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A deep learning method for current anomaly detection

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***Abstract* – The development and spread of Machine Learning methodologies have also involved the field of anomaly detection, particularly focused on fault detection. This is one of the main goals of Industry 4.0, as it is necessary to optimize repair time and cost. In this regard, Machine Learning is needed to identify precursor features of possible failures that would be difficult for a human operator to discern. However, compared to Deep Learning methodologies, these cannot be fully automatic because of the need to make choices about the features identified by the system. This paper aims to propose a Machine Learning-based system for detecting electrical anomalies attributable to malfunctions in connected industrial machinery. Specifically, the proposal is a fusion of unsupervised learning and traditional methodology to minimize human intervention while maintaining an explainable, white-box approach, contrary to proposals based on Deep Learning. The results demonstrated better performance to techniques of the state of the art.**

Keywords* – *IMEKO, Industry Innovation and Infrastructure

I. INTRODUCTION

Today's industrial revolution, which is leading to a transition to a smart industrial concept, likewise known as Industry 4.0, is an approach to the industrial world that emphasizes the efficiency of production processes both for environmental reasons and to improve the quality of work [1],[2].

The Industry 4.0 paradigm has foundations in the bursting spread of decision-making processes based on Big Data. This paradigm requires the production and storage of large amounts of structured and unstructured data for the purpose of capturing features that can be decisive for decision-making. However, the identification and interpretation of these features, which may be patterns, values or other occurrences in the data, is often not feasible by means of traditional data analysis algorithms. In particular, it can also be difficult or even impossible for humans to identify relations of interest in the large amount of data acquired [3].

For these reasons, the Industry 4.0 revolution necessarily had to make use of Artificial Intelligence techniques, especially Artificial Neural Networks (ANN). These tools can learn data patterns to perform classification, regression and prediction operations. This is due to the inherently nonlinear nature of neural networks, which consequently enables them to learn highly nonlinear relationships between data [4]-[8].

Among the various fields of use of Industry 4.0, the most interesting one is fault detection. In fact, through early and preventive fault detection, it is possible for a company to significantly reduce repair costs and also avoid machinery downtime in industrial production lines. Predictive maintenance, aimed at avoiding failures, can be carried out on the basis of physical and electrical parameters and can thus be employed for batteries, bearings, motors etc. In this specific case, this has been done in the literature through acoustic monitoring, vibration analysis, oil analysis and electrical analysis [9]-[14].

The study of these faulty behaviours falls within the more general scope of Anomaly Detection. Indeed, this branch of data analysis aims to detect patterns that fall outside the state of "normal functioning." Given the extremely general nature of Anomaly Detection, which can be applied to electrical signals, vibrations, and manufacturing shapes and materials, it has always been very difficult to identify features that would give high reliability in reporting anomalies [15]-[19].

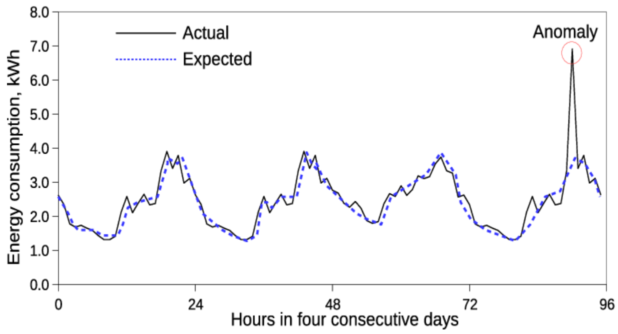

Fig.1 Example of anomaly detection on Time Series [20].

One of the most widely used Anomaly Detection modes for monitoring industrial machinery is monitoring power grid loads. In particular, it is possible to monitor the operating status of three-phase electric motors, which are widely used in certain industrial processing and are characterized by an ohmic-inductive load [21]-[23]. An example of anomalous Time Series is shown in Fig.1.

