Noureddine Menasri[*]*, Noureddine Aimeur*

FAULTS DIAGNOSTICS OF CEMENT DRAFT FAN USING ARTIFICIAL NEURAL NETWORK (ANN)

DIJAGNOSTIKA VENTILATORA U CEMENTARI PRIMENOM VEŠTAČKE NEURONSKE MREŽE (ANN)

Originalni naučni rad / Original scientific paper
UDK /UDC:

Rad primljen / Paper received: 9.11.2021

Adresa autora / Author's address:
University of M'sila, Laboratoire de Matériaux et Mécanique des Structures (LMMS), Algeria
[*]email: noureddine.menasri@univ-msila.dz

Keywords
- draft fans
- bearings
- diagnostics
- spectral analysis
- artificial neural network (ANN)

Ključne reči
- ventilatori za provetravanje
- ležajevi
- dijagnostika
- spektralna analiza
- veštačka neuronska mreža (ANN)

Abstract

Fans are the key components of any cement manufacturing process. Without them, the process does not work very well, or it would not be effective. They can be subjected to a large number of damages (wear, unbalance, etc.) occurring during the operation and whose causes are multiple. One problem of great importance in industrial monitoring is performing fault detection and determining the faulty component, or at least the suspect area in the schema of the system. To address this issue, the diagnostics of most defects that may affect the fans is investigated in this work using spectral analysis of vibration which allows the construction of signatures defects. These signatures are dedicated to automating the diagnostics by artificial neural network.

Izvod

Ventilatori su ključne komponente u svakom postupku proizvodnje cementa. Bez njih postupak nije izvodljiv, ili nije efikasan. Ventilatori mogu pretrpeti veliki broj oštećenja (trošenje materijala, neuravnotežen rad, itd.), koja se javljaju tokom rada, gde su uzroci višestruki. Jedan problem od velikog značaja u industrijskom monitoringu je detekcija grešaka i otkrivanje oštećene komponente, ili bar otkrivanje sumnjivog sklopa u okviru sheme sistema. Za rešavanje ovog problema, u ovom radu se istražuje dijagnostika većine grešaka koje mogu uticati na rad ventilatora primenom spektralne analize vibracija, kojom se omogućava dobijanje slike signala grešaka. Ovim odzivima se postiže automatizacija u dijagnostici putem veštačke neuronske mreže.

INTRODUCTION

In the industrial sector, production systems are increasingly more complex and cannot be free of disturbances and failures, affecting the quality of the product, which may cause an immediate stop of a machine and affect the proper functioning of an entire production system. Fault diagnosis of these machines is based mainly on monitoring symptoms related to different degradation conditions.

Industrial fans are integral and indivisible parts in modern industry. A defect, fixing or alignment may compromise the production and lead to a technical and economic decline of the company. The establishment of an effective and constant control of these machines is therefore an important aspect to be taken into account at the level of different management policies of any production system. The surveillance of these machines is based mainly on the extraction of revealing information on the encountered degradation conditions. In this context, several sources have been exploited and experimented in the past with more or less efficiency. These include oil analysis, temperature analysis, acoustic emission, and vibration analysis with greater intensity. Vibration analysis is becoming more and more important in the detection and diagnosis of defects in rotating machines, because of the increasingly high performance in terms of signal processing. Over the last few decades, a series of articles have been published /1/. First approaches explored the analysis of lubricants, sound analysis, and special attention to vibration analysis. In another study published in 1988 /2/, the author provides state-of-the-art analysis and vibro-acoustic diagnosis: he describes a very promising new discipline. He noted the lack of reliable indicators for different failures that could affect the operation of rotating machines. The extraction of representative indicators of time signals was first investigated; among the first works found proposing a method for detecting defects in the bearings by counting the number of peaks in the time signal, /3/. Other indicators characterising the temporal form of the vibration signal are explored. Thus the works are one of the first applications of the kurtosis for monitoring bearings in operation, /4/. Other works followed using this same indicator or combining and comparing with other indicators such as the scalar RMS and peak factor, /5-7/. In order to improve detection performance of some indicators, filtering techniques of vibro-acoustic signals in some frequency bands have been experimented in several studies /8-10/. With implementation of the Fourier transform in diagnostic tools, vibration analysis took full advantage of the conversion of signals in the frequency domain for diagnosing defects in rotating machines. Several works have been published, /11-15/. Although this technique is now considered major for diagnosing rotating machines, it has proved efficient in some cases more than in others. Hence, the need to combine it with other more advanced techniques. Demodulating the signal using envelope analysis after filtering around a resonance frequency band has emerged as a promising technique for the detection of bearing defects. The first applications of vibration signals emerged in the early 1970s with research in Burchillet et al. /8/, followed by several investigations and the first state-of-the-art appeared in 1984 /16/. The significant technological advances in electronics and computer science have enabled massive exploitation of this technique and its implementation in many industrial diagnostic tools, /15-22/.

