International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 9 (2017) pp. 1836-1843

A Parallel Approach for the Diagnosis of Electrical Asynchronous Training Anomalies

Nejib Khalfaoui [1], Mohamed Salah Salhi [2] and Hamid Amiri [3]

[1]*ISET Jendouba, LR SITI – ENIT Tunisia.*

[2]*ISSAT-Mateur, LR SITI - ENIT Tunisia.*

[3]*ENIT- Tunisia, Directeur de LR SITI*

Abstract

The aim of this work is to address the problem of massive anomalies diagnosis by adopting suitable anomalies detection and isolation techniques in the face of massive data which come from monitoring sensors which are placed on different organs over an Electric drive system. These data have different types including electrical, mechanical and vibratory signals. Firstly, we applied a neural network system SOM (Self organizing Map) which takes as input three signals from different sources, the result is obtained after 34min. Thus, the management of the allocated time and the analysis of Big Data are systematically associated with a distributed data architecture, namely the Map-Reduce SOM. This approach deals with the parallel processing of the three signals introduced. Adopting a parallel diagnosis has considerably reduced the processing time to reach 12min.

Keywords: Parallel diagnosis, Neural network SOM, Map-Reduce, Drive System Anomalies.

INTRODUCTION

Ongoing monitoring and proper diagnosis of production systems is a daily concern for many industrialists whose primary objective is to obtain a safe and reliable system in order to guarantee continuous production. Indeed, due to the increasing complexity of modern electrical systems, their operating costs, mainly related to maintenance, have increased. Most manufacturers use systematic maintenance, widely used in systems critical to safety or reliability. This is why, in order to be more efficient, it is being discussed more and more in the industrial sector. This thriving diagnostic field has emerged mainly during the last half century, notably in the defense, aeronautics, space, nuclear, telecommunications and transportation sectors.

To this end, the development of the automatic diagnostic system appears to be a somewhat more costly solution to investment, but it is amortizing over the long term. Measurable signals such as currents, voltages, torque, velocity, vibration or temperature can provide significant information on defects and can be used to determine a set of parameters representing the signatures of anomalies in industrial processes. It is precisely on the basis of these parameters that the implementation of decision-making methods can make it possible to design efficient diagnostic systems based on artificial neural networks.

The rapid development of intelligent systems, such as neural networks, has improved the effectiveness of monitoring and diagnosis of industrial processes in order to detect and classify anomalies. This research axis is considered to be one of the most active in the industrial field.

Much research is published [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], they treat neural systems dedicated to the detection of anomalies, such as the SOM card which represents a powerful tool for diagnostic tasks in various fields. This card is capable of representing, as many data entries, having multidimensional characteristics, as the number of unit or hierarchy that develops. It acts at the same time as classifier and quantifier, in addition, the SOM is adapted to the general processing of the important data flow. It can be dynamic by integrating the time factor which has the help of feedback (recurrence), as the case of the RSOM model proposed by Thomas Voegtlin in 2002.

It is precisely the very objective of this article which aims to develop further Efficiency of this method and to apply it in the detection of anomalies on an induction machine, given the precision of the monitoring and the time factor demanded by the industrialists, it is necessary to control all the elements of the training system, We are called to analyze massive data comes from different signals captured, so we propose a so-called SOM Mapper-reduce approach based on the processing of massive data that are systematically associated to a distributed data architecture and then comparing the performances obtained Compared to that of the SOM map.

STRATEGY OF ANOMALIES DETECTION

Teuvo Kohonen realized a particular neural network map called SOM (Self organizing Map). It is based on modeling by networks of biological inspiration. The implementation of a number of formal neurons operating in parallel and massively interconnected (FIG. 1), gives them learning and decision-making abilities to detect abnormalities. The constituted network is enriched by a form of generalization following its learning by a well-defined database [1], [3], [6], [7].

