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EFFECTIVENESS OF RSOM NEURAL MODEL IN DETECTING INDUSTRIAL ANOMALIES

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Abstract

Continuous monitoring and proper diagnosis of production systems are daily concerns that involve many manufacturers. In this context, this paper proposes a feasible and effective diagnostic methodology. It is based on a recurrent dynamic neural model application, in industrial anomaly detection, with a high identification rate. The general context of this approach is summarized in the improvement of the detection and control mechanisms using intelligent systems. These tools can collaborate objectively in industrial processes diagnosis, then in anomalies detection and classification to intervene correctly. The final purpose of this paper consists in guaranteeing the operational safety for processes, ensuring their reliability and affirming the production continuity.

Keywords: RSOM model, defect diagnosis, industrial processes

List of Symbols/Acronyms

RSOM - Recurrent Self Organizing Map;
SVM - Support Vector Machine model;
KNN - K-Nearest Neighbors;
Vpi - The weight vector of introduced Data to a Neuron
Ei - The Euclidean distance between an input data and each of the dendrite weights of a neuron;
BMU - The Best Matching Unit (Neuron) to the input Data
ΔW_i - Ruler of neuron weight updates;
Ω - is the rotation speed of a mechanical bearing;
PSD - is the Power Spectral Density of an electrical or a mechanical signal.

1. INTRODUCTION

Productivity is the most sensitive element in the industrial world. Thus, the failure diagnosis of industrial systems, if conducted efficiently, makes it possible to detect degradation early. It, therefore, represents one principal means for contribution in the said productivity improvement. Owing to this, important research has been conducted around the diagnostic problem, whether for dynamic systems, distribution or telecommunications networks. Within this framework, this research paper is included. It aims to develop a neural model allowing classification and recognition of various anomalies, which can impede the process productivity. This model has to process delivered signals from the doubted system modules. The application of this model processing tools on the delivered signals allows early estimation of the correction parameters. This work requires in-depth knowledge regarding:

- mathematical modeling of processes.
- a mastery of signal processing tools for modeling and analysis.
- knowledge of artificial neural networks and their applications.
- a good command of the implementation language such as Matlab or Python.

The evaluation of the proposed model is performed on all mechanical vibration signals, electrical and magnetic signals extracted via a piezoelectric accelerometer or other sensors from a real test bench. The diagnosis should be made in real time.

The main challenges arise when detecting anomalies by conventional methods, which we quoted, are:

- Control of anomalies in eclectic training systems, in real time.
- vibration monitoring characterized by a precision lack and sensitivity to disturbances. Thus, it is expensive for the measurement chain.
- spectral analysis having as side effects the harmonics amplification with noise sensitivity.

To overcome these limits and ensure reliability in anomalies detecting, this paper proposes an approach based on the application of a dynamic recurrent neural model RSOM. It is a robust classifier that can minimize the time and detection operation cost. This model is thus articulated to a parallel approach based on a Map-Reduce paradigm to solve a large volume of data extracted from the process to be detected.

This paper is organized as follows: the second section is dedicated to a literature review of industrial processes, their modeling, the main defects, and the classical diagnostic techniques adopted. The third section describes the proposed strategy for anomaly detection. The fourth section is reserved for experiments and obtained results.

2. LITERAL REVIEW

The industrial processes are based on the drive systems that are the machines.
The anomaly origins in these systems can be electrical, mechanical, thermal or environmental. The main defects, which result from it cause either an excessive vibration, or an abnormal heating, or a slowing down or a total shutdown of the system. From these effects appear several interventions and anomaly detection techniques, including the vibration analysis method, spectral analysis of received signals from the system, and electrical control. The most provided solutions by these techniques remain trapped in local optimum. Consequently, their efficiency ratio remains minimal. This idea caused the appearance of other techniques expressed in the following figure 1.

