture towards an edge-cloud hybrid system for predictive maintenance and energy monitoring (section 5.1).

As presented in Section 4, most NILM applications to predictive maintenance analysed the wavelengths of current and voltage to compute energy characteristics like active and reactive power, power factor, harmonics etc. PREDIVIS proposes a hybrid Edge-cloud system (section 5.1) (b) energy monitoring based on high frequency data sampling, intelligent feature extraction, coupled (section 5.2) with (c) statistical techniques and NNs to analyse the data towards energy efficiency and predictive maintenance (section 5.3).

5.1 *Edge computing*

IoT is generating vast amounts of data, in the case presented the data sampling frequency is 64 kHz for 6 datapoints sampled, this produces approximately 1.1 Mb of raw data per second. In order to transfer these raw data through the internet an initial study showed that is almost impossible with the current available bandwidth rate. Edge computing can help to address the problem by decreasing the volume of information by at least three orders of magnitude.

Most systems intended for industrial energy monitoring are composed of a sensor network to sample data at points of interest, a gateway system responsible for communication and data collection and a centralised datacentre/service provider.

Cloud computing has a major role in the IoT ecosystem but as the amount of data increases faster than the communication advances, different topologies have been introduced. Fog and Edge computing can provide a solution to the problem by dividing the computational power and the storage needed by centralized infrastructures, decreasing the overall cost and increasing the overall computational power and storage.

Fog systems are mainly nodes, gateways and datahubs that are on site, the main target is to collect data from the different sensors and CPSs. Fog computing is assigning the computational power to local area network instead and assists in processing the data locally to only transfer meaningful information to the cloud. Fog systems are capable of providing advanced human interfaces and data analysis on site and usually the data processing is being held within hubs or nodes. [23]

Edge systems are mainly sensor devices equipped with microcontrollers and processors capable of sensing, collecting and processing and transferring data capabilities. Edge computing is assign's the workload to the sensing devices offloading the overall system on network requirements and provides network failure tolerance as each device is capable of acting on its own. Control and intelligence are shifted away from central nodes to the CPS or even the sensors. Processing data on site, the system can share information between sensors or deployed devices faster. [24]

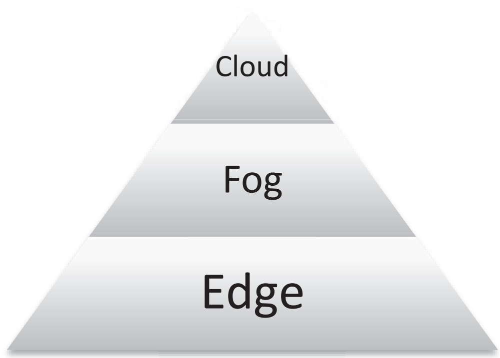

Figure 2 IoT ecosystem layers

PREDIVIS is mainly utilizing the power of Edge computing to provide powerful agents to analyse the sampled data on site decreasing by multiple orders of magnitude the amount of data transferred. Additionally, through cloud computing an agent can receive a retrained model tailormade for the specific installation that is deployed through knowledge sharing between other agents. Finally, it can provide local services without the need to be connected to the internet all the time to give a continuous service.

5.2 *Developed hardware*

The current prototype is a data sampling device that uses the components shown in Table 1. This device can support the deployment of trained models for energy disaggregation. The prototype is currently operating in a commercial installation. The next version of the prototype will include FPGA components to support hardware acceleration for NN.

Table 1. Hardware components of PREDIVIS prototype

Name	Purpose	Additional information
Raspberry Pi 3	Communication, data gathering	
ADS 131e08	ADC data sampling	64 kHz sampling rate
HACS 100A	Current transformers	Current sensing equipment
VT 100	Voltage transformer	Voltage sensing equipment

The developed prototype is sampling data at 64 kHz[a].The dataset of PREDIVIS consists of more than 2 Tb of consumption data from high frequency sampling and 200 Mb of ground truth data from smart-plugs and low frequency energy meters. The data sampled in a commercial case 3-phase installation as described in previous work [21].

