International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 /doi:10.14445/22315381/IJETT-V69I9P213

Volume 69 Issue 9, 97-106, September, 2021

Implementation of a Diagnostic Approach Based on Vibration Analysis: Case Study of a Hydroelectric Group

Imad El Adraoui[1], Mohammed Bouaicha[2], Hassan Gziri[3], Mourad Zegrari[4]

[1,3]Laboratory of Engineering, Industrial Management and Innovation (IMII), The Faculty of Sciences and Technology (FST), Hassan 1st University, PO Box 577, Settat, Morocco.
[2,4]Laboratory of Structural Engineering, Intelligent, and Electrical Energy (LISSIEE), The National Higher School of Arts and Crafts (ENSAM), Hassan II University, Mers Sultan BP 9167, Casablanca, Morocco.

[1]aimadeladraoui@gmail.com, [2]bouaicha.med@gmail.com, [3]hgziri@gmail.com, [4]zegrari.ensam@gmail.com

Abstract *- This paper deals with the implementation of a diagnostic approach on a hydroelectric group; the technique implemented is based on the analysis of the vibrations acquired. This analysis makes it possible to monitor and control the state of the running system during operation in a relevant way. To do this, tests are carried out to visualize the behavior of the hydroelectric group for different cases in order to judge its state of health. Each test is generated by several measurements, and the latter is taken by vibration sensors at various predefined points. The hydroelectric group is considered to be in poor operating condition if it does not meet the requirement of ISO 10816-5. Consequently, an intervention by the maintainer must be taken into account.*

Keywords *— Approach, Diagnosis, Degradation, Vibration analysis, Hydroelectric group.*

I. INTRODUCTION

During operation, all rotating systems and components deteriorate physically. This degradation occurs considerably over time, which leads to a decrease in reliability. Degraded behavior is caused by a set of types of degradation, namely: wear, vibration, cracking, corrosion, etc.

As an example of wear, a study was discussed in [1], researchers developed a diagnostic model of a rotating guide bearing. The model is based on a tribological approach in order to determine the rate of wear on the most stressed area. The wear rate helps predict the horizon of bearing failure. Then, a technological solution was introduced to improve the life of the bearing. Therefore, the degradations pose relevant issues for the maintainer, in order to provide an idea on the maintenance strategy to be implemented to guarantee:

- Operational safety,
- Cost minimization,
- Improved system life.

To do this, there are several approaches used by researchers to diagnose systems, including the vibration analysis-based approach.

Diagnosis based on vibration analysis is a powerful tool, which became a priority technique in maintenance. This approach is generally oriented to rotating machines. Its main purpose is to monitor the state of the systems during operation, based on sampling signals at a few measuring points [2] and [3]. However, this approach falls within the domain of maintainers specializing in the systems to be monitored, whose objective is to meet expectations, cost, and security requirements [4]. In [5], the authors implemented an experimental diagnostic approach, and this approach is based on vibration analysis with a test bench. The purpose of this technique is to study the behavior of the test bench in the presence of an unbalanced fault. In the experiment, the authors installed an accelerometer (piezoelectric sensor) at the most stressed bearing. The signals acquired by the sensor were correlated to obtain the function of the associated behavior. The behavior shows that the response of the test bench to the unbalance fault evolves according to an exponential law from a certain time. Therefore, it is necessary to take into consideration the value of the defect not to be exceeded according to the standards. Thus, the technique of vibratory analysis aims to:

- Monitor the system,
- Keep the information acquired for maximum variability,
- Combine spectra,
- Carefully analyze the critical component.

In order to diagnose the running system anomaly. In this context, in [6], the researchers approached a study whose aim is to develop capacity *(CCS)* in two aspects:

- 1st aspect: Exploit the automation of the process by testing its capacity with different learning techniques.
- 2nd aspect: Consider the energy of the spectrum a characteristic.

So this technique is used to detect the imbalance problem. However, the authors in [7] noted that the technology remains more or less limited because of the dependence of the data acquired in temporal continuity for the diagnosis.

The technique is based on:

- Antagonistic neural networks,
- The multi-sensor data fusion technique.

Their goal is to generate new data to be used for Data-Clearing. In this framework, two distinct modes are carried out on the basis of the logic of data fusion:

- A pre-fusion *GAN* mode,
- A post-merger *GAN* mode.

The work cited previously in the literature is relevant. It is largely interested in the diagnosis by the use of several sensors. This technique is generally applied to complex systems. Therefore, the need for multiple acquired signals is paramount for diagnosis.