However, many diagnostic techniques available currently require a lot of expertise to apply them successfully. New techniques are required that allow relatively unqualified operators to make reliable decisions without knowing the mechanism of the system and analysing the data. New techniques are required to monitor a mechanical system. So, reliability must be the most important criterion of the operation. Artificial neural networks (ANN) are suitable for this type of problem. They have been researched and applied in real systems, /14, 23-29/.

DAMAGE ENCOUNTERED ON FANS

Shaft defects

The faults of rotating shafts and more globally rotors are quite common in rotating machines. In reality it is virtually impossible to achieve perfect alignment of all elements of a rotor causing an unbalance in rotating machinery. An unbalance can have many origins as initiator; machining defects, assembly, or mounting of the rotors. The rotors may also be deformed under the influence of unsymmetrical heating. Some events that cause the appearance of unbalance are described as follows, /21, 30-32/.

- Unbalance of mechanical origin

Loss of material: an unbalance may be caused by loss of material, for example, by the loss of a blade or the breaking of a blade. We then observe the instantaneous elevation of vibration levels.
Creep: an unbalance may also be observed due to a creep phenomenon of creating a permanent deformation of the shaft and generating high vibration. This phenomenon is often encountered after an extended shutdown of the machine.
Erosion: the erosion of blades in most cases creates unbalance. Unbalance is manifested, then with a slow evolution of the vibrations to the rotational frequency.

- Unbalance of thermal origin

An unbalance can occur following a symmetric rotor deformation under thermal stress effect; this happens when the rotors are not homogeneous or when the temperature is not evenly distributed. This kind of phenomenon can be detected by correlating the temperature variations and vibrations. The speed of evolution informs on the origin of a fault.

Unbalance faults can be classified into:
Static unbalance: the centre of gravity of the rotor is not on the axis of rotation, but the principal axis of inertia remains parallel to the axis of rotation.
Dynamic unbalance: the rotor centre of gravity is on the axis of rotation, but the principal axis of inertia is not parallel to the axis of rotation.

Damage encountered in bearings

The main damage may be classified into, /6, 22, 33-36/:
Damage due to fatigue: this type of damage is manifested by the appearance of a crack that grows until shucked.
Abrasive wear: destruction of an element by progressively removing the surface material and particle formation.
Scuffing and adhesive wear: produced at high slip resulting in localised welding, and surface roughness of a material transfer between surfaces.
Footprints: it is related to the Hertzian contact. The effect of load produces a plastic deformation when a particle is trapped in the contact, causing surface defects.
Unbalance heat: the temperature rise causes destruction of the lubricant.

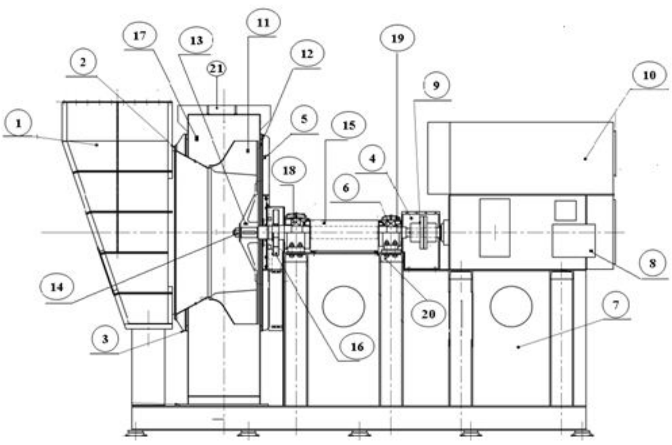
EXPERIMENTAL WORK

Description of draft fan

The fan type FN 280 is provided for transporting hot gases whose grit content is limited. The fan (Fig. 1) is of an aspirant type without an inlet box.

Figure 1. Images of cement draft fan.

The fan (Fig. 2) consists of the impeller (11) with impeller mounting (13), shaft (15), cooling fan (16), bearings (18 and 6), and fan casing (17) to the conical dish (front cheek) (3), base (rear flange) (5) and coned inlet (2). The impeller (11) is constructed as a closed wheel consisting of a cast hub (13) to which the wheel itself is bolted. The adjustment between shaft and hub (13) is a sliding fit *h/H*. The impeller has undergone a dynamic balancing. The shaft is made of steel. Bearings (18 and 6) are spherical thrust roller bearings, basic designation 22332/C3 for (18) and 22328/C3 for (6), as sintered on the shaft. One, designed as a guide bearing is mounted near the motor. The other is movable in the body. All these bearings are mounted in bearing FLS cast housings (19) mounted on the stool (20). A cooling turbine (16) is mounted on the shaft near the casing because the fans must work at temperatures above 125 °C. The fan casing consists of the casing itself (17), front cheek (3), rear flange (5), and coned inlet (2). The fan casing is sealed by stuffing rope (12) and is provided with an inspection hatch (21). The front cheek is bolted to the casing.