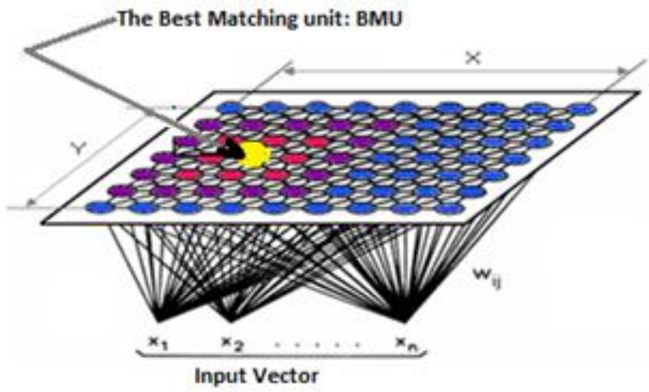

Figure 1: Representation of the map SOM

The weight vector of neuron unit n° i, designated by Vpi is shown, for j input data, as follows:

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

Each neuron will receive elements characterizing the input vector. The nearest neuron representation by minimizing a Euclidean distance, the input vector is called the BMU 'Best Matching Unit'. At the end of each iteration 'learning cycle or test map' each neuron has a weight vector, which will be compared by calculating the distance to the input vector to give a single winner neuron. This is the one that is assumed
The BMU is, then, the neuron unit that can best join the input vector. It is still the unity of winning neuron owing to iterations. The quantization error associated with the neuron i is given by the Euclidean distance:
the closest distance from the input vector.

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

Thus, for a given input vector, the winner neuron "v" is the unit that minimizes the quantization error from which we will have:

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

For each learning or test iteration, a single neuron is activated; it is the BMU; this is the neuron whose prototype vector (weight vector) best represents the input vector. This activation propagates along the map SOM by following the form of a Mexican hat (Figure. 2); this is described in Kohonen algorithm by updating equation of synaptic weights of the neurons. The learning rule updates the weight of neurons in the vicinity of activated neuron ' winner ', bringing them close to the input vector :

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

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

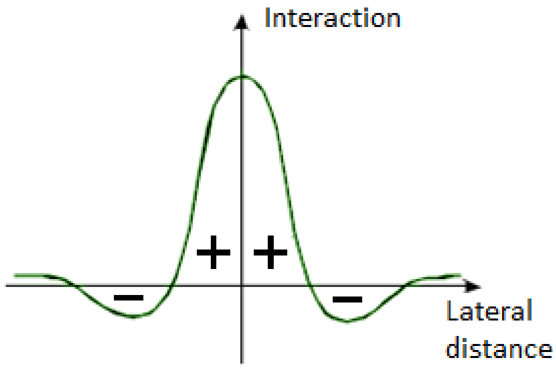

Figure 2: Mexican Hat describing the activation rules for the winner neuron and its neighborhood in a competitive SOM

Kohonen learning algorithm.

During the competition phase the winning neuron determines the center of an area of the map called the neighborhood zone whose extension (radius) varies with time. The next phase, called update or adaptation, changes the position prototype to reconcile the individual presented to the network [6], [7].

The prototypes are even closer to the individual in question they are close on the map of the winner neuron. The weighting is used to determine the significance of changes in position and in space is thus a function of distance on the map between the winner neuron and the considered neuron.

The steps of the Kohonen algorithm are as follows:

1. Initialization prototypes
2. Selecting an individual
3. Determination of the winner neuron for that individual in a competition phase.
4. Modification of all the map prototypes: stage adaptation and update.
5. Resume stepping 2 if the stop condition is not satisfied.

SOM Process Steps

The different steps for detecting anomalies and their evolution sequences are given by the following activity diagram:

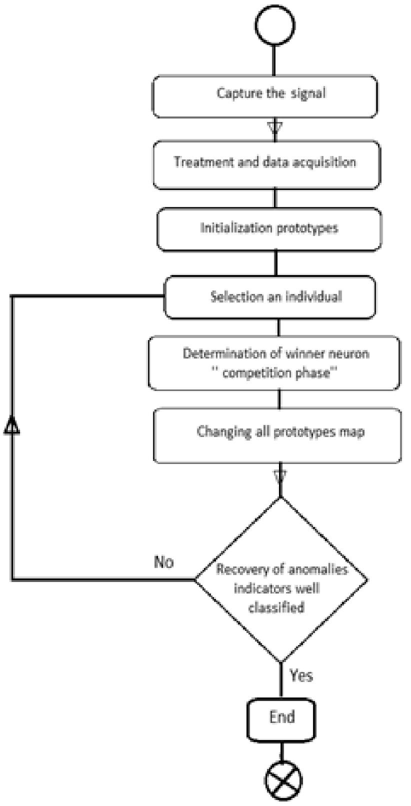

Figure 3: UML activity diagram for the SOM map learning

The SOM map Learning in anomalies detection

Several parameters can influence the detection rate of anomalies such as:

- The data vector size to recognize, presented to the SOM classifier inputs. In this case a sample of the received signal is converted into a matrix of coefficients characteristic MFCC which has twelve windows (12 columns). Each line of this matrix means an anomaly wording.
- The size of the map that is the vector quantization space 2D or 1D.
- The number of neurons in the SOM map. A judicious choice of the SOM map size must be based on the number of anomalies in question and the number of the map neurons. The total number of Nn neural map is approximated by
  Nn = 2.5C. Where C corresponds to the number of individuals employed in learning.
- The topological structure of the map: The mesh at the base of the neural network is generally square, rectangular or hexagonal. A hexagonal mesh is particularly suitable for the visualization of classes.

- **The type of learning is sequential or parallel.**

The displayed data by the SOM map represents the anomaly indicators [12], [13], [14], [15], [16], [17], [18], [19], [20]. They are indicated by their characteristic frequencies, as follows:

- h : healthy
- fr is the rotor rotational frequency
- fs is the electrical network frequency
- fb is the ball rotational frequency
- fc is the cage rotational frequency
- fbi is the rotational frequency of the inner ring
- fbo is the rotational frequency of the outer ring
- fes is the frequency of static eccentricity
- fed is the frequency of dynamic eccentricity
- feg is the frequency of global eccentricity
- fco is the commutation frequency
- fbg is the bearing frequency
- fbr is the frequency of broken bar rotor
- fsb is the frequency of Short rotor bar circuit
- fic is the frequency of short - circuit portion of the rotor ring
- fsc is the frequency of short circuit coil
- fps is the frequency of phase short-circuit
- fim is the frequency of imbalanced
- fsa is the frequency of short circuit between phase and batty
- fre is the resonance frequency

EXPERIMENTAL RESULTS

Measurement of the stator current (Signal 1)

The measurement of the stator current on the experimental bench, at a given time during the nominal operation, with three broken bars on the rotor which causes a sound machine, is represented by figure 4.

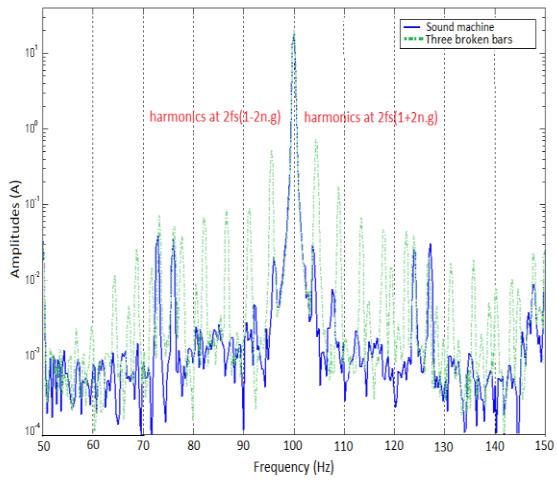

Figure 4: Spectrum of the stator current related to a rotor "three broken bars" accompanied by a "sound machine"

The experiment is done when the machine is fully loaded. So, the default three broken bars at full load shows the fault identification, because the peaks at frequency 2fs (1 ± 2n .g) reflect a strong modulation of the line current.

Indeed, the slide being greater in fully charged, then the lines at 2fs (1 ± 2g) are slightly farther from the double frequency line (2fs) of the fundamental.

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 9 (2017) pp. 1836-1843

Vibration signal results of the bar break (Signal 2)

The vibration spectrum measured by an accelerometer is defined by figure 5; the effective value of the amplitude component at the rotation speed (≈25Hz) is important and it is equal to 17.16mm / s; so, the harmonics of this component are notable.