The identification of vibration-based faults for rotating systems is a well-known approach in industries. But, Its application remains directly difficult to establish. In [8], the authors used two similar platforms:

- 1st platform: The acquired vibration signals were collected with separate foundations under different conditions.
- 2nd platform: The measured vibration signals were analyzed in a frequency domain, the aim of which is to calculate the spectra.

In the same framework we find in [9], the researchers have developed a technique, which is based on deep convolutional neural networks. The objective of this technique is to diagnose the fault. The particularity of this method is:

- Taking into account the characteristics of the raw data,
- Optimization of the combination of several levels of fusion.

The two preceding points make it possible to meet the requirements of anomaly diagnosis. Thus, in [10], the authors used the networks of Fuzzy Neurons to diagnose a hydraulic pump; this technique allows it:

- To learn the data acquired, in order to predict the future state of the pump before the failure,
- To optimize the classical model by switching from the discrete model to the continuous model.

This approach is based on processing data through the use of artificial intelligence. Several functions have been established to lead to the previous points, namely:

- Identity function,
- Threshold function,
- Piecewise linear function,
- Sigmoid function,
- Hyperbolic tangent function,
- Gaussian function.

Relevant work in [11] has proposed a technique called: the end-to-end solution with long-term memory networks. In this solution, the Spatio-temporal characteristics of the data acquired (measured vibration signals) by the sensors are processed in two stages:

- Signal extraction,
- Signal assembly.

These two steps are achieved by the Internet of Things (*IoT*). The advantage of this solution is:

- Diagnose the failure with high precision,
- Extract long-term temporal characteristics,
- Reduce the computational complexity of layers.

In [12], the authors set up an experiment on a test bench in order to verify the state of health of the bearings. The objective of the vibratory approach used is to obtain real results related to the degradation of the bearings. The bearings are subjected to constant and variable operating conditions.

In line with this approach cited in the literature, thanks to its relevance, this research work is used to implement this technique in the diagnosis of a hydroelectric group. To do this, several sensors (Accelerometers and Probes) are used at several predefined points, the objective of which is to diagnose and validate the state of health of the hydroelectric group according to the *ISO10816-5* standard.

This research paper is divided as follows: Presentation of the group to be diagnosed, instrumentations used, results/discussion, and conclusion.

II. PRESENTATION OF THE HYDROELECTRIC GROUP

The production of electrical energy in a production unit is done through 3 similar hydroelectric groups. Each group has a total electrical power of around *240 MW* (Fig. 1). The hydroelectric groups are managed by the dispatching, which depending on the network, i.e., stopping or starting energy production.

Fig.1 Hydroelectric group

The installation of these groups was carried out in the *90s*, and the groups now have cracks at the level of some welds of the cross members.

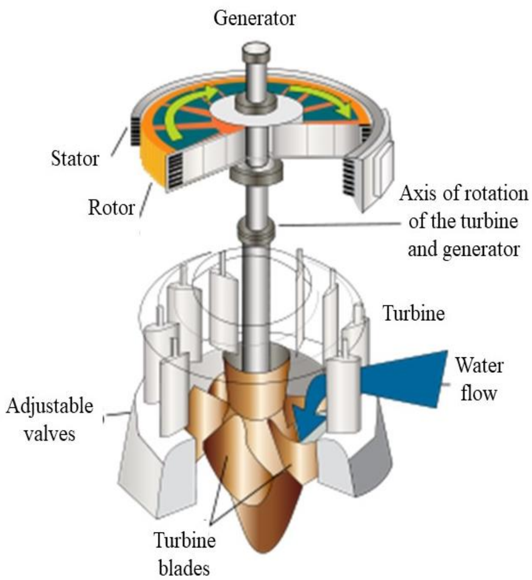

Fig.2 Components of the hydroelectric group

The components of a hydroelectric group are illustrated in (Fig. 2):

- The generator is a device that makes it possible to produce electrical energy from another form of energy,
- The stator is the fixed part of the hydroelectric group,
- The rotor is the mobile part of the hydroelectric group,
- The turbine is a rotating device that converts the internal energy of the fluid into mechanical energy, thanks to the blades arranged on a shaft.
- Adjustable valves are devices for regulating the flow of fluid entering the turbine.
- The turbine blade is a hydrodynamic device intended to transform motive energy in the acceleration of the fluid, in which it moves or, on the contrary, to transform the energy of displacement of the fluid into motive energy.
- The axis of rotation is a device that simultaneously drives the turbine and the generator.

Table. 1 describes the characteristics of the hydroelectric group.