1-fan casing and outlet, 2-coned inlet, 3-conical dish (front cheek), 4- cover coupling, 5-base (rear flange), 6-bearings (22328/C3), 7-motor pedestal, 8-motor, 9-flexible coupling, 11-impeller, 12-stuffing rope, 13-impeller mounting, 14-nut, 15-shaft, 16-cooling fan, 17-casing, 18-bearings (22332/C3), 19-bearing cast housings FLS, 20-stool, 21-inspection hatch.

Figure 2. Assembly drawing of FN280 fan.

Technical fan characteristics

The fan is essentially comprised of: a drive motor ABB; flexible coupling; an impeller blade mounted on shaft with two SKF bearings fitted with tapered roller thrust bearing. Fan and motor technical data are given in Tables 1 and 2.

Table 1. Fan technical data.

Type		MTSS 224/224
Number of blades		16
Temperature		84 °C
Speed		985 tr/min
Roller bearings	bearing 1	22328/C3
	bearing 2	22332/C3

Table 2. Motor technical data.

Mark		ABB
Power		500 kW
Tension		11000 V
Weight		53 kg
Intensity		33 A
Speed		995 tr/min
Roller bearings	DE	6324/C3
	NDE	6326/C3

Calculation of frequencies occurrence defects of fan elements

The calculation of equipment kinematics is necessary for defining the appearance of anomaly frequencies and defines the minimal and maximal threshold vibration amplitudes of each part. Tables 3 and 4 summarize the frequencies of occurring defects in fan and motor bearings, and minimal and maximal threshold vibration amplitudes of each element according to the ISO10816-3 standard, /36-38/.

Table 3. Frequency faults in fan and motor bearings.

	Bearing	f_{RE} [Hz]	f_{bext} [Hz]	f_{bint} [Hz]	F_c [Hz]
Motor	6324/ C3	72.74	51.93	80.74	6.49
	6326/C3	72.89	51.95	80.72	6.49
Fan	22328/C3	88.86	102.46	146.29	6.83
	22332/C3	90.24	102.76	145.99	6.85

f_{bint}-frequency of inner ring; f_{bext}-frequency of outer ring;
f_c-frequency of cage; f_{RE}-frequency of rolling element;
f_r-frequency of mechanical rotation

Table 4. Threshold RMS (mm/s) for motor- and fan shaft.

Measuring point	Warning	Alarm	Fault
M 1 A	2.7818	7.1000	11.2000
M 1 H	6.5717	7.1000	11.2000
M 1 V	4.4760	7.1000	11.2000
M 2 A	2.2400	7.1000	11.2000
M 2 H	5.6928	7.1000	11.2000
M 2V	2.5217	7.1000	11.2000
F 1 A	4.7919	7.1000	11.2000
F 1 H	4.8756	7.1000	11.2000
F 1 V	5.2785	7.1000	11.2000
F 2 A	6.4134	7.1000	11.2000
F 2 H	3.6907	7.1000	11.2000
F 2 V	4.1555	7.1000	11.2000

Measurements and interpretations

To analyse the vibrations generated by parts of the gear unit, measurements are carried out in three directions (axial, horizontal, and vertical) of the four points bearing shafts (Fig. 3) using an accelerometer A0760GP SNP66223. Signal acquisition is made by vibrating machine CSI 2130 Machinery Health analysed with sampling time T_s = 0.15 s. Spectral analysis is done using AMS Suite version 5.3.

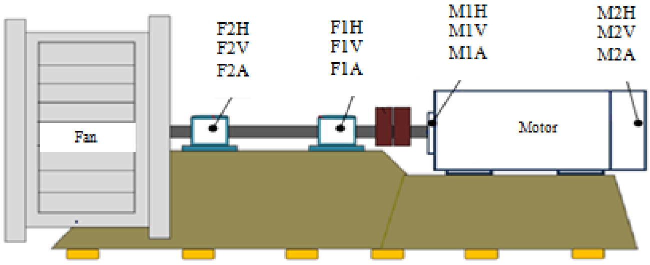


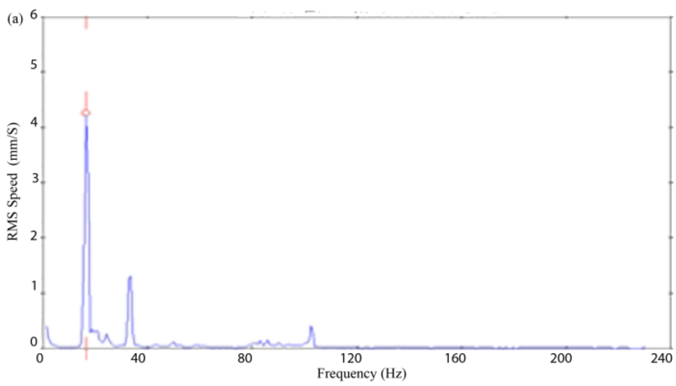
Figure 3. Points for measuring vibration signals.

To locate the fault, spectral points are assessed in three directions.