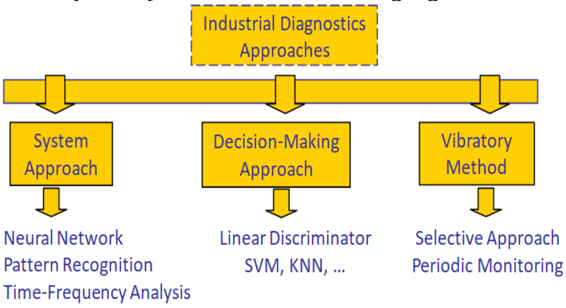

Fig. 1. Principal diagnostic approaches in industrial domain

The limits of the first technique lie in the fact that they require early learning and costly time. The second technique undergoes a long and costly time. However, the third method presents noise, which can mask useful information and reduce precision while accompanying costly time [1].

Currently, the induction machines fleet and the static converters ensuring their orders are increasingly applied in industrial processes. In particular, electric drive systems based on induction machines are widely used in industrial applications because of their low cost, performance and robustness. These machines are ubiquitous in many applications, especially in high-tech sectors such as aerospace, nuclear, chemical industries, transport related to elevators, metros, trains, vehicles and ship propulsion, in industry; machine tools, winches [2], [3].

The anomaly distribution that can affect an induction machine is expressed by the following histogram represented by figure 2.

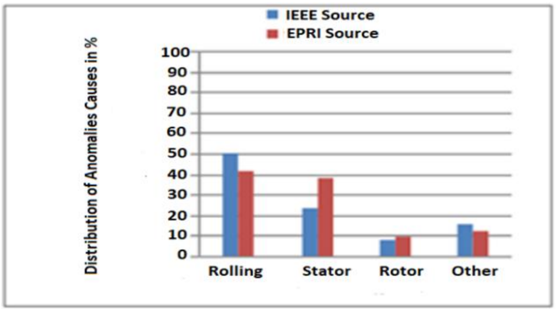

Fig. 2. Overall anomaly causes in induction machines

3. THE RSOM STRATEGY IN ANOMALY DETECTION

The application of neural networks in industrial processes diagnosis is an important factor in preventive maintenance. The SOM model is one of the most relevant types in processing and analyzing applications [4]. However, it is effective for statically received information. To integrate the temporal aspect and make it dynamic, it is possible to exercise recurrence loops under the RSOM name [5]. It, therefore, becomes effective in identifying and recognizing variable signals from the process to be controlled.

In order to contribute to the robustness of the RSOM model, this paper proposes its enrichment by an aggregation technique for different received signals in real time. This technique is so called Map-Reduce [6]. The following figure 3, shows the RSOM map architecture.

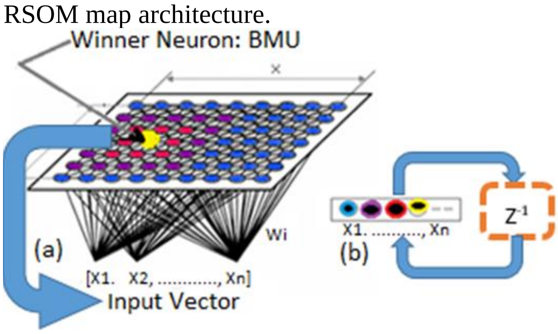

Fig. 3. Representation of the recurrent self-organizing model RSOM

The figure (a) represents the RSOM model in dimension 2 card; while figure (b) represents the same model in dimension 1 string.
The operator (Z^{-1}), is a return loop associated with a previous output storage, thus qualifying the model by a certain dynamism.
The input vector represents a captured signal sample, such as vibratory, electrical or mechanical.

The weight vector Vpi, related to a neuron (i) within the neural network, for j input data, is given by the equation below:

$$V_{pij} = \{w_{i1}; w_{i2}; w_{i3};...; w_{ij}\} \qquad (1)$$

The Best Matching Unit BMU is therefore the neural unit that can better reach the input vector over iterations. The difference margin between an input data and each of the dendrite weights of a neuron is calculated by adopting the Euclidean distance expression.

$$E_i = \|x(t) - w_i\| \quad (2)$$

So, the BMU "v" is that having the minimum difference margin.

$$E_v = min\, E_i\, ; i \in N \quad (3)$$

Following test or learning iterations, only one unit should be activated; by applying the updated ruler adopted by the Kohonen algorithm introducing the RSOM map functionality.

$$\Delta w_i = \gamma . h_{iv}(x(t) - w_i) \quad (4)$$

With γ is a learning coefficient and h_{iv} is a neighbor function, which decreases with the distance between the units i and v on the map.