TABLE1.CHARACTERISTICS OF THE HYDROELECTRIC GROUP

Type	Francis
Axis	Vertical
Rotation speed	333 (rpm)
Power	80 MW
Number of blades	17
Number of guide bearings	2
Number of bearing or pivot bearings	1
Number of directors	24
Number of poles	18
Alternator bearing clearances	460 µm
Intermediate level clearances	460 µm
Turbine bearing clearances	420 µm

The objective is to carry out a diagnosis based on the vibratory analysis of the hydroelectric group in order to determine whether the vibrations are at the origin of these cracks at the level of certain welds of the braces. The turbines are of the Francis type with a nominal rotation speed of *333 (rpm)*.

The hydroelectric group has 3 levels:

- A turbine bearing *(PTU)*,
- A lower alternator bearing *(PAI)*,
- An upper alternator bearing *(PAS)*.

III. INSTRUMENTATION

The instrumentation is made up of 3 accelerometers per level in the directions: *Upstream (Am)*, *Right bank (RD*), and *Axial (Ax)*. As well as 2 proximity probes per level in the *Upstream (Am)* and *Right Bank (RD)* directions.

Fig.3 and Fig.4 illustrate the installation of instrumentation on the hydroelectric group:

- 3 accelerometers per step (*points 1 to 9*),
- 2 displacement probes per level placed at *90°* (*points 10 to 15*).

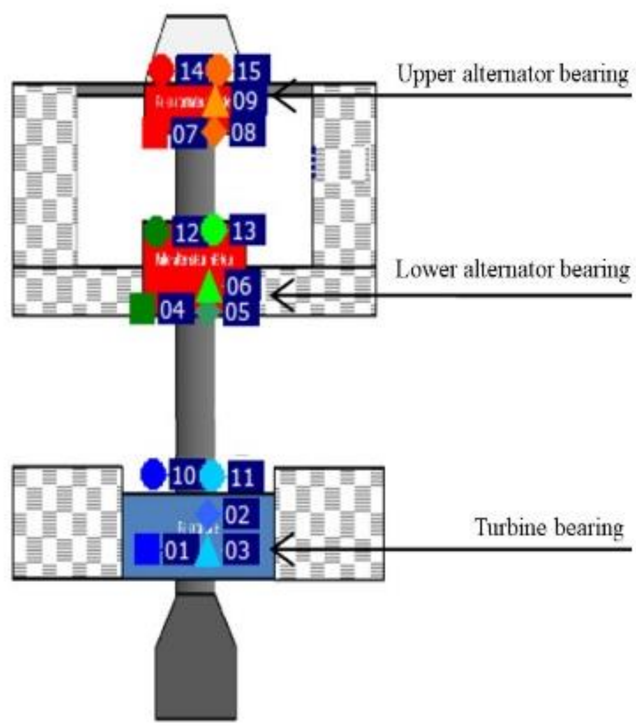

Fig.3 Positions of measurement points

PTU accelerometer

PTU probe

PAU probe

PAI accelerometer

PAS probe

PAS accelerometer

Fig. 4 Location of measurement points

Table. 2 describes the locations of the accelerometers in each point and their associated direction.

TABLE2.MEASUREMENT POINTS, LOCATIONS AND DIRECTIONS

Measurementpoint	Location	Direction
01	PTU	Am
02	PTU	RD
03	PTU	Ax
04	PAI	Am
05	PAI	RD
06	PAI	Ax
07	PAS	Am
08	PAS	RD
09	PAS	Ax
10	PTU	Am
11	PTU	RD
12	PAI	Am
13	PAI	RD
14	PAS	Am
15	PAS	RD

The test protocol carried out for the group to be diagnosed as follows:

- MAVNE: No-load operation not excited,
- MAVEX: No-load excited,
- MQUART: Operation at *20 MW*,
- MDEMI: Operation at *40 MW*,
- M3QUARTS: Running at *60 MW*,
- MPMAX: Full load operation *(80 MW)*.

IV. RESULTS AND DISCUSSION

Table.3 and Table.4 show all the values measured by the accelerometers and point probes. The values taken are illustrated in a relevant way by curves in Fig.5 and Fig.6.

The point *(02 RD + PTU*) has a maximum acceleration level of around *0.76(g eff)* for an *MPMAX* test. Thus, the point *(03 Ax + PTU)* presents a maximum speed level of around *1.95 (mm/s eff)* for the *MQUART* test.

