A Non-Intrusive Load Identification System Based on Frequency Response Analysis

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***Abstract*— The Non-Intrusive Load Monitoring (NILM) systems measure the energy consumption of individual electrical equipment and appliances connected to a home or building, over time intervals of a few days or weeks. The analysis of the energy consumed by each single device makes it possible to identify the least efficient or malfunctioning ones and to implement the appropriate actions aimed at reducing consumption. NILM systems are also useful when it is necessary to identify the devices in use at a given moment, regardless of the information associated with their consumption. This information is useful in fulfilling the feedback needs of modern smart home, energy management and assisted living systems. In this work an analysis method based on the Sweep Frequency Response Analysis (SFRA) technique, for the identification of loads, is analyzed. SFRA techniques are widely used in diagnostics and mainly for fault finding in transformers and electric motors. More specifically, in this work the SFRA technique has been applied for the identification of the signature of household appliances, for NILM applications, proposing a new system based on the machine learning (ML) technology.**

Keywords—Non-intrusive load monitoring (NILM), load signatures, energy management, load identification, sweep frequency response analysis (SFRA), machine learning (ML), Support Vector Machines (SVMs).

I. INTRODUCTION

The NILM technique has become one of the most relevant solutions for estimating energy consumption at the appliance level. This estimation provides benefits to both consumers and utility companies, such as overview of electricity usage and costs. The main advantages of non-intrusiveness are the possibility of detecting devices with a single meter, and the greater electrical safety of the system.

The attention towards these systems has been favored by the introduction of modern Smart Home and Energy Management systems, which monitor and control domestic parameters such as lighting and house temperature, and manage the use of household appliances, with the aim of energy saving [1].

NILM systems are often associated with Ambient Assisted Living, an intelligent environment that autonomously adapts to the needs of users, such as people with disabilities, to live independently [2].

The NILM is based on measuring the total energy consumption of users and identifying the consumption of each individual load. This method requires the measurement of voltage and current, or often the measurement of the current alone, and the processing of the measurements with an algorithm that applies the technique of "load disaggregation".

Hart [3] was the first to propose a non-intrusive load monitoring system in the early 1990s. Since then, increasingly advanced disaggregation algorithms have been proposed which have allowed a significant improvement over this. In the last decade, interest in this research topic has undergone a significant increase.

Most NILM systems perform event detection and load classification through traditional algorithms [3], [4], and through artificial intelligence algorithms, especially through modern machine learning (ML) techniques [5]-[15]. Artificial intelligence systems have been widely proposed for energy and power monitoring [16], [17], consumption prediction [18]-[22] and data management technologies [23], [24]. ML involves computers learning from data provided so that they carry out certain tasks; these systems continue to improve over time with minimal human intervention as they learn using more data [25].

Most of the proposed systems analyze the active power absorbed by the monitored system, sometimes also the reactive power. However, other solutions have been proposed that provide for the analysis of other quantities, which differ from each other due to their belonging to different domains (time or frequency), or due to their different stationary or transient nature. The type of information that can be extracted from voltage and current strongly depends on the sampling frequency. Surely the absorbed real power is a fundamental parameter for the discrimination of the different loads, but sometimes also the absorbed reactive power and the power factor can provide substantial information [25], therefore the power measurement must be performed adequately [26].

A brief summary of the different characteristics used in the literature for NILM is reported below [27]. 1) Active power *P*: this characteristic is generally integrated by measuring the duration and the appliance's frequency of use. 2) *P*-*Q* plan: step changes in the active and reactive power *Q* allow easy

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identification of the ON/OFF status of high-power equipment. 3) Combination of the *P-Q* plane with extended transient characteristics: it is suitable in identifying devices with relatively long transients and significant peaks of power. 4) Characteristics based on *P*, *Q*, *I*, and *V* at low frequencies: these combinations exhibit good performance in identifying ON/OFF appliances. 5) *P-Q* and harmonic planes: the harmonic content or the spectrum of high-frequency sampled currents is usually combined with the *P-Q* characteristics. 6) Short-Time Fourier Transform (STFT): the spectral envelopes allow the identification of non-linear and variable load devices. 7) *V-I* trajectories: it is suitable in identifying loads, starting from the signal shape. 8) Non-active current: it is suitable in identifying some special equipment. 9) Unconventional features: the analysis of voltage–noise spectrum or electromagnetic interference voltage noise has been proposed by several authors. An almost complete summary of the relevant techniques has been reported in [27].