To overcome an expensive processing time and an RSOM learning overload problem, we integrated the SOM Map-Reduce approach, allowing us to offer a parallel approach for simultaneous anomaly detection of different nature; electrical, mechanical or other. The principle of the SOM Map-Reduce algorithm is represented in figure 4 below.

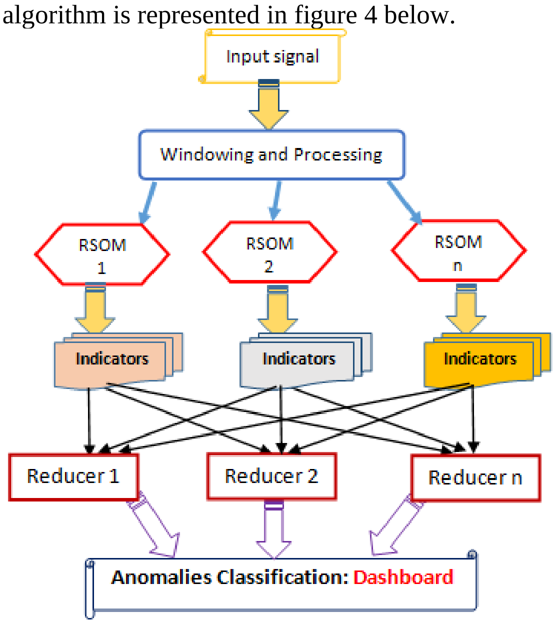

Fig. 4. Schematization of the SOM-map reduce model

This model seems effective in the case of data aggregation when it comes to Big Data analysis. So, this strategy guarantees the possibility of processing for a massive signal volume, minimizing the processing cost from a time viewpoint, with acknowledged processing (by batch).

4. EVALUATION OF THE ADOPTED MODEL

The chosen experimental platform to evaluate our adopted model represents a system the most answered in the industry today. It is formed by a mechanical load driven by an electric machine. This is supplied in three-phase through a variable speed drive made up of a rectifier bridge, a filter and a transistor inverter. The experimented model is represented by figure 5 below.

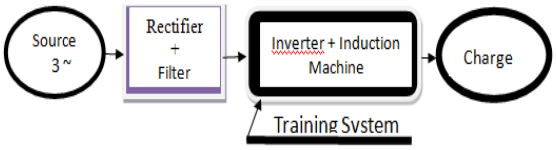

Fig. 5. Modelling of experimental process

This machine has as characteristics:

- s power of 4 kW;
- s lightweight Microlog portable terminal for the acquisition and storage of sensor measurements.
- the sensor is a piezoelectric accelerometer.

Any type of electrical or mechanical fault will be immediately reflected on the stator current. Thus, defect treatment returns to the analysis of this current.

The following flow diagram; figure 6, expresses the different stages of the adopted strategy.

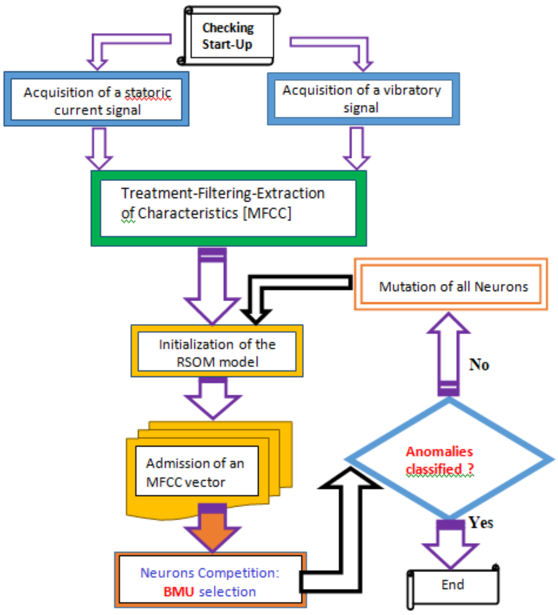

Fig. 6. Flow diagram for the RSOM map application in anomalies identification

The unsupervised learning of the RSOM model should be done upstream of the test phase. It should be applied, even when the industrial process is stopped, on as broad as possible basis, containing the derivatives and primitives of different anomaly types that can occur on the machine. These defect characteristics will be denoted by appropriate frequencies. The application of this model in anomaly diagnosis can be done at the desired instant or when there is doubt of an abnormal functioning.