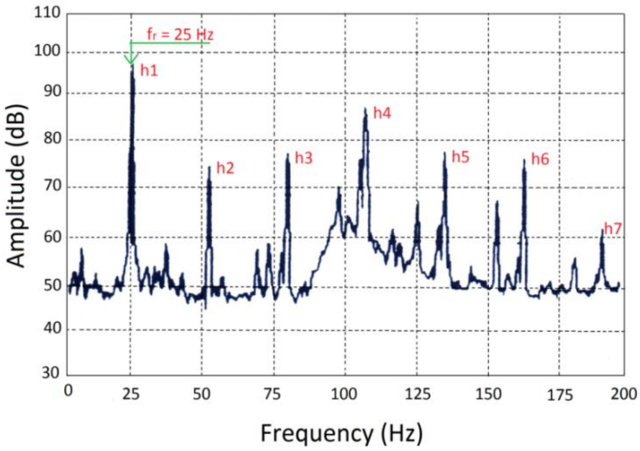

Figure 5: Vibration signal measured by an accelerometer following a rotor bar break

All of the information provided by figure 5 spectrum, can diagnose a major fault in one of the rotor bars; this fault causes, among other things, a large unbalance (f_r ≈25Hz) and amplitude modulation (at a frequency twice the slip frequency) by the forces associated to the rotor .

Vibration signal results of the inner ring anomaly (Signal 3)

The experimental measurement shows the vibrations of the balls caused by an indentation defect on the inner ring of a rotary induction machine having a speed equal to 1480 rpm. The zoom mode around 680.2Hz, characterizing the anomaly in the fifth harmonic of the frequency f_{bint} due to an indentation on the inner ring, shows lateral stripes spaced from the rotational frequency (25 Hz), which reflects a modulation amplitude.

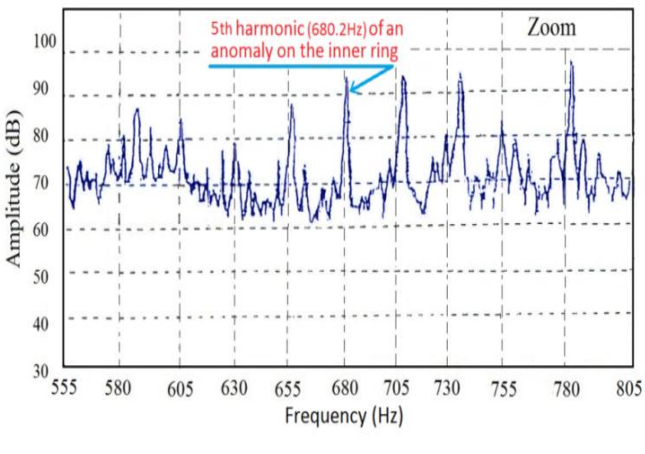

Figure 6: Spectrum zoom mode of an inner ring anomaly

The vibration signal from the sensor reveals the following information:

- The amplitude evolution of harmonic components is in the manner of: (555 + k25) Hz,
- k = 0, 1, 2, 3... indicates different frequencies due to the passage of the balls on the indentation.
- The development of the amplitudes near 100dB around 780 Hz which represent the structure resonance, can be attributed to the 31th harmonic resonance of the rotation (780.2 / 25 = 31.2).
- We can identify the harmonic of order 5 (680.2/136 = 5) representing the inner ring anomaly on the spectrum zoom mode.

Learning result of detection anomalies

The entrance to the SOM map is the vibration signal vector from the experimental test, after treatment and data acquisition, the result is given by the following topology:

Figure 7: Anomaly detection result by SOM

Our interpretation of the above results shows that:

-the vibration signal is treated to extract the indicators used to rank the frequency characteristics of anomalies.

-the anomalies were detected by the SOM map, were classified on three types:

a. The inner ring anomaly characterized by the **fbi** frequency indicated by the neuron.
b. The rotor break bars characterized by the **fbr** frequency indicated by the winner neuron.
c. The resonance frequency of the induction machine structure indicated by **fre** frequency.