Nowadays there is no adequate technique for the unambiguous discrimination of electrical loads. The features that can be evaluated depend above all on the type of installation. In fact, the non-intrusive processing system can be placed either directly on the electrical panel through the use of microcontrollers, or at a great distance, through a computer that remotely processes the data transmitted to a cloud database by the local smart energy meter.

While a local system is capable of acquiring voltage and current (with sampling rates down to a few kHz), processing them and displaying the results or storing them on a remote server [28], remote systems are able to use only the available data in the cloud with lower measurement frequencies, typically between 1 Hz and 3 Hz, due to limited data transmission and storage capabilities [39].

NILM systems can be further grouped into two different categories, according to their purpose. They can be used to disaggregate the energy consumption of a user, as illustrated in many of the aforementioned works, but they can also be used for the sole purpose of detecting which devices are powered at a given moment. In this second case, the measuring system does not continuously monitor the system, but detects the connected loads only when required by other control devices or by the users themselves.

In this work, a monitoring system installed inside a house is proposed. The system is able to detect which appliances are powered by the system through the Sweep Frequency Response Analysis (SFRA) technique, which are well-established tools in various research sectors regarding the identification of faults in transformers and induction motors. This measurement technique allows to obtain a unique signature for each system power condition which will then be processed by an artificial intelligence algorithm.

II. Frequency Response Analysis

The SFRA is a non-destructive diagnostic technique that detects the displacement and deformation of windings, among other mechanical and electrical failures, in power and distribution transformers. This analysis is conducted off-line according to requirements and prescriptions of international standards [30, 31]. SFRA proceeds by applying a sinusoidal voltage signal of constant amplitude and variable frequency between one terminal of the phase winding under test and ground. The response is measured between the other winding terminal and ground. Both input and output signals are acquired and processed. The obtained result is the Transfer Function (TF) of the transformer windings over a wide frequency range. The operation of this technique can be explained by considering the equivalent electrical circuit of the device under test.

The possibility of characterizing household appliances through the trace obtained from SFRA measurements has already been observed in previous works [32]. In this work we want to evaluate the possibility of using these traces in order to identify which appliances are powered at the time of the measurement. For this purpose, a variable frequency sinusoidal signal is applied between the terminal of the power phase conductor and ground, then both the applied input signal and the output signal between the neutral conductor terminal and earth are measured and processed.

The test instrument generates a sinusoidal input signal of constant amplitude and frequency variable in the range between 10 kHz and 1.5 MHz. The results obtained on the electrical system are analyzed on a temporal basis, comparing them with those previously obtained on the same system. The measurement techniques follow the IEC 60076-18 standard [30], which regulates the test execution methods, the characteristics of the instruments used, the connection methods and the analysis of the results.

A. *Electrical Test System*

The proposed measurement apparatus has been installed in the test system designed for generating electrical loads of domestic users, shown in Fig. 1. The loads are integrated in a structure similar to that of a residential building, in order to reproduce the real problems of conditioning and measurement of the signals. Tests have been carried out using the electrical power network of a medium-sized house with an area of about 74 m^2, consisting of an entrance, kitchen, living room, bathroom and two bedrooms. This system was built on a panel, synthesizing the parasitic parameters of each line segment with the equivalent value of a concentrated parameter RLC network, with a double π configuration. In this panel, 3 separate circuits are arranged to supply the utilities:

- light line: protected by 10 A magneto-thermal switch;
- sockets line: protected by 20 A magneto-thermal switch;
- kitchen line: protected by a 16A magneto-thermal switch.

A high sensitivity 30 mA residual-current device is installed before these switches, to ensure protection against indirect contacts. In the system, there are a total of 9 light points and 26 socket points.

B. *Household Appliances Signature*

In order to reproduce the power supply conditions of a typical domestic system, the following loads have been considered:

- a compact fluorescent lamp, to emulate the light points widely present in domestic, industrial and commercial systems;
- a hairdryer;
- an electric heater;

- an induction hob.