The learning result is displayed by the following topology; figure 7, of the RSOM map.

Empty neurons indicate a fault identification confusion, which implies that out of 100 neurons, either matrix of 10x10, there are 4 neurons do not respond. It involves that we have an anomaly recognition rate of approximately 96%.

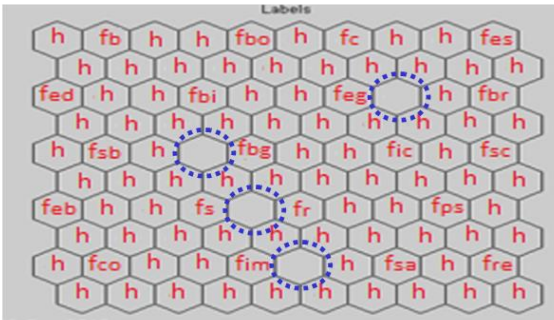

Fig. 7. The RSOM topology following a learning phase

The displayed variables by the RSOM topology are anomaly indicators libeled by their frequency such as:
- h means healthy.
- fb is the ball rotation frequency.
- fes is the static eccentricity frequency.
- fed is the dynamic eccentricity frequency.
- feg is the global eccentricity frequency.
- fco is the switching frequency.
- fbg is the rolling frequency.
- fbr is the broken bar rotor frequency.
- fps is the phase short circuit frequency.
- fim is the imbalance frequency.
- fre is the resonance frequency.

Any defect, whether of an electrical or mechanical nature, affects the stator current variations of the machine under control. Consequently, during the test phase using the RSOM map, we introduce a sample vector from the stator current, with close filtering and coding, into an appropriate data structure.

4.1. Case of an inverter- switching defect

We adopt a commutation defect within one of the inverter arms that supplies the machine, the result is given through the following topology; figure 8.

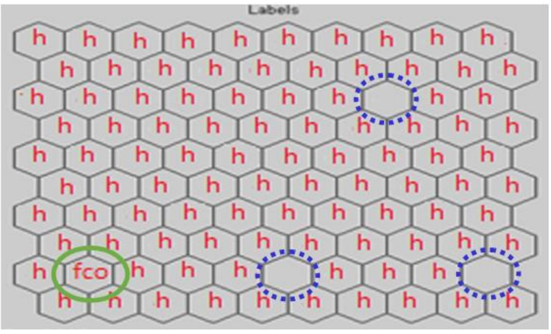

Fig. 8. Signaling of a switching defect by RSOM

This topology clearly shows that the admitted signal to the RSOM neural model has a single defect related to a Transistor switching within the inverter. This anomaly is characterized by its frequency denoted Fco.

4.2. Case of anomaly on ball bearing

A cavity fault on the inner or outer ring of the ball bearing causes a force in a radial plane. This force is situated in a frame of reference (ox_i, z_i), having a rotation speed Ω; It is libeled by the frequency (Fbint) and represented in figure 9 below.

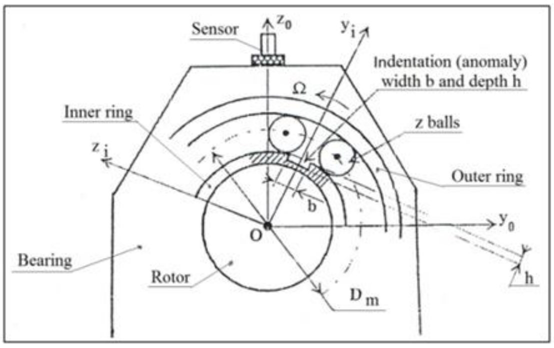

Fig. 9. Representation of a mechanical bearing anomaly

The figure 9 above shows a cavity at the level of the hatched inner ring. Such a defect is due to a mechanical overload [7].

This anomaly meets a zone between θ1 and θ2 as shown in the following figure 10.