- At the level of motor bearing

Figures 4a and 4b show spectrum points M1H and M2H of the vibration image in the frequency range [0-1000 Hz]. It is noted that the overall vibration behaviour is acceptable of the motor:

- unbalance normal motor;
- misalignment (motor-fan) normal;
- state of motor bearings are normal.



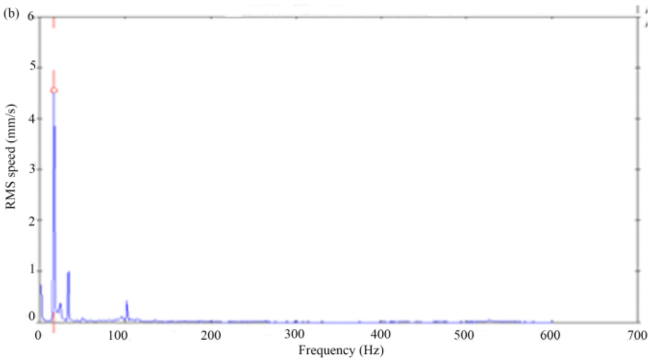


Figure 4. Spectrum signals of points: a) M1H; and b) M2H.

- At the level of fan bearings

The analysis in the high frequency band (Fig. 5) shows the peaks of shocks and a clear comb (signal modulation) around the frequency [2217-3542 Hz] whose pitch is approximately 103.9 Hz which corresponds to the outer ring fault of the bearing SKF 22332/C3.

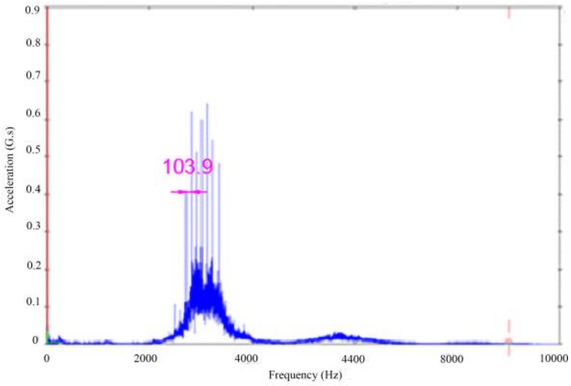


Figure 5. Spectrum signal of point F2H (fault of outer ring in bearing SKF 22332/C3).

Low-frequency analysis (Fig. 6) shows the spectrum to an important amplitude of 4.24 mm/s at the turbine rotational frequency, thus reflecting a significant unbalance vibration of the fan, due to clogging of material on the fins or advanced wear, highlighting an occurrence of a fault on the outer ring bearing SKF 22332/C3. Advanced degradation of the bearing outer ring is clearly visible in the spectrum (Fig. 5).

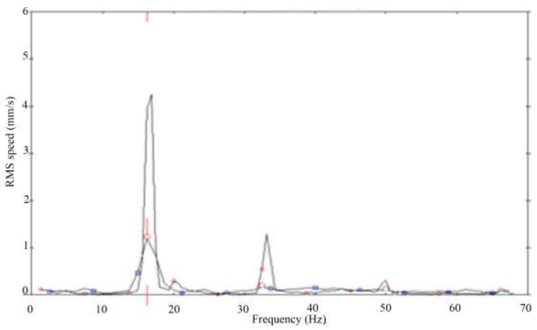


Figure 6. Superposed spectrums with and without fault unbalance.

Figure 7 shows the spectrum a failure to lubrication.

We observe that in the absence of a defect the spectrum is flattened. If there is a lack of lubrication there will be a rolling defect. The fault is represented by a modulation in the high frequency band.

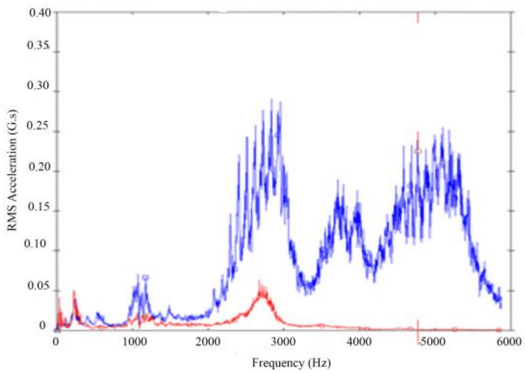


Figure 7. Superposed spectrums with and without lubrication fault.

AUTOMATION OF DIAGNOSTICS USING ARTIFICIAL NEURAL NETWORK

In the following, we apply the neural networks approach with a set of real measurement data of draft fan (FAN 280) without faults or defects (bearing failure, unbalance, and lubricating fault).

Construction of the ANN block

The neural network we have chosen is a network that uses a multilayer retro propagation algorithm for learning. This method gave good results in many applications /14, 23-27/. To apply it suffices to have the input and output data. Stages of construction and validation of the neural network are divided into three phases:

- Choice of network inputs

The selected inputs are twelve amplitude values of low frequency band acceleration spectrum and twelve amplitude values of high frequency band acceleration spectrum for point 2 in the horizontal direction. The latter has 24 inputs of the input layer that are sampled values of acceleration spectra (Fig. 8).