Several measurements have been made, keeping the instrument at a fixed socket and varying from time to time the electrical outlet and the operating conditions of each appliance. The Fig. 2 shows the traces obtained by the SFRA measurement system in the presence of different powered loads, while Fig. 3 highlights the possibility of using these traces to discriminate the different conditions of simultaneous loads.

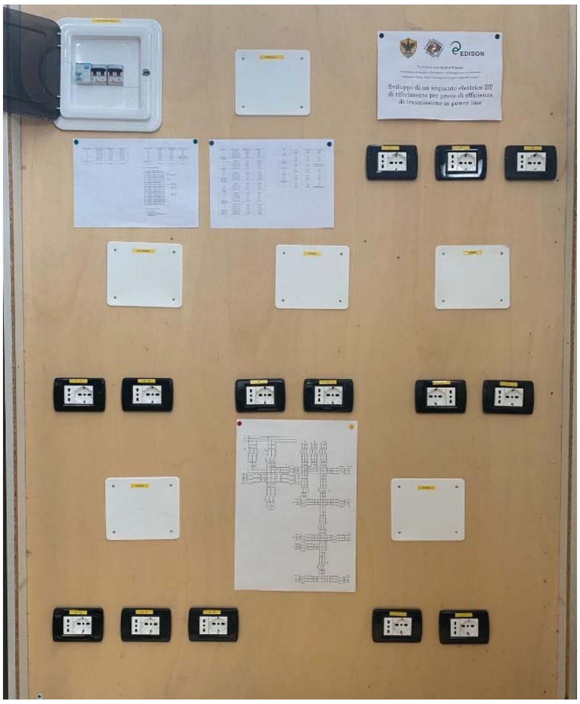

Fig. 1. Electrical test system.

A variable frequency sinusoidal signal was applied between the terminal of the power phase conductor and ground. Both the applied signal and the output voltage between the neutral conductor terminal and earth have been measured and processed. The test instrument generates a sinusoidal input signal of constant amplitude (a few tens of volts) and frequency variable in the range between 10 kHz and 1.5 MHz.

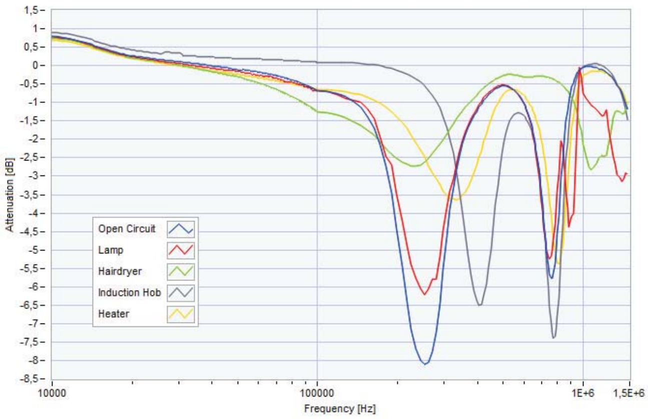

Fig. 2. SFRA tests of different household appliances.

To this end, we have created a machine learning system which, through the use of these curves, is able to provide information on which devices are powered by the monitored system. A system of this type makes it possible to obtain a plug-in solution that can be connected in a very simple way to any domestic socket to obtain useful information for modern smart home systems.

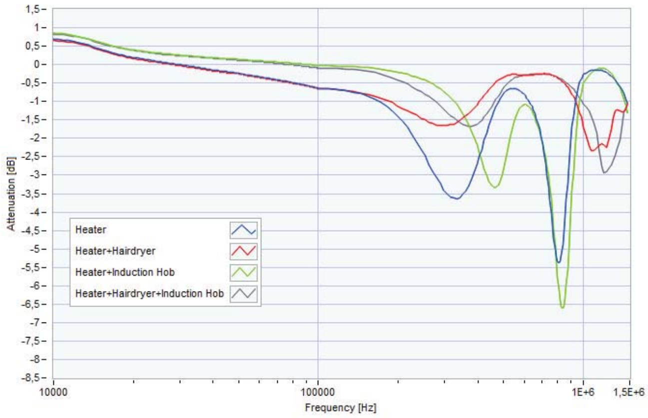

Fig. 3. SFRA tests with simultaneous loads powered.