This paper aims to propose a methodology for classifying this type of anomaly using only the data from the three-phase power grid of an industrial plant. In particular, the goal was not to employ Deep Neural Network-based methodologies, as widely used in the literature, but machine learning algorithms. This is motivated by the need to justify the causes of fault reporting: Deep Neural Networks do not provide the patterns or even the features used for fault reporting, given their "black box" nature. Instead, this work has aimed to have the Deep Neural Networks manually select the specific features that may indicate a malfunction in a specific piece of machinery while automating the fault analysis and classification procedure.

II. PROPOSED METHODOLOGY

The methodology proposed in this paper bases its operation on the K-means algorithm for unsupervised clustering. Using two features of the three-phase electrical system, it is possible to create and separate clusters of the points representing the nominal and abnormal operation of the rotating machinery connected to that network.

To increase the robustness of the algorithm, a fusion with the Short-Time Fourier Transform (STFT) algorithm was also proposed to validate, in the frequency domain, the anomalous points identified in the time domain.

The features used were the RMS value of the current delivered by one of the three phases of the three-phase system and the Total Harmonic Distortion (THD) value. In more detail, the proposal is structured as follows: The time series are analyzed with a peak detection and a detrend function; the former analysis provides the input values for K-Means Clustering, while the latter is for STFT analysis. Peak detection, in particular, reduces computational load and, thus, processing time. At the same time, detrend eliminates any detectable continuous components from the STFT, reducing possible misclassification errors.

The final fusion of the two algorithms is done by comparing the predictions of the two methodologies, confirming the anomaly if the two agree. A summary of the proposed methodology is shown in the flowchart in Fig.2.

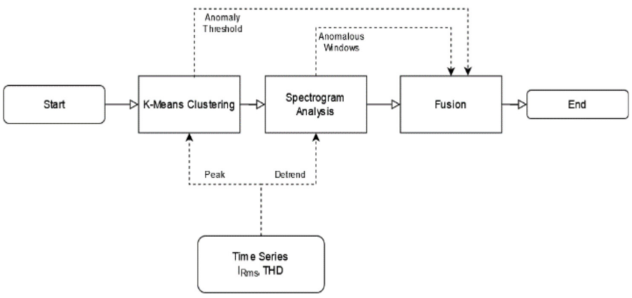

Fig. 2. Flowchart of the proposed methodology.

III. ALGORITHM DEPLOYMENT

As described earlier, the proposed methodology was deployed using the RMS value and THD features of the current of one of the three phases of the three-phase electrical system of an industrial plant.

The two main algorithms necessary for the operation of the proposed methodology will be described here.

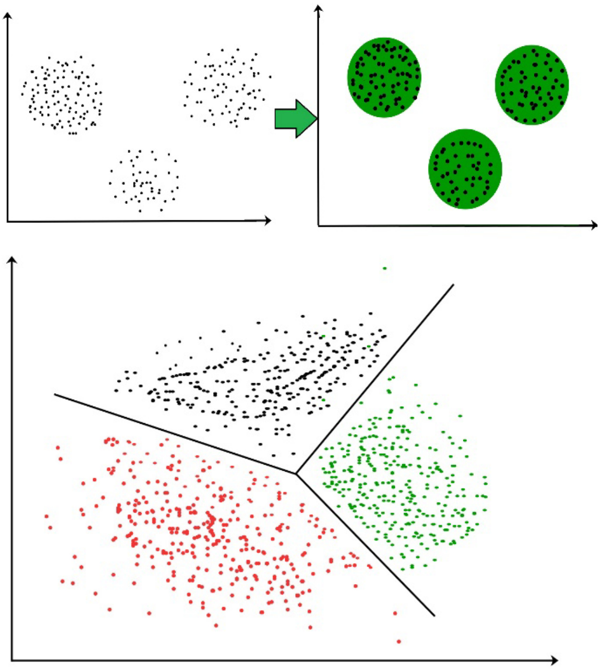

Fig.3. Clustering types illustrations [24].