-the result is given following an apprenticeship of **98**٪

MapReduce MODEL

Map Reduce is a distributed processing technique based on java. Knowing that the MapReduce algorithm contains two important tasks, namely Map and Reduce. The Map takes one data set and converts it to another dataset, where the individual elements are decomposed into tuples (key / value pairs). As a result, reduce the task, which takes the output of a map as an input and combines these tuples data into a smaller set of tuples [10].
However, the major advantage of MapReduce is that it is easy to mount data processing on multiple compute nodes. Under the MapReduce model, the data processing primitives are called mappers and reducers. The decomposition of a data processing application in mappers and reducers is sometimes unusual. But, once we write an application in the MapReduce form, scaling the application to run on hundreds, thousands, or even tens of thousands of machines in a cluster is simply a change of configuration. This simple scalability is what has attracted many programmers to use the MapReduce model for mass data processing.

*The Algorithm

The Generally MapReduce paradigm is based on sending the computer to where the data resides. Indeed the MapReduce program runs in three steps, namely step map, step shuffle, and reduce step.
The task of the map or the mapper is to process the input data. Typically, the input data is in the form of a file or directory and is stored in the Hadoop file system (HDFS) [11]. The input file is passed to the line-by-line mapping function. The mapper processes the data and creates several small pieces of data.
Reduce step: This step is the combination of the Shuffle step and the Reduction step. The work of the reducer is to process the data that comes from the mapper. After processing, it produces a new output set, which will be stored in the HDFS.
Most of the computing takes place on nodes with data on local disks that reduce network traffic. After completion of the given tasks, the cluster collects and reduces the data to form an appropriate result and returns it to the Hadoop server

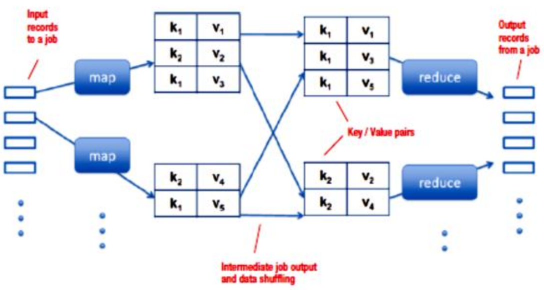

Figure 8: Synoptic diagram of MapReduce network

APPROACH OVERVIEW

The proposed approach is based on Map Reduce, which is a model of massive parallel data processing. It has been popularized by Google in the implementation that uses a file system distribution to exchange data [10]. However, other implementations have appeared that target different architectures and communication channels, such as shared memory systems or distributed systems with communications.
The time allocated by the SOM map in anomalies detection is important. In our case the processing procedure of the three signals take 34min duration. To remedy this problem, we propose a distributed approach of Electrical and Mechanical signals processing using the SOM map to detect and isolate anomalies. This approach is based on Big Data (Hadoop Map-Reduce) [11] processing techniques and the SOM map for the isolation and classification of anomalies with appreciable time. This approach is illustrated by the following synoptic diagram:

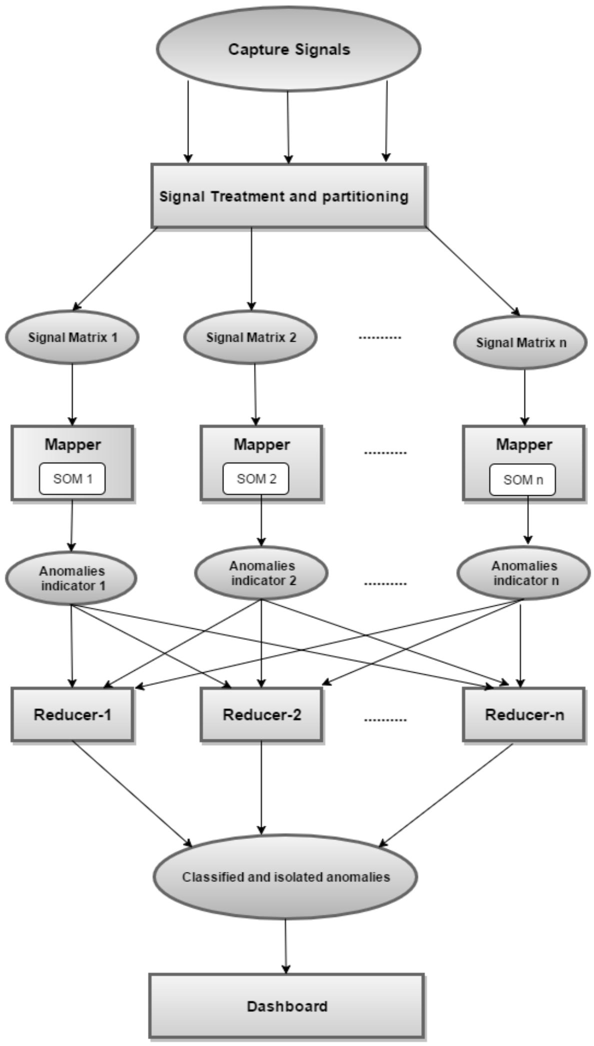

Figure 9: SOM Map-Reduce (approach) detection and isolation of anomalies

After processing the signals, a partition of each signal matrix to the corresponding mappers (SOM) for analysis and anomalies detection by their subsequent indicators will be distributed to the reducers which issue the final list of classified and isolated anomalies, subsequently the result will be illustrated by a dashboard

The Mappers work according to the following algorithm1:

Algorithm 1. Map Function

Require: signals matrix Mi

Ensure: key/value pairs of sources anomalies

1: REi ← SOM (Mi)

2: $An_i = Ø$

3: FOREACH Frequency f in RE_i **DO**

4: **IF** f != h **THEN**

5: Add f to An_i

6: **END IF**

7: END FOR

8: EmitIntermediate ($Source_i$, An_i)

The Reduce algorithm is as follows:

Algorithm 2. Reduce Function

Require :set of key/value pairs <source, anomalies>

Ensure key/value pairs, <source, anomalies>

1: FOREACH source $_i$ **DO**

2: EmitIntermediate ($Source_i$, anomalies)

3: END FOR

anomalies are characterized by a representative frequency. The following pair is an output example returned by the Reduce function:

<$signal_1$; { fbr3 }>

Here, the key signal1 is captured from the process while the value {fbr3} represents the frequency indicating anomalies.

After isolation and classification of anomalies the result will be displayed by the Dashboard as follows:

<$signal_1$; { fbr3 }>
<$signal_2$; { fbr1 }>
<$signal_3$; { fbin; fre }>

EXPERIMENTAL BENCH

The experimental bench is composed of:

- A three-phase induction machine. The machine is controlled by an inverter ' OMRON '. The rotor shaft is coupled to a DC generator which feeds into a rheostat to control the load.
- Characteristics of the considered induction machine are:

4. Nominal power 4 Kw

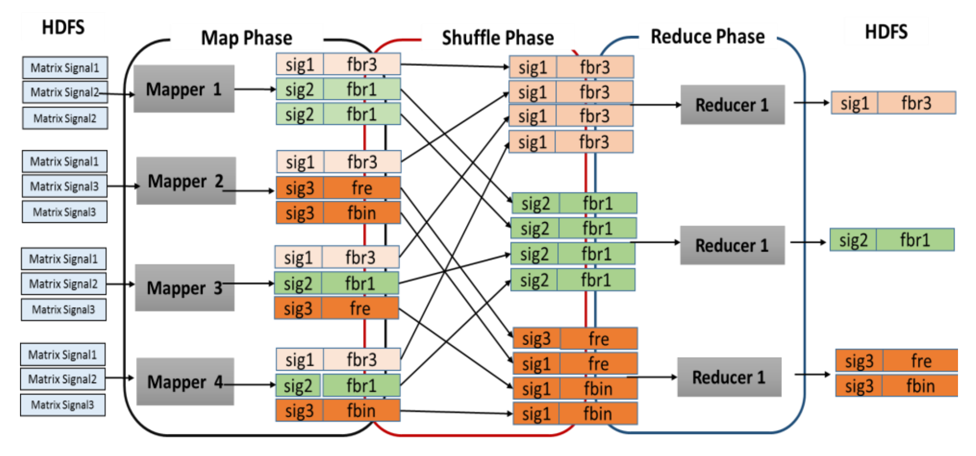

Figure 10: Execution of MapReduce Approach

Illustration of the MapReduce SOM approach

The different processing phases of our case of the three signals are described in figure 10. The result shows that fbr3 corresponds to three broken bars and fbr1 expresses the break a single bar.