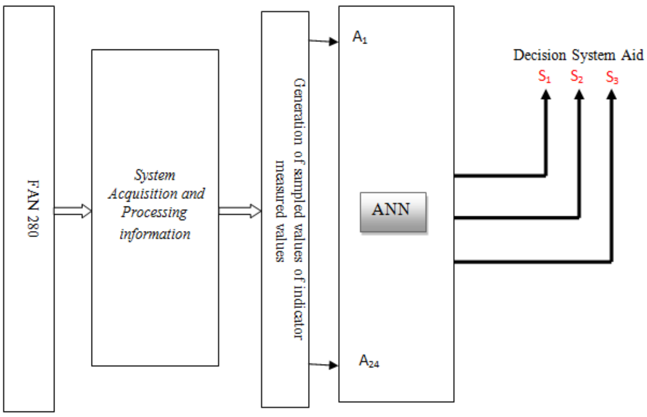


Figure 8. Diagram of the diagnostic system by neural network.

- Choice of network outputs

Our network has three outputs since in our case we have considered not many faults (see Fig. 8). We associate each fault a code, i.e., each fault is represented by three output neurons (see Table 5). When detecting a fault, the network must indicate any binary number (e.g. 100) at its output, which corresponds to this type of fault (fault of the outer ring of bearing SKF 22332/C3). In other words, each output of the network has a single digit, as 1 or 0.

Table 5. Classification of types of faults of FAN 280.

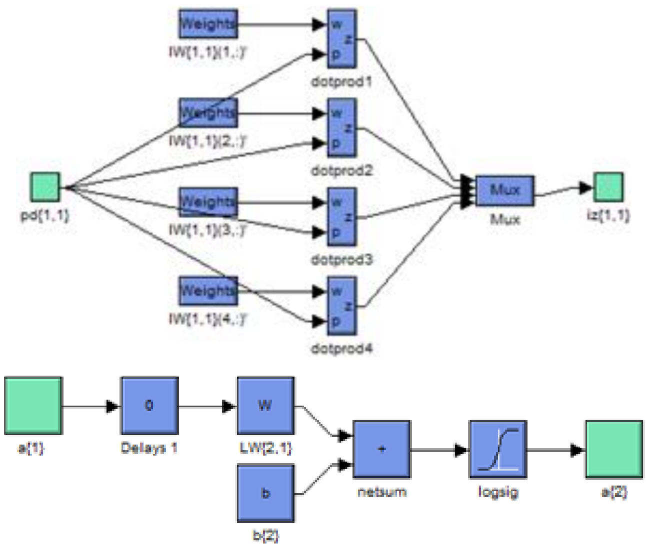
Cat.	Type of fault	Symbol	Code		
			S1	S2	S3
1	faultless	NF	0	0	0
2	wear of outer ring SKF 22332/C3	WB SKF 22332/C3	1	0	0
3	unbalance	UNF	0	1	0

Learning of selected neural network

The network used is a multi-layer network (Fig. 9), comprising an input layer corresponding to the retina, an output layer corresponding to the decision, and a hidden layer. The number of neurons in each layer is given in Table 6. The selected network is entrained by the retro propagation algorithm.

Table 6. Number of neurons in each layer.

Network constructed	input layer	Hidden layer	output layer
Numbers of neurons	24	4	3



(a)

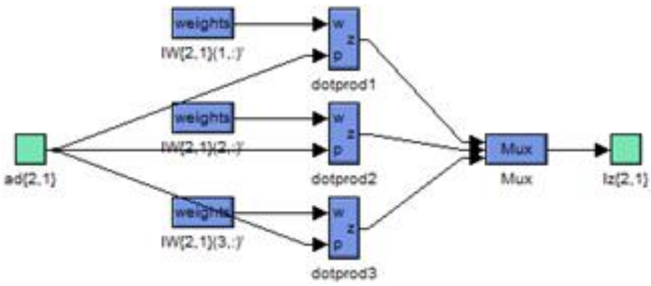


Figure 9. Structure of the selected network.

We created automatic learning using MATLAB (SIMULINK) until the smaller squared error. The mean square error is the smallest obtained after 12 iterations equal to 1.5026E-07.

Simulation test of the artificial neural network

Once the neural network is constructed and its learning achieved satisfactory performance, we move to the test step with examples to the input of the network. In fact, these examples belong to two databases, the first being the learning base and the second based on tests where we proceed to test the network capacity to recognise examples not learned. This last operation is used to estimate the capacity generalisation of the network (see Fig. 10a). Tests are performed according to the following procedure: sane system, then fault 1, sane system, then fault 2, sane system, then fault test not learned, and that for a 3 s period of time for each test. It is evident that the tests of the neural network on the learned examples (Fig. 10b) gave better results, because all types of running (anomalies and normal running) were identified exactly by the network. This can be explained by results obtained in the learning phase of the network (including the value of the mean square error close to zero).