TABLE3.GOLBAL ACCELERATION LEVELS (NGA)

NGA (0-4000 Hz) (g eff)	MAVNE	MAVEX	MQUART	MDEMI	M3QUARTS	MPMAX
01 Am + PTU	0.50	0.47	0.30	0.29	0.13	0.42
02 RD + PTU	0.64	0.62	0.41	0.38	0.18	0.69
03 Ax + PTU	0.68	0.65	0.46	0.46	0.21	***0.76***
04 Am + PAI	0.06	0.06	0.05	0.05	0.02	0.06
05 RD + PAI	0.05	0.05	0.04	0.05	0.02	0.05
06 Ax + PAIO	0.12	0.11	0.09	0.09	0.05	0.10
07 Am + PAS	0.03	0.03	0.03	0.03	0.02	0.04
08 RD + PAS	0.03	0.03	0.03	0.03	0.03	0.05
09 Ax + PAS	0.05	0.05	0.07	0.06	0.03	0.05

TABLE 4.GLOBAL SPEED LEVELS (NGV)

NGV (2-1000 Hz) (mm/s eff)	MAVNE	MAVEX	MQUART	MDEMI	M3QUARTS	MPMAX
01 Am + PTU	1.00	0.94	0.96	1.37	0.29	0.56
02 RD + PTU	0.94	0.88	0.93	1.39	0.31	0.63
03 Ax + PTU	1.70	1.70	***1.95***	1.76	0.50	1.32
04 Am + PAI	0.38	0.38	0.43	1.23	0.25	0.38
05 RD + PAI	0.30	0.32	0.36	1.18	0.19	0.34
06 Ax + PAI	0.56	0.60	0.66	1.26	0.21	0.42
07 Am + PAS	1.21	1.10	1.08	1.54	1.02	1.14
08 RD + PAS	1.18	1.15	1.14	1.55	1.07	1.09
09 Ax + PAS	0.73	0.80	1.13	1.72	0.75	0.75