As seen in algorithm 2 above, the Reducer starts by calculating for each source the corresponding anomalies. Since several pairs can have the same value, the Reducer must sort them in ascending order of frequency and according to the number of anomaly.

Finally, the Reduce function returns the key / value pairs as <Source, anomalies>, where Source is a processed signal and

5. Nominal speed 1480tr/min
6. Moment of inertia J= 0.013kgm^2
7. Number of pair of stove P =2
8. Rolling type ball SKF 6208, with a mechanical rotational frequency from f_r = 25Hz.
9. The frequencies of outer ring, inner ring, and ball cage are respectively f_{bo} =89.4Hz,
   f_{bi} =136Hz, f_c = 9.94Hz et f_b = 58.4Hz.
10. A light Micro-log portable terminal for acquiring and storing from the sensor measurements.
11. The sensor is a piezo-electrical accelerometer.

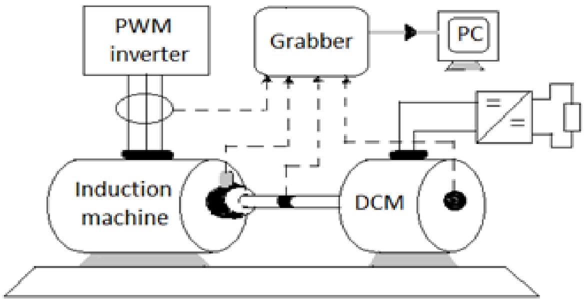

Figure 11: Schematic block diagram of the experimental bench

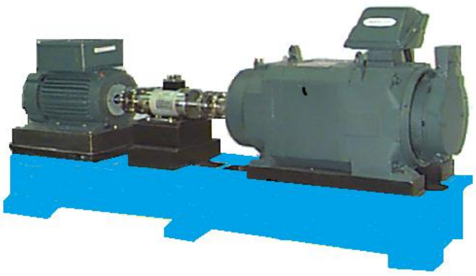

Figure 12: Photography machines of experimental bench

CONCLUSION

To minimize the processing time of Big Data it is necessary to use the parallel processing technique as our case, it gave satisfactory results.

However, the adoption of the SOM algorithm to the Map Reduce programming, thus making the SOM computable on parallel data processing systems massive, opening up a field of new potential applications. Data mining is becoming increasingly important and demands from most major applications for the detection and classification of industrial process anomalies for real-time diagnostics. The results of the implication of this approach gave a very satisfactory finality by minimizing the time of execution in comparison with the SOM map. On the other hand the implementation of the proposed algorithm in Hadoop seems to be a natural choice as it is particular is widely used. Our implementation is a formulation of algorithms 1 and 2 where the dual output is implemented using Multiple Outputs while the triple acceptance is implemented using the Hadoop distributed file system. However, when implementing support applications, Hadoop native file formats (especially the sequential file) were found to be particularly useful for storing training data with the SOM card. Due to the nature of Hadoop, it can easily be integrated into an Eclipse RCP application which is used to analyze the resulting SOM by calculating the Matrix and allowing a search for nearest weight vectors in the training samples. So, to improve the performance of this approach one can use the dynamic map RSOM with Map-Reduce.

REFERENCES

[1] A. Rauber, D. Merkl, and M. Dittenbach: "The growing hierarchical selforganizing map: Exploratory analysis of high-dimensional data", IEEE Transactions on Neural Networks, vol. 13, no. 6, pp. 1331–1341, 2002

[2] M. Dittenbach, A. Rauber, and D. Merkl: "Uncovering hierarchical structure in data using the growing hierarchical self-organizing map", Neurocomputing, vol. 48, pp. 199–216, 2002.