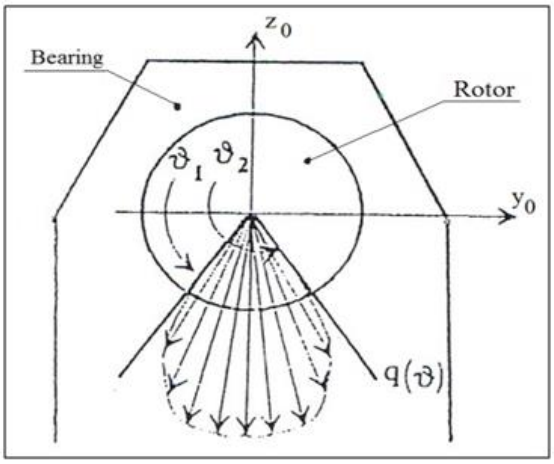

Fig. 10. Highlight of resulting defect forces

The resulting radial force f (t) progresses in a cyclic pulse during the machine operation. The value τd indicates the cavity dimension and Td expresses the repetition cycle. The signal of this force is represented in figure 11 below.

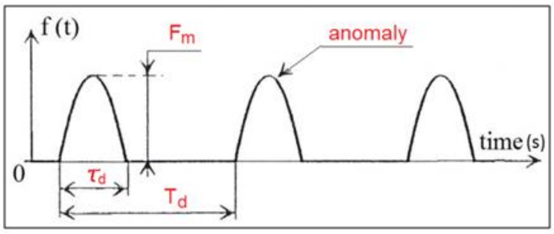

Fig. 11. The shape of the resulting radial force

As (Fr) refers to the rotor rotation frequency, the resulting force is defined as below:

$$f_{Radiale}(t) = q(t).SHA_{\frac{1}{f_{b\,int}}}(t) * SHA_{\frac{1}{f_r}}(t) \quad (5)$$

Knowing that (SHA), is the Dirac distribution, the transfer function will be:

$$h(t) = h_o(t)[1 + \gamma_1 \cos 2\pi f_r\, t] \quad (6)$$

The output signal from the accelerometer sensor can be written in the following form:

$$S(t) = h(t) * f_{Radiale}(t)$$
$$S(v) = H(v).F_{Radiale}(v) \quad (7)$$

The spectral visualization of the signal of detected anomaly is represented by the figure 12 below.

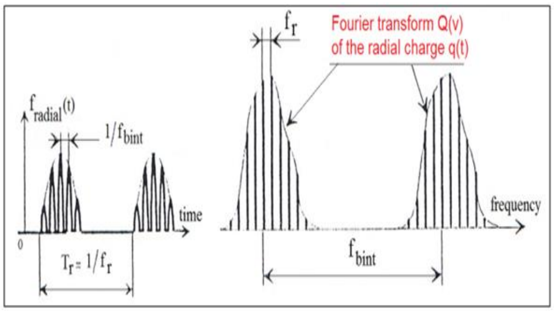

Fig. 12. Spectral visualization of the defect

This figure shows us, in Fourier domain, the indentation defect which is represented by the force and the radial load.

This indentation anomaly at the bearing inner ring has effects the load torque. During the bearing rotation there are shocks causing vibrations and torque jolts which are repeated periodically over time by inducing load torque oscillations measured by a torque meter [8], [9], [10].

The load torque can be represented by a continuous component of amplitude C_0, equal to the machine electromagnetic torque (Cem), and by a series of (Cn) harmonics [11], [12].

$$C_{charge}(t) = C_0 + \sum_n C_n \cos(\omega_n t) \quad (8)$$

The power spectral Density (PSD) of this torque is represented in figure 13 below.

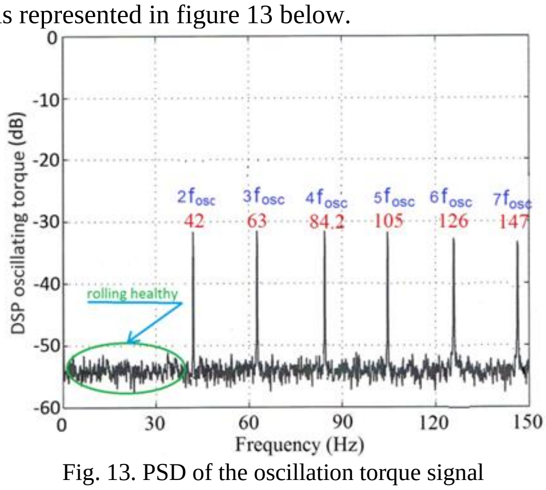

Fig. 13. PSD of the oscillation torque signal (fosc ≈ 21 Hz)

The PSD, acronym of power spectral density, highlights the signal power distribution according to the frequencies.