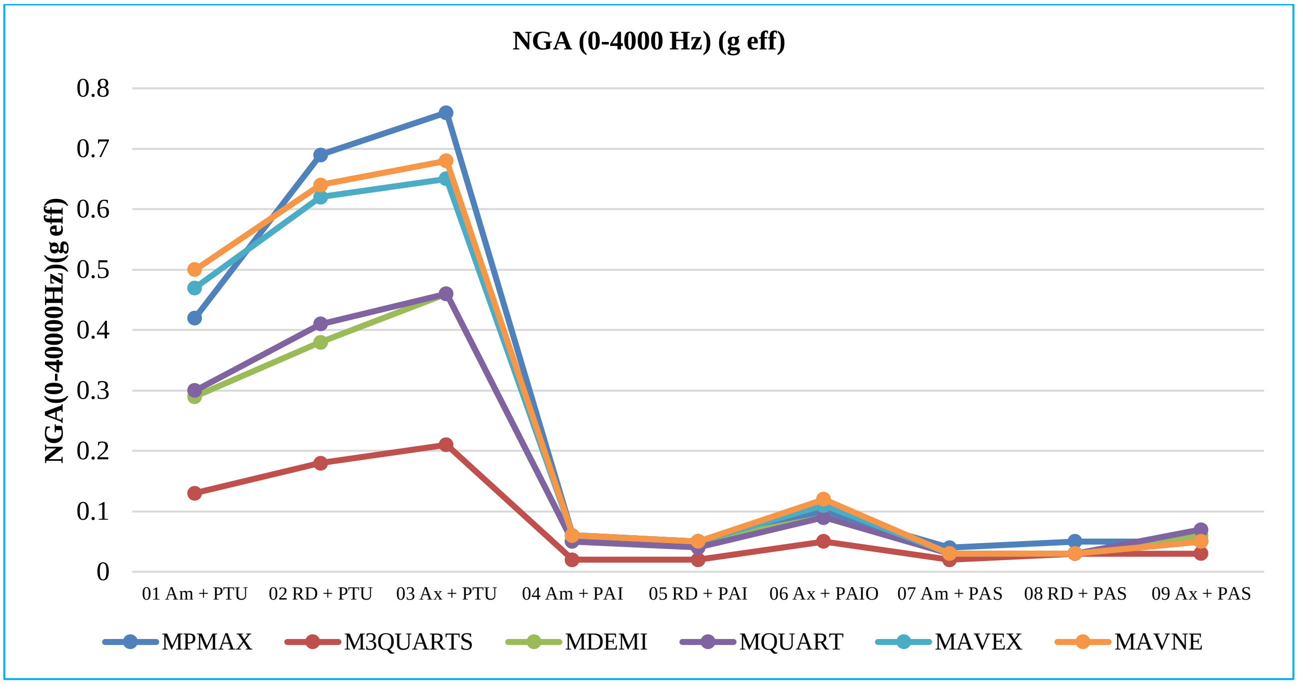

Fig.5 Evolution NGA(0-4000Hz) hydroelectric group

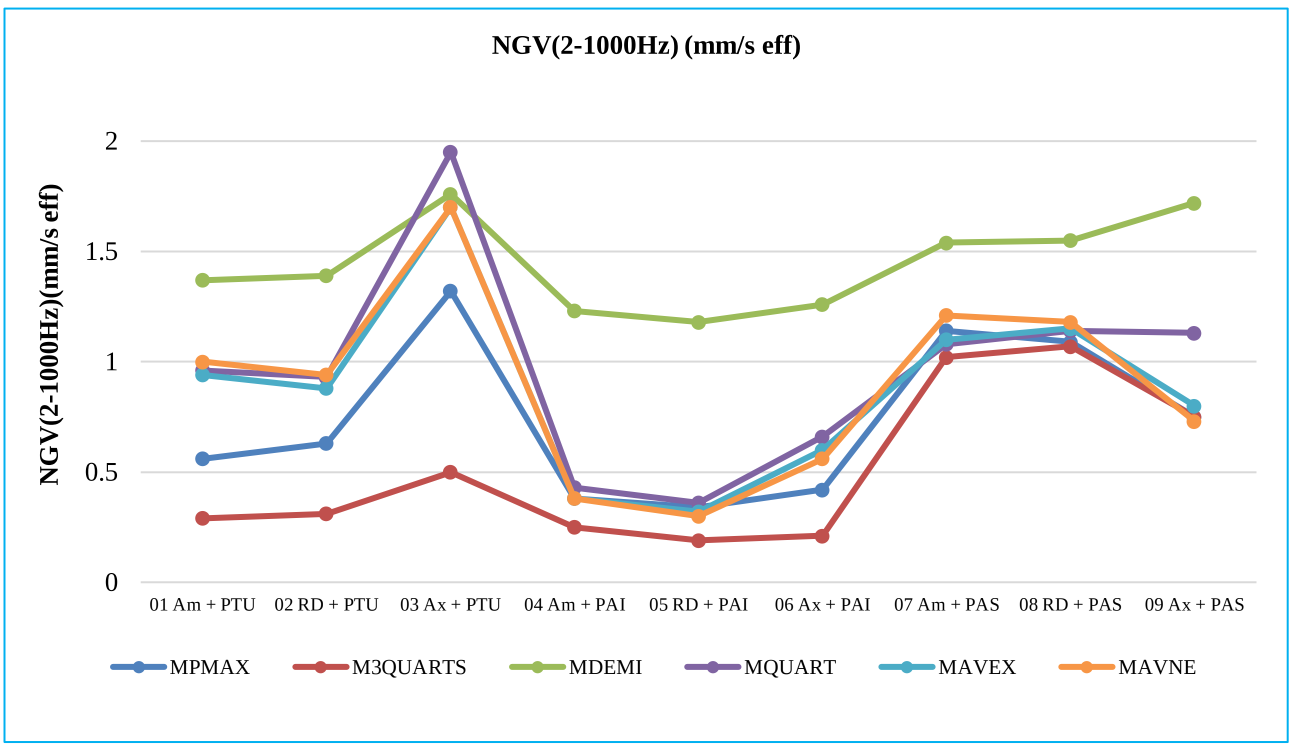

Fig. 6 Evolution NGV(2-1000 Hz)hydroelectric group

Fig.7, Fig.8 and Fig.9 illustrate the orbits of the bearings of the hydroelectric group, the results presented show that the acceptable vibration levels, since:The maximum *NGV (2-1000Hz)* is raised to *20 MW* in the axial direction on the turbine bearing with *1.95 mm/s*, balancing of the shaft line is acceptable with a maximum of *1.18 mm/s*and analysis of the spectra does not reveal any anomalies.