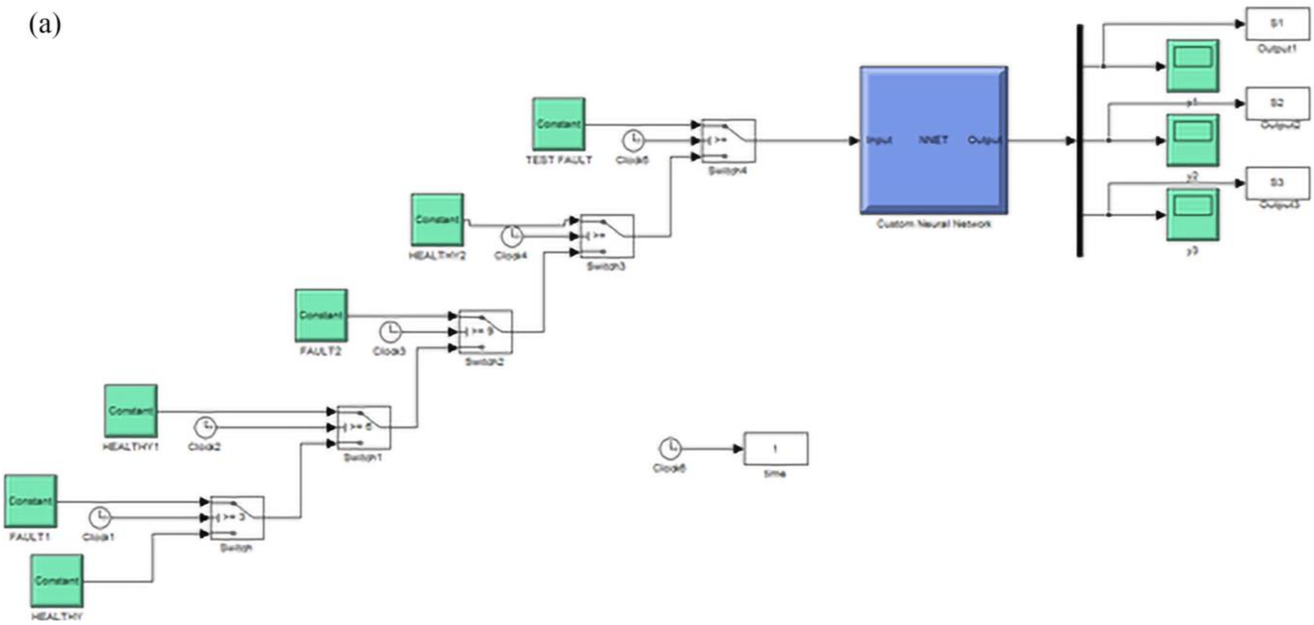


Figure 10a. Simulation test of neural network.

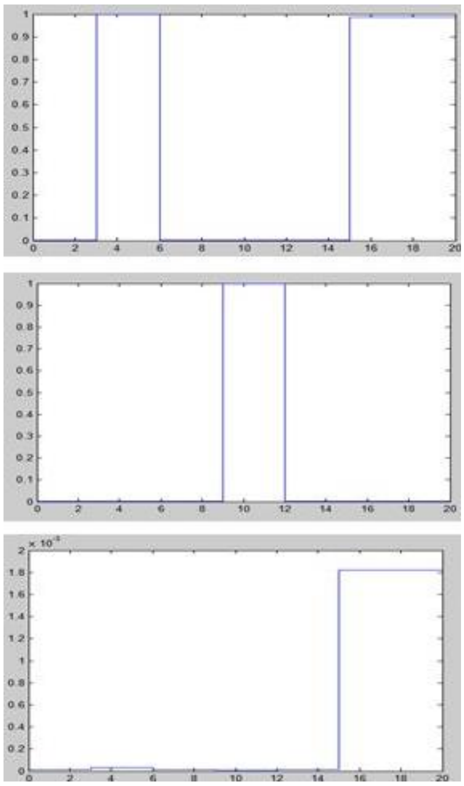


Figure 10 b. Graphical representation of testing the Artificial Neural Network (ANN).

CONCLUSION

Monitoring this vibration signature can detect faults at an early stage because each fault shows a well specified signature. An unbalance fault is detectable in the low frequency band which is manifested by high amplitude, but the rolling defect is manifested by the appearance of peaks of shocks and a clear comb (a modulation whose pitch is equal to the occurrence frequency of the rolling element defect, namely the inner ring, the outer ring, or the rolling element) in the high frequency band.

The difficulty of interpretation of a form, value, makes delicate operations of the monitoring. The automation of this process by the neural network hidden layer with retro propagation learning gave correct results. This work has validated the performance of neural networks for a classification problem.

ACKNOWLEDGEMENTS

The authors would like to thank the engineers from the Lafarge Ciment de Msila (LCM), Algeria for their help.