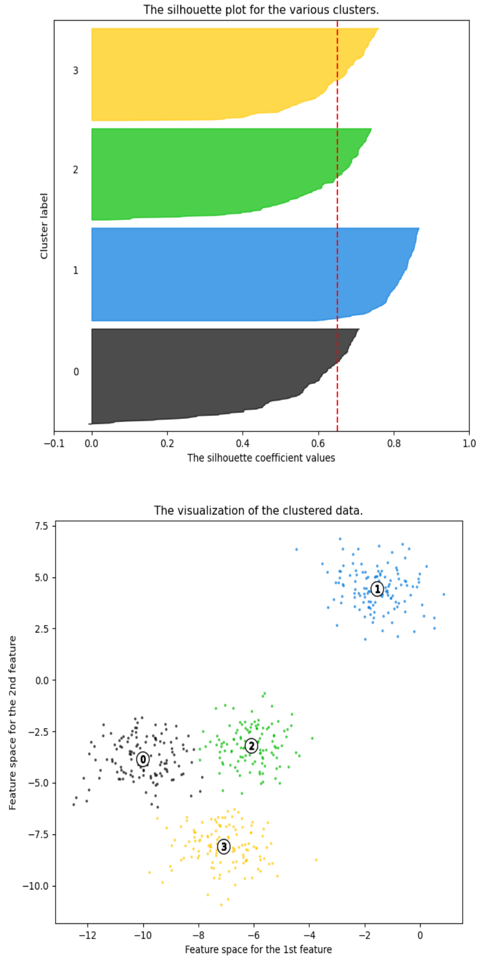

Fig.4. Silhouette analysis example [25].

A. Clustering

The first stage of the algorithm involves unsupervised clustering of the two time series. To speed up the clustering

Algorithm 1: Silhouette Method

Input: *i, samples*
Input: *Cluster of the samples*
Input: *Cluster* $C \neq C_i$
Output: s_i, *Silhouette Coefficient*

$\boldsymbol{a_i} \leftarrow$ *distance of the point from the other points of* C_i

$\boldsymbol{b_i} \leftarrow$ *distance of the point from the other points of C*

$$\boldsymbol{s_i} = \frac{(b_i - a_i)}{max\,(a_i, b_i)}$$

end

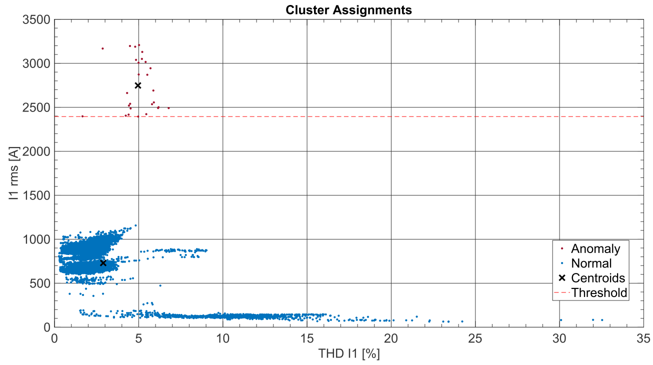

Fig.5. K-Means clustering example.

process and to reduce the computational burden given the large amount of data, the time series are first processed with a "Peak Detect" algorithm, which performs a decimation of the points based on the change in signal slope. A conceptual illustration of data clustering is shown in Fig.3.

To achieve the goal of full automation of the system, it was also necessary to automate the choice of parameter *k*, the number of clusters into which the k-means algorithm must segment the provided data. This was achieved by the Silhouette method, limiting the search for *k* from 1 to 4. In this way it was possible to limit the computational burden of the k-search algorithm. For the k-search a Silhouette Method [26]-[28] has been employed, as presented in Algorithm 1 pseudocode and in Fig.4.

The result of the clustering procedure therefore were the anomalous and non-anomalous clusters, together with a threshold value of the I_{rms}, to be used during fusion with the STFT algorithm. The clustering procedure is shown in Fig.5.

B. STFT Analysis

For spectrogram generation, it was first necessary to preprocess the time series with a "detrend" function. In this way, it was possible to highlight the frequency features of the anomalies more clearly.

The STFT algorithm was configured to use rectangular windows having a length of no more than 5% of the entire signal analysis window. Instead, the sampling rate was dictated by the sampling period of the data logger.