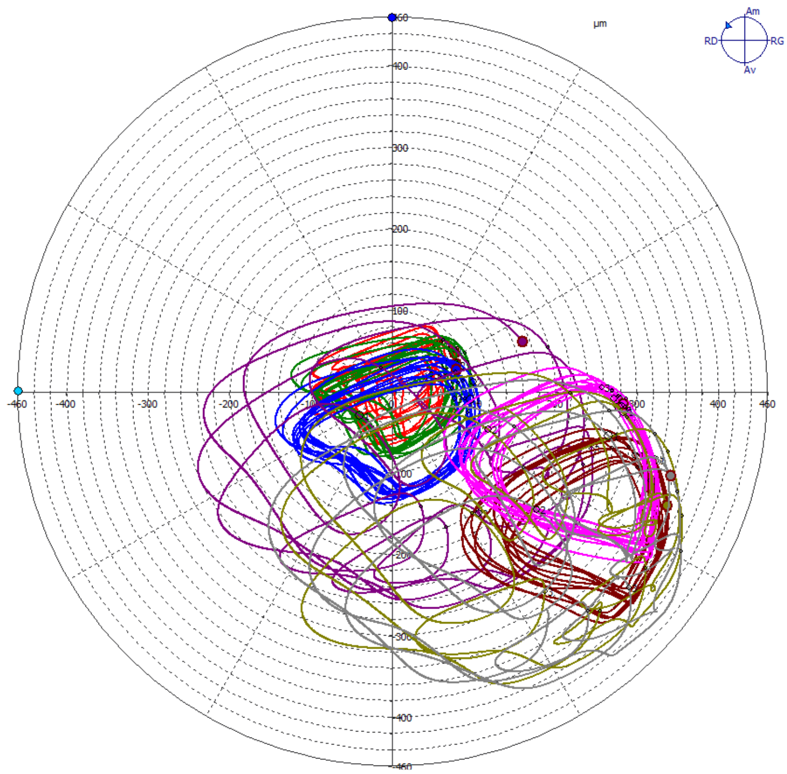

Fig. 7 Turbine bearing orbit

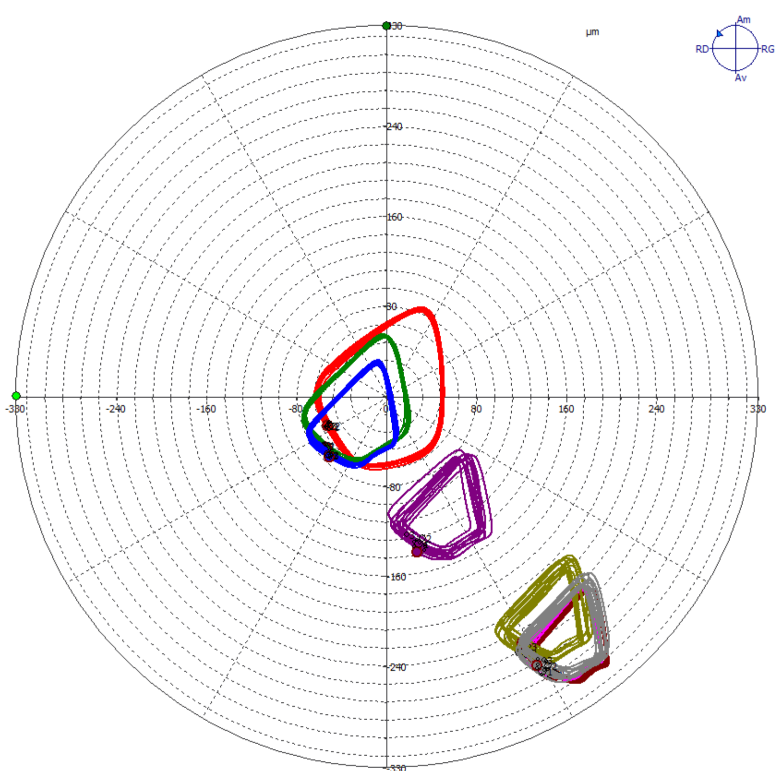

Fig. 8 Lower alternator bearing orbit

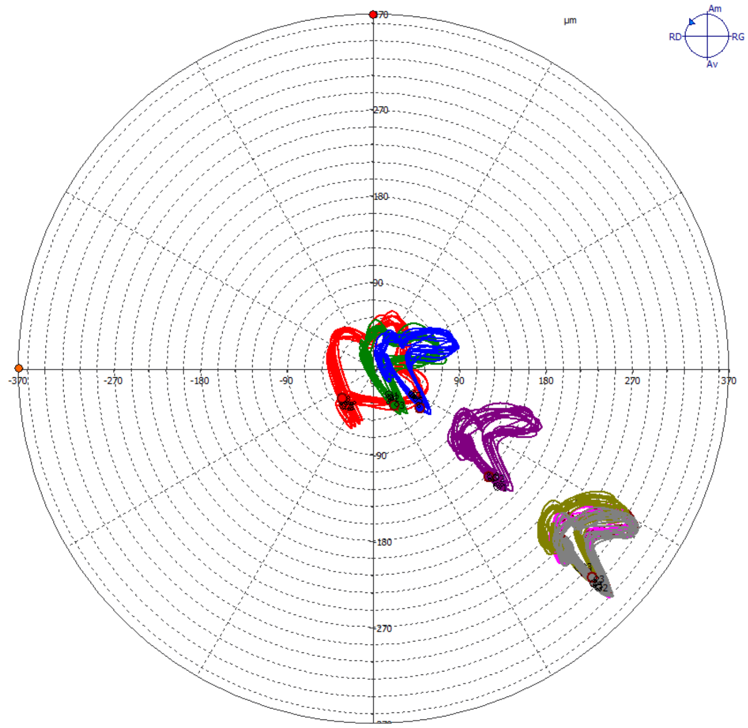

Fig. 9 Upper alternator bearing orbit

TABLE 5. ISO 10816-5 STANDARD

NGV 2-1000 Hz (mm/s eff)	Well (A/B)	Acceptable (B/C)	Not satisfying (C/D)	Unacceptable (D)
Upper alterator bearing	***2.5***	4	6.4	>6.4
Other bearings	***1.6***	2.5	4	> 4

According to the *ISO 10816-5* standard (Table.5), the unit is located in zone *A/B* (operation for unrestricted operation.

The use of the experimental approach based on several provides significant results to validate the performance of the hydroelectric group, the validation is linked to the reference of the standard (*ISO10816-5*) imposed, the latter consists in validating the phenomenon of vibrations during operation (production of electrical energy).

The results in the present study gave the choice of the diagnostic approach considered in this case study, which justifies the trend of the methodology in the research works cited in the literature. According to the three vibration diagnostic configurations, the accelerations measured at the level of the three bearings (turbine bearing, lower alternator bearing and upper alternator bearing) represent good results compared to the value set by the Standard in order to avoid any kind turbine failure, energy loss and bearing fatigue.

Therefore, any kind of optimization is a gain in the concept of "*Energy-Efficiency*".

V. CONCLUSION

Through this article, we have established an approach based on vibration analysis. This approach is considered to be a powerful tool for diagnosing and verifying the health of rotating machines. The diagnosis of the hydroelectric group gave an idea of the conformity according to the *ISO10816-5* Standard.