The communication between the Raspberry Pi and the ADC is through SPI interface. The second version of the prototype will evaluate the ability of the prototype to integrate the model of the neural network on embedded logic and the next step is to integrate a new prototype with the FPGA to test the data exchange and the hardware acceleration of neural networks.

5.3 *Analysis of load data*

Energy load data are mainly the current and voltage wavelength sampled by the device mentioned in Section 5.2. We analyse the wavelengths to produce additional features to analyse. By performing Fourier transformation, we extract the Harmonics that represent the deviation of the sampled waveforms form the fundamental sinusoidal waveforms. Harmonics are mainly present due to non-linear loads connected to the power circuit.

Aside from the Harmonics we are computing other useful features like the active and reactive power, the phase shift of the sampled signal from the fundamental one etc. These features are used as inputs in a 3-layer feed forward NN to classify the devices working at a given time. This procedure is taking place in 1, 2, and 3 phase systems to analyse the load of each phase. The process we are using until now is based on supervised learning to train the network to classify the appliances and devices working at a given time.

The energy analysis through Neural Networks is trying to evaluate the ability of generalization to train on case A and test on case B. The cross validation of the algorithms can help us in the analysis where some activities are tight to a specific schedule and processes. The analysis up to now is time agnostic to remove the above mentioned constrain from the analysis process.

A centralized infrastructure gathers the results of the analysis and maintains a database of electrical signatures to assist the energy disaggregation. The distributed devices will be updated over the air from the centralised infrastructure with tailor made models for each installation. The central node of the system will be responsible at early deployment stage for the training and the distribution of the models to the edge devices [22].

The benefits from this approach are significant. In effect, the data load transfer is limited to a small amount of data, compared to the raw inputs, to report only events, the processing power is distributed between agents and the overall system is more robust towards network failures.

6. Case study

6.1 S*imulated environment*

This section presents an experiment to check the assumption that the analysis of energy loads using the tools and the architecture so far developed within the PREDIVIS project can assist in predictive maintenance applications. We consider a motor working under different conditions and we use the prototype of Section 5.2 to monitor its load consumption in each case.

Three operation cases are considered:

- Normal operation where the motor is working properly (Figure 1),
- Operation under medium restrain (Figure 2), and
- Operation with very large restrain, such that the motor is unable to perform a full rotation (Figure 3).

The sampled power current and the harmonics of the device are presented in Figures 3, 4 & 5. The harmonics presented in the three cases, showed that there are major changes between the

[a] The data sampling refers to 1280 points in one period of the electrical signal in fundamental frequency of 50Hz.

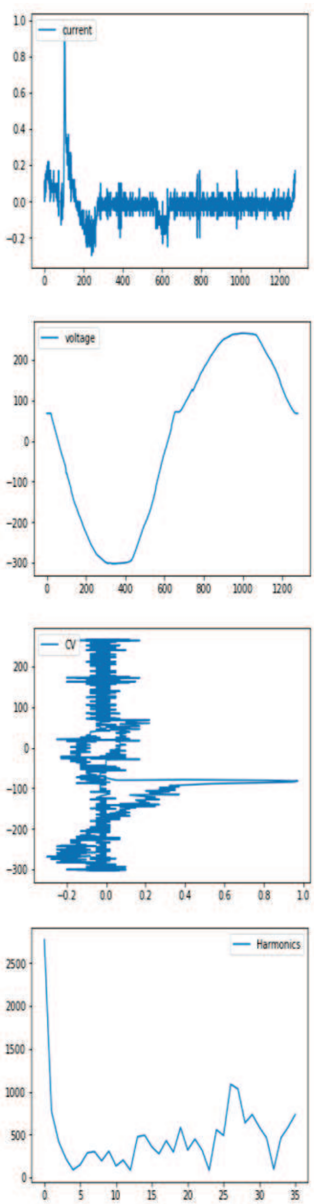

Figure 3 Normal motor operation wavelengths of Current & Voltage, V-I trajectory and Harmonics