REFERENCES

1. Dowson, D. (1970), *Monitoring: 1-Introduction to tribological prognosis*, Tribology, 3(3): 138-139. doi: 10.1016/0041-2678(70)90109-0
2. Cempel, C. (1998), *Vibroacoustical diagnostics of machinery: An outline*, Mech. Sys. Signal Proces. 2(2): 135-151. doi: 10.1016/0888-3270(88)90039-8
3. Gustafsson, O.G., Tallian, T. (1962), *Detection of damage in assembled rolling element bearings*, ASLE Transactions, 5(1): 197-209. doi: 10.1080/05698196208972466
4. Dyer, D., Stewart, R.M. (1978), *Detection of rolling element bearing damage by statistical vibration analysis*, J Mech. Des. 100(2): 229-235. doi: 10.1115/1.3453905
5. Tandon, N. (1994), *A comparison of some vibration parameters for the condition monitoring of rolling element bearings*, Measurement, 12(3): 285-289. doi: 10.1016/0263-2241(94)90033-7
6. Wang, Y., Xiang, J., Markert, R., Liang, M. (2016), *Spectral kurtosis for fault detection, diagnosis and prognostics of rotating machines: A review with applications*, Mech. Syst. Signal Process. 66-67: 679-698. doi: 10.1016/j.ymssp.2015.04.039
7. Zheng, W., Pu, W., Xuejin, G., Yachao, Z. (2015), *Fan fault diagnosis based on wavelet spectral analysis*, In: 34th Chinese Control Conference (CCC), Hangzhou, China, 2015, IEEE, pp. 4756-4760, doi: 10.1109/ChiCC.2015.7260375
8. Burchill, R.F., Frarey, J.L., Wilson, D.S. (1973), *New machinery health diagnostic techniques using high-frequency vibration*, SAE Tech. Paper 730930. doi: 10.4271/730930
9. Rogers, L.M. (1979), *The application of vibration signature analysis and acoustic emission source location to on-line condition monitoring of anti-friction bearings*, Tribol. Int. 12(2): 51-58. doi: 10.1016/0301-679X(79)90001-X
10. Choudhury, A. (2019), *Vibration Monitoring of Rotating Electrical Machines: Vibration Monitoring*, In: M. Irfan (Ed.), Advanced Condition Monitoring and Fault Diagnosis of Electric Machines, IGI Global. pp.163-188. doi: 10.4018/978-1-5225-6989-3.ch008
11. Wang, T., Han, Q., Chu, F., Feng, Z. (2019), *Vibration based condition monitoring and fault diagnosis of wind turbine planetary gearbox: A review*, Mech. Syst. Signal Process. 126: 662-685. doi: 10.1016/j.ymssp.2019.02.051
12. Saidi, L., Fnaiech, F., Henao, H., et al. (2013), *Diagnosis of broken-bars fault in induction machines using higher order spectral analysis*, ISA Trans. 52(1): 140-148. doi: 10.1016/j.isatra.2012.08.003
13. Bélaid, B., Nacer, H. (2013), *Early Detection of Mechanical Defects by Neural Networks 'Spectral Analysis'*, In: Haddar, M., Romdhane, L., Louati, J., Ben Amara, A. (Eds.), Design and Modeling of Mechanical Systems, Lecture Notes in Mechanical Engineering. Springer, Berlin, Heidelberg, pp.225-234. doi: 10.1007/978-3-642-37143-1_28
14. Fontes, A.S., Cardoso, C.A.V., Oliveira, L.P.B. (2016), *Comparison of techniques based on current signature analysis to fault detection and diagnosis in induction electrical motors*, In: W.D. Prasad, A. Rajapakse (Eds.), Proc. 1st Int. Conf. on Electrical Engineering, IEEE Inc., 2016, pp.74-79. https://ieeexplore.ieee.org/xpl/conhome/7818135/proceeding
15. Feldman, M. (2011), *Hilbert transform in vibration analysis*, Mech. Syst. Signal Process. 25(3): 735-802. doi: 10.1016/j.ymssp.2010.07.018
16. Camarena-Martinez, D., Osornio-Rios, R., Romero-Troncoso, R.J., Garcia-Perez, A. (2015), *Fused empirical mode decomposition and MUSIC algorithms for detecting multiple combined faults in induction motors*, J Appl. Res. Technol. 13(1): 160-167. doi: 10.1016/S1665-6423(15)30014-6
17. Harmouche, J., Delpha, C., Diallo, D. (2014), *Improved fault diagnosis of ball bearings based on the global spectrum of vibration signals*, IEEE Trans. Energy Conv. 30(1): 376-383. doi: 10.1109/TEC.2014.2341620
18. Huang, S.-R., Huang, K.-H., Chao, K.-H., Chiang, W.-T. (2016), *Fault analysis and diagnosis system for induction motors*, Comp. Electr. Eng. 54: 195-209. doi: 10.1016/j.compeleceng.2016.01.028
19. Agrawal, P., Jayaswal, P. (2020), *Diagnosis and classifications of bearing faults using artificial neural network and support vector machine*, J Inst. Eng. India: Ser. C, 101: 61-72. doi: 10.1007/s40032-019-00519-9