III. Support Vector Machine

To process the characteristics obtained from the SFRA measurement, a Support Vector Machine (SVM) was used. SVM is one of the most popular artificial intelligence algorithms and is a supervised learning algorithm used primarily for solving classification problems. Unlike generic classification algorithms that discriminate on the basis of characteristics common to each class, SVM focuses on the samples that are most similar to each other but belonging to different classes, which are therefore the most difficult samples to discriminate. Based on these samples, the algorithm will build an optimal hyperplane able to separate them and which can then be used to discriminate the new samples. These samples are called support vectors because they are the only samples that support model creation, while all other samples are useless.

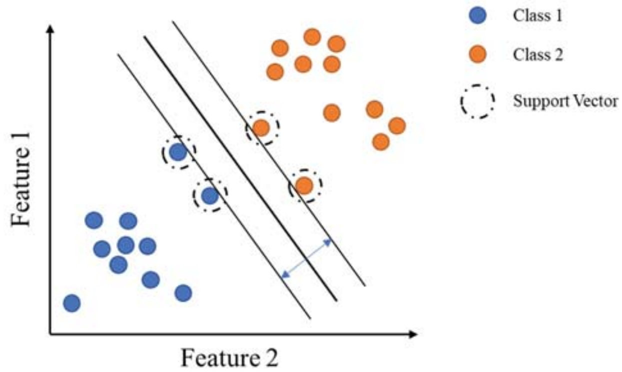

Fig. 4. Representation of a linear classification problem in which the samples are defined by only two features.

Taking as an example a two-dimensional case, or a case in which the samples to be classified are defined by only two features, the optimal hyperplane is reduced to a straight line. As shown in Fig. 4, the algorithm will look for the line that maximizes the margin between the two samples indicated as support vectors.

In non-linear classification problems, where it is not possible to separate classes by a straight line, the kernel trick is used [33].

In particular, a polynomial kernel was chosen for this work, thus examining not only the given characteristics of the input samples to determine their similarity, but also their combinations.

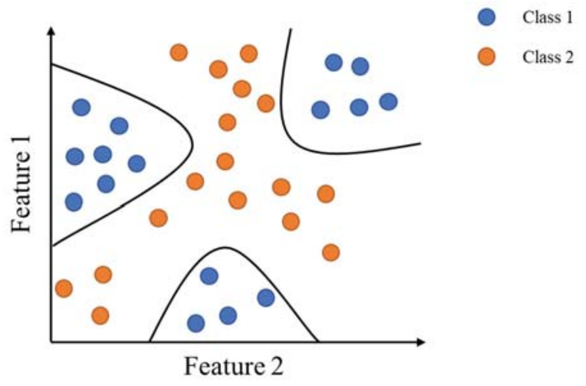

Fig. 5. Representation of a non-linear classification problem in which the samples are defined by only two features.

In our case the problem is obviously not be two-dimensional. Since the SFRA measuring system returns an array of 320 points, which represent the values of the TF measured at the different values of the frequency bins, the inputs of the SVM have been set at 320. So the size of the problem is also 320. To solve the problem of identifying which appliances are powered, starting from the result of the SFRA, four SVM classifiers were used, each of which performs a binary classification, identifying the presence or absence of the appliance associated with it.

IV. Performance Evaluation

In order to evaluate its performance, the proposed measurement apparatus was installed in a test system, designed for the generation of electrical loads of domestic users, and located in an area of the Electrical Engineering Laboratory of the University of L'Aquila (I). The measurement uncertainty of the proposed SFRA system has already been discussed in [34]. The proposed algorithm was subjected to 9 different scenarios, each for a certain number of tests, in which the different appliances were powered individually or simultaneously. The different scenarios are summarized in Table I.