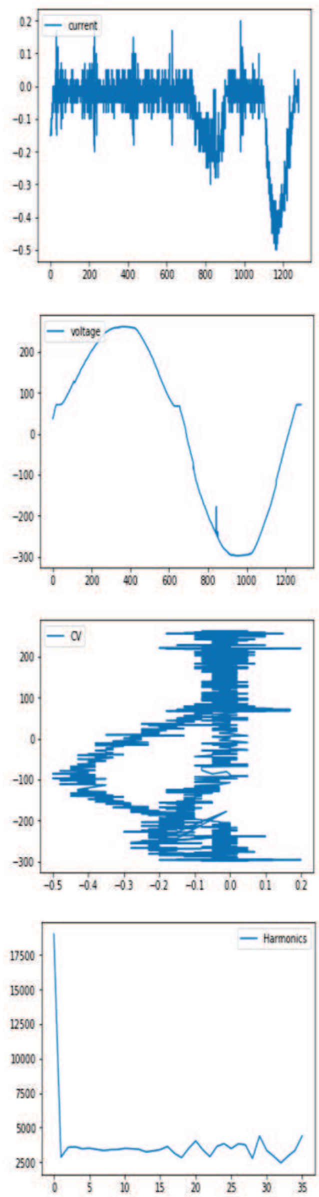

Figure 4 Medium restrain motor operation wavelengths of Current & Voltage, V-I trajectory and Harmonics

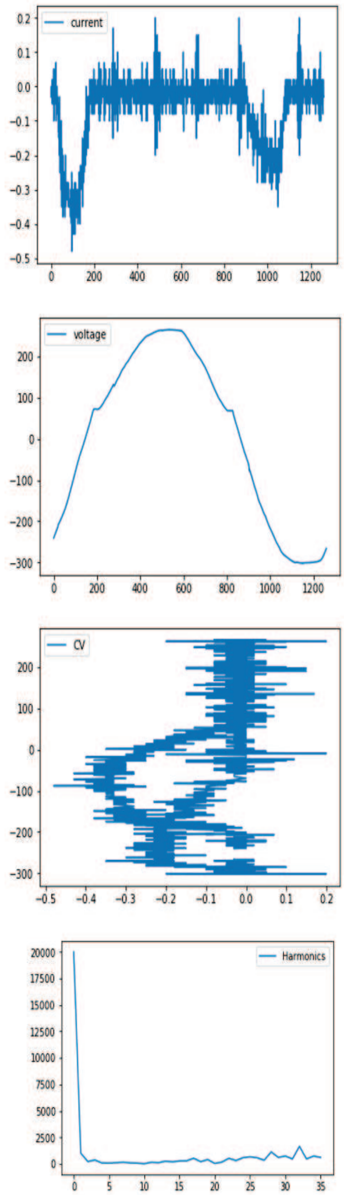

Figure 5 Maximum restrain motor operation wavelengths of Current & Voltage, V-I trajectory and Harmonics

three working conditions, analysis showed that this change can be identified.

Anomaly detection is possible by paying close attention to individual device workload and harmonic distortion. Removing the first harmonic due to its magnitude the fingerprint of the device changes dramatically for different working states. Harmonic distortion is also changing and can indicate the change of behaviour. Identification of the problem in early stage can assist in detection of malfunction of the system to prevent faults that might stop the operation to appear. To minimize data input in our model we use the frequency domain to analyse the device power consumption. Fourier transformation assists the transition from time domain (where the wavelengths of current and voltage are) to the frequency domain. Using the harmonics, we can create additional features to assist the data analysis process.

5.4 *Discussion*

As demonstrated in the above case study, it is possible to analyse the operation of a device or a device component and apply different techniques to identify anomalies using their energy load signal. Since the energy load of this device or component are usually aggregated with the other loads, we need to apply energy disaggregation tools in order to unravel the individual signal patterns from the aggregated signal.