20. Zhang, M., Wang, T., Tang, T., et al. (2019), *A synchronous sampling based harmonic analysis strategy for marine current turbine monitoring system under strong interference conditions*, Energies, 12(11): 2117. doi: 10.3390/en12112117
21. Qiu, M., Chen, L., Li, Y., Yan, J. (2017), *Fault Diagnosis and Status Monitoring of the Bearing*, In: Bearing Tribology, Springer, Berlin, Heidelberg, pp.239-306. doi: 10.1007/978-3-662-53097-9_9
22. Karabacak, K., Cetin, N. (2014), *Artificial neural networks for controlling wind-PV power systems: A review*, Renew. Sustain. Energy Rev. 29: 804-827. doi: 10.1016/j.rser.2013.08.070
23. Attia, A.A., El-Bana, M.S., Habashy, D.M., et al. (2017), *Optical constants characterization of* $As_{30}Se_{70-x}Sn_x$ *thin films using neural networks*, J Appl. Res. Technol. 15(5): 423-429. doi: 10.1016/j.jart.2017.03.009
24. Verbert, K., Babuška, R., De Schutter, B. (2017), *Combining knowledge and historical data for system-level fault diagnosis of HVAC systems*, Eng. Appl. Artif. Intell. 59: 260-273. doi: 10.1016/j.engappai.2016.12.021
25. Wang, H.Q., Chen, P. (2011), *Intelligent diagnosis method for rolling element bearing faults using possibility theory and neural network*, Comp. Indust. Eng. 60(4): 511-518. doi: 10.1016/j.cie.2010.12.004
26. Yin, J., Zhao, W. (2016), *Fault diagnosis network design for vehicle on-board equipments of high-speed railway: A deep learning approach*, Eng. Appl. Artif. Intell. 56: 250-259. doi: 10.1016/j.engappai.2016.10.002
27. Rahmoune, M.B., Hafaifa, A., Abdellah, K., Chen, X. (2017), *Monitoring of high-speed shaft of gas turbine using artificial neural networks: predictive model application*, Diagnostyka, 18(4): 3-10.
28. Popiołek, K., Pawlik, P. (2016), *Diagnosing the technical condition of planetary gearbox using the artificial neural network based on analysis of non-stationary signals*, Diagnostyka, 17(2): 57-64.
29. Vlasov, A.I., Grigoriev, P.V., Krivoshein, A.I., et al. (2019), *Smart management of technologies: predictive maintenance of industrial equipment using wireless sensor networks*, Entrepr. Sustain. Issues, 6(2): 489-502. doi: 10.9770/jesi.2018.6.2(2)
30. Rahman, M.M., Uddin, M.N. (2015), *Online unbalanced rotor fault detection of an IM drive based on both time and frequency domain analyses*, IEEE Industry Appl. Annual Meeting, Addison, TX, USA, IEEE. doi: 10.1109/IAS.2015.7356825
31. Romero-Troncoso, R.J., Garcia-Perez, A., Morinigo-Sotelo, D., et al. (2016), *Rotor unbalance and broken rotor bar detection in inverter-fed induction motors at start-up and steady-state regimes by high-resolution spectral analysis*, Elect. Power Syst. Res. 133: 142-148. doi: 10.1016/j.epsr.2015.12.009
32. Noureddine, M., Ali, B. (2018), *Experimental investigation of bearing wear of a gear unit DMGH 25.4 of horizontal cement mill*, World J Eng. 15(1): 54-61. doi: 10.1108/WJE-12-2016-0157
33. Choudhary, A., Goyal, D., Shimi, S.L., et al. (2018), *Condition monitoring and fault diagnosis of induction motors: A review*, Arch. Computet. Methods Eng. 26: 1221-1238. doi: 10.1007/s11831-018-9286-z
34. Zachwieja, J. (2019), *Effectiveness of diagnosing damage to an industrial pump rotor by analysing its vibrations*, Diagnostyka, 20(1): 33-39. doi: 10.29354/diag/99604
35. Pawlik, P. (2019), *The diagnostic method of rolling bearing in planetary gearbox operating at variable load*, Diagnostyka, 20(3): 69-77. doi: 10.29354/diag/111567
36. Benbouaza, A., Elkihel, B., Delaunois, F. (2013), *Analysis and diagnosis of the different defects of asynchronous machines by vibration analysis*, Int. J Comp. Sci. Eng. 5(4): 258-269.
37. Kumar, S., Goyal, D., Dang, R.K., et al. (2018), *Condition based maintenance of bearings and gears for fault detection - A review*, Mater. Today: Proc. 5(2, Part 1): 6128-6137. doi: 10.1016/j.matpr.2017.12.219