TABLE I. Training and Test Sets

Scenarios	Training samples	Test samples
Open Circuit	10	50
Lamp	10	50
Hairdryer	10	50
Induction Hob	10	50
Heater	10	50
Hairdryer + Induction Hob	10	50
Hairdryer + Heater	10	50
Induction Hob + Heater	10	50
Hairdryer + Induction Hob + Heater	10	50
Total	90	450

Since, as already explained above, each appliance has an associated SVM algorithm that reveals its presence or not, the performance of the four algorithms have been assessed individually. To allow a comparison with the algorithms developed by other researchers, precision, recall and F1-Score during classification were evaluated [35]. These parameters were obtained using the number of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) as follows:

$$precision = \frac{TP}{TP + FP} \tag{1}$$

$$recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1 - score = \frac{2\,x\,precision\,x\,recall}{precision + recall} \tag{3}$$

The achieved scores were reported in Table II.

TABLE II. Achieved Scores

Parameters	SVM Lamp	SVM Hairdryer	SVM Induction Hob	SVM Heater
TP	42	200	200	200
FP	0	0	0	2
TN	400	250	250	248
FN	8	0	0	0
Precision	1	1	1	0,99
Recall	0,84	1	1	1
F1-score	0,91	1	1	0,99

V. Conclusions and Final Remarks

In this paper, a non-intrusive identification system for household appliances has been proposed. It is based on the SFRA technique, which allows to measure transfer functions, through which it is possible to characterize different power supply conditions. These transfer functions were used to train an SVM algorithm. The system has been implemented in the Python open source development environment, also to reduce system costs.

The results obtained by subjecting the system to new measurements were presented. The results were more than satisfactory, highlighting the system's ability to identify the presence of the various devices both when powered individually and simultaneously. The system made no mistakes in determining the state of the hairdryer and induction hob, reaching F1-Scores equal to 1. Performance is excellent even in the case of lamp and heater, for which F1-Score of 0.91 and 0.99 have been achieved , respectively.

A system of this type is particularly interesting as it allows the creation of a plug-in solution that can be installed in any domestic, industrial or commercial environment.

Furthermore, the detection technique takes into account the physical characteristics of household appliances and the resulting transfer function. Consequently, the identification of multi-state or continuously variable appliances is simplified compared to processing time-varying signals such as real power, current, etc. Finally, another important advantage lies in the use of an SVM algorithm, which shows good performance without an excessive need for training samples.

Workshop on Metrology for Industry 4.0 & IoT, 2020, pp. 570-575, doi: 10.1109/MetroInd4.0IoT48571.2020.9138198.

REFERENCES

[1] Hill, Jim (12 September 2015). "The smart home: a glossary guide for the perplexed". T3. Retrieved 27 March 2017.

[2] Ruano, A., Hernandez, A., Ureña, J., Ruano, M., & Garcia, J. (2019). “NILM techniques for intelligent home energy management and ambient assisted living: A review”. Energies, 12(11), 2203.

[3] G. W. Hart, "Non-intrusive appliance load monitoring," Proceedings of the IEEE, vol. 80, no. 12, pp. 1870–1891, Dec. 1992, DOI: 10.1109/5.192069.

[4] G. Bucci, F. Ciancetta, E. Fiorucci, S. Mari, "Load identification system for residential applications based on the NILM technique," in Proceedings of IEEE Instrumentation and Measurement Technology Conference I2MTC 2020, Dubrovnik, Croatia May 25–20.

[5] S. Barker, S. Kalra, D. Irwin, P. Shenoy, "Powerplay: creating virtual power meters through online load tracking," in Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings, 2014, pp. 60–69.

[6] R. Dong, L. J. Ratliff, H. Ohlsson, S. S. Sastry, "Energy disaggregation via adaptive filtering," in 2013 51st Annual Allerton Conference on Communication, Control, and Computing (Allerton), Monticello, IL, 2013, pp. 173–180. DOI: 10.1109/Allerton.2013.6736521.

[7] G. Tang, K. Wu, J. Lei, J. Tang, "A simple model-driven approach to energy disaggregation," in 2014 IEEE International Conference on Smart Grid Communications (SmartGridComm), Venice, 2014, pp. 566–571. DOI: 10.1109/SmartGridComm.2014.7007707.

[8] G. Bucci, F. Ciancetta, E. Fiorucci, S. Mari, A. Fioravanti, “Deep Learning applied to SFRA Results: a Preliminary Study” Accepted for the publication in the Proceedings of 7th International Conference on Computing and Artificial Intelligence ICCAI 2021, April 23-26.