5.3 *Current and future work*

The PREDIVIS project is currently in the development of a more sophisticated device utilizing FPGA to apply NN algorithms through hardware acceleration. Due to the differences in the cases (household, commercial, industrial) the project is trying to address, more devices for high frequency sampling will be developed and deployed to enrich the dataset with additional data on heterogenous cases.

In parallel fine-tuning of the already developed NNs and algorithms to evaluate in real-time use cases. Benchmarking on different datasets and heterogenous systems to provide meaningful efficiency metrics on the ability of NNs to generalize and adapt to different environments with little or no training acting as unsupervised/meta algorithm utilizing the knowledge of previous sampled and recognized devices.

6. Conclusions

Energy disaggregation can assist the process of device monitoring by providing the individual signals for different components of a device. If the energy disaggregation can achieve a good result on braking down a signal to the individual ones we can observe the components and provide useful insights towards predictive maintenance.

The PREDIVIS project aims to address the problem of energy efficiency and predictive maintenance through energy analysis. The project is targeting energy disaggregation with a novel method to overcome the obstacles and provide, with adequate accuracy, the individual power load curves of a system’s components. The analysis and observation of the individual power signatures aims to provide PdM features to industrial, commercial and household cases.

This paper considers the case of a single component and demonstrates how the proposed software and hardware tools for sampling and signal analysis provide insights into the operation of the device and detect operation anomalies. In the real-world different components are working together providing the aggregated signal. Furthermore, each component’s power consumption is different, and the power peak of a load can hide smaller signals from devices using less energy. Though this is a main barrier to overcome in order to provide meaningful results. Current work in the project tries to address these challenges by developing and benchmarking advanced data analysis tools for efficient energy disaggregation.

7. Acknowledgments

This work is financially supported by the Programme of Industrial Research Fellowships of the Stavros Niarchos Foundation.

References

[1] Hashemian, Hashem M., and Wendell C. Bean. "State-of-the-art predictive maintenance techniques." IEEE Transactions on Instrumentation and measurement 60, no. 10 (2011): 3480-3492.

[2] Orhan, Sadettin, Nizami Aktürk, and Veli Celik. "Vibration monitoring for defect diagnosis of rolling element bearings as a predictive maintenance tool: Comprehensive case studies." Ndt & E International 39, no. 4 (2006): 293-298.

[3] Beebe, Raymond S. Predictive maintenance of pumps using condition monitoring. Elsevier, 2004.

[4] Susto, Gian Antonio, Andrea Schirru, Simone Pampuri, Seán McLoone, and Alessandro Beghi. "Machine learning for predictive maintenance: A multiple classifier approach." IEEE Transactions on Industrial Informatics 11, no. 3 (2015): 812-820.

[5]de Faria Jr, Haroldo, João Gabriel Spir Costa, and Jose Luis Mejia Olivas. "A review of monitoring methods for predictive maintenance of electric power transformers based on dissolved gas analysis." Renewable and sustainable energy reviews 46 (2015): 201-209.

[6] March, Salvatore T., and Gary D. Scudder. "Predictive maintenance: strategic use of IT in manufacturing organizations." Information Systems Frontiers (2017): 1-15.

[7] Corne, Bram, Bram Vervisch, Colin Debruyne, Jos Knockaert, and Jan Desmet. "Comparing MCSA with vibration analysis in order to detect bearing faults—A case study." In 2015 IEEE International Electric Machines & Drives Conference (IEMDC), pp. 1366-1372. IEEE, 2015.

[8] Salomon, Camila P., Wilson C. Santana, Erik L. Bonaldi, Levy EL de Oliveira, Jonas G. Borges da Silva, Germano Lambert-Torres, Luiz E. Borges da Silva, A. Pellicel, Marco

AA Lopes, and Gonçalo C. Figueiredo. "A system for turbogenerator predictive maintenance based on Electrical Signature Analysis." In 2015 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) Proceedings, pp. 79-84. IEEE, 2015.