Compliance is checked by means of the values obtained for the speeds and accelerations measured at the predetermined points.The curves and orbits clearly illustrate the behavior of the measurements at each point.

This behavior is considered normal, despite the existence of cracks at certain welds of the cross members. That is to say, the results obtained for various tests make it possible to see the good functionality of the turbine.

So from this diagnostic method based on vibration analysis, it can be concluded that its operation is relevant to ensure the validity and performance of the hydroelectric group in the presence of cracks at certain welds of the cross members.

The research work carried out by the diagnosis based on several sensors will be a track to generate an algorithm by the *SVM* method used in several literature namely [13]-[14], to improve the approach in order to optimize maintenance and energy efficiency at the level of the hydroelectric group.

NOMENCLATURE

Symbol	Designation
PTU	Turbine bearing
PAI	Lower Alternator Bearing
PAS	Upper Alternator Bearing
Am	Upstream
RD	Right bank
Ax	Axial

APPENDIX A.TURBINE BEARING DISPLACEMENTS

Test	SMAX (µm)	Excent. (µm)	Sp1 (µm)	Sp2 (µm)	Spp (µm)	Gap X (µm)	Gap Y (µm)
01 MAVNE	97	5	147	177	190	-4	2
02 MAVEX	127	14	151	221	222	-1	-14
04 MQUART	140	58	189	251	251	-5	-58
05 MDEMI	284	120	374	484	486	38	-114
06 M3QUARTS	161	301	238	254	259	244	-176
07 MPMAX	183	261	239	264	298	240	-102
08 MDEMI +Q	323	260	382	491	491	187	-181
09 MDEMI -Q	337	272	378	506	508	183	-200

APPENDIX B.DISPLACEMENTSOF THE LOWER ALTERNATOR BEARING

Test	SMAX (µm)	Excent. (µm)	Sp1 (µm)	Sp2 (µm)	Spp (µm)	Gap X (µm)	Gap Y (µm)
01 MAVNE	86	1	144	115	152	0	-1
02 MAVEX	68	22	114	96	117	-20	-11
04 MQUART	59	33	96	81	99	-23	-24
05 MDEMI	59	119	98	92	100	55	-106
06 M3QUARTS	53	279	85	73	86	169	-222
07 MPMAX	52	276	82	72	85	164	-222
08 MDEMI +Q	61	248	95	86	99	147	-200
09 MDEMI -Q	61	270	97	82	102	163	-215