[9] M. Figueiredo, B. Ribeiro, A. de Almeida, “Electrical signal source separation via non-negative tensor factorization using on site measurements in a smart home,” IEEE Transactions on Instrumentation and Measurement, 2014, vol. 63, no. 2, pp. 364–373. DOI: 10.1109/TIM.2013.2278596

[10] D. Egarter, V. P. Bhuvana, and W. Elmenreich, "PALDi: online load disaggregation via particle filtering," IEEE Transactions on Instrumentation and Measurement, Feb. 2015, vol. 64, no. 2, pp. 467–477. DOI: 10.1109/TIM.2014.2344373.

[11] J. Z. Kolter, T. Jaakkola, "Approximate inference in additive factorial hmms with application to energy disaggregation," in Proceedings 15th International Conference on Artificial Intelligence and Statistics (AISTATS) 2012, La Palma, Canary Islands, Volume XX of JMLR: W&CP XX. pp. 1472–1482.

[12] F. Ciancetta, G. Bucci, E. Fiorucci, S. Mari, A. Fioravanti, “A New Convolutional Neural Network-Based System for NILM Applications”. IEEE Transactions on Instrumentation and Measurement, Volume 70 (November 2020), Article number 9246573, https://doi.org/10.1109/TIM.2020.3035193.

[13] R. Jia, Y. Gao, C. J. Spanos, "A fully unsupervised non-intrusive load monitoring framework," in 2015 IEEE International Conference on Smart Grid Communications (SmartGridComm), Miami, 2015, pp. 872–878. DOI: 10.1109/SmartGridComm.2015.7436411.

[14] G. Bucci, F. Ciancetta, E. Fiorucci, S. Mari, A. Fioravanti, “Multi-State Appliances Identification through a NILM System Based on Convolutional Neural Network” Accepted for the publication in the Proceedings of IEEE Instrumentation and Measurement Technology Conference I2MTC 2021, May 17-21.

[15] B. Cannas, S. Carcangiu, D. Carta, A. Fanni, C. Muscas, ‘‘Selection of Features Based on Electric Power Quantities for Non-Intrusive Load Monitoring’’ Appl. Sci. 2021, 11, 533. https://doi.org/10.3390/app11020533

[16] W. M. Ashraf, G. M. Uddin, M. Farooq, F. Riaz, H. A. Ahmad, A. H. Kamal, S. Anwar, A. M. El-Sherbeeny, M. H. Khan, N. Hafeez, A. Ali, A. Samee, M. A. Naeem, A. Jamil, H. A. Hassan, M. Muneeb, I. A. Chaudhary, M. Sosnowski, and J. Krzywanski, “Construction of Operational Data-Driven Power Curve of a Generator by Industry 4.0 Data Analytics,” Energies, vol. 14, no. 5, p. 1227, Feb. 2021.

[17] A. Massaro, S. Selicato, R. Miraglia, A. Panarese, A. Calicchio and A. Galiano, "Production Optimization Monitoring System Implementing Artificial Intelligence and Big Data," 2020 IEEE International Workshop on Metrology for Industry 4.0 & IoT, 2020, pp. 570-575, doi: 10.1109/MetroInd4.0IoT48571.2020.9138198.

[18] A. Massaro, o et al. “Overview and Application of Enabling Technologies Oriented on Energy Routing Monitoring, on Network Installation and on Predictive Maintenance.” International Journal of Artificial Intelligence & Applications 9 (2018): 01-20.A. Ibrahim, A. Dalbah, A. Abualsaud, U. Tariq, A. El-Hag, "Application of machine learning to evaluate insulator surface erosion," in IEEE Transactions on Instrumentation and Measurement, Feb. 2020, vol. 69, no. 2, pp. 314–316. DOI: 10.1109/TIM.2019.2956300.

[19] Y. Liu, Y. Li, H. Liang, J. He, and H. Cui, “Energy Routing Control Strategy for Integrated Microgrids Including Photovoltaic, Battery-Energy Storage and Electric Vehicles,” Energies, vol. 12, no. 2, p. 302, Jan. 2019.