Anomalous time windows were employed by analyzing and comparing the power spectral density values of the entire band under investigation among all time windows. It was experimentally verified that an optimal threshold value is 85% of the maximum spectral power of the entire analyzed signal. Time ranges exceeding the indicated threshold have then been flagged as anomalous. An example of STFT analysis is reported in Fig.6.

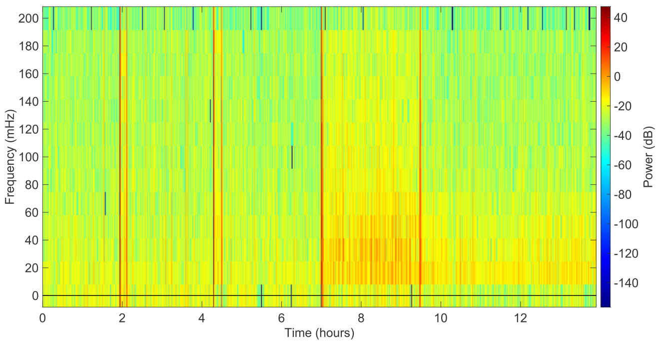

Fig.6. STFT analysis example.

C. Algorithm Fusion

The results of the two previously presented algorithms were, at this point, merged to provide more effective and robust fault detection. Specifically, the latter step consists of a decision maker that reports the fault only if both algorithms are successful. This then compares the timestamps of the samples flagged as anomalous by the k-means algorithm and checks whether they exceed the threshold analyzed and set by the STFT algorithm. If both of these conditions are met, the algorithm reports the outlier and, thus, a fault.

IV. RESULTS

The proposed method was deployed in an industrial plant characterized by the presence of numerous machines equipped with an electric motor, and thus an ohmic-inductive load. The electrical characteristics of the studied three-phase network are as follows: a nominal voltage of 380V and a maximum RMS current value of 1kA. The acquisition was done with a sampling rate of 16 kHz to allow for a broad frequency analysis, which is also necessary for THD calculation. The anomalous events in the time frame analyzed were reported, together with timestamps, by the company's experts in order to compare performance with the proposed methodology.

The methodology was then tested on 10 datasets with different durations and different anomalies. The results are shown in Table 1, while the K-Search computation time achieved with a common low-end Personal Computer are presented in Table 2.

As can be seen, the methodology showed excellent results in terms of both True Positives (TP) and False Positives (FP) and False Negatives (FN). Notably, no false positives were reported even in the sequences that did not contain any reported malfunctions. This demonstrates the high robustness of the proposed methodology, but also the low propensity to ignore a true anomaly.

Table 1. Algorithm deployment results.

#	Length [hh:mm:ss]	True Anomalies	TP	FP	FN
1	02:04:03	2	2	0	0
2	02:06:01	0	0	0	0
3	03:26:57	6	6	0	0
4	03:28:18	0	0	0	0
5	06:58:13	3	2	0	1
6	06:59:51	13	12	0	1
7	13:52:09	31	29	0	2
8	13:57:02	4	4	0	0
9	34:44:29	0	0	0	0
10	51:36:47	28	28	0	0

Table 2. K-search computation time

k range	Computation Time
1:2	00:01:31
1:3	00:02:22
1:4	00:03:07
1:5	00:04:01

V. CONCLUSIONS

This paper presented a new methodology for fault detection of industrial rotating machinery based on the analysis of electrical anomalies on three-phase systems. Specifically, the methodology combined the advantages of Machine Learning, Deep Learning and traditional techniques, allowing robust and automatic fault detection but without losing the white box approach, as is the case with Deep Learning systems.

The core of the methodology is the fusion of an unsupervised clustering methodology, k-means, and frequency analysis with STFT. The system showed excellent performance on the industrial system tested and required almost no human operator intervention, limited to choosing which electrical system metrics to use for analysis (in the application case I_{rms} and THD). Subsequent evolutions will concern the implementation of the proposed methodology in industrial work and production environments.

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