APPENDIX C. DISPLACEMENTSOF THE UPPER ALTERNATOR BEARING

Test	SMAX (µm)	Excent. (µm)	Sp1 (µm)	Sp2 (µm)	Spp (µm)	Gap X (µm)	Gap Y (µm)
01 MAVNE	66	1	122	105	129	1	-1
02 MAVEX	60	21	98	90	103	19	10
04 MQUART	62	38	90	87	98	36	10
05 MDEMI	61	139	92	97	100	118	-73
06 M3QUARTS	63	286	93	87	97	223	-178
07 MPMAX	65	284	97	91	104	220	-180
08 MDEMI +Q	64	268	97	94	101	209	-167
09 MDEMI -Q	62	288	93	89	102	223	-182

REFERENCES

[1] I. El Adraoui, H. Gziri, A. Mousrij. Integration of a Prognosis Model of a Rotating Microwave Oven Guidance System Subject to Linear Degradation. Lecture Notes in Mechanical Engineering, (2021) 446–458.

[2] T. Fakhfakh, F. Chaari, and M. Haddar, Numerical and experimental analysis of a gear system with teeth defects. International Journal of Advanced Manufacturing Technology, 25 (5) (2005) 542-550.

[3] Z. Li, X.Yan, C. Yuan, Z. Peng, L. Li, Virtual prototype and experimental research on gear multi-fault diagnosis using wavelet-autoregressive model and principal component analysis method. Mechanical Systems and Signal Processing, 25 (2011) 2589–2607.

[4] El. Semma, A. Mousrij, H. Gziri, « Development of a conditional maintenance implementation approach based on vibration analysis». MOSIM 2014, 10th Francophone Conference on Modeling, Optimization and Simulation, Nancy, France, (2014).

[5] I. El Adraoui, H. Gziri, A. Mousrij,, Diagnosis and Prognosis Based On the Vibration Analysis of Rotating Machines: Study of a Vibration Test Bench». International Journal of Advanced Science and Technology, 29(3) (2020) 14199 - 14211. Retrieved from http://sersc.org/journals/index.php/IJAST/article/view/31871.

[6] Y-K. Akilu, and C. Ruifeng, Towards Developing an Automated Faults Characterisation Framework for Rotating Machines. Part 1: Rotor-Related Faults,. Energies, 13 (1394) (2020), doi:10.3390/en13061394.

[7] L. Qianjun, M. Guijun, and C. Cheng, Data Fusion Generative Adversarial Network for Multi-Class Imbalanced Fault Diagnosis of Rotating Machinery. IEEE Access, 8 (2020) DOI: 10.1109/ACCESS.2020.2986356.

[8] A. Yunusa-Kaltungo, and J. Sinha, Generic vibration-based faults identification approach for identical rotating machines installed on different foundations. In VIRM 11 - Vibrations in Rotating Machinery, (2016) 499-510.

[9] L. Jing, T. Wang, M. Zhao, and P. Wang, An Adaptive Multi-Sensor Data Fusion Method Based on Deep Convolutional Neural Networks for Fault Diagnosis of Planetary Gearbox. Sensors, 17 (2017) 414, doi:10.3390/s17020414.

[10] I. El Adraoui, H. Gziri, and A. Mousrij, Prognosis of a Degradable Hydraulic System: Application on a Centrifugal Pump. International Journal of Prognostics and Health Management, 11(2) 013 (2020) 11.

[11] S. Hao, F.X. Ge, Y. Li, and J. Jiang, Multisensor bearing fault diagnosis based on one-dimensional convolutional long short-term memory networks. Measurement, 159-107802, (2020), https://doi.org/10.1016/j.measurement.2020.107802.

[12] P. Nectoux, R. Gouriveau, K. Medjaher, E. Ramasso, B. Chebel-Morello, et al., PRONOSTIA: An experimental platform for bearings accelerated degradation tests. IEEE International Conference on Prognostics and Health Management, PHM'12., Denver, Colorado, United States, (2012) 1-8. hal-00719503.

[13] B. Kahramanoğlu, E. D. Ülker, S. Ülker, Integrating Support Vector Machine (SVM) Technique and Contact Imaging for Fast Estimation of the Leaf Chlorophyll Contents of Strawberry Plants. International Journal of Engineering Trends and Technology 69(3) (2021) 23-28.

[14] T. Aggab., Prognosis of complex systems by the joint use of hidden Markov model and observer. University of Orleans, 2016. French. <NNT: 2016ORLE2051>. <tel-01674253>.