[20] D.-L. Wang, Q.-Y. Sun, Y.-Y. Li, and X.-R. Liu, “Optimal Energy Routing Design in Energy Internet with Multiple Energy Routing Centers Using Artificial Neural Network-Based Reinforcement Learning Method,” Applied Sciences, vol. 9, no. 3, p. 520, Feb. 2019.

[21] A. Massaro, G. Meuli, A. Galiano, “Intelligent Electrical Multi Outlets Controlled and Activated by a Data Mining Engine Oriented to Building Electrical Management”, International Journal on Soft Computing, Artificial Intelligence and Applications (IJSCAI), Vol.7, No.4, November 2018.

[22] P. Shine, J. Upton, P. Sefeedpari, and M. D. Murphy, “Energy Consumption on Dairy Farms: A Review of Monitoring, Prediction Modelling, and Analyses,” Energies, vol. 13, no. 5, p. 1288, Mar. 2020.

[23] A. Massaro, A. Galiano, “Re-engineering process in a food factory: an overview of technologies and approaches for the design of pasta production processes”, Production & Manufacturing Research, 13 Apr 2020.

[24] G. Filho, J. Ueyama, L. Villas, A. Pinto, V. Gonçalves, G. Pessin, R. Pazzi, and T. Braun, “NodePM: A Remote Monitoring Alert System for Energy Consumption Using Probabilistic Techniques,” Sensors, vol. 14, no. 1, pp. 848–867, Jan. 2014.

[25] A.G. Ruzzelli, C. Nicolas, A. Schoofs, G.M.P. O’Hare, Real-time recognition and profiling of appliances through a single electricity sensor, 2010 7th IEEE Comm. Society Conf. on Sensor, Mesh and Ad Hoc Communications and Networks (SECON) (2010), pp.1–9.

[26] E. Fiorucci, “The measurement of actual apparent power and actual reactive power from the instantaneous power signals in single-phase and three-phase systems”. Electr. Power Syst. Res. 2015, 121, 227–242

[27] N. Sadeghianpourhamami, J. Ruyssinck, D. Deschrijver, T. Dhaene, C. Develder, “Comprehensive feature selection for appliance classification in NILM,” Energy and Buildings, vol. 151, Sept. 2017, pp. 98–106. DOI: 10.1016/j.enbuild.2017.06.042.

[28] M. Zeifman, C. Akers, K. Roth, "Non-intrusive monitoring of miscellaneous and electronic loads," in 2015 IEEE International Conference on Consumer Electronics (ICCE), Jan. 2015, pp. 305–308.

[29] O. Parson, S. Ghosh, M. Weal, A. Rogers, "Non-intrusive load monitoring using prior models of general appliance types," in Proceedings of the National Conference on Artificial Intelligence, Toronto, Canada, 2012-07-22–2012-07-26. URI: http://eprints.soton.ac.uk/id/eprint/336812.

[30] IEC 60076-18:2012 Power transformers - Part 18: Measurement of frequency response

[31] "IEEE Guide for the Application and Interpretation of Frequency Response Analysis for Oil-Immersed Transformers" in IEEE Std C57.149-2012 , vol., no., pp.1-72, 8 March 2013, doi: 10.1109/IEEESTD.2013.6475950.

[32] A. Fioravanti, A. Prudenzi, G. Bucci, E. Fiorucci, F. Ciancetta, S. Mari, "Non intrusive electrical load identification through an online SFRA based approach", Speedam 2020, Sorrento (Italy), 24-26 june 2020.

[33] T. Hofmann, B. Schölkopf, A. J. Smola, “Kernel methods in machine learning,” Ann. Statist., vol. 36, no. 3, pp. 1171–1220, 2008.

[34] Dolce, S., Fiorucci, E., Bucci, G., D'Innocenzo, F., Ciancetta, F., Di Pasquale, A., “Test instrument for the automatic compliance check of cast resin insulated windings for power transformers”, (2017) Measurement: Journal of the International Measurement Confederation, 100, pp. 50-61.

[35] S Makonin, F Popowich, "Nonintrusive load monitoring (NILM) performance evaluation," Energy Efficiency, Dec. 2014, vol. 8, no. 4, pp. 809–814. DOI: 10.1007/s12053-014-9306-2.