The figure 14 below shows the PSD of the stator current resulting after an anomaly.

This curve expresses that the torque oscillations mainly induce harmonics on the stator current frequency, denoted by : | Fs ± fosc |, with fosc ≈ 21 Hz. [13], [14], [15].

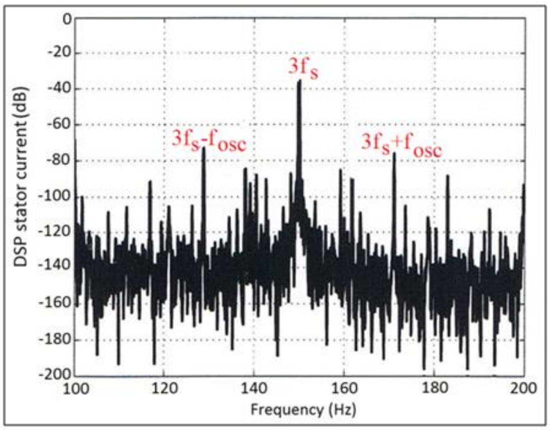

Fig. 14. PSD of the stator current resulting from the anomaly

The implementation of the RSOM model in this anomaly detection requires the admission of a vibration signal vector from the experimental stand. After data acquisition and processing, the result is established following the topology below; figure 15.

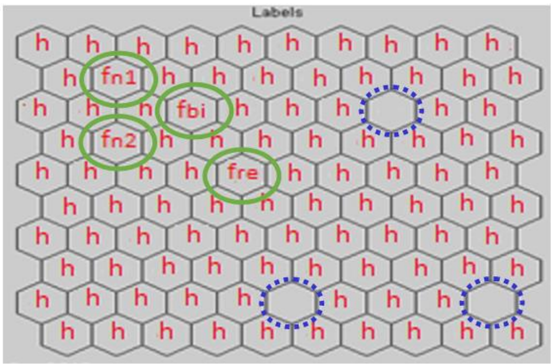

Fig. 15. Highlighting of mechanical defects by RSOM

4.3. Results Interpretation

The processing of the vibratory signal was conducted to extract the useful indicators in the anomaly frequency classification.

In section 4.2, the detected anomaly by RSOM is located on the inner ring. It is assigned to a frequency (fbi) signaled by the winning neuron.

This defect also generates the resonance of the total structure in that there is an appearance of (fre) frequency in the BMU 'best matching unit' vicinity. Alternatively, the neighboring neurons indicate frequencies (fn1) and (fn2), which respectively, represent (fbi + fc) and (fbi-fc).

The topology of the RSOM model in Figure 15 is expressive. Indeed, we find the harmonic frequencies (fn1) and (fn2) placed on the two sides of the main defect (fbi), while the frequency (fre) of the induced resonance defect is located in another level of neighborhood.

The test result obtained after the RSOM learning, by a large data basis containing all frequencies of likely defects, is 97%. This result is highlighted by figure 16-topology. It shows that out of 100 neurons (10 x 10), there are only 3 empty neurons marked in blue circles.

Otherwise, the experimental results show that the RSOM model is more precise than the vibration analysis that shows an erroneous structure of lines under the resonance effect. However, the effectiveness of anomaly recognition is strongly linked to the learning quality of the developed system. The way in which the vibration signal, or stator current, or torque and speed, are segmented into stationary atoms is a critical factor in the improvement of anomaly recognition rates.

5. CONCLUSION

The RSOM model represents one of the principal smart systems. It is considered a powerful tool in classification and identification of events that occur any dynamic signal. Its unsupervised training algorithm reinforces its ability in checking industrial defects in adverse environments, and over the use of large data volumes.

Various experimental results show that the RSOM-adopted strategy is more objective and precise than spectral analysis, due to its easiest topology in expressing industrial issues.

The hybridization of the RSOM algorithm with the Map-Reduce programming technique makes the RSOM computable on parallel processing systems for big data, opening up a potential field for new applications.

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