[3] Marc Strickert, Barbara Hammer:"Merge SOM for temporal data", Institute of Plant Genetics and Crop Plant Research Gatersleben and Technical University of Clausthal Preprint submitted to Elsevier Science 19 October 2004.

[4] Ozge Yeloglu, Student Member, IEEE, A. Nur Zincir-Heywood, Member, IEEE, Malcolm I. Heywood,Senior Member, IEEE: "Growing Recurrent Self Organizing Map", 2007.

[5] Heni Ben Amor and Achim Rettinger: "Intelligent Exploration for Genetic Algorithms Using Self-organizing Maps in Evolutionary Computation", February 4, 2005.

[6] Kohonen, T.: "The self-organizing map", Proceedings of the IEEE, 78 (9), 1464-1480, 1990

[7] Kohonen, T.: "Self-organizing maps", Springer, Berlin, 1995

[8] Boucher, A., Seto, K.C., Journel, A.G.: "A novel method for mapping land cover changes: incorporating time and space with geostatistics", IEEE Transactions on Geoscience and Remote Sensing, 44 (11), 3427-3435, 2006

[9] M.Cottrell, S. Ibbou & P. Letrémy: "SOM-based algorithms for qualitative variables", Neural Networks, vol, 17, p.1149-1167, 2004.

[10] J. Dean and S. Ghemawat, "MapReduce: simplified data processing on large clusters," Commun. ACM, vol. 51, no. 1, pp. 107-113, 2008.

[11] Hadoop web page, 12 2009.

[12] F. Immovilli, C. Bianchini, M. Cocconcelli, A. Bellini, R. Rubini, "Bearing Fault Model for Induction Motor With Externally Induced Vibration," IEEE Trans. ind. Electron., vo1.60, no. S, pp. 340S-341S, Aug. 2013. ,

[13] N. Khalfaoui, M. S Salhi, H Amiri'' Modeling and effect of the anomaly of a ball rolling on the stability of the induction machine operating'' IOSR Journal of Electrical and Electronics Engineering, Volume 10 Issue 3 pp 16-30 May-June. 2015.

[14] M. Amar,l. Gondal, andC. Wilson,"Vibration Spectrum Imaging: A Bearing Fault Classification Approach," IEEE Trans. ind. Electron., vol. no.99, pp. I,ldoi: 10.1109/TIE.2014.2327555. 2014.

[15] Y. Gritli, L. Zarri, C. Rossi, F. Filippetti, G.-A. Capolino, and D. Casadei, "Advanced diagnosis of electrical faults in wound rotor induction machines," IEEE Trans. Ind. Electron., vol. 60, no. 9, pp. 4012–4024, Sept. 2013.

[16] M. Blodt, M. Chabert, J. Regnier, J. Faucher, Mechanical load fault detection in Induction motors by stator current time-frequency analysis, IEEE Transactions on Industry Applications, vol. 42, no. 6, Novembre - Décembre 2006, pp. 1454-1463.

[17] M. Blodt, P. Granjon, B. Raison, G. Rostaing, Models for bearing damage detection in induction motors using stator current monitoring, IEEE Transactions on Industrial Electronics, vol. 55, no. 4, Avril 2008, pp. 1813-1822.

[18] J .R Stack, T.G. Habetler and R.G. Harley, ‘’Fault classification and fault signature production for rolling element bearings in electric machines, IEEE Trans. On Industry Applications, vol. 40 n. 3, pp.735-739, May-Jun. 2004

[19] Jordi Cusidó, Luis Romeral, and Juan A. Ortega Fault Detection in Induction Machines Using Power Spectral Density in Wavelet Decomposition IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, VOL. 55, NO. 2, FEBRUARY 2008 , 633

[20] H. HEN AO, GÉRARD-ANDRÉ C. , M. FERNANDEZ-CABANAS, FIOREN ZO F. , CLAUDIO B. , ELIAS S. , REMUS P. , JORGE E., M. RIERA-GUASP, AND S. HEDAYATI-KIA "Trends in Fault Diagnosis for Electrical Machines " June 2014 ©2014IEEE industrial electronics magazine 31.