[9] Antonino-Daviu, Jose, Larisa Dunai, and Vicente Climente-Alarcon. "Design of innovative laboratory sessions for electric motors predictive maintenance teaching." In IECON 2017-43rd Annual Conference of the IEEE Industrial Electronics Society, pp. 3965-3970. IEEE, 2017.

[10] Langone, Rocco, Carlos Alzate, Bart De Ketelaere, Jonas Vlasselaer, Wannes Meert, and Johan AK Suykens. "LS-SVM based spectral clustering and regression for predicting maintenance of industrial machines." Engineering Applications of Artificial Intelligence 37 (2015): 268-278.

[11] Li, Te-Sheng, and Cheng-Lung Huang. "Defect spatial pattern recognition using a hybrid SOM–SVM approach in semiconductor manufacturing." Expert systems with Applications 36, no. 1 (2009): 374-385.

[12] Wang, H. Q., and P. Chen. "Fault diagnosis of centrifugal pump using symptom parameters in frequency domain." Agricultural Engineering International: CIGR Journal (2007).

[13] Rajakarunakaran, S., P. Venkumar, D. Devaraj, and K. Surya Prakasa Rao. "Artificial neural network approach for fault detection in rotary system." Applied Soft Computing 8, no. 1 (2008): 740-748.

[14] Lu, Yang. "Industry 4.0: A survey on technologies, applications and open research issues." Journal of Industrial Information Integration 6 (2017): 1-10.

[15] Peralta, Goiuri, Markel Iglesias-Urkia, Marc Barcelo, Raul Gomez, Adrian Moran, and Josu Bilbao. "Fog computing based efficient IoT scheme for the Industry 4.0." In 2017 IEEE International Workshop of Electronics, Control, Measurement, Signals and their Application to Mechatronics (ECMSM), pp. 1-6. IEEE, 2017.

[16] Hart, George William. "Nonintrusive appliance load monitoring." Proceedings of the IEEE 80, no. 12 (1992): 1870-1891.

[17] Nguyen, Trung Kien, Illia Azarkh, Benjamin Nicolle, Gilles Jacquemod, and Eric Dekneuvel. "Applying NIALM technology to predictive maintenance for industrial machines." In 2018 IEEE International Conference on Industrial Technology (ICIT), pp. 341-345. IEEE, 2018.

[18] Shrinivas, Gokul. "Minion: The World's Smallest Energy Auditor." In Proceedings of the 24th Annual International Conference on Mobile Computing and Networking, pp. 861-863. ACM, 2018.

[19] Bernard, Timo. "Non-Intrusive Load Monitoring (NILM): Combining multiple distinct Electrical Features and Unsupervised Machine Learning Techniques."

[20] Faustine, Anthony, Nerey Henry Mvungi, Shubi Kaijage, and Kisangiri Michael. "A survey on non-intrusive load monitoring methodies and techniques for energy disaggregation problem." arXiv preprint arXiv:1703.00785 (2017).

[21] Kotsilitis, S., E. C. Marcoulaki, E. Kalligeros, and Y. Mousmoulas. "Energy efficiency and predictive maintenance applications using smart energy measuring devices." In Safety and Reliability–Safe Societies in a Changing World, pp. 987-994. CRC Press, 2018.

[22] Sarantis Kotsilitis, Effie Marcoulaki, Emmanouil Kalligeros, Yorgos Mousmoulas. "Distributed edge computing paradigm with dedicated devices for energy efficiency and predictive maintenance applications." In IoTsm2018. 2018.

[23] Roman, Rodrigo, Javier Lopez, and Masahiro Mambo. "Mobile edge computing, fog et al.: A survey and analysis of security threats and challenges." Future Generation Computer Systems 78 (2018): 680-698.

[24] Chen, Baotong, Jiafu Wan, Lei Shu, Peng Li, Mithun Mukherjee, and Boxing Yin. "Smart factory of industry 4.0: key technologies, application case, and challenges." IEEE Access 6 (2018): 6505-6519.